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Høgskulen på Vestlandet

MASTER'S THESIS

Machine learning as an optimisation enabler for ship management companies.

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Acknowledgements

This thesis is dedicated to my wife Andrea, who has supported me for over 16 years and made it possible for me to pursue my passion in studies. I also want to dedicate the thesis to our two beautiful sons Simon and William which have thoughtfully allowed time for me study at times without disturbances. I also want to thank my parents Gerd and Knut for all their help and support.

I also want to express my deepest gratitude to my supervisors Associate Professor II Joel Scanlan with University of Tasmania and Professor Margareta Holtensdotter Lützhöft with Western Norway University of Applied Sciences. The advises, guidance and our discussions have been essential for my progress, and I am humble and lucky to have had such knowledgeable and good supervisors.

This thesis concludes two years of study at Western Norway University of Applied Sciences and University of Applied Sciences Emden/Leer in Germany, and it has been very busy at times studying full-time combined with also working full-time in a very demanding job. Working also on planes, in airports, and hotels during travels using every opportunity, I am proud to have managed to complete the studies within the shortest possible time.

I have gained extremely much knowledge during the studies and manged to enhance my understanding in a professional field I have been working for more than two decades. The knowledge has given me a deeper insight into several fields, and I have obtained deeper understanding supported by recent research, into new technology and computer science. I am confident this knowledge will help me to approach solutions and opportunities with more in-depth understanding.

Table of contents

Figures and tables

Abstract

The strong focus on sustainability from global and local perspectives is affecting the shipping industry, with new regulations coming into force and expectations aiming to create greener ship transportation and operations. This research explores machine learning as a tool for optimisation within ship management companies, which could reduce fuel consumption and lower emissions of greenhouse gasses.

Machine learning is a modern technology with powerful capabilities surpassing human capacity in several areas. This research explores if ship management companies take advantage of the available technology, and the research question is to which degree machine learning is applied for optimisation on ships. It also identifies where machine learning may have an application for ship optimisation, and the study investigates how optimisation is utilised on ships today.

The research question is explored using a case study methodology with a qualitative approach, interviewing several ship management executives from ship management companies with head offices in Norway. The companies participating in the research were selected from public registries and comprised major ship management companies operating fleets of ships providing services to the offshore oil and gas industry.

The study provides insights into the current practices of optimisation on ships and provides knowledge of what influences optimisation at both high and low levels organisationally. The results indicate that machine learning can considerably enhance fuel optimisation and performance, although it has yet to be commonly implemented on ships. The thesis provides valuable insights to ship management companies considering implementing machine learning on their ships and for other parties providing products and services for on-ship applications. The thesis also provides a list of key learnings that may be used as recommendations for ship management companies implementing machine learning or new technology onboard.

1 Introduction

We have the most important work in our lifetime ahead of us. We are at a critical point where we need to take action for future generations to live and prosper by working to achieve the UN Sustainable development goals (Kingo, 2016). Climate action is one of the 17 goals (UN, undated), which includes reducing emissions of greenhouse gasses (GHG). Around us we can see initiatives to reduce emissions from the use of fossil fuels, and most nations have agreed to reduce emissions of GHG (Paris Agreement, 2015). The countries demonstrate their commitment to reduce emissions of GHG also within maritime transport by participating in the regulatory development through the International Maritime Organization (IMO). The focus on fuel reduction also brings a discussion about optimising fuel consumption on ships and ensuring that the energy inherent in the fuel is utilised in the best possible manner. Reducing emissions of GHG often revolves around the discussion of alternative fuels (DNV, undated), but there may be other means to reduce the emission of greenhouse gas for the existing tonnage.

Computer technology, artificial intelligence (AI) and machine learning (ML) have made great achievements during the last decades (Schatsky et al., 2014). ML is a form of AI that can have several applications for optimisation on ships (Akyuz et al., 2019). Instead of making large investments in new energy sources on board, ship management companies may implement ML into their systems to utilise the existing energy sources on board more efficiently. This may be a more sustainable and cost saving approach compared to building new ships or installing new equipment, and scrapping the old.

Can smart machines create a breakthrough in the operational optimisation of ships? Machine learning is one of the greatest technological achievements humans have ever made, and it may be considered a revolution compared with the industrial revolution (Doorsamy et al., 2020). How does this technology help optimise ship operations?

The aim of the thesis is to provide knowledge of the current use of machine learning as a tool for operational optimisation within ship management companies. Digitalization is a trend in the world, and it is to an increasingly degree impacting our lives (United Nations, 2019). You may unlock your smartphone just by looking into its built-in camera, and you can get your photos automatically sorted and arranged in digital photo albums (Goodwin, 2020). Algorithms with artificial intelligence understand the content of every picture we have on our cell phones (Krizhevsky et al., 2017).

As the algorithms become more advanced, they may to an increasing degree be able to perform tasks that only humans could perform earlier (Schatsky et al., 2014). A neuroscientist may be able to understand the basic principles in the brain of the chess world champion Magnus Carlsen, why some neurons are activated while others are not (Goodwin, 2020). Magnus Carlsen's brain could be considered to be an extremely powerful algorithm with extraordinary abilities to play chess surpassing any other human, but even he is beaten by AI chess computer programmes (Goodwin, 2020).

There is substantial interest in environmental questions globally, and the IMO have decided on a strategy for reducing total emissions of GHG from shipping with at least 50% within 2050, based on the 2008 levels (IMO, 2018). The IMO introduced the Energy Efficiency Existing Ship Index (EEXI) and Carbon Intensity Indicator (CII) which entered into force in January 2023. CII focuses on how ships above 5000 gross tonnage optimise the transport of goods or passengers (DNV, Undated), which makes optimisation highly relevant during the next years.

From an environmental perspective, optimisation may entail an optimal use of fuel or the energy sources onboard (IMO, 2022). Making use of as much as possible of the inherent energy contained in the fuel per amount of transported cargo, will normally result in lower emissions of GHG (IMO, 2022). In order to make the most of the energy in the fuel, the vessel must be operated and designed in an optimal way. Operating a vessel in the most optimal way could include using less fuel and time to transport the vessel and cargo from port to port or between locations. This would depend on factors like ships trim, engine torque, heading, sea state, wind, current, combination of propellers, propeller pitch, choice of shipping routes, engine combinations, placing of cargo, hull polishing among others. (IMO, Undated). Machine learning may be used as a powerful tool for optimisation in a reliable and methodical way based on collected performance data from ships (Huang et al., 2022). Several ship management companies collect performance data from their ships (The Maritime Executive, 2020), which could form an extensive foundation for training machine learning models.

Optimisation may also be considered from an economical perspective by making the most value creation with the least amount of resources consumed. Optimisation of the operation of ships is also increasingly important due to high fuel prices and a constant focus on cost. Ship management companies operating their ships optimally could gain a competitive advantage over other shipping companies who do not operate their ships as optimised. This makes research on machine learning and optimisation increasingly valuable not only for ship management companies, but also for other stakeholders such as shipyards building ships, manufacturers of machinery and equipment for ship applications, and software developers.

Considering my background in nautical science and business administration and as a seagoing officer worldwide for several years, I was excited to explore how ML could be applied to ship management. My interviews with the ship management executives emphasised the importance placed on efficiency and cost-effectiveness in all aspects of the business. Also, working within the industry for several years and being involved in several optimisation initiatives, combined with studies of applied tools for optimisation using ML, I acknowledged the potential power of ML in improving efficiency, reducing costs and optimisation.

1.1 Structure of thesis

Chapter one provides an introduction to the thesis addressing the topic, the reason why it is so important, why it can be useful for ships management companies and the powerful technology behind ML for optimisation. Building on the introduction, chapter two will look at the background and central terms regarding previous research, optimisation, fuel and machine learning which are the four topics the rest of the thesis will revolve around. Chapter two will also address how ML may be applied for ship optimisation and create a structure for the next chapters. Founded on the background, the research question will also be presented in the end of the chapter two.

On the basis of chapter two the methodology is presented in chapter three, addressing the qualitative approach that was chosen including research design, justifications, decisions, interviews and processing of data. Several interviews were carried out, and the results will be presented in chapter four, which contains six sections where the first section presents major themes affecting optimisation, and the next four sections address each of these individually.

Chapter five discuss the results from the previous chapter and connects the results to earlier research. The chapter discusses to which degree ML is applied on ships, and the potential for further application. The chapter also contains a discussion about who may be interested in the results of this research and contains key learnings.

Chapter six contains the conclusions and the contribution to the research that has been made. The key learnings from the research are summarized along with the limitations of the research and suggestion for further research.

2 Background

With the UN sustainability goals it is certainly needed to optimise fuel, this chapter will provide an overview of fuel optimisation in maritime industry, the techniques that perform the optimisation, fundamentals about machine learning and how it may be applied for optimisation on ships.

First, it is necessary to understand why it is so important to save fuel on ships and in order to do that, the next section will look at the significance of ship emission and drivers for fuel optimalization.

2.1 Fuel and the maritime industry

There are 103,000 merchant ships registered in the world (United Nations Conference on Trade and Development, 2022), and for most of these it may be difficult or impossible to convert to alternative fuels due to limited space onboard or costs. The ship owners are then forced to look at other ways to save fuel, within their existing tonnage.

Ships influence the environment in several ways, but a significant environmental aspect is normally the emission of exhaust gas into the atmosphere (Transport & environment, undated). Marine fuel oil is the most widely used type of fuel for commercial vessels, basically used to propel the ship and to generate power onboard (Marine Insight, 2019). Marine fuel oil is normally converted into energy in a combustion engine where there is a significant loss of energy in the process, and exhaust gas is generated (Kuiken, 2008). Maritime transportation is responsible for 2,5% of the emission of GHG in the world (European Commission, undated), while at the same time ships deliver over 80% of the world trade (United Nations Conference on Trade and Development, 2021). Although maritime transport is considered an environmentally friendly way of transporting goods, there are also expectations that ships should reduce their emission of greenhouse gasses, both from the regulatory side through the international maritime organization (2018) and from financial parties (Poseidon Principles, undated).

Shipping is a major contributor to global greenhouse gas emissions and reducing fuel consumption can help to reduce the shipping industry's carbon footprint. Countries have adopted regulations to reduce emissions from ships, such as the International Maritime

Organization's Energy Efficiency Design Index (EEDI) and Ship Energy Efficiency Management Plan (SEEMP) (DNV, Undated). Saving fuel can also help ships comply with these regulations.

Fuel is one of the largest operating costs for ships (Branch and Stopford, 2013), so reducing fuel consumption can lead to significant savings for ship operators. During recent years the fuel prices have been significantly affected by political events, and the fuel price reached a historical peak in 2022 (Ship & Bunker, 2022). This makes reduction of fuel consumption even more important for the cost of operating ships. Ship operators that are seen as being environmentally responsible may also be more likely to win business from environmentally conscious customers (Lister, 2015). By saving fuel, ships may contribute to less emission of GHG and make maritime transportation even more environmentally friendly. Most ship management companies have an objective to save fuel and the incentive to save fuel is often to save cost, but it may also be to have a better environmental performance and appear greener.

Despite stricter requirements to reduce emissions, ships using combustion engines must use fuel to create the necessary energy but how can ships then save fuel? This may be achieved through optimisation which we will look further into in the next section.

