CHALMERS

Artificial Intelligence as decision maker in engine room maintenance planning

A case study based on interviews with Swedish shipowners of product tankers and their opinions regarding risks, advantages, and challenges

Bachelor thesis for Marine Engineering Program

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DEPARTMENT OF MECHANICS AND MARITIME SCIENCES

CHALMERS UNIVERSITY OF TECHNOLOGY
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PREFACE

Som avslutning på Sjöingenjörsprogrammet (180 hp) vid Chalmers tekniska universitet görs ett examensarbete som omfattar 15 högskolepoäng och därmed motsvarar halva sista vårterminen. Utöver den teoretiska utbildningen har även praktik ute på svenska fartyg av olika typ och ”trad” tillkommit vilket har givit en fin insikt i vad det framtida yrket innebär. För min del har praktiken gett en stor förståelse kring vikten av underhåll av system ombord, samtidigt som den teoretiska delen i utbildningen både har kunnat kopplat samman min erfarenhet ombord med teorin och sporrat en till att tänka framåt. Det finns förstås många aspekter på hur ”framåt” kan göras men artificiell intelligens har knappast frångått någon på senare tid, även om konceptet faktiskt är mycket äldre än mig och sannolikt även dig som läsare så verkar det på senare tid ha uppnått en mer användbar mening med hjälp av modern processorkraft. Vid första inläsningen får jag syn på att detta faktiskt är något som industrin anammar och kallar för en del av Industry 4.0 medan forskningen berättar att sjöfarten ligger efter, varför?

Jag vill tilldela ett stort tack till min handledare Magnus Hellman för goda diskussioner, enormt viktiga erfarenheter ”från sjön”, din fascination för ämnet och din kunnighet genom hela processen samt även för din goda positiva anda och för gott tålamod trots att ämnet stundtals lämnade oss sjöingenjörer.

Jag vill också tilldela ett tack till ”Alice & Helge Källssons Stiftelse för utbildning och forskning” som tilldelat mig både medel och motivation för att slutföra min studie.

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SAMMANDRAG (in Swedish)

Inom sjöfarten så bygger en stor del av fartygssäkerheten på underhåll av det maskineri som fartyget förlitar sig på. De flesta regler för sjöfarten ställs ut av IMO, EU och klassningssällskapen - i Sverige omvandlas oftast reglerna till nationella lagar. För produkttankerindustrin finns dock också OCIMF som ställer än högre krav och kontrollerar fartyg som godkänts för transport av oljeprodukter. För all sjöfart så är underhållskostnader en större del av de operativa kostnaderna och för att följa regelverken krävs att man följer tillverkarens rekommendationer vilket kan innebära att man byter ut delar i förtid. För att komma bort ifrån det har man redan utvecklat s.k. konditionsbaserat underhåll där man analyserar delars verkliga status, exempelvis med hjälp av sensorer. Numera har AI blivit en gångbar metod tack vare modern processorkraft och har redan blivit vanligt förekommande inom processindustrin på land för att förutse underhåll av maskiner. Denna studie syftar i att ta reda på åsikter inom den svenska produkttankersektorn vad gäller AI som beslutsfattare i underhållssystemet i maskinrummet ombord – vilka risker, fördelar och hinder kunde ses. Studien fann att utveckling av sådana AI system nog måste härstamma från tillverkarna av motorer eller andra system, för att kunna bli klassade och senare godkända av oljebolagen. En minskad arbetsbörda ombord var både en potentiell vinning och ett krav samtidigt som risken var att arbetsbördan kunde öka hos rederiet om systemet inte fungerade så som tänkt.

Nyckelord: artificiell intelligens, maskininlärning, befraktning, underhållssystem, sjöfart, produkttanker

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ABSTRACT

The safety and security of a maritime vessel is to a big extent due to the maintenance of the machinery which supports it. In the maritime industry, regulations from the International Maritime Organization and classification societies set regulatory standards of operation. In the product tanker sector, OCIMF sets an even higher standard and controls the vessels which are shipping oil products. For all parties in the shipping industry, maintenance costs are a big part of the operating expenses and following the manufacturers' recommendation and parts are in many cases changed prematurely. To combat this, already approved methods of condition-based maintenance exist with sensors monitoring machinery. However, due to the new processing power of computers, AI is becoming a prevalent tool in the manufacturing industry (Industry 4.0) and in the evolution towards predictive maintenance, extending the lifetime of parts. This thesis was aimed to find the opinions of AI as a decision maker in engine room shipboard systems based on interviews with shipowners of Swedish flagged product tanker vessels as well as the risks, advantages, and challenges. The study found that development will most likely need to come from the manufactures of systems, be class approved and be shown to improve workload before implementation. The thesis also concludes that it is not likely that the workforce in the engine department could be lowered if an AI maintenance system was introduced and that the general opinion is that the risk of such system is that the workload increased.

Keywords: artificial intelligence, machine learning, shipping, maintenance system, maritime, product tanker

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ACRONYMS AND TERMINOLOGY

AI	Artificial Intelligence
ANN	Artificial Neural Networks
CBM	Condition-based Maintenance
CM	Corrective Maintenance
CMMS	Computerised Maintenance Management System
DoC	Document of Compliance
EU	European Union
FMEA	Failure Mode and Effect Analysis
FMECA	Failure Mode, Effect and, Criticality Analysis
FTA	Fault Tree Analysis
GT	Gross Tonnage
HMI	Human-Machine Interface
IACS	International Association of Classification Societies
IMO	International Maritime Organization
ISM	International Safety Management
MARPOL	The International Convention for the Prevention of Pollution from Ships
ML	Machine Learning
MW	Mega Watts (Power)
OCIMF	Oil Companies International Marine Forum
PdM	Predictive Maintenance
PM	Preventive Maintenance
PMS	Planned Maintenance System
RCM	Reliability Centred Maintenance
RO	Recognised Organisation
ROI	Return On Investment
SIRE	OCIMF’s Ship Inspection Report Programme
SMC	Safety Management Certificate
SMS	Safety Management System
SOLAS	The International Convention for the Safety Of Life At Sea
UN	United Nations

1. INTRODUCTION

Artificial intelligence (AI) offers a transformative potential which can be compared to the implications of the industrial revolution within a wide range of industrial, intellectual, and social applications. The pace of change in this new AI technological age is staggering (Dwivedi et al., 2021). Simulations show that 70 percent of companies might have adopted at least one type of AI technology by 2030 and show a widening gap in cash flow between companies that fully absorb AI tools by 2030 and those that do not (Bughin et al., 2018).

In the manufacturing industry, which currently undergoes a transformation called the fourth industrial revolution (Industry 4.0), AI tools are becoming prevalent. Maintenance is one area where cost and machinery down time can be lowered by adopting predictive maintenance (PdM) powered by AI (Abidi et al., 2022) which extends a condition based maintenance (CBM) approach to maintenance (Achouch et al., 2022). The main advantage of PdM is to predict when maintenance is needed (Abidi et al., 2022), hence not waiting for a failure before changing parts in an unplanned manner as in corrective maintenance (CM), nor changing parts unnecessarily and prematurely as in preventive maintenance (PM) (Pascual, 2015).

In the maritime industry, the maintenance costs of a ship can represent between 20% and 30% of the ship's operational expenses. Also, unexpected repairs and down time can risk the operability of the ship and the possibility for the shipowner to generate profit from the ship's operation (Lazakis & Ölçer, 2016). Currently less than 2% of the world fleet employ a CBM arrangement, although, this is expected to rise to 10% in the next 10 years and can result in cost reductions for the shipowner partly due to improved maintenance scheduling (DNV GL, 2021, April 7). In the past decade, several research articles discusses approaches to AI powered PdM for different marine engine room shipboard systems as discussed by Berghout et al. (2021), Cheliotis et al. (2022), Coraddu et al. (2016), Jimenez et al. (2020), Makridis et al. (2020), Moschopoulos et al. (2021), and Park & Oh (2023).

However, challenges to adopting AI exist. For example, large amount of data may be needed in training the AI to be able to correctly recognize a developing machinery failure, and such data might not exist for a ship's machinery systems (Cheliotis et al., 2020). Other challenges include labour impact, reskilling of workers, deciding to which extent AI can operate autonomously, how to make AI decisions transparent and explainable enough for humans to trust and, who has the responsibility following an AI decision (Dwivedi et al., 2021; Makridakis, 2017).

1.1 Background

Historically, the maintenance approach of machinery in the industry has shifted from repairs only after a failure was noticed, to a more systematic approach of preventative maintenance and to the most modern approach of predictive maintenance based on the actual condition of a machine etc. If the analysis of a machine's condition and its components is done accurately, planning of maintenance could be optimized and the maintenance cost could be lowered as well as obtaining a lowered risk of unexpected failures and costly down-times (Pascual, 2015).

Today, most of the marine maintenance approaches on board merchant ships follow a preplanned schedule in line with PM and only a small portion of the world fleet employ a CBM approach (DNV GL, 2021, April 7; Kimera & Nangolo, 2019). According to Kimera & Nangolo (2019), CBM and PdM are the preferred approaches to maintenance in newer builds of merchant ships. As an example, one major marine engine manufacturer offers PdM for marine ships as a remote service driven partly by AI and partly by experts (Wärtsilä Corporation, 2021). In the manufacturing industry, application of artificial intelligence is becoming prevalent and can efficiently predict future conditions of components as demonstrated by Abidi et al. (2022).

1.2 Aim of the study

The report aims to investigate the current opinions of using AI as decision maker in engine room maintenance planning systems of Swedish flagged product tanker vessels. It will be based on interviews with Swedish shipowners in line with the delimitations of the report. The report aims to find opinions regarding risks, advantages, and challenges of such systems and for which engine room machinery or shipboard system AI might be suitable.

1.3 Research questions

- What are the Swedish shipowners' opinions of using AI as decision maker in engine room maintenance planning systems:
    - what risks, advantages, and challenges can the shipowners identify?
- For which engine room machinery or engine room shipboard system might AI be suitable?
    - Are there differences in opinions when looking at different onboard systems such as the main engine, auxiliary engines or other auxiliary systems?

1.4 Delimitations

Only Swedish shipowners which operates product tanker vessels under Swedish flag are selected for this thesis. Vessels with propulsion power less than 3 MW and vessels solely trading in inland waters will be excluded. Also, only engine room shipboard systems and machinery will be discussed in the thesis. The thesis will not discuss the economic perspective of AI system implementation. AI systems designed for surveillance and control of the crew will not be discussed, nor the possible social impact of such systems.

2. THEORY

2.1 Maintenance in maritime shipping

In international shipping, the International Maritime Organization (IMO) is the United Nations' (UN) specialized agency responsible for measures to improve the safety and security of international shipping and to prevent pollution from ships. IMO currently has 176 member states of which Sweden is included and is obliged to comply with the IMO treaties by implementing the treaties into national law (International Maritime Organization, 2019). Further, the European Union (EU) may adopt the treaties for its member states and following the regulations by IMO described in this chapter, both the EU (Regulation of the European Parliament and of the Council 2006/336/EC) and Sweden have adopted the regulations into their legislations (TSFS 2009:1; TSFS 2017:26). Furthermore, Classification (Class) Societies provide assurances that ships are up to standards and stated class rules, historically for insurance purposes however nowadays also to provide services of issuing certificates as Recognised Organisations (ROs) on behalf of states. More than 90% of the world's cargo carrying tonnage (GT) is covered by class rules set by the 12 member societies of the International Association of Classification Societies (IACS).

2.1.1 Regulations concerning marine maintenance

The International Convention for the Safety Of Life At Sea (SOLAS), amended by all flag states through the International Maritime Organization (IMO), states in Chapter IX (9) of SOLAS: it is mandatory to comply with the International Safety Management (ISM) code for all passenger ships and for trading vessels (e.g. oil tankers, cargo ships) of 500 gross tonnage (GT) and greater. Moreover, the regulation applies to ships since 1 July 1998 regardless of construction date and states that the ship operating company must hold a Document of Compliance (DoC) and the ship, a Safety Management Certificate (SMC) issued by the flag state's administration (International Maritime Organization, 2020). To comply with the parts of the ISM code concerning maintenance, a Safety Management System (SMS) must be developed and adopted which includes maintenance schedules, procedures for maintenance and inspection. Also, the ISM code requires documentation, record-keeping, and audits to assess the ship's effectiveness of the SMS and ongoing compliance with the requirements of the code (International Maritime Organization, 2018).

To support its members, IACS has published "A Guide to Managing Maintenance in Accordance with the Requirements of the ISM Code" which explains how to interpret the ISM code regarding maintenance of the ship. The first paragraph of the ISM code concerning maintenance states:

"The Company should establish procedures to ensure that the ship is maintained in conformity with the provisions of the relevant rules and regulations and with any additional requirements which may be established by the Company." (International Maritime Organization, 2018). According to IACS (2018) the previous paragraph should be interpreted as:

"The procedures should be documented, and should ensure that applicable statutory, class, international (e.g. SOLAS, MARPOL) and port state requirements are met, and that compliance is maintained in the intervals between third-party surveys and audits. The maintenance procedures should also include any additional requirements established by the Company. These may arise, for example, from an analysis of the maintenance histories of machinery and equipment, from the particular demands of a ship's operations, or from a manufacturer's recommendations.".

In addition, several other clauses in the ISM code apply and are further explained in the guide along with keys to establish a systematic approach to maintenance (IACS, 2018).

2.1.2 Systematic approach to marine maintenance

In following a systematic approach to marine maintenance, every ship should establish a database of machinery and equipment based on risk assessments which for every object includes maintenance intervals, method and frequency of inspections, acceptance criteria (pass/fail), responsibility assignment and reporting requirements – a Planned Maintenance System (PMS) which includes the following according to IACS (2018):

- The maintenance intervals are established based on the manufacturer's recommendations, condition monitoring techniques, practical experience, and historical trends in the results of inspections. Also, the intervals depend on the equipment's use, if used continuous, as stand-by or in case of emergency. Moreover, class, conventions, flag state and the shipping company may have specific requirements.

- Inspections should be based on planned routines where acceptance criteria are established as well as how the inspection is performed and recorded. For example, inspections may be conducted by visual inspection or by vibration/pressure/temperature/electrical/load measurement or testing water tightness and should be performed with calibrated and accurate testing equipment.

- Records of the maintenance reports not only demonstrate compliance with the ISM code, but they also serve as valuable information from which analysis can be conducted and in turn lead to changes in the established procedures for inspection and maintenance, reducing unnecessary work and the frequency of failures.

To summarise, a Swedish flagged product tanker vessel is obliged to follow the regulations set by the IMO which are adopted into regulations of the European Union and in Swedish law. Concerning maintenance, SOLAS and ISM (adopted by Swedish law) requires approval from the Swedish Transport Agency (Transportstyrelsen or appointed RO) to gain a DoC for the shipping company and a SMC for each ship, approval of an established SMS and in turn, approval of an established PMS which governs and records the ship's maintenance tasks. The above described vessel is subject to audits from the flag state (Sweden), the port state (visiting state), Class (RO) and, OCIMF (described below in *2.1.4*), all which audits the compliance with the regulations and rules set by the above mentioned governmental or non-governmental bodies.

2.1.3 Engine record book

For Swedish flagged vessels, Sjölagen (SFS 1994:1009) and Transportstyrelsen (TSFS 2010:18) also regulates that an engine record book which represent a legal document must be kept onboard. Concerning maintenance, the engine record book must contain any maintenance performed on machinery under the Chief engineers responsibility. Also, any alarms, malfunctions, accidents or audits must be logged in the record book. In case of an accident or an incident, the engine record book must be presented to the authorities in charge of an open investigation into the accident or incident. TSFS 2010:18 allows for the use of approved methods of electronical record keeping to replace a physical record book, or to replace part of the required record keeping in the physical book (see *Chapter 2.2.5*).

2.1.4 Oil Companies International Marine Forum and SIRE

Within the maritime shipping industry concerning the shipment of oil products, the oil companies have united and created the Oil Companies International Marine Forum (OCIMF) which is non-governmental, as a response in a concern of safety and standards within the tanker sector. Its primary aim is to promote safe and environmentally responsibility transportation of oil and gas products. To achieve this, OCIMF performs inspections called "vetting" in which a vessel employed in shipment of oil products is inspected every 6 to 12 months. In a vetting, compliance of IMO regulations and compliance of rules from the classification societies are checked to ensure the vessel maintains a high standard of safety and is allowed to transport products from OCIMF's members. OCIMF's Ship Inspection Report Programme (SIRE) is used in the inspections which guides the survey agent in assessment of the vessel, its crew, and the company. In the SIRE Vessel Inspection Questionnaires for Oil Tankers (VIQ), assessment of the ship's PMS is included (OCIMF, 2019).

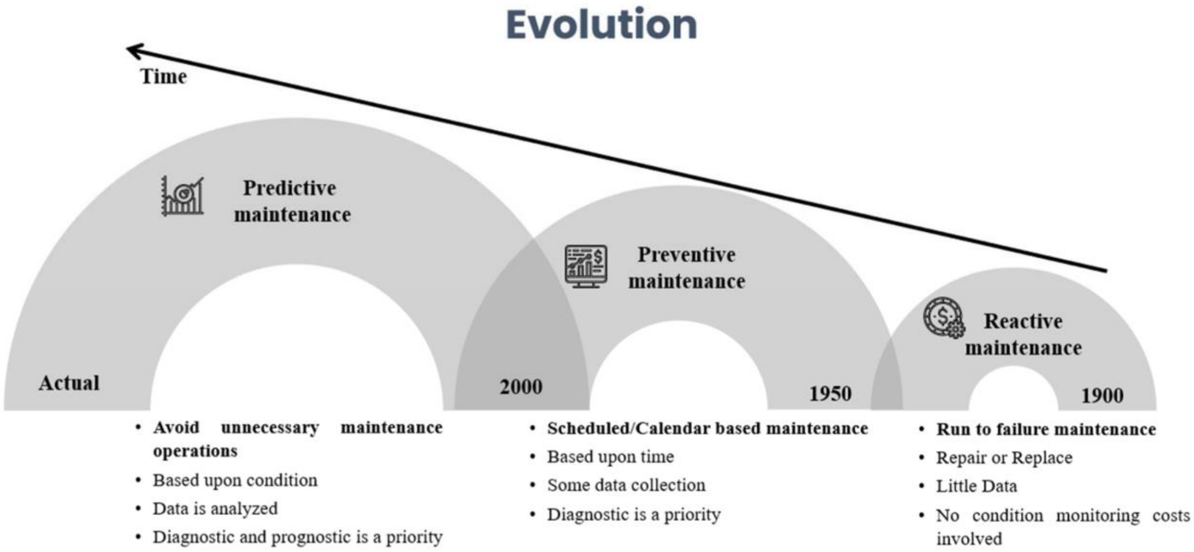
OCIMF currently develops SIRE 2.0 and the new survey programme will provide a more accurate assessment of vessels using modern web-enabled tools which makes for a more equal valuation and possibilities for the surveyor to be more standardised (OCIMF). Expressed by both the representatives Company A and B and evaluated in *Chapter 5*, SIRE 2.0 could have a major impact upon maintenance systems as according to them, all maintenance must be done "according to manufacturer's recommendations".