2.2 Optimisation

Optimisation can be seen as a process of finding the best solution to a problem, among a set of possible solutions (Diwekar, 2020). The possible solutions are found within the search space, and the optimised solution is the one that gives the best value (Obitko & Slavek, 1999). To find the optimal solution, we may use optimisation algorithms, which are mathematical techniques that search the search space for the solution that satisfies certain criteria (Obitko & Slavek, 1999). There are many different types of optimisation algorithms, each with its own strengths and limitations, and the choice of algorithm depends on the specific problem being solved (Diwekar, 2020).

Finding the best algorithm and solution may have several benefits, but what are the practical options ship management companies actually have to save fuel? We will explore applications in the next section.

2.3 Current fuel optimisation in maritime industry

Ship management companies are currently using several methods to save fuel and consequently emission. Slow steaming is a well-known method for reducing and optimising fuel consumption on board ships, which basically means reducing the speed of the ship to save fuel while transporting the same amount of cargo (Tezdogan et al., 2016). Slow steaming can significantly reduce the fuel consumption up to 30% (Healy & Graichen, 2019).

Weather routing was first developed to find the fastest route, but ship management companies nowadays are also using it to save fuel, hence optimising the ships voyage (Shao & Thong, 2012). Based on weather forecast, sea condition and the characteristics of the ship, weather routing is utilised to find the optimum engine speed and power for the ocean voyage (Shao & Thong, 2012).

Hull cleaning, propeller cleaning and propeller polishing is also widely used by ship management companies to save fuel, and while hull cleaning can reduce fuel consumption 1% - 5%, propeller cleaning and polishing can reduce fuel consumption 3% - 4% (Horton et al. 2022). Fouling on the ship's hull and propeller can increase drag and friction through the water which reduces the ship's speed and consequently increase fuel consumption, but by regular thorough cleaning and propeller polishing, the surface finish may be improved to reduce resistance and increase the fuel efficiency (Horton et al. 2022).

To reduce fuel consumption and emissions, ship owners also make investments in energy-efficient technologies including waste heat recovery systems, LED lighting, and high-efficiency engines. Fuel consumption can be reduced by up to 30% by employing energy-efficient technologies, according to a study by the International Transport Forum (ITF, 2018).

There are many types of fuels or mediums that may provide energy onboard ships, and there are several initiatives to find energy sources with reduced, or without emission of GHG (DNV, undated). Ship management companies are investigating, testing, and installing alternative energy sources onboard ships such as wind power, fuel-cells, battery-packs, LNG fuel, hydrogen fuel, methanol fuel, ammonia fuel and other types (DNV, 2022). With the increasing focus on reducing emissions and addressing climate change, the shipping industry will need to continue finding ways to reduce its environmental impact and improving fuel efficiency will play a key role in this effort (DNV, 2022).

ML in a ship context is a relatively new research field that started in 2015, and the majority of papers have been published after 2020 (Huang et al., 2022). ML is expected to grow enormously with the increased focus one green shipping during the coming years, primarily as a tool for ship design, ship performance and route planning (Pena et al., 2020; Huang et al., 2022). Optimisation in shipping could contribute to reduce the emission of GHG and increase sustainability (Huang et al., 2022). Different research perspectives have been used for application of ML in operational performance of ships to predict fuel consumption under operational conditions (Tillig, 2020; Coraddu et al., 2017), taking into consideration ship design and dimensions as well as effect of wind, waves, current, temperature, fouling, among others.

Ships operate in a highly complex dynamic environment influenced by waves, wind, acceleration, gravity, buoyancy, frictional- and several other forces, that impact the performance (Faltinsen, 1990). Hence, the collected performance data quickly also becomes very complex. However, ML can be trained on large amounts of complex data and suggest optimised solutions, which may be a viable and inexpensive solution for ship management companies to save fuel.

Whether or not ship management companies have adopted ML for fuel optimisation in any substantial way today, remains unknown but there has been some research addressing ML for optimising of propeller designs, prediction of fuel consumption, weather routing, trim optimisation and route optimisation. Comparative research from 2019 concluded that ML has had very little application in the maritime industry so far (Akyuz et al., 2019). The mentioned article took a broad look at the application of ML in the maritime industry including voyage optimisation, sustainability of transportation, maintenance and repair forecasting, controlling of freight rates, reinforcement learning, energy efficiency management and maritime security improvement.

By optimising the fuel consumption, significant costs and emissions may be saved, and with the introduction of computer technology even further reductions might be possible. It has already been acknowledged and proven that the use of computer algorithms has surpassed human capabilities in several areas (Goodwin, 2020). Especially when vast amounts of data comprise the foundation for decisions, computer algorithms demonstrate their superior power (Schatsky et al., 2014).

We have discussed several possible applications for saving fuel, where ML may be utilized. To better understand how machine learning may be applied for optimisation and how the technology works, it is necessary that we understand the theory behind it. In the next section we will look specifically at machine learning.

2.4 Machine learning

All activities that take place in the human brain are functions of neurons working together in a complex interaction (Squire et al., 2012). All decisions and all actions conscious or unconscious that the human body performs, is a result of neuron activity in the brain. Neurons completing tasks may also be created artificially in a computer, which can be combined into complex artificial networks. By combining artificial neural networks, one may create intelligent networks which have the ability to learn (Goodwin, 2020).

Some algorithms may be very simple and are only capable of completing simple tasks, while other algorithms may have the capability to learn, and can be considered intelligent (Goodfellow, 2016). An algorithm may also be considered an instruction for how to perform tasks or how to behave.

ML is a type of artificial intelligence that allows software applications to become more accurate in predicting outcomes without being explicitly programmed (Bonaccorso, 2020). There are different types of ML, including supervised learning, unsupervised learning or semi-supervised learning (Chapelle, 2006).

In supervised learning, the algorithm is trained on a labelled dataset, where the correct output is provided for each example in the training set (Chapelle, 2006). These labels serve as the ground truth for training a machine learning model, allowing it to learn patterns in the data and make predictions on new, unseen examples (James et al., 2021). The goal is for the algorithm to make predictions on new, unseen examples that are drawn from the same distribution as the training set (Chapelle, 2006).

In unsupervised learning, the algorithm is not given any labelled training examples. Instead, it must find patterns and relationships in the data on its own (Chapelle, 2006). Semi-supervised learning is a combination of supervised and unsupervised learning, in which the algorithm is given some labelled training examples and some unlabelled examples (Chapelle, 2006). Another type of ML is reinforcement learning which involves training an agent to interact with its environment in order to maximize a reward (Sutton & Barto, 1998).

ML produces a model describing knowledge of the system based on a set of data (Brastein, 2022). In order to make efficient use of ML, it is critical that we know what the machine should learn, and that the data contains the knowledge. Any mathematical expression or model describing a system, must contain knowledge about the system (Brastein, 2022). By providing the data and the results to the machine learning, we allow the computer to create a model based on the data which may be used to predict future results. It is much easier to tell the computer which results we want to have, and let the computer determine the model, compared to us explaining to the computer how to calculate the answer (see Figure 1).

Based on the collected data containing several variables, software such as e.g. Matlab (Mathworks, undated) may create ML algorithms for optimisation (see Figure 2 overpage).

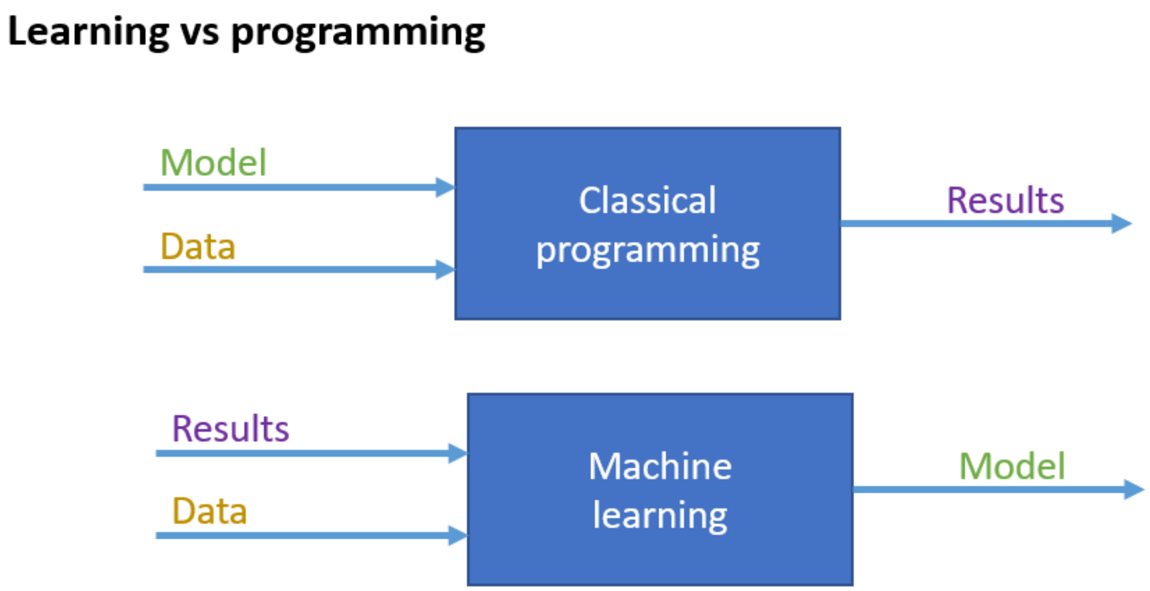

Figure 1 Learning vs programming adapted from Brastein (2022)

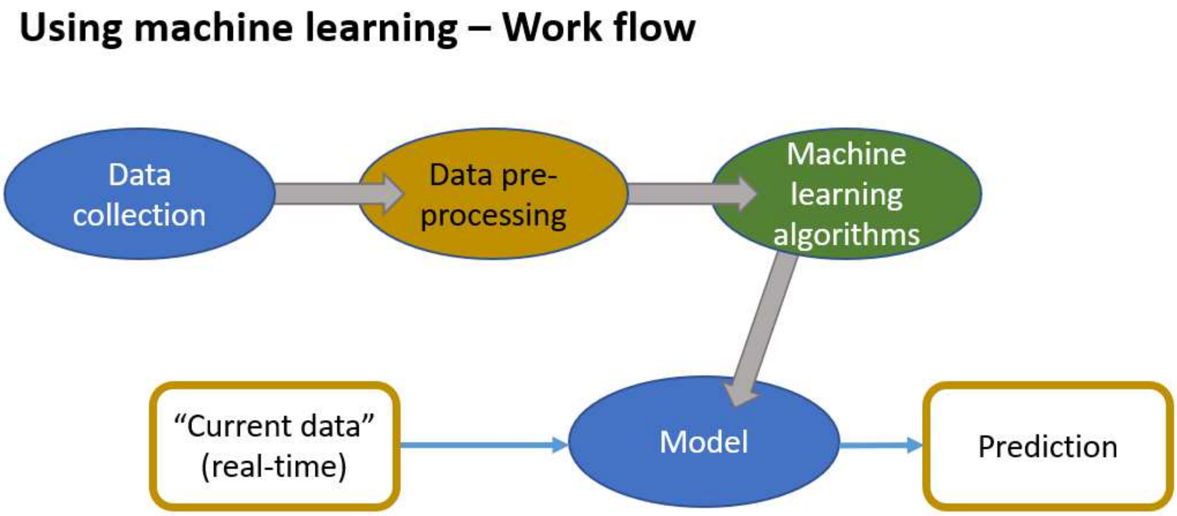

Figure 2 Using machine learning – Workflow adapted from Brastein (2022)

The criteria could be to have the lowest possible fuel consumption, or any other optimisation task that may be drawn from the collected data.

Understanding the theory about machine learning makes it interesting to look at how this technology may be further applied on ships. There has been research about this with promising results and we will look at this in the next section.

2.5 Machine learning for ships

A digitalization wave has been seen in shipping during recent years, which may also impact ML implementation (Minim et al., 2020). Some of the biggest concerns however is the risk of cyber-attacks (Fruth & Teuteberg, 2017; Sanchez-Gonzalez et al., 2019) and integration of new technologies and systems (Heilig and Voß, 2017).

In order to reduce fuel consumption on ships, it is important to understand which factors influence fuel consumption, and a research paper from Yuan and Wei (2018) concluded that weather routing and trim optimisation can reduce the fuel consumption, but speed reduction has the largest abatement amount. They used statistical models and ML to identify the influencing factors for fuel reduction (Yuan and Wei, 2018).

The relationship between how a ship is performing and factors such as weather, maintenance condition and operating speed, may be expressed mathematically by use of

ML (Huang et al., 2022). However, the variables used for creating the mathematical expressions play a very important role, and Soner et al. (2019) researched which were the most influential ones. They found that the variance of starboard level, trim, port pitch, and starboard pitch had considerable effects on the fuel consumption of ships (Soner et al., 2019).

A significant factor for the ship's fuel consumption is the trim of the ship (Altosole et al., 2016). Trim optimisation is an easy way to save fuel as it does not require any installation onboard to change the ship's trim, and Coraddu et al. (2017) found that implementing a model for optimising trim could save 2% fuel. Advanced computational fluid dynamics (CFD) has been applied to optimise trim (Lee et al., 2014) but by combining it with ML, the results became more accurate and had the highest physical plausibility (Coraddu et al. 2017). The research also indicated that ML by itself outperformed CFD in trim optimisation (Coraddu et al. 2017).

Marine antifouling has also been addressed in research as an area where ML may have an impact, taking into account cleaning of the hull and propeller (Coraddu et al., 2019), "days since last clean" and " significant wave height" (Laurie et al., 2021). Marine growth on the hull and propeller is an important factor which increases fuel consumption on ships due to the additional resistance through the water (Hakim et al., 2017). This makes ML for predicting when the propeller and hull should be cleaned very relevant in order to save fuel, and research results clearly shows applying ML has a better accuracy and reliability (Coraddu et al., 2019) than the often used ISO 19030 "Measurement of changes in hull and propeller performance". Marine growth may depend on several factors, such as temperature, trading area or biological factors (Floerl, 2003), and this should be taken into consideration when determining the hull cleaning intervals.

ML makes it possible to predict fuel consumption online and in real-time, which if implemented, may have a significant impact to save fuel on ships, reach the emission targets, and save cost (Hu et al., 2019). Pedersen and Larsen (2009) and Bes¸ikçi et al. (2016) predicted the propulsive power based on data from noon reports. They managed to achieve a predictive error of 7%, but Tarelko and Rudzki (2020) managed an even better accuracy of 0,8 – 2,8% deviation. Petersen et al. (2012) used NN to predict fuel consumption based on continuous monitoring open-source ferry data and managed an error of only 1,50%. Petursson (2009) used algorithms to predict shaft power with high accuracy, and Chaal (2018) combined algorithms, decision tree regression and NN, and achieved very similar results. Soner et al. (2019) used a type of ML algorithm called "random forest" to predict fuel consumption, based on the same data that Petersen et al. used, and managed to get a reduction in the error of 43,5L/h compared with 47,3L/h achieved by NN. Laurie et al. (2021) combined high-frequency continuous monitoring data from seven container ships, with sea-states information from satellite, to predict power consumption. The ML algorithm was the most effective and predicted the shaft power with an error of 1,17%. Wang et al. (2018) tested several methods for predicting the fuel consumption of several container ships and found that an ML algorithm produced the best results. Ahlgren and Thern (2018) found that ML may estimate the performance of each engine on a cruise ship related to fuel consumption without installing a fuel flow meter. Different techniques of ML may be suitable in different cases, but even though different techniques of ML were used, all performed similarly well for accurately predicting fuel consumption (Huang et al., 2022). Uyanik et al. (2020) tested different ML models for estimating fuel consumption, including also engine parameters such as main engine rpm, main engine cylinder values, scavenge air and shaft indicators, and found a high correlation with fuel consumption. To further investigate which ML method is best suited for fuel prediction, it is recommended to develop standard datasets for different ships (Petersen et al. 2012).

Fuel consumption for ships is not only related to the propulsion of the ship, but rather the total energy consumption such as heating, ventilation among others. and ML may also be used for predicting waste heat recovery performance (Yang et al., 2018). Operational optimisation of ships and fuel consumption would also be influenced by the state of the machine(s) producing the energy, as an engine may use more fuel due to failure or even break down (Huang et al., 2022). Raptodimos and Lazakis (2018) also linked ML to monitoring of data from machinery to predict the risk of failure.

Another operational application for ML is to use it for propulsion systems, and Perera et al. (2016) used ML for combining power management with propulsion control systems for the different engine room operations. The system combined engine power, ship's speed, shaft speed and fuel consumption where ML based on big data sets could give advice to the ship officers on optimal speed (Huang et al., 2022). This is also very relevant as the focus on emission of green-house gasses continues, hybrid solutions with alternative energy sources onboard ships are introduced (Huang et al., 2022). The optimisation of energy sources could also impact the fuel consumption, and Planakis et al. (2022) developed a system based on ML which would choose the energy source in a hybrid battery and diesel engine ship propulsion setup. The system could reduce the fuel consumption with 8,5% (Planakis et al., 2022), which is a big impact. Similar energy management systems are designed also for other types of hybrid configurations on ships, using ML for optimal use of the different energy sources (Wu and Bucknall, 2020), (Wu et al., 2021).

Research on the application of ML for voyage planning and weather routing has also been carried out taking into consideration wind, wave height, direction, current, air densities, air temperature and radar systems (Huang et al., 2022), (Moradi et al., 2022). Voyage route planning tools may use ML to calculate the fuel consumption of different alternative routes based on the available historical and real-time data and suggest the route that returns the least fuel consumption, continuously re-calculating as the conditions change (Yuan et al., 2021). The suggested routes may also take into consideration ice conditions e.g., in the Arctic, and even if it is not the shortest route, the tool may suggest a route that avoids significant ice conditions (Li et al., 2021). ML for weather routing has shown very promising results and Grifoll et al. (2022) found that on an intercontinental voyage, up to 9% in timesaving and 28% CO_2 reduction could be achieved with ML software. ML results also indicate that weather routing influences the fuel consumption significantly more than the actual displacement / draft of the ship and emphasise the importance of following a route with favourable weather in order to save fuel (Li et al., 2022).

Related to cost benefit analysis for ship management companies, ML has also several applications (Akyuz et al., 2019). ML can be used to analyse historical data on ship operations, such as fuel consumption, maintenance costs and voyage duration, to predict future costs and revenues. This can help ship management companies make informed decisions about which routes to operate, which ships to deploy, and how to optimise their operations to ensure cost efficiency. Some shipping companies have already integrated ML into several of their processes, and suggests even more implementation (Hapag-Lloyd, 2018).

The degree that ML has been implemented by ship management companies, may have an impact on their fuel performance. In this chapter we have discussed the four topics of previous research, optimisation, fuel and machine learning. In the next section we will summarize the background of this chapter leading up to the final research question.

2.6 Summary

What is important for ship management companies has been discussed, together with the technology of ML. It does not take major inventions to use the technology, and it has been known for several years (Goodwin, 2020). ML may be an inexpensive solution for ship management companies to save fuel, when performance data from the ships is available. ML is integrated in more and more systems we use every day, but has it been implemented on ships or in ship management companies as well? In 2019 machine learning was to a very little extent implemented (Akyuz et al., 2019), but four years could be considered a long time taking into account the development in technology. This allows for more research to close the knowledge gap between 2019 and today.

ML relies on large amounts of data for training to create accurate and reliable algorithms, but the maritime industry is conservative and reluctant to share data openly (Huang et al., 2022), which may inhibit the implementation of ML. ML needs a digital interface to collect and process data, and if ship management companies are hesitant to integrate such technology due to concerns regarding the risk, it can impact to which degree ML gets implemented.

The expectation to reduce emissions of GHG is also getting gradually stronger every year, which may be achieved by reducing fuel consumption (IMO, undated). Optimisation can contribute to reducing fuel consumption and less emission of GHG, and ML may be a solution. Optimisation can be done from different approaches as discussed earlier in this chapter, but the question remains whether ML is being used by ship management companies?

This leads to the key research question regarding the current implementation of ML and its use for optimisation which this thesis addresses. To date no one has investigated to what degree ML is implemented for fuel optimisation, and so this research question is posed:

To which degree is machine learning used for fuel optimisation in major ship management companies today?

It would be very interesting to know more about this, but a sound methodology is necessary to ensure it is adequately addressed. In the next chapter, the methodology that was used to answer this question will be explained.

3 Methodology

This study is exploring the current industry practice of optimisation and what is the current level of utilization of machine learning methods to drive down business costs and reduce emissions of GHG.

In this chapter, the method of establishing the current industry practice will be discussed, including the design of the approach taken and the choices made during the research with justification for the decisions made. The collection and processing of data will also be explained.

3.1 Design of the research

The aim of the study is to gain knowledge about the current maturity level of optimisation methods used within the maritime industry, with particular attention given to understanding the current level of adoption of ML based approaches for fuel optimisation. This may be considered descriptive or exploratory research and the target group for my research are ship management companies. A case design allows the researcher to perform an in-depth investigation of a topic, and it may produce detailed descriptions of the situation (Jacobsen, 2018). While it is not possible to investigate all ship management companies in the world, a case may be selected providing a good opportunity to understand the integration between the companies and the ML context (Geertz, 1973). The knowledge is gained from researching a group. As the group can be representative for the population, the results might also be theoretically generalized to the population. The group of companies was defined and representative major shipping companies with head offices in Norway operating several offshore ships were used as case.

3.2 Qualitative method

For this thesis a qualitative research method was used to investigate the use of ML for optimisation in the shipping context. This method is suitable when one wants to investigate a small number of respondents and identify variations related to the research question (Jacobsen, 2018). Qualitative research method is also suitable when the goal is to understand and explore a subject in a natural setting, and it is particularly useful for gaining in-depth understanding of complex phenomena or for studying a small number of individuals or groups. This makes the method very suitable for the aim and research question of this thesis. ML and optimisation may also be used in several areas of ship management and in order to identify these areas, a qualitative research design would be most suitable. Considering that ML is a fairly new term, and that optimisation may also be considered an abstract topic, the respondents may not be fully aware of the terms and how they may be used. To ensure a common understanding of the terms in a practical way, the qualitative research design would be best, as one also gain insights and understanding of the experiences, perceptions, and reasoning of the participants.

One of the strengths of a web-based interview is that it allows for a good flow through the interview (Jacobsen, 2022). The interviewer may also observe the interviewee, partly control the interview and as travel is not necessary, it is easier to interview respondents far away (Jacobsen, 2022). Some interviewees may, on the other hand, be reluctant to participate in recorded web-based interviews as they may be unsure what it entails. Furthermore, web-based interviews may not create as much trust and openness as a face-to-face interview, and the interviewer may lose some control over the interview (Jacobsen, 2022). There is a risk that the interviewee could be more distracted due to disturbances in his/her environment (Jacobsen, 2022).