2.2 Maintenance approaches in engine room maintenance

In this chapter, a brief history of the main maintenance approaches tied to the marine sector is described, as well as today's tools for maintaining a PMS (such as computerised PMS/CMMS) and examples of special Class rules for gaining a survey arrangement based on condition-based maintenance.

The evolution of maintenance approaches in the industry (as shown in *Figure 1* below*)* has mainly been driven by profitability, price, reliable delivery, innovation, product quality and safety (Dhillon, 2002). In shipping, safety includes both the environmental hazards and safety for personnel and cargo which are the main drivers of regulations described in *Chapter 2.1*, leading to the requirement of an established PMS on ships. Today, most of the marine maintenance follow a preplanned schedule in line with preventative maintenance (PM) (Kimera & Nangolo, 2019). According to DNV GL (2021, April 7), Jimenez et al. (2020) and Kimera & Nangolo (2019), condition-based maintenance (CBM) and predictive maintenance (PdM) are expected to be the maintenance approaches of choice in the future new buildings of vessels.

Figure 1
Evolution of maintenance activities and methods.



Note. A figure describing the evolution of maintenance approaches in the industry and key attributes. From "On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges" by Achouch, M., Dimitrova, M., Ziane, K., Sattarpanah Karganroudi, S., Dhouib, R., Ibrahim, H., & Adda, M., 2022, Applied Sciences, 12(16), 8081. (https://doi.org/10.3390/app12168081). Copyright 2022 by the authors, reused under the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

2.2.1 Corrective maintenance

Corrective maintenance (CM), also called reactive maintenance (in *Figure 1* above), may be defined as the actions taken to repair an equipment to its operational state following a failure, or deficiencies found during preventive maintenance. CM is usually unscheduled following unpredictable maintenance needs and if deemed necessary to repair urgently, rescheduling of workers planned activities are required (Dhillon, 2002). According to Kimera & Nangolo (2019) and as shown in *Figure 1*, CM is an outdated approach to maintenance as ships are capital intense assets where maintenance cost is about 20-30% of ships' operational budget, and unexpected repairs and down time risk the ships' profit and safety as CM cannot prevent failure (Abidi et al., 2022; Lazakis & Ölçer, 2016).

2.2.2 Preventive maintenance

The main objective of preventive maintenance (PM) is to keep equipment in a satisfactory operational state through scheduled inspection, detection and maintenance prior to failure occurs. Elements of PM are periodical inspections, servicing (e.g. cleaning, lubricating), calibration, testing, alignment and adjustment, and installation, where the latter consists of periodic replacement/overhaul of items with limited lifetime. Compared to CM, PM allows for better workforce scheduling and maintenance planning and less down time due to failures which also promotes better health and safety for maintenance workers. PM do also have disadvantages including using more spare parts which could be costly, down time and risks during installation, and failures in new parts (Dhillon, 2002). According to Kimera & Nangolo (2019), PM is the most practiced maritime maintenance approach where a preplanned schedule depending on the machinery's age or running hours call for maintenance, regardless of maintenance being required or not. Also, as it is not possible to perform every maintenance activity while the ship is operational, ships are routinely scheduled for dry dock maintenance every 2-5 years.

However, PM cannot anticipate “random” failures occurring before a planned inspection or installation in which case it falls back on CM (Abidi et al., 2022; Kimera & Nangolo, 2019).

2.2.3 Reliability Centred Maintenance

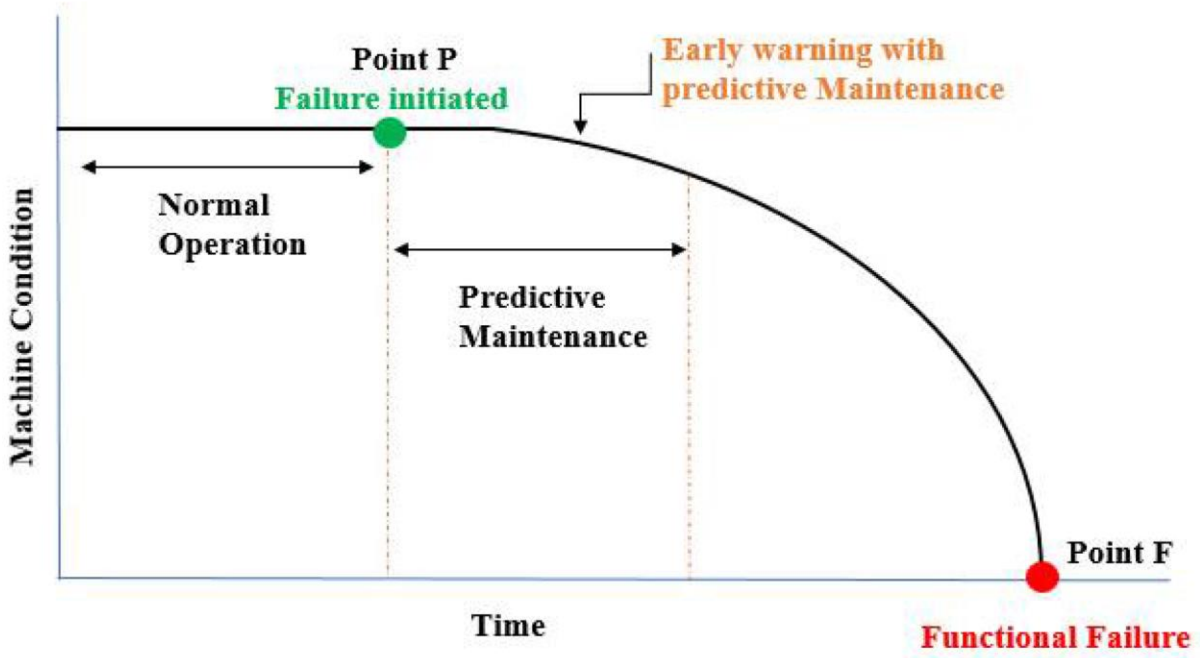
Originating from the aircraft industry, reliability centred maintenance (RCM) can be seen as a mixture of CM, PM and predictive maintenance (Jimenez et al., 2020) and aims at maximising safety of equipment and people, and minimising unnecessary costs of maintenance by focusing on the necessary function of a system while removing or avoiding unnecessary PM tasks where possible (Rausand, 1998). Historically, a focus on age-related failures dominated and experience governed how to find the best schedule for maintenance. However, several studies have shown that random failures occur more often than the age-related failures in as much as 89% to 11% of failures, and for which as mentioned above, a PM approach can not anticipate nor prevent (Nowlan & Heap, 1978). Following an analysis of a system through data analysis of components and a Failure Modes, Effects and, Criticality Analysis (FMECA) as the main methods included in RCM - one could decide which maintenance schedule to adopt for each part based on the results of the analysis. The main tasks for a component’s maintenance could be categorised into: scheduled on-condition task (condition-monitoring/inspection), scheduled overhaul, scheduled replacement, scheduled function test or, run-to-failure (CM) – depending on its criticality and effect on the system and the safety of equipment and people and, economy (Rausand, 1998).

2.2.4 Condition-based maintenance and Predictive maintenance

As sensors for condition-monitoring, data-processing power and, their associated costs all have improved – a shift from manual analysis toward computer assisted analysis could be seen since RCM was introduced (Jimenez et al., 2020; Pascual, 2015). With real-time monitoring and assessment of equipment’ condition, condition-based maintenance (CBM) can detect early signs of potential failure to determine when maintenance should be performed. Various condition monitoring techniques exist such as oil and water analysis, thermographic, pressure, vibration, acoustic, or electrical analysis etc. and with preset alarm levels it is possible to prevent a failure or problem. By extrapolating the historical values from the condition monitoring techniques, estimations of when alarm levels will be reached may be calculated and further give information used to plan maintenance and avoid failure ahead of time, which is called predictive maintenance (PdM) and shown in *Figure 2* below. Furthermore, with knowledge of the actual condition of the components, changing the component prematurely and unnecessarily as in PM can be avoided, increasing the lifetime of the component (Pascual, 2015).

Figure 2

Potential failure diagram presenting inspection intervals and predictive maintenance.



Note. A diagram illustrating when predictive maintenance should be performed in time based on the machines condition. From "On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges" by Achouch, M., Dimitrova, M., Ziane, K., Sattarpanah Karganroudi, S., Dhouib, R., Ibrahim, H., & Adda, M., 2022, Applied Sciences, 12(16), 8081. (https://doi.org/10.3390/app12168081). Copyright 2022 by the authors, reused under the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

However, manual gathering of appropriate data with portable measurement equipment (offline) or sampling systems (e.g. oils sampling) may be time consuming and if not recorded correctly and analysed using maintenance software, data may be rendered useless. On newer ships, fixed installation of sensors which gather data in real time (online) are gaining popularity, despite their higher initial cost (DNV-GL, 2021; Kimera & Nangolo, 2019). Kimera & Nangolo (2019) summarizes that PdM is the most preferred maintenance approach for mechanical systems in new ship designs although currently less than 2% of the world fleet employ CBM according to DNV GL (2021, April 7) who also expects a rise in this maintenance approach in the near future. Moreover, Jimenez et al. (2020) concludes that PdM within shipping will undergo an accelerated development as the manufacturing industry is ahead in the science of data and the benefits of PdM powered by artificial intelligence is substantial and a great tool for data analysis and anomaly recognition, where a human eye might miss such patterns.

2.2.5 Planned maintenance system and Computerised maintenance management system

Following the regulations described in *Chapter 2.1*, a PMS function is to keep records of all the ships equipment including deck, engine, firefighting, and lifesaving equipment as well as their maintenance schedules, maintenance records, history of breakdowns, spare parts, dates of Class surveys etc. (IACS, 2018). Responsibility at Class surveys of different parts of the PMS is divided between deck and engine officers, and for the machinery PMS the Chief engineer has responsibility according to DNV-GL (2022), which is a member society of IACS and also states which equipment belongs to which department in its rules for ships.

It is safe to say that most modern ships of the size covered in this report, uses computer software to manage the PMS efficiently. In the manufacturing industry, such software is categorised as a computerised maintenance management system (CMMS) (Pascual, 2015). However, in the shipping industry, different Class societies have different terms for CMMS. For example, DNV-GL (2022) uses the term machinery PMS or MPMS with the addition of requirements that it must use an approved computer based software. If complying with all requirements, the ship may be approved for MPMS survey arrangement which shifts part of the survey from manual inspections of machinery toward confirmation that maintenance has been conducted and recorded accordingly in the software. Moreover, DNV-GL offers a survey arrangement called machinery PMS digital (MPMSD) which also transfers PMS data to the Class society servers, enabling parts of a survey to be conducted at a distance. Furthermore, DNV-GL offers a machinery CBM (MCBM) survey arrangement where the manager is allowed to adjust maintenance intervals based on condition monitoring of approved parts of the ship (DNV-GL, 2022). According to Kimera & Nangolo (2019), the majority of CMMS installed on ships are used for PM and does little analysis of the maintenance data reports.

Several companies which develop CMMS software exist, and some companies extend the software into an information management system for managing a fleet of vessels where CMMS is one part of the software's capabilities. One example is K-Fleet which regarding engine room maintenance, also has functionality for spare part inventory keeping onboard and electronical engine record book keeping (see *Chapter 2.1.3*) as well as functionality for Class and OCIMF surveys (Kongsberg, 2024).

2.3 Artificial Intelligence

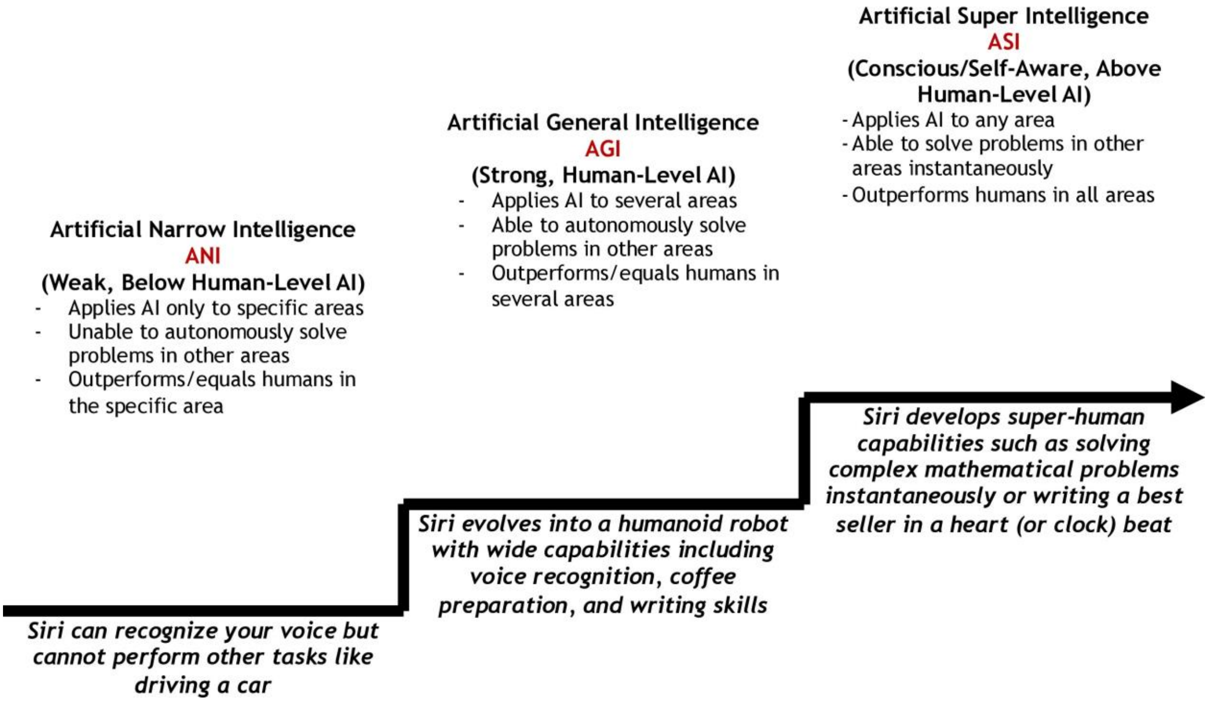
In this chapter, a brief description of artificial intelligence (AI) technology is given as well as examples of previous research into using AI for predictive maintenance onboard ships. Lastly, challenges and risks which could be seen by previous researchers of AI, are described.

2.3.1 Definition of Artificial Intelligence

"Artificial intelligence (AI) - defined as a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation". Furthermore, AI could be classified based on its stage of evolution or intelligence (described in *Figure 3* below) and its type of competence (shown in *Figure 4* below) (Kaplan & Haenlein, 2019).

Figure 3

Stages of Artificial Intelligence



Note. A figure showing different classifications of AI and their attributes. From "Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence" by Kaplan, A., & Haenlein, M., 2019, Business Horizons, 62(1), 15-25. (https://doi.org/10.1016/j.bushor.2018.08.004). Copyright 2018 Kelley School of Business, Indiana University. Reused with permission.

Within the scope of this report, the stage "Artificial Narrow Intelligence" and competence "Analytical AI" are of interest. In contrast to AI, Expert systems is described by Kaplan & Haenlein (2019) as a preprogrammed set of rules lacking the ability to learn from external data and such system solves problems by comparing to a list of criteria. However, according to Kühl et al. (2022), AI could be built based on rules or formulas although most modern AI cases utilize a machine learning (ML)-based executing backend, either as a once-trained static ML model or an adaptive ML model which continuously learns and builds up experience.

Figure 4

Types of AI systems.

	Expert Systems	Analytical AI	Human-Inspired AI	Humanized AI	Human Beings
Cognitive Intelligence	×	✓	✓	✓	✓
Emotional Intelligence	×	×	✓	✓	✓
Social Intelligence	×	×	×	✓	✓
Artistic Creativity	×	×	×	×	✓
		Supervised Learning, Unsupervised Learning, Reinforcement Learning			

Note. A table of different types of AI and their included intelligence attributes. From "Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence" by Kaplan, A., & Haenlein, M., 2019, Business Horizons, 62(1), 15-25. (https://doi.org/10.1016/j.bushor.2018.08.004). Copyright 2018 Kelley School of Business, Indiana University. Reused with permission.

Analytical AI includes the skill of cognitive intelligence with competencies related to pattern recognition in data and systematic thinking with which the model uses to inform future decisions based on learning from experience – it generates a cognitive representation of its world. To achieve its experience from past data, different types of training or learning processes exist: Supervised learning, unsupervised learning, and reinforcement learning (Kaplan & Haenlein, 2019).

- Supervised learning consists of labelled data which maps a set of inputs to a set of labelled outputs. For example, a large database of labelled images to separate those images showing a Chihuahua and those showing a muffin.
- Unsupervised learning where instead the inputs are labelled but not the output. The algorithm needs to derive the output from the structure of the data itself and it is not possible to assess the correctness. For example, speech recognition (Siri, Alexa etc.).
- Reinforcement learning, where the system is designed to maximize its output variable with its decisions which impacts the output. For example, an AI system learning to play Pac-Man where a higher score rewards the system.

According to Achouch et al. (2022), a large group of different AI techniques which are inspired by the human brain cells are called artificial neural networks (ANNs) or deep learning. Both supervised and unsupervised techniques exist with the goal to learn from unstructured or unlabelled data. Deep learning techniques can be useful in fault detection and failure prediction as a mean to learn from a large amount of sensor data and to mitigate the challenges of data labelling further explained in the following sections.