During the web-based interview, the interviewee expresses his/her opinion and attitude towards the topic, and as a result the researcher may collect a large number of different viewpoints (Jacobsen, 2018).

3.3 Selection of interviewees

Known for its cutting-edge and inventive technology, especially in the field of environmental sustainability, Norwegian registered ships are the target of the investigation within this study. With a significant emphasis on research and development in shipbuilding and related technologies, Norway has been a pioneer in the maritime sector for a very long time (Norwegian Government, 2019). ML may be considered a new technology and considering the fleet's innovative history, the ship management companies are early movers to adopt innovative solutions. Combining the environmental sustainability focus and willingness to try new technology, the likelihood of finding evidence of integration of ML may be higher in these ship management companies than elsewhere. Whereas if the same number of interviews, across multiple countries, could have more variables to account for in the diversity of responses. Hence this research will only investigate Norwegian companies, providing knowledge of the topic through interviews.

When companies or organizations in general are established in Norway, they are registered in the national public register Brønnøysund Register Centre, for commercial and liability purposes. The register contains information about every company registered in Norway, and it is possible to search their registries for the general public (The Brønnøysund Register Centre, 2021). During registration an industrial code is assigned to all organizations which indicate the main activity of the company. Industrial code 50.2 is the code for sea and coastal freight water transport, which includes freight ocean transport, freight coastal transport, tugs, supply and other sea transport offshore services (The Brønnøysund Register Centre, 2023) and the description fits very well for ship management companies. There are 2190 registrations with this industrial code in Norway as per January 23rd 2023, including a range of company sizes (The Brønnøysund Register Centre, 2023).

To gain full benefits of ML, it is necessary that the available performance data is collected from the ships. The data needs to contain the relevant information that can influence the objective of the optimisation (Brastein, 2022). Not all companies collect such data, as the required infrastructure to collect and analyse the data requires investment to be made in advance. Smaller companies with few employees may have smaller margins and less resources to invest, or to allow time for analysis of performance data. Based on this, the selection of companies invited was limited to those with more than 50 employees. There are 57 companies registered with industrial code 50.2 with more than 50 employees in Norway (The Brønnøysund Register Centre, 2023).

Maress is a software specially designed to collect real time performance data from ships and fleet energy management (Veritas Petroleum Service, Undated). A prerequisite for ML is to have available data to train the algorithms and when the purpose is to optimise, the performance data from the ships plays a key role. This highlights the importance of collecting and having access to performance data to be able to benefit from ML. Oil companies are chartering platform supply vessels (PSV) and anchor handling tug supply vessels (AHTS) for offshore work in Norway, and the environmental performance of the ships on charter may impact the decision of which ships will be awarded the contracts. In 2020 some of the biggest charterers of offshore ships in Norway announced that chartered PSV's and AHTS's vessels operating in Norway would implement the Maress software for tracking the footprint and performance data from the vessels (The Maritime Executive, 2020), (Energy-Pedia News, 2020). This is of importance for the study as it indicates that companies operating PSV and AHTS for the biggest oil companies on the Norwegian continental shelf are collecting performance data. Industrial code 50.204 is the code for supply and other sea transportation services for offshore, and there are 10 registered companies operating such ships in Norway (The Brønnøysund Register Centre, 2023). All these organizations are long standing industry members and have been in operation for many years, including during the COVID-19 pandemic.

The companies were invited to contribute to the research and each company selected one person to be interviewed. Each company was asked to select a person that had as much information about fuel and fuel performance in the fleet as possible. Six companies decided to participate in the research, and in total 6 persons were interviewed. The available resources also limited how may interviewees it was possible to interview. As the different interviews progressed, a lot of similarities in the data between the individual interviews were found, and the last interviews did not reveal new data that was significantly different from the data already was found from the previous interviews. This may indicate that a continued effort interviewing more respondents, would have been unlikely to reveal new information which could add to the research. Jacobsen (2022) suggests that this indicates a sufficient number of individuals have been interviewed.

3.4 Collection of data

The interviews were prepared with an interview guide (see Table 1) based of the research question, containing 6 relevant questions as a guide for the researcher. A completely open conversation without any form of structure could have led to data which would be too complex or too comprehensive to analyse (Jacobsen, 2022). This is more a top-down or theoretical thematic analysis approach where the researcher's focus is on the research questions and the interview guide, than a bottom-up or inductive approach where the interviews are driven by the data itself (Braun & Clarke 2006). The interviews were however carried out as an open conversation where the interviewees were free to answer in their own opinion, with minimal interference from the interviewer which could introduce bias.

Table 1. Interview guide: Six questions used to guide the researcher in their discussion.

Question	
1	Can you tell me about your fuel consumption management?
2	What type of performance- and fuel consumption data is collected from vessels operated by your company?
3	Can you tell me what measures are most important for reducing fuel consumption?
4	Can you tell me about your plans for fuel optimisation in the future?
5	What is your opinion on IT-solutions for fuel optimisation?
6	What would be the obstacles to doing more advanced fuel optimisation?

Data was collected during individual interviews which each lasted between 46 and 56 minutes. The interviews were performed on Zoom during normal working hours. The interviews were recorded to ensure accurate registration of the data, and a transcript were made for each interview. Each interview started with a short introduction to the research project, and all the interviews had an identical introduction which was prewritten.

During the interviews, the researcher took occasional notes and sometimes asked follow-up questions to confirm that the interviewees were understood correctly, and to ensure full coverage of the intended topic.

3.5 Analysis of data

The transcribed interviews comprised a large amount of text material that had to be analysed. An inductive approach was selected for the analysis, as this type of analysis is more suitable when the aim is to carry out more exploratory research (Jacobsen, 2022). A deductive approach was not used as this type of analysis to a much higher degree limits the processing of the text and is consequently more suitable for testing previous research or for testing validity of a theory in a specific context (Jacobsen, 2022).

The analysis was not started until all the interviews were completed to avoid any findings introducing bias on the remaining interviews. When all the interviews were completed, the researcher familiarized himself with the transcribed data. Notes and first impressions were also noted down during the familiarization, and the researcher had a broad understanding of both the theory and data when the analysis continued.

Thematic analysis was chosen to do the initial analysis of the data as this is a suitable method to look for patterns and themes within each interview and across all the interviews (Maguire & Delahunt, 2017). It is a widely used method within several research fields including psychology, sociology, education, and healthcare for analysing qualitative data such as interviews (Floersch et al., 2010). It allows for deeper understanding of the phenomenon by identifying categories within the data and interpret them (Braun & Clarke, 2006), it is flexible and is a useful tool for researchers seeking to gain insights into the perspectives of individuals or groups (Floersch et al., 2010). The method includes systematically coding and categorizing data (Floersch et al., 2010).

Following the thematic analysis process, the text transcripts were re-read and ideas and meanings that were expressed during the interviews, were drawn out as interview extracts. Each meaning or idea represented by the interview extract was put into individual cells in the first column of a blank spreadsheet. This was repeated for each interview transcript and comprised a total of six individual files altogether. Each spreadsheet consisted of 30 – 48 interview extracts, and a total of 220 of ideas or concepts were identified. The interview extracts consisted of sentences of various lengths and had to be analysed further using open coding. The intention was to break up the large amount of data into smaller parts of meaning and by manually using in-vivo open coding, all extracts were examined thoroughly. In-vivo in this context, means that the emphasis was on the spoken word of the interviewee (Manning, 2017) instead of each line of the transcripts, and open coding means that no codes were pre-defined but were developed during the coding process (Maguire & Delahunt, 2017). Each interview extract was analysed, and the sentences were further broken down into shorter summary codes where possible, and new codes divided the sentences into different topics. Each code should contain only one topic and be described with as few words as possible. Only when the meanings could not be shortened further down without losing meaning, this step was considered done. The process of breaking down the interview extracts into different topics was repeated several times, continuously refining the codes gradually for each step. For every refinement the new or unchanged codes were transferred into the next column in the same worksheet – enabling full traceability of the coding process. When all the codes were determined, they were divided into categories based on their key topic. Several columns were created where each column represented a separate category, and the codes in the spreadsheet were transferred into their respective categories, however remaining in the same row in the worksheet as the original transcript extract. This made it possible to easily trace back each code to the original transcript extract. To illustrate the process of open coding an example is given in Table 2.

When all the codes had been created and put into categories, the interview extracts were revisited a second time to look for evidence of information in the data that had been not sufficiently addressed during the first analysis. Indications of topics that had been missed, were identified during the second analysis which further added to new codes and new categories being determined.

Table 2: Below is a sample of thematic analysis that was undertaken including examples of open and axial coding.

Interview extracts from interviews	**Open coding**	**Axial coding**	**Theme**
Voyage planning is based on experience.	Seafarers' behaviour to adopt new technology.	Seafarers' maturity for ML.	Seafarers' Factors.
Logistics planning is important.	Seafarers' motivation to seek information about sailing plans.	Seafarers' information seeking.	
Wind must be considered during voyages.	Seafarers' behaviour to monitor weather forecasts.		
We log this in SEEMP which is our environmental accounts, which go on modes, sailed distance and things like that.	Ships mode data.	Data collection.	Company Aspects.
	Sailed distance data.		
We have daily monitoring of the fuel consumption on the ships.	Daily consumption monitoring.		

The next step was to look for interrelations between the identified codes and investigate if they could be further merged into themes. All the identified categories were highlighted as individual circles on a work document and the researcher grouped these into categories. Some categories were found to have overlap with each other and could be merged, while others had no overlap and consequently remained as separate categories. When any overlapping categories were merged, and all the rest of the remaining categories remained as individual categories, all the categories were grouped into four groups of high-level themes based on the nature of the categories.

When the high-level themes had been created, a new spreadsheet was created where each theme had a separate sheet. Each sheet representing a separate theme was further divided into rows representing each category within the high-level theme. The interview spreadsheets for each respondent were then revisited, and each interview extract for each identified category was then transferred into the spreadsheet containing the high-level themes. It was then easy to see which interview quotes that belonged to each category and high-level themes. This made a good foundation for continuing the analysis and looking at the results.

3.6 Quality of the research

Two central terms when we come to research quality is *validity* and *reliability*. *Validity* is related to if we measure what we want to measure, and *reliability* is related to if the research is trustworthy (Jacobsen, 2022). Both will be discussed under separate headings below.

3.6.1 Validity

Validity may also be divided into *internal validity* which means if the conclusions we made actually has a proper foundation in the data we have collected, and *external validity* which means if the conclusions we made is also valid in other groups outside the group we researched (Jacobsen, 2022). The external validity represents to which degree the conclusions may be generalized also to other groups, and to do so it is a requirement that the interviewees are representative for the group we want to generalize to. The different individual viewpoints collected during the interviews may not be generalised to a group of people (Jacobsen, 2018), as they are the personal opinions of the interviewees. In this research, the interviewees were selected from a group of comparable companies which had several similarities with regards to type of business, company size, country of main office among others. and the persons interviewed were selected based on their knowledge of the topic. Even if only 6 interviews with different persons were carried out, there were no indication that the persons or companies were not representative for the group, and the conclusions may in this regard enable generalization at least to the rest of the 10 companies. The researcher found that no new relevant data was found on the last interview, which differentiated much from the other interviews, and this may also be an indication that sufficient data had been collected and that the results may be generalized to the rest of the 10 companies (Jacobsen, 2022). For groups outside the group of the 10 companies, generalization may apply to less extent as the interviewees may not be representative for other organizations depending on their type of business context, among others. The more different other organizations are, the less likely it is that the results apply to them.