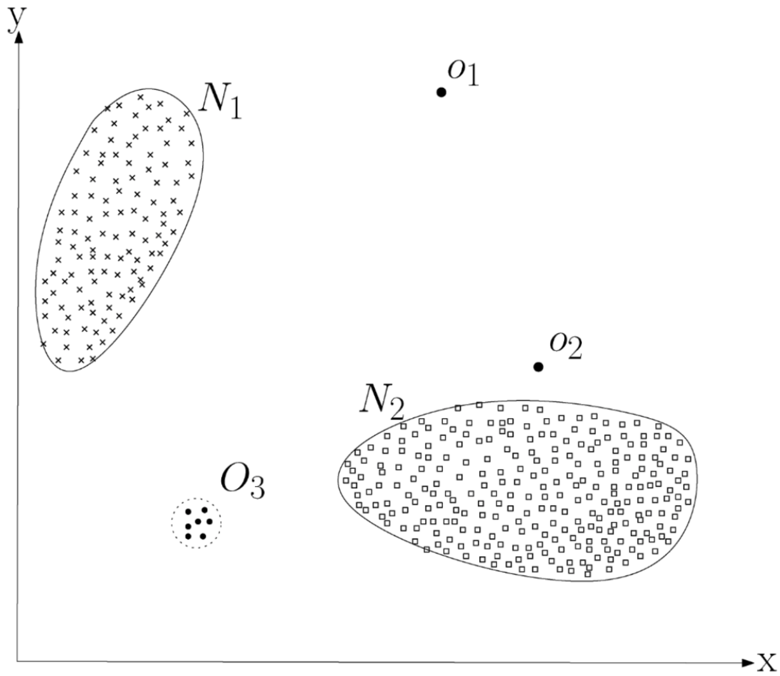
2.3.2 Artificial Intelligence in fault detection

In fault detection of mechanical systems, anomalies are required to be detected from the observed data obtained from different types of sensors. If the model is accurate, the anomaly might originate from a defective part in need of attention. Hence, the model needs to be trained with data to determine what is labelled *normal* and what is labelled *anomalous* to be able to compare against the observed data. However, labelling of the data is often done manually by human experts and to obtain anomalous data covering all possible failures, might be impossible or expensive. For example, in air traffic a failure resulting in gaining anomalous data might also result in a catastrophic event. Consequently, supervised learning with a training data set of both labels normal and anomalous, is challenging to obtain (Chandola et al., 2009).

Chandola et al. (2009) discusses that normal data originating from components without defects are typically available in which case a semi-supervised training technique is applicable. In semi-supervised training, only data labelled as normal is used as training data and the model treat observed data not recognized as normal, as anomalous. In *Figure 5* below, most observations lie in the normal labelled regions (N1, N2), however some points (O1, O2, O3) lie outside those regions and are treated as anomalies.

Figure 5

A simple example of anomalies in a two-dimensional data set.



Note. A simple example of anomalies in a two-dimensional data set. From "Anomaly detection: A survey" by Chandola, V., Banerjee, A., & Kumar, V. (2009). ACM Computing Surveys, 41(3), pp 1-58. (https://doi.org/10.1145/1541880.1541882). Copyright 2009 ACM (Association for Computing Machinery). Reused with permission.

Furthermore, Chandola et al. (2009) describes that techniques for anomaly detection exist which operate in an unsupervised learning mode and do not require training data. Instead, the assumption is made that normal data is far more frequent than anomalies in the observed data and the model can derive its experience from that data. However, if the model cannot see that the assumption is true in the observed data, a false alarm may be produced.

2.3.3 Artificial intelligence in predictive maintenance

Numerous different techniques for developing ML methods and algorithms are described in the literature and a selection of relevant literature reviewed in this report are presented in *Table 1*. However, discussing ML algorithms in detail are not within the scope of this report while an overview of key steps in building an AI-driven PdM system, is of interest. Achouch et al. (2022) summarises a workflow of a PdM project with 5 essential steps based on the research by Sipos et al. (2014) and Ton et al. (2020), illustrated in *Figure 6* below:

Figure 6
Workflow of predictive maintenance.

Note. Workflow for building an AI based predictive maintenance system. From "On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges" by Achouch, M., Dimitrova, M., Ziane, K., Sattarpanah Karganroudi, S., Dhouib, R., Ibrahim, H., & Adda, M., 2022, Applied Sciences, 12(16), 8081. (https://doi.org/10.3390/app12168081). Copyright 2022 by the authors, reused under the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Understanding the project's needs
   Includes a full understanding of the system and all equipment of interest and their operation to be able to decide what should be measured, which sensors are needed and what type of failures could occur.
2. Data collection, understanding and preparation
   Collection and transfer of sensor data to a database, understanding of what data to analyse, its quality and relationships of other sensor data. Preparation of data includes removal of noise, errors, and missing data to be able to structure the data in a way which a model could use as input.
3. Data modelling
   Choosing and testing algorithms to obtain the best ML model to receive correct output based on the input.
4. Evaluation and deployment
   Evaluation of the model's accuracy and relevance. Deployment, if the model performs satisfactorily.
5. Decision making
   If a fault is recognised by the model, the problem needs to be identified and a plan set up to rectify the problem based on the criticality of equipment, repair time and cost. Action of maintenance is scheduled including checking availability of manpower and

spare parts. Also, if maintenance of other parts could be done to advantage in combination with rectifying the main problem, this could be scheduled as well. Lastly, the decisions taken should be reviewed and evaluated to allow for future improvements.

Table 1
List of relevant literature.

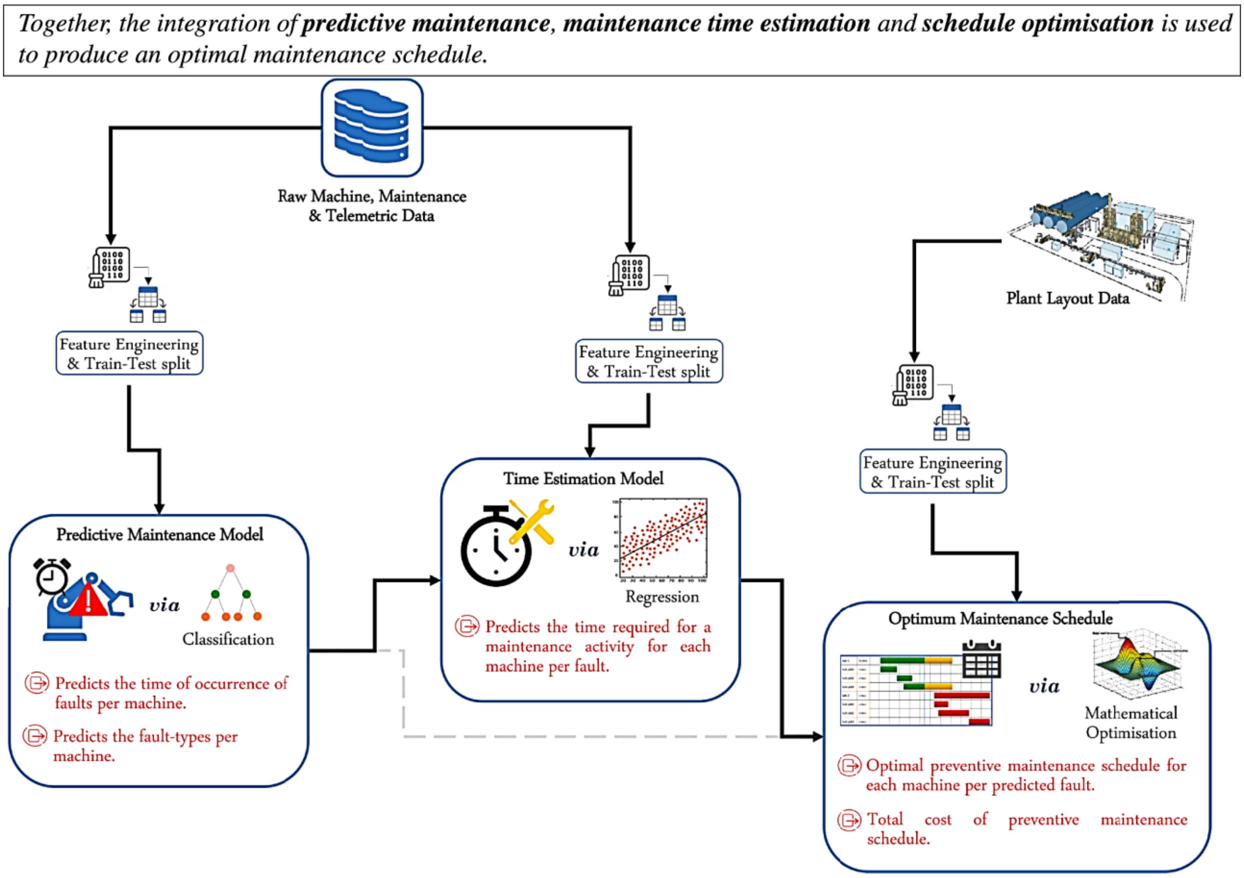
Author (Year)	Features	Conclusion
(Coraddu et al., 2016)	Forecasts degradation of a simulated marine COmbined Diesel eLectric And Gas turbine propulsion plant.	Shows effectiveness of proposed ML approaches and a first step toward effective and actionable CBM systems, powered by ML.
(Lazakis et al., 2018)	Artificial Neural Networks (ANN) used to predict main engine cylinder exhaust temperatures through monitoring affecting systems obtained through Fault Tree Analysis (FTA) and Failure Mode and Effect Analysis (FMEA).	Trained with 30 hours of actual data from a Panamax container ship, then predicted exhaust temperatures for the next 10 hours based on other monitored data, with an error rate <1% compared to the actual observed ship data.
(Jimenez et al., 2020)	Initiates development of an AI based PdM solution using real-time monitoring data from a seismic survey ship, preparation of data for development of ML models.	Concludes that the results show great potential for development of a predictive model. However, more research into integrating FMEA and failure detection are some of the issues needed to be solved,
(Yeardley et al., 2022)	Proposes a methodology where ML predicts machine faults and repair time and uses that data to schedule maintenance based on available resources in the manufacturing industry (Industry 4.0).	Concludes that the methodology provided high quality maintenance schedules and that predictive maintenance showed lower cost, personnel requirement, and overall maintenance times when maintenance was predicted and scheduled before failures, compared to maintenance performed after a failure had occurred.
(Achouch et al., 2022)	Literature review of PdM in Industry 4.0	Presents a platform that aims at implementing a plug-and-play type of maintenance hardware with integration of different types of sensors and maintenance approaches featuring PdM and presented in one human-machine interface (HMI).

Note. A table describing the most relevant scientific literature for this thesis.

Further integration of AI is proposed by Yeardley et al. (2022), where AI also makes decisions in order to also optimise a work schedule of maintenance tasks. In contrast to the workflow described above and by Achouch et al. (2022), Yeardley et al. (2022) adds two more stages, as shown in *Figure 7* below. The second stage, a ML model uses maintenance history to estimate time consumption for a maintenance activity followed by stage 3 which optimises a work schedule. The latter is based on available personnel and maintenance is scheduled to take place before a failure has occurred.

Figure 7

A flowchart of the ensemble of machine learning techniques used to produce an optimum maintenance schedule.



Note: A flowchart of the ensemble of machine learning techniques used to produce an optimum maintenance schedule. From “Integrating machine learning techniques into optimal maintenance scheduling“ by Yeardley, A. S., Ejeh, J. O., Allen, L., Brown, S. F., & Cordiner, J., 2022, Computers & Chemical Engineering, 166, 107958. (https://doi.org/10.1016/j.compchemeng.2022.107958). Copyright 2022 by the authors, reused under the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

2.3.4 Challenges

2.3.4.1 Data quality and availability

Importing condition monitoring data into a database which the AI model can use, can be challenging. Different types of sensors generate different data types and sampling rates and the data needs to be generalised (Pascual, 2015). Data from sensors may contain signal noise which is hard to remove and might resemble an anomaly. In addition, sensors are subject to downtime, degradation or failures and if the data is not properly cleaned from noise and other sensor malfunctions, the model will not work properly (Achouch et al., 2022). Furthermore, it is hard to find all normal behaviour data and a distinguished line between a normal and an anomalous observation. Also, the availability of labelled data for training the AI model may be problematic and failure data might not exist (Chandola et al., 2009).

If sensors, controllers, or other data sources do not provide accurate information, predictive maintenance may face challenges with the necessary confidence in the data which could result in incorrect predictions and missed urgency for maintenance or false alarms (Achouch et al., 2022).

2.3.4.2 Integration with existing systems and cost of development

Integrating AI into systems not designed for the purpose, may be challenging and require careful planning and substantial investment (Achouch et al., 2022). A distance between different sciences needed to fully understand and implement the system could be a challenge, with a mixed team of information technology experts and system engineers etc. (Paleyes et al., 2023). This thesis does not aim to calculate the costs further, however, it is safe to say that development of AI systems could be costly and it could be necessary to rebuild onboard systems to be able to extract the information correctly from sensors etc.

2.3.4.3 Skill of personnel and technical expertise

Machine learning models or AI systems which continuously re-train themselves using a feedback loop, can suffer from a weakened reliability in its results if the integrity or relevance of the data is not verified continuously, and could introduce anomalies in the normal data set (Paleyes et al., 2023). To avoid this drift phenomenon, the machine learning model needs to be updated by modifications to the code, model and the data which compared to traditional software updates is much more complex and require technical expertise. For the sake of this thesis, it is safe to say that these competencies normally do not exist in the onboard crew, nor in the shipowners’ staff on land.

3. METHODS

3.1 Summary of methods

In this chapter the methods used to answer the research questions are described, where the aim is to gain knowledge on the current opinions of using AI in maintenance planning for Swedish vessels according to the delimitations of the report. For this cause, the method chosen for data collection was semi-structured interviews with technical representatives from three Swedish shipping companies with different fleet size, presented in *Table 2* below. The results of the interviews were analysed and presented in the report and a conclusion towards the research questions was made (Denscombe, 2014). As such, the report was based on qualitative data gathered from exploratory case studies to reach detailed insight within the topic from a small sample group (Höst et al., 2006).

Steps taken during the study:

- Research was done to gain theoretical knowledge within the topic (see *3.3*, *5.1.1* and *Chapter 2*)
- Selection of interviewees was done (see *3.4* and *5.1.2*)
- Interview questions were constructed along with a presentation of the study meant to introduce the study to the interviewees (see *Appendix 1* and *Appendix 2*)
- Interviewees were contacted (see *3.4*)
- Interviews were conducted (see *3.5*)
- Transcription of the recorded interview material was done (see *3.3* and *5.1.1)*
- Coding and analysis of the material was done (see *3.3* and *5.1.1)*
- Research into emerged theory not previously foreseen was done (see *5.1.1)*
- The results were presented in the report and the analysis was laid ground for comparison against the theory, discussed and conclusions were made (see *Chapter 2, Chapter 4* and *Chapter 5*)

3.2 Theory material

In gaining knowledge of the main phenomena of using AI in maintenance planning, a thorough research into maintenance approaches, regulations and relevant areas had to be done as well. To be able to produce relevant interview questions and to analyse the data gathered, relevant literature had to be processed (Denscombe, 2014). The theory material was based on scientific articles mainly found through the online database “Web of science” and the referred material within those articles as well as relevant books. In finding material describing AI in connection with maritime maintenance, both “Artificial intelligence” and “Machine learning” were used as keywords.

3.3 Data collection and analysis

Data was gathered through semi-structured interviews with technical representatives of different shipping companies, as described in 3.5 Interviews.

Analysis of data was done in accordance with the guide by Bryman (2016), where the interview recordings were transcribed and the material was then coded into concepts and categories, or indexed. To fit the concepts, new theory material was gathered (see 3.2 Theory material) in case the theory to ground those concepts was not in the original. Also, as new concepts emerged, new questions for the following interviews were developed. The coded data from all interviews was summarized into categories, presented and discussed grounded in the theory material and a conclusion was made (Bryman, 2016).

3.4 Selection of interviewees

Selection of interviewees was done strategically in accordance with the guide by Bryman (2016) where sampling was done purposely and as a typical case sampling approach with the goal to sample cases which exemplifies a dimension of interest and are relevant to the research questions of the report. Being a non-probability approach, the results were not transferable or generalizable to a population. Two of the interviewees were contacted by telephone, one by e-mail and all agreed to an interview.

3.5 Interviews

To be able to get a good understanding of the shipping companies' opinions towards the research questions, a semi-structured interview approach was chosen. In addition to the precompiled main and supplementary questions, spontaneous questions derived from the interviewees' answers, further developed the interviews (Denscombe, 2014). Two of the interviews were conducted at the interviewees' offices in Swedish and recorded with the interviewee's permission. One interview was conducted in Swedish thru e-mail.

In advance of the interviews, each interviewee received an introduction to the study and its subject, and an anonymity guarantee (*Appendix 1*) along with the precompiled main questions (*Appendix 2*) to be able to give more accurate answers during the interview (Denscombe, 2014).

3.6 Ethical aspects

The interviewees, shipping companies and ships' names were treated with confidentiality and made anonymous in the report as protection for the interviewees against personal consequences (Denscombe, 2014). Companies were denoted "A", "B", "C" in the report as well as interviewees were denoted as representative of "Company A" etc. Only the author had knowledge of non-coded identities.

4. RESULTS

Following an analysis of the transcribed material obtained from the interviews of the shipping companies described in *Table 2*, the results are presented below.

Table 2
Interviewed shipping companies

Shipping company	Vessels in fleet	Engine crew size	Interviewee position
A	01-10	4-5	Technical Manager
B	11-20	3	Technical Coordinator
C	21-30	4	Vessel Operator

Note. A table of the sample group describing each shipping company's fleet size and typical vessel size based on engine crew size as well as the position of the interviewee.

4.1 General approach to AI in engine room maintenance

All the interviewed shipping companies had previously been introduced to the concept of AI analysis of the machinery in the engine room maintenance system. While all the interviewees believe that AI will have a part in such systems in the future or could see a potential of such systems, none of the companies have yet implemented or take part in development of AI systems. The common opinion is that development of such systems most likely will need to originate from the manufacturers of machinery systems and be approved by the classification societies. Furthermore, Company A and B points out that the oil companies own regulations for tanker vessels only allows for maintenance according to the manufacturers' recommendations in the coming SIRE 2.0. All the companies find that AI in maintenance systems needs further development and be approved by all regulatory authorities before being a system to consider implementing in their fleets. Also, any new system must be shown to be reliable and to decrease the workload for the engine crew before being considered for implementation. The representative of Company B also pointed out that it is not likely that vessels already built would be able to make a return on investment (ROI) with aftermarket fitting of an AI system and that it more likely would be introduced in a newbuilding.

4.2 Current engine room maintenance practices

All the companies' engine room maintenance system are mostly time-based maintenance or based on the running hours of a machinery in accordance with the classification societies approval and the manufacturers' recommendation, i.e., PM. To a varying degree, the different companies do employ condition-based maintenance on some vessels in their fleet.

Company A states that beyond following the preventative maintenance approach, they do performance tests and oil sampling tests. On their newest vessels, Company B do have class approval for CBM on the main engine which can allow for postponement of part replacement if in good condition. For example, changing pistons and cylinder liners could recently be postponed for one vessel at dry dock. Furthermore, the representative of Company B gave an example of where they have an after-market solution installed for the gearbox in some vessels, continuously monitoring vibration sensor data which are sent to the manufacturer of the internal bearings for analysis. From the analysis, Company B receives a current condition of the bearings and can predict maintenance. However, according to the representative, the analysis does not involve AI. Company C also employ CBM in some cases and on some vessels, with monitoring of some bearings and oil sample analysis as well as monitoring of the main engine, where data is sent to the manufacturer which then can give recommendations for maintenance.