The interviews produced considerable information and it provided a foundation for drawing conclusions. Previous research indicates that people may not always reveal the truth during interviews (Alvesson, 2011), and this has to be taken into consideration when evaluating the internal validity. The interviews focused on optimisation, fuel saving and machine learning which were the key topics of the research and combined with the background chapter of previous research in the area, the topics have been investigated from different perspectives. A significant effort was made to identify previous research, a considerable number of articles were studied and investigated including studying the articles referenced and later citations of the articles. Several independent articles indicated the same and several overlaps were found in the documented literature. This indicates that the main sources of documented data were sufficiently identified and taken into consideration during the research background.

The invited companies were asked to participate by appointing a representative that had best knowledge of fuel optimisation in the company, as the researcher had limited knowledge about the organizations and of which persons had which responsibilities. All the interviewees received written information before the interviews about the purpose of the research and the interview time, hence it should be clear to them, and they all had consented to participate. The topic was not sensitive, the technology was based on open information, and the researcher found no indication that anybody lied or tried to hide something. There was no indication that the interviewees did not have sufficient knowledge within the topics or the organization, they appeared to have first-hand information and they openly shared it and appeared to have long experience within the topic. This indicates a good internal validity.

3.6.2 Reliability

The interviews were carried out by Zoom and the researcher made an effort to remain as objective as possible without interrupting, in order to avoid influencing the participants in any way. Interruptions could however be justified in cases where the respondent said something that the researcher wanted to make sure he understood correctly, or if the interviewee mentioned something that the researcher wanted the respondent to elaborate further on. Another reason to interrupt would be if the participant was talking about something completely outside the research topic (Jacobsen, 2018). However, there is no guarantee that the researcher did not influence the interviewee without knowing. There is always a risk of interviewer effect which may influence how the participants answer (Davis et al. 2010). The respondent is always affected to some extent by the way the interviewer talks, the look, the clothes, body language, dialect among others. (Jacobsen, 2018), and this should also be taken into consideration as it may affect the reliability of the research.

During the COVID-19 pandemic, companies had to close down their offices in Norway and employees in the ship management companies had to work from home. This brought along more rapid implementation of computer-based systems for communication such as Teams, Skype, Zoom among others, and made employees increasingly competent in using these tools (Jacobsen, 2022). Hence, there is no indication that the use of Zoom may have affected the results, or that any participants were excluded.

Research has shown that people may answer differently according to the context they are in, and as the interviews were performed during working hours, it may have influenced the opinions (Nevin, 1974). An interviewee could answer different depending on if he/she was in his/her office, at home or somewhere else (Jacobsen, 2022). As the interviews were carried on Zoom, the possibility to verify the location was limited and it may have affected the reliability of the research.

Even if all the interviewees appear honest, they may have had motives to present their company in a more favourable way than they normally would. Motives could have existed to promote the company they were employed, the department they worked in or other motives, which could have affected their opinions. This could also have influenced the reliability of the results (Jacobsen, 2018) and even it is difficult to identify, it should be taken into consideration. The conclusions were however not based on single opinions, but the sum of opinions.

During interviews in general information is collected in various ways. The interviewee makes a statement as a response to a question from the interviewer or as a spontaneous additional statement on one's own accord. The latter is known to indicate the respondents' true opinion of the topic (Jacobsen, 2022), and should consequently have a higher weighting when making the conclusions. This was also taken into consideration during the discussion.

There is always a risk that the researcher may have overlooked data or obtained incorrect information, but every selection during the research process has been discussed and justified making it possible to replicate. This may add to the quality of the research.

3.7 Summary

During this chapter the methodology of the research was explained together with the choices made, supported by their justifications. A case design with a small group of representative major shipping companies in Norway was selected for the research, and a qualitative web-based approach was justified as the aim was to explore the topic and create in-depth understand for the researcher. The flexibility of the method also allowed for gaining knowledge about the complex phenomena.

The interviewees where selected based on public registries of companies in Norway and to narrow down the selection of companies, the industry code identifying the core business of all companies was used. The selection of such companies may be replicated at any time, and the companies were invited to participate by selecting a person with the best knowledge of the topic.

The data was collected through open interviews where the researcher used an interview guide as support, and transcripts of the interviews were made after all the interviews had been completed. To analyse all the data, thematic analysis was used allowing to explore the complex topic, using open coding, axial coding, determining categories and identify high level themes.

Finally, the quality of the research was discussed addressing internal- and external validity together with reliability.

With the methodology outlined in this chapter, the focus now turns to the results of the study. The data analysis produced several results by systematically applying the methodology described in this chapter. The results identified both high-level themes, and lower-level categories that impact implementation of optimisation, contributing to new knowledge about the topic. Both the high-level themes and the categories will be presented in the next chapter supported by statements from the respondents. The chapter will reveal not only variables which has a related value or pattern connected to them, but also motivations and levels of maturity which may be considered more abstract. Still, the results indicate that they both influence optimisation and as the results are presented, they will further provide inputs to the discussion and conclusions of the research.

4 Results

The purpose of this study was to investigate the use of optimisation tools within ship management companies, and within this chapter the results of interviews conducted with 6 companies following the methodology outlined in the previous chapter is presented.

The interviews produced a considerable amount of data, which needed to be interpreted in the context of the existing research to ensure the research question was answered. This included literature from the fields of optimisation and technology combined with the industry goal of making ship transport more environmentally friendly in the context of societal concerns relating to climate change. The high-level themes that emerged from the analysis are discussed first, before each then serve as the main headings in this chapter.

4.1 Major themes

The analysis of the data provided insight into current industry practice which identified four high-level themes impacting optimisation.

The first high-level theme was *Optimisation Variables* which comprised variables which were liable to change and did not have a fixed value. Several of the categories that were highlighted by the participants were variables which plays a large role in optimisation and were included under this high-level theme.

The next high-level theme was *Optimisation Motivation* where the motivation to control the variables speed and power were discussed, as very different aspects of this were identified during the interviews.

Seafarers' Factors were also identified as a high-level theme, comprising a critical factor in any form of optimisation onboard. The ships were operated by seafarers and their actions to optimise were influenced from different perspectives which will be discussed under this high-level theme.

The last high-level theme that was identified was *Company Aspects* which also played a significant role in the optimisation of the ships. Decisions taken by the ship management company controls how the ships were operated and how they were equipped. This will be discussed under the high-level theme.

The high-level themes were:

- Optimisation Variables
- Optimisation Motivation
- Seafarers' Factors, and
- Company Aspects.

Each of these high-level themes will be presented individually in this chapter, and supporting interview extracts are shown as indented italics.

The high-level theme optimisation variables were the theme that had the most categories and contained categories that were addressed by all the participants. The first section addresses this theme.

4.2 Optimisation Variables.

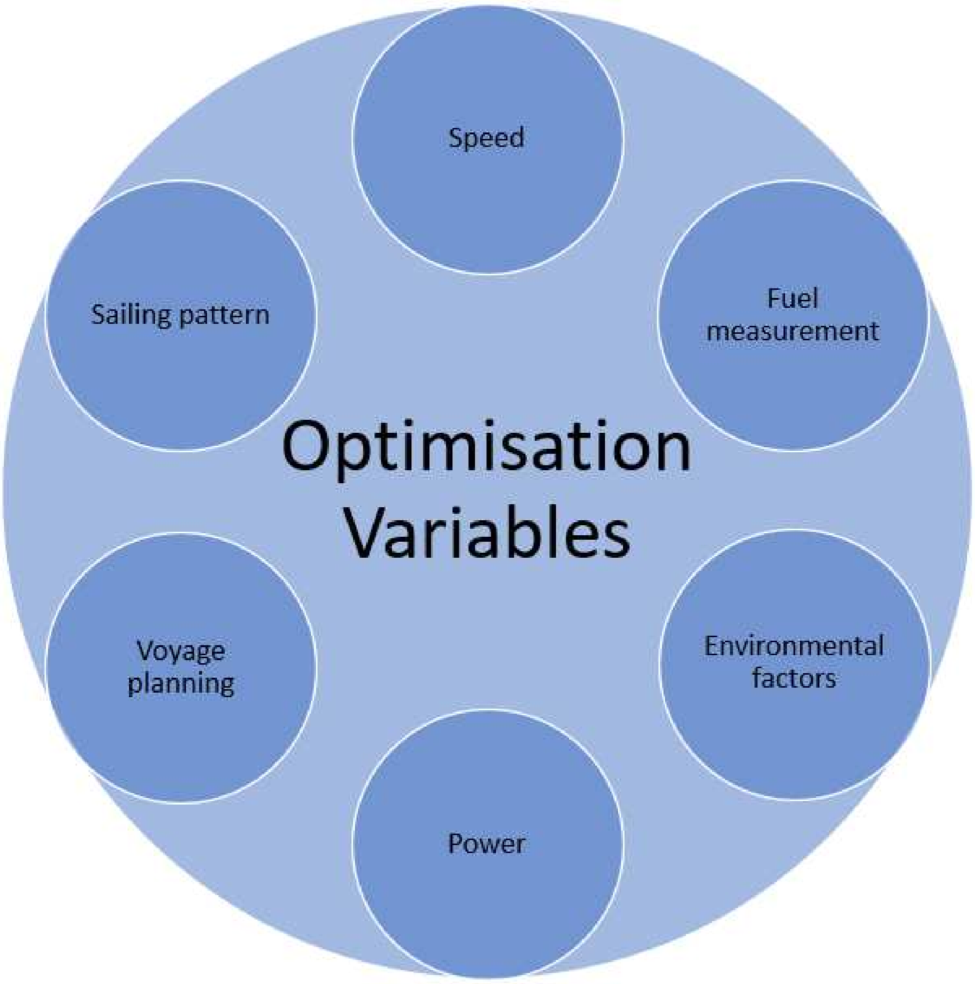

Figure 3 High-level theme Optimisation Variables with categories affecting optimisation.

Optimisation variables, as one of the main high-level themes, emerged naturally as all the interviewees expressed thoughts relating to which variables they used for optimisation. Each of these variables related to values that were not consistent or had a fixed pattern but were liable to change. The variables were speed, power, voyage planning, fuel measurement, sailing pattern and environmental factors. These are also illustrated in figure 3, and in this section, we will look at each of them under separate sub-headings.

Speed

Speed was an example of an optimisation variable that could be changed relatively easy. Several interviewees mentioned speed as one of the top three most important variable they employed for optimisation, together with battery installations and use of shore power.

> *To be conscious about the speed will be the most significant variable and the biggest potential to waste fuel.*

Interestingly there were different approaches to optimising speed among the interviewees: One expressed that the speed should be monitored to ensure a defined maximum speed was not exceeded; while another expressed that speed should be ignored in favour of ensuring that the engine load was optimal for efficiency of the engine(s). Both approaches however, reflected that an engine running on high load uses an unfavourable high amount of fuel. This leads into the next identified category labelled power which was also highlighted by all interviewees.

Power

Power played a significant role in ship fuel consumption, and all power or energy consumed onboard had to come from an energy source. The type of ships operated by the interviewed ship management companies relied on internal combustion engines, with primarily diesel as fuel. The ships were designed to maintain position accurately at sea even under challenging weather conditions, and they used dynamic positioning (DP) as a main tool for position keeping. There are different DP classifications (DNV, undated) and the high focus on safety in the Norwegian offshore oil industry required redundant systems where loss of one system should not result in loss in position keeping. Propulsion was required to be powered by independently redundant energy sources (DNV, undated), and consequently, the ships operating in this segment were typically designed with several engines.

Our ships have four diesel-electric engines with two small and two big engines, so there is a question if the ship should sail with two small engines, two big, one big and one small or all four engines running at the same time.

The engines varied in size which enabled different combinations of engines during operations and during transits. Depending on the available time during transits or other operations apart from DP-operations, the ships had the flexibility to combine engines ensuring that only the necessary power was produced, and that the engine(s) were running on a load that provided the best engine efficiency. Actively considering how many engines to run during the different operations or transits were highlighted by several of the interviewees as one of the main approaches to save fuel. Although some ships had digital tools to suggest the best combination of engines for the different types of operations, no interviewees used machine learning for this purpose, but relied on experience to determine an optimal combination of the engines.

A bus-tie breaker is a device connecting or disconnecting switchboard sections, and a closed bus-tie meant the electricity could flow openly between the switchboards (IMO, 2017). Several interviewees expressed their reflections about the use of an open bus-tie breaker, as this significantly impacted the fuel consumption.

During DP operations it is a requirement to operate with open bus, which means that the switchboards are split, and it has a big impact on the consumption.

In short, ships used open bus-tie breakers during DP operations due to risk and safety concerns (DNV, 2015), meaning that both the two redundant power sources onboard should be running in parallel. The rationale is that an equipment fault of one power source should not result in a total loss in continuous position keeping. This implied that more engines were running, which further implied a higher fuel consumption than strictly necessary.

Installation of battery packs on the ships had introduced a new element to the power source management onboard. Several ships had battery packs installed onboard to support the demand for energy, but the biggest fuel saving would be when the batteries were charged from shore power while the ships were alongside. Several companies expect to install more battery packs on their ships going forward, and they indicated that the battery packs would be bigger and possibly also replace one of the engines onboard.

> *...we see that charging power from shore with a larger battery pack than what we have, can also be very efficient.*

Having energy supplied from shore could save fuel, both by charging the battery pack onboard and to avoid having the engines running when the ships were alongside. This was acknowledged during the interviews, and several ships had been converted with facilities to receive shore-power when it was available.

Power consumption was also a topic that several interviewees discussed, as the energy produced by the combustion engines could be used more efficiently. This included consumption or loss of heat and energy through cooling water, engine exhaust, engine room ventilation, accommodation, lights and other big and small consumers onboard.

> *…the energy that you cannot take care of or use for propulsion goes out via exhaust temperature and out via cooling water and other things.*

The companies evaluated to implement new technology to utilize the energy most efficiently and focus on stopping equipment that was not necessary to have running.

Fuel measurement

Another interesting optimisation variable identified as relevant to fuel saving was fuel measurement. Measuring the actual fuel consumption and controlling how much fuel was consumed was vital to identify trends or determine any increase or decrease in consumption. The accuracy of fuel measuring and how fuel measuring was done played a significant role. Still, the consumption was in most cases only based on calculated estimates, tank soundings and manual recording.

> *...the fleet are registering the fuel consumption measurements manually, which means they are not so accurate.*

This implied that the fuel consumption figures were not accurate or detailed, but fairly reliable in a long perspective. Some companies had mechanical flow meters, and one company had recently introduced more accurate fuel consumption measuring devices on some ships.

Voyage planning

Voyage planning was also a category where earlier research indicated a significant potential for saving fuel. However, none of the interviewed companies indicated that they used any form of machine learning for optimisation within this area.

> *We apply experience to this, we know exactly how many nautical miles there are to each installation and take into account waves, weather, wind, draft and such things and adjust the departure time to meet arrival time.*

Voyage planning was based on experience and available information such as weather forecasts and other available sources of information. The voyages were planned based on at what time the ship had to be on the location offshore or arrive in port. This lead to the next category labelled sailing pattern.

Sailing pattern

Efficient operation and optimisation were highly reliant on how the customers utilized the ships for transport. Most cargo transported to and from offshore oil exploration units was transported by ships. The offshore units' managers, together with the planning units ashore, decided where cargo had to be transported, and ordered the ships accordingly. The ships could then plan according to this, and depending on the urgency, it could be possible to perform the voyage with a speed that was optimised. However, several interviewees indicated that due to the planning from the customers' side, it did not always allow for fuel savings.

> *They may for example receive orders to sail with best possible speed out to the location, which means that we open up for higher fuel consumption.*

Some companies were focusing on cooperation with the platform managers and the customers’ planning units, to try to influence them allowing for more efficient operation of the ships. Utilising the ships capacity both to and from the offshore field, spending time alongside instead of waiting offshore and good logistics planning were mentioned as vital elements for optimisation.

Weather and environment

Ships at sea are exposed to meteorological and environmental factors such as wind, current and waves, which also played a significant role in influencing the fuel optimisation.

> *We optimise based on wind- and wave conditions and plan our route based on the information.*

The North Sea is known for its rough sea states, strong winds and frequently changing weather conditions. Planning and carrying out the voyages required access to reliable information and continuous evaluation of the prevailing conditions. The impact of the environmental factors could to some degree be compensated for by planning a favourable route, and the interviewees indicated that planning was based on experience.

Marine growth on the submerged parts of the ship was also something that affected the fuel consumption and was depending on external environmental conditions such as temperature, sunlight and biology. Hence, the area the ship was trading had to be taken into consideration when assessing the degree of marine growth. This was a variable that might be different from ship to ship, which could guide the companies’ efforts to prevent or remove fouling. Several interviewees mentioned that they were using silicone-based antifouling which was considered the best antifouling available.

Variables Summary

Altogether the research found that machine learning had not been implemented for any of the optimisation variables discussed above, the data indicated that the variables were important for optimisation of the ships’ performance. An experience-based approach was applied for optimisation of the ships’ performance, which emphasises the importance of having experienced seafarers to achieve optimisation.

Having investigated the optimisation variables, and what was possible to physically change, it was now a question about what was the motivation behind the variables that change. This will be examined in the next section.

4.3 Optimisation Motivation

The preceding section provided a thorough examination of the optimisation variables, and this section will shift the focus to motivation for optimisation (see Figure 4). It was

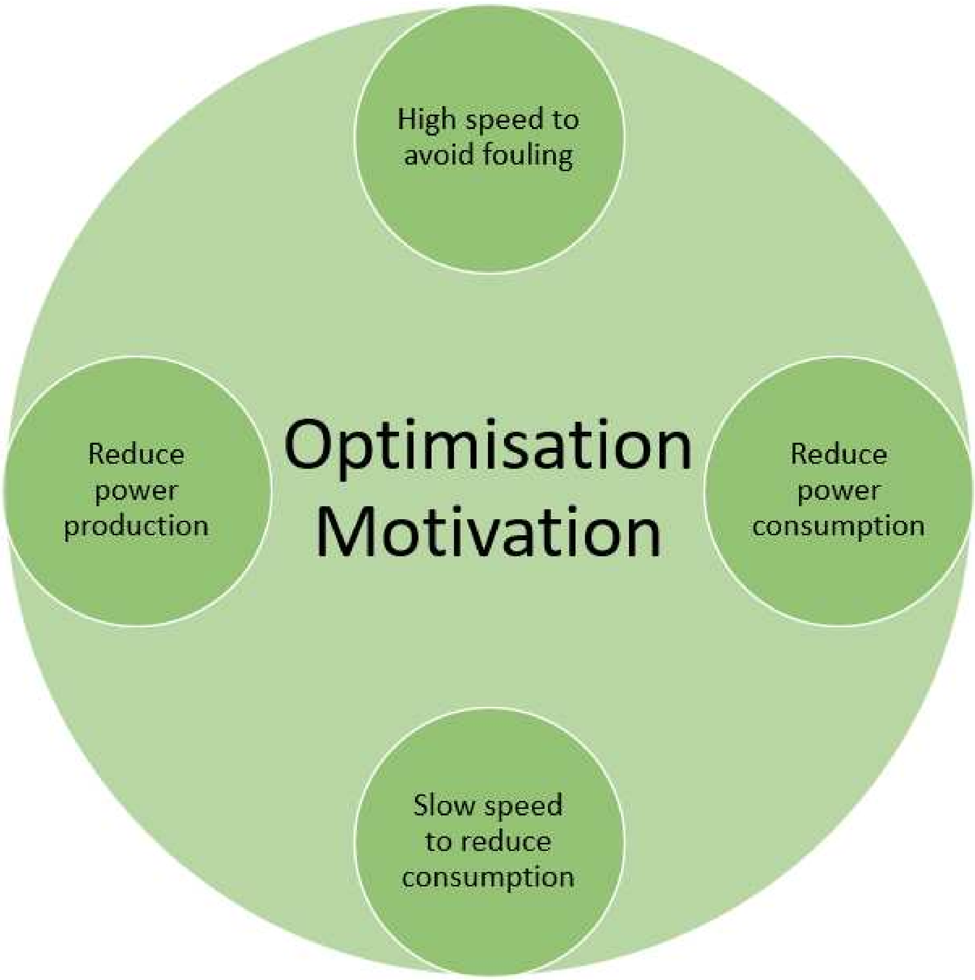

Figure 4 High-level theme Optimisation Motivation with categories affecting optimisation.

different from the variables themselves, but yet it was a driving force affecting the value of the variables discussed. The categories included in this were high speed to avoid fouling, slow speed to reduce consumption, reduce power consumption and reduce power production, which will be discussed in this section and speed will be addressed first.

Speed was one of the most important variables affecting fuel consumption as discussed in section 4.2. A slower speed required lower fuel consumption as less power was required, and fewer engines had to be running. A higher speed required significantly more power, which resulted in a significantly higher fuel consumption.

> *When you reach this speed and if you want to increase the speed with one knot, you may have to use double the engine power.*

This indicated that the motivation was to keep the speed low, and most companies had given instructions or guidance to their fleet to follow when they were operating. Some companies even logged each case in which a ship was not able to follow the company's instructions, as non-conforming situations. But there were counter incentives to keep the speed as high as possible including keeping the speed high for good manoeuvrability. The anti-fouling's ability to prevent fouling was also very dependent on speed through the water.

> *The anti-fouling contains poison that prevents the algae's from sticking to the hull, and if you do not sail enough, you will not be able to renew the self-polishing effect of the antifouling.*

When water flow over a surface treated with self-polishing anti-fouling, the water flow slightly erodes away the upper layers of the anti-fouling, gradually also removing any biological material attached to the surface. Speed through the water was necessary to have this process running as intended, but offshore support vessels normally spent a lot of time waiting, maintaining position offshore on DP or staying in port. So, there was a conflict in motivation to keep as low speed as possible, compared with the motivation to keep as high a speed as possible. Marine growth on a ship's hull created added resistance and higher fuel consumption, and more power to maintain the speed also caused higher fuel consumption. Power was also a category that had different approaches related to optimisation motivation, which will the topic next.