4.3 Advantages and challenges of an AI based maintenance system

All the companies identified a reduced workload for the engine crew or the shipping company as a potential advantage of an AI based maintenance system. At the same time, a reduced workload was identified as a common prerequisite for the companies to even consider such a system. All interviewees expressed concerns in introducing an AI system that is not yet shown to be fully developed and fully trustworthy with the common opinion that this might instead increase the workload, either onboard for the engine crew or by having a need for a support team on land which monitors the system.

Both companies A and B identified postponement of parts replacement as an advantage - if an AI system could successfully predict the condition and maintenance need of the part. However, the representative of Company B addressed that for the main engine the main advantage is probably to get notified well before an imminent failure occurs, as postponement of part replacements for the main engine which are usually done at dry dock are not likely to further be postponed compared to the already established methods - the parts scheduled for replacement at a 5-year dry dock interval is not likely to last until the next dry dock if current methods would not approve the part. Furthermore, the representative of Company B develops that an AI maintenance system might be of more value for redundant systems, for example air compressors or the auxiliary engines. Company C expresses that it is important to start in a small scale to ensure that both data collection and analysis is done correctly by an AI system.

4.4 Safety and security

Companies B and C expressed concerns for a false sense of safety if an AI system falsely approves the state of machinery, which could lead to the crew being unaware of dangers, and accidents.

All respondents identified security risks with online data transfers. Companies A and B further developed that already today a great amount of data is transferred and that the classification societies have rigorous regulations for data security. Company B described that it is important data could only be allowed to travel in one direction to make it harder to influence the vessels data. Also, that they have means to physically interrupt the data stream to the vessels.

4.5 Engine crew and training

Both companies A and B believes there is no need to fundamentally change the education of the crew if AI systems are introduced and function the way which they could imagine. However, some courses might be necessary, and it is important that the crew have an interest in learning the system. Company B clarifies that an AI system will probably come from a third party or a manufacturer and should not affect the crew other than in assisting them. None of the companies believe such system will affect the number of personnel in the engine department while it might give the crew more time to complete more tasks. The representative of Company A expresses it is important not to ignore the crew's competence in introducing new systems. However, due to the difficult labour market in finding personnel, the representative sees that an AI system might be a necessity in the future and a solution might be to have fever personnel constantly traveling with a vessel and instead a support team which travels between vessels and conducts maintenance.

4.6 Engine room systems

The representative of Company A believes that AI analysis could serve in engine room shipboard systems which are not regularly maintained in which the crew seldom obtain an expertise. For example, the refrigeration and air conditioning systems which also are bound by regulations for handling coolants and logging transfers of coolant. The representative of Company B expressed that for the main engine it is not probable to postpone part replacement further, however gaining a notice well before a failure would be an advantage. Furthermore, the representative believes AI to be more advantageous in other systems which are redundant and in which there would be a greater gain in postponing part replacements. For example, air compressors and possibly even the auxiliary engines.

4.7 Summary of the results

- The shipping companies are positive to artificial intelligence in believing it will have a part in future engine room maintenance planning. However, none of the companies take any part in development of such systems.
- Development of an AI maintenance system must probably originate from the machine or engine manufacturers to get approval from classification societies. Also, in the tanker sector, oil companies own regulations for shipment of oil products further forces shipping companies to follow manufacturers' recommendations in maintenance.
- The main advantages of AI in engine room maintenance planning are thought to be a reduced workload and postponement of unnecessary replacement of parts. Also, to get notified before an imminent machine failure and avoiding accidents.
- Challenges of AI in maintenance planning are a need to be fully developed and trustworthy before shipping companies can consider adopting such a system as well as show to reduce workload and have economic gains.
- Risks identified by the shipping companies were a possible false sense of safety if the AI system does not make the correct decision and data security concerns. However, data security is already a concern in today's communications with the vessels and included in regulations from the classification societies.
- It is not likely that the engine room crew size could be made smaller than is today with an AI system. Other education for managing an AI system should not be necessary for the crew as the system itself should originate from third party or a machine manufacturer and be easy to use.
- Engine room shipboard systems mentioned where AI was thought to have most advantages were auxiliary systems and redundant systems as these could more likely gain from postponement of replacements compared to the main engine where warnings before a failure would be the main advantage.

5. DISCUSSION

5.1 Method discussion

In addressing the research questions of the thesis, an exploratory case study methodology was adopted according to Höst et al. (2006). This approach was deemed appropriate due to it allowing for an in-depth exploration of the thesis's topic in investigating a complex phenomenon within its real-life context based on semi-structured interviews with a small sample group. Semi-structured interviews were selected as the primary data collection method to allow for flexibility in exploring the participants' perspectives, only guiding the conversation towards relevant topics (Bryman, 2016). Three interviews were conducted to gain the results presented in the thesis. A larger sample group might have led to a broader result but not necessarily to a better understanding as the author believes that with the results from the interviews with the sampled group, the thesis's research questions were able to be answered with the expertise of the respondents. However, with different interviewees or a different sample group such as manufacturers of machinery equipment or engine manufacturers, the results may have been different.

5.1.1 Data Collection and analysis

As stated in *Chapter 3.3*, the main data collection method was through semi-structured interviews with technical representatives of Swedish shipping companies in the product tanker sector. At first, the idea was to cover a variety of shipping sectors, e.g., Tankers, RORO, and ROPAX. However, due to the time constraint of the thesis project it was necessary to limit the number of interviews to one sector. Consequently, it was not possible to compare opinions from different shipping sectors. Due to the results discussed in *Chapter 5.2*, the author believes that it is likely that the same challenges of system approvals from classification societies exist in all sectors and that a better result could be obtained through interviews directed toward the classification societies (i.e., IACS) and engine room shipboard system manufacturers, also proposed in *Chapter 7*.

In preparation of the interviews, theory material for the thesis which was considered relevant was gathered with the purpose of gaining knowledge required to conduct the interviews and, to present the concept for the reader. The theory material was primarily sourced from databases such as "Web of science" as the requirement for the thesis was to only use peer-reviewed sources. However, with AI being a relatively new concept in maintenance planning, most of the peer-reviewed science in the topic showed data science heavy simulation models while the concepts developed and in use in the industry were not available to study.

As the analysis of the gathered data from interviews were done according to Bryman (2016), the data needed to be categorized and grounded in the theory. However, with data being from semi-structured interviews, data could be very different and hard to categorize or compare as the interviewee was only guided to develop its own perspective. In some cases, the author found that the answers became very hypothetical and dependent of how a future system would work. To gain a more generalizable result, a structured interview might have been preferred and easier to analyse. However, the author believes that the results of the analysis gave an in-depth view of the opinions from the shipowners included, and that the main findings in the result could answer the research questions of the thesis and propose further research on the topic based on the findings.

5.1.2 Selection group

The goal of the selection was to cover a variety of shipping companies based on their fleet size in the product tanker sector. Also, as the main idea was to conduct the interviews in person and for this cause, interviewees were chosen according to their distance from Gothenburg. According to Höst et al. (2006), a different or larger sample group might have produced a different result. In analysis of the results, the author found that it would have been interesting to also interview classification societies, manufacturers of engine room shipboard system and developers of CMMS for use in engine room maintenance planning to gain a better understanding of the development of AI enhanced maintenance systems and their challenges. Unfortunately, this could not be done within the time constraints of the thesis.

5.1.3 Interviews

All companies contacted agreed to an interview and showed a great interest towards the thesis and its topic. Also, they all managed to schedule an interview surprisingly fast. Interviews were primarily done in person and beforehand the interviewee was sent an introduction and the main interview questions (see *Appendix 1* and *Appendix 2*) to better be prepared for the interviews. Interviews were conducted with ease and developed naturally and covered a broad spectrum of the topic while staying within the delimitations of the thesis. Following the methods described by Höst et al. (2006) and Bryman (2016) for a semi-structured interview, open ended questions gave the interviewees room to develop their perspectives. As such, the interviews became longer than originally planned and gave much appreciated data while also resulting in a more time-consuming transcription and analysis of the recorded interview data. Within the time limit of the thesis project, the author believes that a larger sample group could have become unmanageable.

5.1.4 Reliability, validity, and generalization

According to Bryman (2016), it is hard to evaluate a qualitative study in the same way as a quantitative study. One problem being that it is impossible to replicate a social setting and the circumstances which play a part in gathering data in a qualitative study. Consequently, it is hard for another interviewer to obtain the same answers from an interviewee in a different social setting, time or with the interviewer not focusing on the same responses as the original interviewer. In turn, this affects the reliability and validity of a qualitative study.

Generalization cannot be considered for this study as it is not possible for a qualitative study according to Denscombe (2014).

5.2 Result discussion

5.2.1 General approach to AI in engine room maintenance

The interviews showed that the concept of artificial intelligence in maintenance planning was well known and had been discussed or heard of within the companies. Moreover, all companies could see the potential of AI in maintenance planning consistent with the science presented in the theory chapter of this thesis. The general belief was that AI will be a part of future maintenance systems and bring advantages for the shipowners and the crew (further discussed in *Chapter 5.2.3*).

Implementation and development of AI in maintenance systems could be problematic as all the respondents had a need to see a fully functioning and reliable system before considering implementation in their fleet and none of the respondents took part in development at this point.