Power was a category that was addressed under the optimisation variables theme, but it also deserved attention under the motivation theme. Two different approaches were used by different companies, where one focused on reducing the power consumption and the other focused on reducing power production. Both approaches connected, in the sense that if you managed to reduce the power consumption you were also able to reduce the power production.

> *What we have a very big focus on, is power consumption on board, continuously. It's about turning off and shutting down the equipment we don't need to have running,*

During the last few years, more and more energy efficient equipment has become available in the market, such as for example LED lights, motion sensors and other equipment. This might reduce the energy consumption of devices and equipment that has to be turned on. Some devices or equipment such as deck cranes, cargo pumps, deck lighting may also be turned off during the periods when they are not in use instead of having them running continuously. Seafarers being conscious about turning off such devices and equipment might reduce the power consumption of the ship. The submerged part of the ship might also be regarded a power consumer, as it consumes energy moving through the water, and several interviewees emphasised that keeping the hull and propeller free of fouling had a significant impact on reducing the power consumption. When new ships were built, the hulls were tested during the design stage to find the designs that had the lowest resistance through the water. Some interviewees also expressed that trim, ballast and draft were important for the power consumption, while some considered this was not important due to the relatively short voyages. It could not be clearly determined what was the optimal trim or ballast, and the practice appeared to be based on personal preference of each individual master. Personal preferences were different from person to person, and it might impact the fuel consumption directly as a result of the decision-making processes.

Motivation summary

There were conflicting interests when it came to speed and there were motivations to keep the speed both high and low, which could affect optimisation. Power also had a significant impact, and companies could look at it from a power production perspective or a power consumption perspective. Reducing power production or reducing power consumption could both contribute to optimisation and as such serve the same purpose.

Having explored the optimisation motivations is this section, the next section will examine the Seafarer Factors.

4.4 Seafarers’ factors

During the analysis it became clear that the individual preferences of the seafarers operating the ship played a significant role in fuel optimisation. This resulted in the definition of the third high-level theme labelled Seafarers’ Factors. It included the categories of seafarers' behaviour, seafarers' maturity for ML, seafarers' information seeking and seafarers' motivation to optimise. This was illustrated in figure 5, and the categories are discussed in this section under different sub-headings.

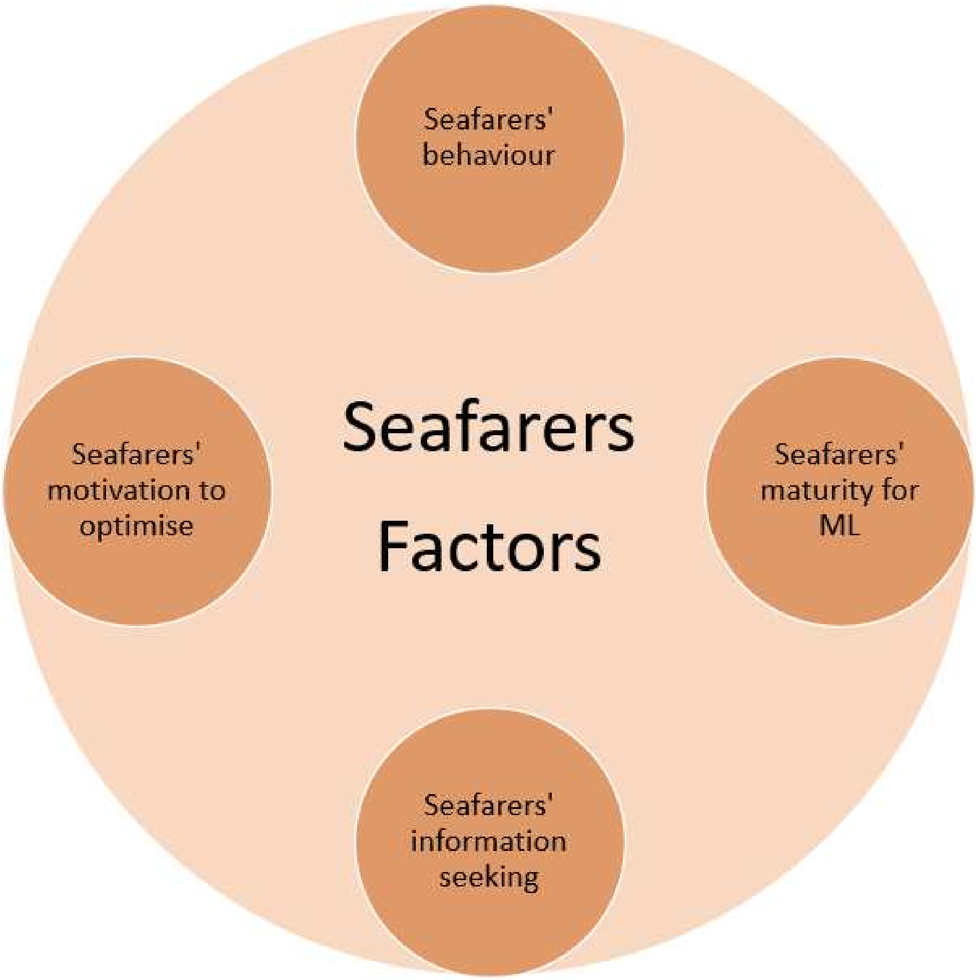

Figure 5 High-level theme Seafarers’ Factors affecting optimisation.

Seafarers’ behaviour

Seafarers’ behaviour addressed actions the seafarers carried out. Without any actions from the seafarers on board there would be very few changes, and from an optimisation perspective it was hard to imagine that any optimisation would occur.

Some masters preferred to have a lot of ballast on board, while others preferred to have less. However, having a lot of ballast increased both the ships draught and the submerged volume of the hull, resulting in higher resistance through the water and increased power consumption from the hull.

Voyage planning was an activity that has an impact on optimisation and involved human efforts and decision making. Both during voyage planning and during the voyage itself, it was necessary that the officers take action to achieve an optimised voyage. The wind and wave conditions, normally collected from meteorological forecasts, as well as information about ocean current and previous experience of the waters provided valuable input when planning a voyage. However, different navigation officers might utilise this information and plan the voyage very differently depending on factors such as their background, experience, education, training and how they perceive the effect the elements may have on the ship. This may also impact how they responded differently to changing conditions during the voyage as the conditions change.

> *..you plan ahead of a sea voyage and if you see you get a lot of headwinds, you set a course that is longer on paper, but gives a better progress and a lower fuel consumption,*

Different officers would consider the effect of the winds and the currents on the ship differently, and their behaviour would reflect this. Were they prioritising a comfortable voyage with a lot of ballast or no ballast with the least fuel consumption, were they planning to depart from port earlier to keep an optimised speed when this was possible, or did they wait in port as long as possible when there is room to do so, to save fuel by using shore power? These were mentioned by the interviewees, and they were decisions that the seafarers made based on their experience, which impacted optimisation greatly.

Speed was also an issue as discussed earlier, but in the end, it was the master's decision, instructions, and the behaviour of the ships' officers accordingly that decided the speed of the ship, how many engines should be running and how the battery power should be integrated.

> *If you invest a lot in battery packs and shore power but continues to waste fuel, the investments are wasted.*

Utilising the equipment as optimally as possible and taking advantage of the possibilities was very important if you want to save fuel. This leads to the next category within the same theme labelled information seeking.

Seafarers' information seeking

To be able to know the possibilities, the operators of the equipment, the seafarers, should have acquired this knowledge from somewhere. The information should be available, and it is a regulatory requirement that for example manuals should be available on board for the installed equipment (SOLAS, 1974, Reg. 19.2.1.4). However, it was often up to each seafarer and his/her behaviour to seek information that determined how well he/she is aware of the possibilities and how well they took advantage of them.

Seeking information about customers' plans, and in this way having knowledge about the plans may also enable the ships officers to operate the ship more optimally.

> *We try to cooperate with the platform manager and the oil company for planning, so we don't have to rush and use excessive fuel with high speed.*

Cooperation with the customers in planning the ship's schedule may contribute to optimisation by utilising the cargo carrying capacity better, planning time of departure and arrival with a more optimised speed and maybe also serving more offshore units at the same time. It also led to gaining more predictability.

The Norwegian fleet of offshore support vessels is known to be technically advanced compared to the rest of the world fleet. The ships have a lot of possibilities but as already discussed, it was up to the seafarers to operate the ships the most optimal way. This lead to the next category labelled seafarers' motivation to optimise.

Seafarers' motivation to optimise

The possibilities were there, but did the seafarers actually take advantage of them to optimise, and what was the driving force behind their action?

> *When we are in standby and waiting without any particular preparedness, we shut down what is not necessary to have running and we may also drift using minimum power.*

Motivation plays a large role if you want to attain success within an area. The interviewed companies made efforts to influence the motivation of the seafarers, and while one company had used short fuel campaigns annually where they put extra focus, information and training on saving fuel in the fleet for a limited period every year, other companies made live performance information for each ship available to all ships in the fleet, thus creating a competitive environment.

> *We had an advantage by having two similar vessels with batteries and shore power, which means there are four different shifts, making it possible to compare them.*

Having the best fuel performance might influence the motivation of the seafarers, and through the common performance monitoring system implemented by all the companies, the best performers were easily identified. The implemented system could even identify differences between the seafarers' shifts, which made it even more personal, hitting the competitive nerve of each individual.

Having the motivation to optimise could inspire the seafarers to use all available means to be the best performer. ML is a tool that may have potential for optimisation, but are the seafarers ready to implement such tools in the operation of ships? The next category labelled seafarers' maturity for ML will look at this.

Seafarers' maturity for ML

Several digital tools have been implemented on ships during the last decades such as dynamic positioning systems, digital radars, electronics charts, planned maintenance systems, automation, safety and control systems. Interfacing with computers to operate the ships is normal, especially for the modern fleet serving the offshore oil industry in Norway. Yet there is still a lot of experience involved when seafarers manoeuvre and navigate the ships from location to location. When introducing new technology there is a risk that the operators do not want to adopt it, that they do not see the benefit of it, or have doubts regarding it and consequently prefer to work as they have done before. This was highlighted by several of the interviewees, and different factors may influence the implementation.

> *An older master would probably trust himself more than an advisory screen, while younger*

masters would probably use the advice to a higher degree.

The quote above coming from one of the interviewees indicated that age in general could be an influencing factor, and that younger seafarers were more open to technological solutions. Several of the interviewees stated that they had implemented digital solutions for providing operational optimisation advice to seafarers which was voluntary to follow, but it was not always followed. The implemented systems provided guidance on shutting down engines, available power compared to consumed power, DP operations, engine load and other types. Some companies considered the advice as a benefit, while other companies considered it not helpful. New advisory systems were also being developed, which indicates that the level of digital tools would only increase in the years to come. ML could be such a tool, although none of the interviewees said they actually used ML today.

It is important to be able to visualise the fuel saving, then it would be easier to implement.

If ML were available on board today, it would be far from certain that the seafarers would use it, based on the interviews. It might had to mature for some time before seafarers would trust ML, and one interviewee expressed it is important that the algorithms and software are properly tested, trained on the existing data sets and could produce reliable results from the beginning when installed on board.

Seafarers' Factors summary

A key factor for successfully implementing optimisation is to have the support of the seafarers. Optimisation requires to operate the ships by making conscious decisions with a common goal, and individual factors might influence this significantly. Experience, knowledge, and other factors may decide the actions of the seafarers, and together with their motivation to optimise and to seek information, they could have a big impact on optimisation. ML is also a new technology in ship operation, and seafarers might be hesitant to trust it if it is not implemented well.