At the same time, according to Cheliotis et al. (2022), a large amount of data is needed to train an AI model to be able to make correct decisions in relation to the vessels machinery. Also, any implementation needs to be approved by the classification societies and follow the regulations set by IMO,

Furthermore, a consensus was that for the product tanker sector, the oil companies (OCIMF) own rules for approving vessels for oil product shipments might force development of any maintenance systems toward the manufacturers of shipboard systems, as only maintenance “according to manufacturer’s recommendation” will be approved in the coming vetting protocol SIRE 2.0. These rules are briefly described in the theory chapter as a compliment to this finding which was not seen by the author before the interviews.

5.2.2 Current engine room maintenance practices

As the interviewed companies have a different fleet size and a wide range of vessels when it comes to year built, a change in the maintenance approach could be seen in the newest builds which confirms the statements regarding CBM by DNV GL (2021, April 7). However, as this is outside of the thesis main research questions, it is not discussed further in depth – only enlightening that it is an ongoing evolution in maintenance practices in line with the literature.

5.2.3 Advantages and challenges of an AI based maintenance system

In line with Pascual (2015), an advantage in postponement of part replacements could be seen by the interviewees, which both could lower cost for parts and reduce the workload for the engine crew. However, it was interesting to gain insight in the reasoning of the representative of Company B, who explained that for the main engine it probably would not be a further gain in savings from part replacement compared to the methods now used in the newest vessels, as the parts changed at dry dock would not last another 5 years if the CBM method would not allow for it anyway. The main advantage for the main engine would then be to get notified before a failure and be able to avoid accidents.

5.2.4 Safety and security

As Achouch et al. (2022) discussed (presented in *Chapter 2.3.4.1*), an AI based predictive maintenance system faces challenges with the necessity of confidence for the system as sensor data, sensor failures, or noise could affect the system to take incorrect decisions and result in missed maintenance urgency or false alarms. The result of this thesis concludes that this is a known challenge among the opinions of the respondents which sees a risk of a false safety with such systems or a risk of the system causing an increased workload for the engine crew.

5.2.5 Engine crew and training

While Paleyes et al. (2023) discussed the necessity of new competence regarding continuous management of AI systems with updates and securing correctness in training of such systems (presented in *Chapter 2.3.4.3*) – the respondents of the interviews could not see that a successful AI system would result in a need for the shipowner to hire new competence. The result shows that shipowners are more likely to outsource maintenance of the AI system or buying it as a service and not themselves be obliged to manage the system. All interviewees pointed out a prerequisite that the system needs to lower the workload for their company to be of interest. At the same time, one of the respondents did hypothetically discuss having a larger office crew (on land) which overlooks the maintenance system as well as having a travelling maintenance crew, not usually residing on the same vessel. The latter being the only way the engine crew size could be affected by an AI maintenance system as all respondents believed that while a successful system should decrease the workload, it is not likely that it could result in a lesser numbered engine crew onboard, but they would be able to free up time to perform more and better maintenance.

5.2.6 Engine room systems

Becoming a very hypothetical subject and with the interviewees having different ideas of how an AI enhanced maintenance system would work, it is hard to draw conclusions and pinpoint in which engine room system it would be of most interest. However, some conclusions could be made from the results:

- For the main engine, in the product tanker sector usually being a single unit (non-redundant) – the already established CBM-methods in newer vessels for postponing part replacements are not likely to be further enhanced by an AI system, as parts would not persist another 5 years until the next drydock schedule, if the CBM-method would not approve the part. CBM-methods already can improve the lifetime of components as discussed by Pascual (2015).
    - An AI maintenance system for the main engine could have the potential to anticipate random failures as discussed by Abidi et al. (2022) and Kimera & Nangolo (2019), which the representative of Company B expresses could be of the most importance in avoiding possible accidents – notifying the crew well before of a machine failure.
- In redundant systems, it is more likely that shipping companies in the product tanker sector could gain from postponing part replacements in these systems as they are less likely to cause catastrophic consequences if the AI system would make an incorrect decision, which according to Achouch et al. (2022) could be the case due to sensor failures or other sources of incorrect data input to an AI system.
- It could be of great help in assisting the crew in maintenance of engine room shipboard systems which are seldom in need of maintenance, in which the crew usually have little expertise and in which systems could also have a rigorous regulation bound it, for example, refrigeration or air-conditioning systems.

6. CONCLUSION

From the opinions of the interviewed shipowners, the thesis concludes that the shipowners can see a potential in workload reduction from using AI as a decisionmaker in the maintenance system. Also, that the shipowners can see potential economic gains from a lesser frequency of machinery part replacements. However, development of AI systems are not likely to originate from the shipowner, instead it is forced by regulations to derive from the manufacturers of engine room shipboard systems.

The shipowners believe that AI systems will most probably be introduced in the future of maintenance systems and also, that such systems will probably be introduced in a newbuilt vessel and not as an aftermarket solution in older vessels. Furthermore, while having an accident reduction potential for the main engine it has a more economically and workload positive impact if applied in redundant engine room systems.

Shipping companies are not likely to hire new competence in achieving development or for management of a successful implemented AI system, instead they need a fully functioning and reliable system which is shown to reduce workload to consider implementation. The system management is likely to be bought from a third party or from the manufacturers of machinery, which then recommend maintenance for the crew. Crew size is not likely to be affected by an AI maintenance system, however it could and should present benefits in time management for the crew.

Risks identified were a system giving a false sense of safety if making incorrect decisions, and data security risks. However, the latter already being of importance and handled according to rigorous regulations from the classification societies.

7. RECOMMENDATIONS FOR FURTHER RESEARCH

The findings in this thesis suggest that it would be interesting to address the manufacturers or the classification societies in gaining more insight into the development of AI systems in engine room maintenance planning and the future of the shipping industry within this perspective.

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APPENDIX 1: INTRODUCTION SENT TO THE SHIPPING COMPANIES (SWEDISH)

Introduktion till examensarbete

Jag heter Erik Hultgren och skriver mitt examensarbete som avslutning på Sjöingenjörs-programmet under vårterminen vid Chalmers tekniska högskola i Göteborg. Examensarbetet handlar om utvecklingen av underhållssystem och underhållsplanering ombord med inriktning på maskinrummets system samt där analys av mätdata görs med hjälp av maskininlärning och artificiell intelligens (AI) för att förutse underhållsbehov (eng. Predictive maintenance).

Min plan och förhoppning är att genom intervjuer få en inblick i vad svenska rederier inom Ro-Ro, Ro-Pax och tanker-sektorerna anser om utvecklingen inom underhåll, om man ser fördelar med ett mer mätdata-drivet tillvägagångssätt för att diagnostisera maskinsystem (eng. Condition based maintenance) samt framför allt vad man tror om att överlåta det senare till AI för att kontinuerligt förutspå och i längden även planera in när underhåll ska ske.

Examensarbetet kommer att baseras på tillgänglig vetenskaplig litteratur men för att enklast ge en introduktion till ämnet så ger Wärtsilä en bra sammanfattning i sin presentation av tjänsten ”Expert Insight”, där man låter motormätdata skickas i land för kontinuerlig analys av AI varpå människor (i land) ställer diagnos när AI upptäcker att observerad mätdata skiljer sig från det beräknade värdet. Inom vetenskapen för landbaserad industri finns även försök att visa på att AI kan integreras till att både besluta om underhållsåtgärder samt planera och schemalägga tillgänglig personal.

Syftet med mitt forskningsarbete är att ta reda på vad svenska rederier har för inställning till att implementera liknande system ombord på sina fartyg: om man kan se fördelar, nackdelar, hinder eller risker med ett sådant system – ur ett tekniskt, säkerhetsmässigt eller personalmässigt perspektiv.

Jag skulle därför vara väldigt tacksam över att få intervjua en teknisk representant i rederiet. Intervjun tar cirka 15 minuter och utförs allra helst personligen där det passar er men jag har även full förståelse för om videomöte eller telefonsamtal skulle passa er bättre. För alla intervjuer gararanteras anonymitet och svaren kommer endast användas i forskningssyfte.

Med vänlig hälsning
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APPENDIX 2: INTERVIEW QUESTIONS (SWEDISH)

Inledningsfrågor

Befattning/position:	
Utbildning:	
Antal år i branschen:	
Typ av fartyg:	
Antal maskinpersonal:	
Fartområde:	
Ljudinspelning godkänd:	

Huvudfrågor

1. **Hur ser ni som rederi på utvecklingen av mätvärdesdrivna underhållssystem, finns en märkbar sådan utveckling till sjöss?**

2. **Är tillståndsbaserat underhåll (CBM) alternativt prediktivt underhåll (PdM) något som ni som rederi satsar på alternativt redan tillämpar i flottan?**

3. **Jag har hittat forskning samt företagstjänster där man låter artificiell intelligens analysera mätdata i underhållssystemet. Är detta något som ni har hört talas om?**

4. **Vad skulle krävas för att implementera ett AI-drivet underhållssystem i maskin ombord?**

5. **Hur tror ni att besättningen ombord skulle kunna påverkas om AI-drivet underhållssystem infördes?**

6. **Ser ni några potentiella säkerhetsrisker eller andra risker med ett sådant AI-system?**

7. **Som någon potentiellt ny för detta koncept och utveckling, vilken ytterligare information eller resurser skulle behövas för att fullt ut kunna utvärdera kapaciteter och konsekvenser av AI inom prediktivt underhåll ombord?**

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