Having discussed the seafarers' factors above, it was evident that the ship management company also plays a very important role in optimising the ships in the fleet, from both a technical and operational perspectives. Company aspects emerged as a high-level theme during the analysis, with several integral categories. Transitioning into the next section, the focus will shift to the company context and a more specific examination of the identified inherent categories.

4.5 Company Aspects

The high-level theme Company Aspects included the categories illustrated in figure 6, and throughout this section the categories motivation to optimise, companies' information seeking, data collection, companies' maturity for ML and customer relations will be discussed under the different sub-headings.

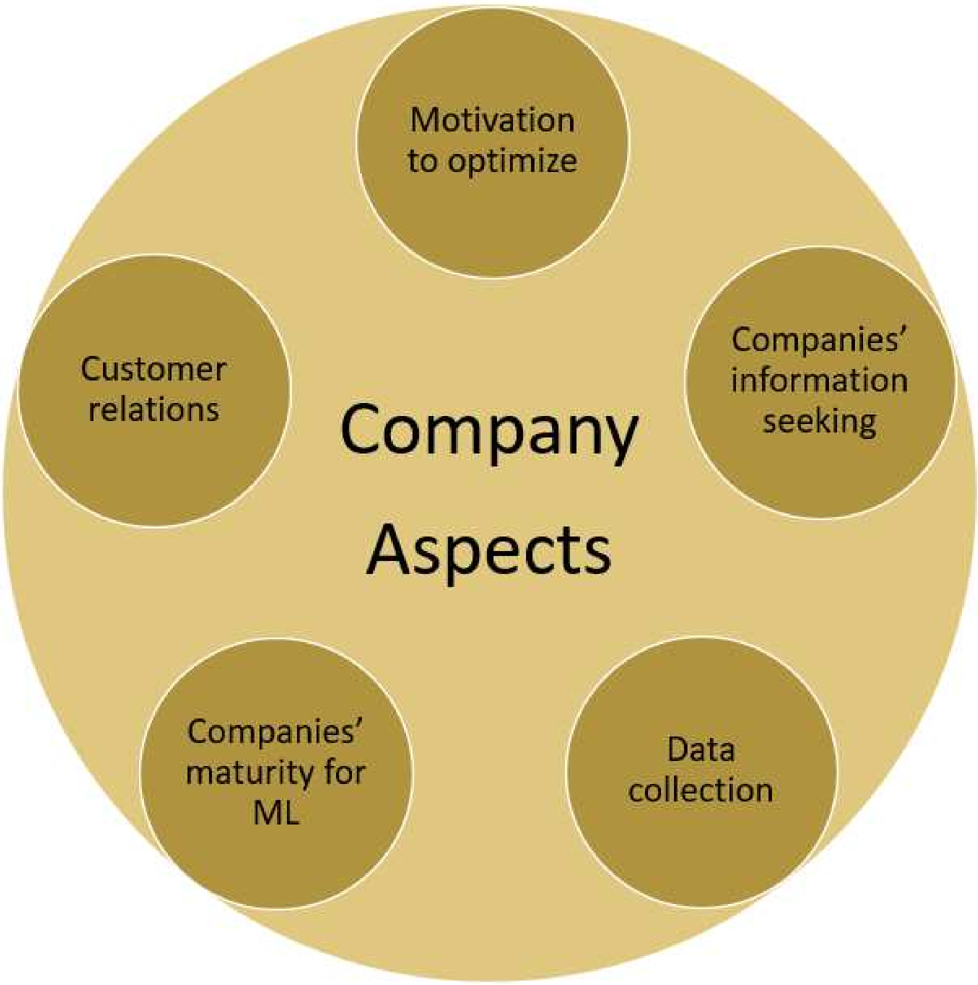

Figure 6 High-level theme Company Aspects with categories affecting optimisation.

Motivation to optimise

One of the most important company aspects was the motivation to optimise, as this might influence the efforts of the company significantly. The ship management company is responsible for the operation of their ships according to international regulation (SOLAS, 1974, Ch. IX; ISM Code, 2018), and decides how the ships should be operated, including setting targets and objectives, creating policies, and defining operational procedures. The interests of the company and owners are reflected in the management system, and the implementation of the management system is verified through audits at least every 12 months (ISM Code, 2018). With the implementation of gradually stricter requirements for environmental performance, the companies are forced to set targets and take action to improve accordingly. Combined with customer pressure, this created a motivation for the company to optimise, and several interviewees highlighted that by optimising, also the running hours for the engines could be reduced and this saved cost for maintenance and replacing worn parts.

> *If we may optimise the use of engines and equipment on board, and get an optimal operation, it also means minimising costs which is important for us.*

Ship management companies needed to focus on reducing emissions and having the best environmental performance by optimising in order to be competitive and be able to operate ships in the future. This should clearly be reflected in the goals of the company, and something one would expect to find in the management system (ISM Code, 2018). What is stated in the management system should also be the guiding foundation for the seafarers on board when performing their tasks. This emphasises how important the company's motivation could be for optimisation.

> *This requires continued focus also from the company and the operators on board.*

Having the ships in operation and having customers willing to pay for the services is a premise for business continuity, and the offshore support ship business have had some difficult years in this regard. This led to the next category labelled customer relations.

Customer relations

Being able to win contracts for their ships and keep them in operation to secure revenue is a key element for a company's survival.

> *We have had a difficult period since 2015 and we had to reduce our fleet considerably, but*

this has been the same for all the other companies as well.

Companies that manage to have satisfied customers will probably be in a better position when the next contract is announced, compared to the companies that do not. This may create a strong motivation to please the customer both from the company's side and from the seafarer's side. The oil companies indicated their emphasis on environmental performance for example by making the fuel performance monitoring system Maress mandatory and having ship management companies install battery packs on their ships.

Maress is something that Equinor and several other oil companies have adopted, and what they want because then they get uniform information from all the suppliers in in the same format and then it is easier for them to compare.

When orders were received from the customer to sail with high-speed causing excessive fuel consumption, the masters followed the customers' requests despite a possible breach of the companies' policy for speed and fuel saving. Some companies made efforts to cooperate with the customers and tried to influence them in various ways, which could allow for a better environmental performance when transporting the cargo to and from the offshore locations.

..we are often overridden by the customer, saying tomorrow we need this ship earlier, so you have to use full speed.

Several interviewees also highlighted the backup requirements during DP operations, which required them to use twice as many engines than actually needed, preventing optimal use of the engines and causing a high fuel consumption.

For offshore ships which are staying a lot of time in DP mode, a classical problem is that we need to have too many engines running due to back up and requirements for split switchboard, which prevents optimal use of the engines and optimal consumption.

This shows there were ways to operate the ships in a more optimised manner, but pressure from the oil companies prevented this in many cases. Another interesting point made during the interviews was that the customer paid for the fuel the ships used while they were on contract. This made investments into fuel-saving technology onboard that had to be paid by the ship management company less plausible, as a lower fuel consumption would be to the benefit of the customer paying for the fuel and not directly to the ship management company. On the other hand, if this also resulted in fewer running hours it could also lead to lower costs for the ship management company. Ships using less fuel could be more attractive in competition with other companies when contracts were negotiated, and it became clear during the interviews that the companies had an interest in monitoring what other companies were doing. Companies' information seeking appeared as a separate category during the analysis, and this will be discussed further in the next section.

Companies' information seeking

Several companies stated that they continuously were seeking information through both monitoring the competitors and participating in forums with customers and stakeholders in the business.

> *We participate in forums, webinars, read materials and keep ourselves up to date on technological development and possibilities.*

Having knowledge about the technological developments and being able to evaluate the possibilities, could be very important when making informed decisions affecting the future of the company. Seeking information could also be regarded as information about own ship's performance and was something which was in the interest of every ship management company. The next section will address the category data collection.

Data collection

All the companies were seeking information about the performance of the ships in their own fleet, which could be used to monitor status and identify improvements. The companies defined how this information was collected and set the requirements for reporting from the ships. Some of the information was collected and reported to the company manually and some was collected automatically. Apart from fuel consumption, companies also collected information about the operational mode the ships had been operating in, sailed distance, GPS position, time, course, speed, use of shore-power, energy, emission, running hours, propeller cavitation, AIS data, and in some cases number of engines running, wind information, wave information, electrical consumption, engine load, sea current, time for starting and stopping equipment, time for opening and closing of the bus tie-breaker, temperature on the different systems, frequency converters, electronic signals and regulation signals. This was information that the companies to a varying degree recorded and logged and for those logging it, it was possible to access the historic data later if needed. Some information was recorded automatically with a higher frequency and accuracy, while the information was collected manually for other ships.

> *We have several vessels where the measurements are automated, where the measurements are automatically collected from the automation systems on board and collected by the software we have, for overview. The rest of the fleet are registering the fuel consumption measurements manually.*

All in all, the companies collected a significant amount of information relevant for the performance of their ships. The interviews showed that it was possible to collect the information, but it was up to the company to decide how accurately they wanted to collect it and what type of information they wished to collect. It was related to the company's information seeking, the purpose of the data collection and how they wished to use this data. ML is a powerful tool that may be able to learn from vast amounts of collected data, which leads into the next category companies' maturity for ML.

Companies' maturity for ML

When asked about the application of ML in their operations, the companies could not present any implementation, but several companies mentioned examples of modern technology implemented on their ships. The purpose of these on-board systems where mostly related to providing advice on fuel optimisation during DP operations, during transit and other operations.

> *…we have also implemented a guiding system which indicate red if the energy consumption is too high based on what is expected in the type of operation.*

There was continuous development of these systems and more functions coming such as speed optimisation and estimated fuel consumption. Some companies had also implemented automated systems for collecting data about fuel consumption, and software for visualising the performance, providing more accurate and detailed information. There were several sources for performance data on board such as engine data, switchboard data, and maintenance data, but the data was not always collected. ML is depending on reliable data sources and several companies had evaluated the technology to varying extent, although they had not yet implemented it for optimisation. Four of the companies stated they used computer systems onboard their ships with software that was being developed for future software releases where ML was expected to be implemented. One company had completed a study for ML implementation onboard their ships, and two companies stated that they participated in forums where ML was discussed to keep themselves updated on the technology. Logistics planning was also suggested as a potential area where ML might be a good tool, for the customers planning the sailing schedule.

The willingness to try and test new technology on board their ships, indicated that the ship management companies were ready to implement ML as well.

Company Aspects summary

Companies related to and adjusted to the context continuously, with regards to customers' needs, and to the collected information from the ships and other sources. Both regulatory- and customer requirements might create motivation for the companies to optimise and seek information about technological possibilities to further improvements. The companies also decided how often and what type of performance data should be collected from the ships, enabling them to evaluate the performance. Several companies indicated interest in ML, although none of them had implemented the technology so far.

4.6 Chapter summary

During this chapter, the high-level themes were presented together with the categories within them that were identified during the interviews. Several variables, motivations, factors and aspects affecting optimisation were highlighted, the company and seafarer controlled some, others were controlled by external factors which were more difficult to control. Combining all the figures (see Figure 7 overpage) used during this chapter provided a map for discussion of the results, and the map of high-level themes could act as an anchor for the rest of the thesis.

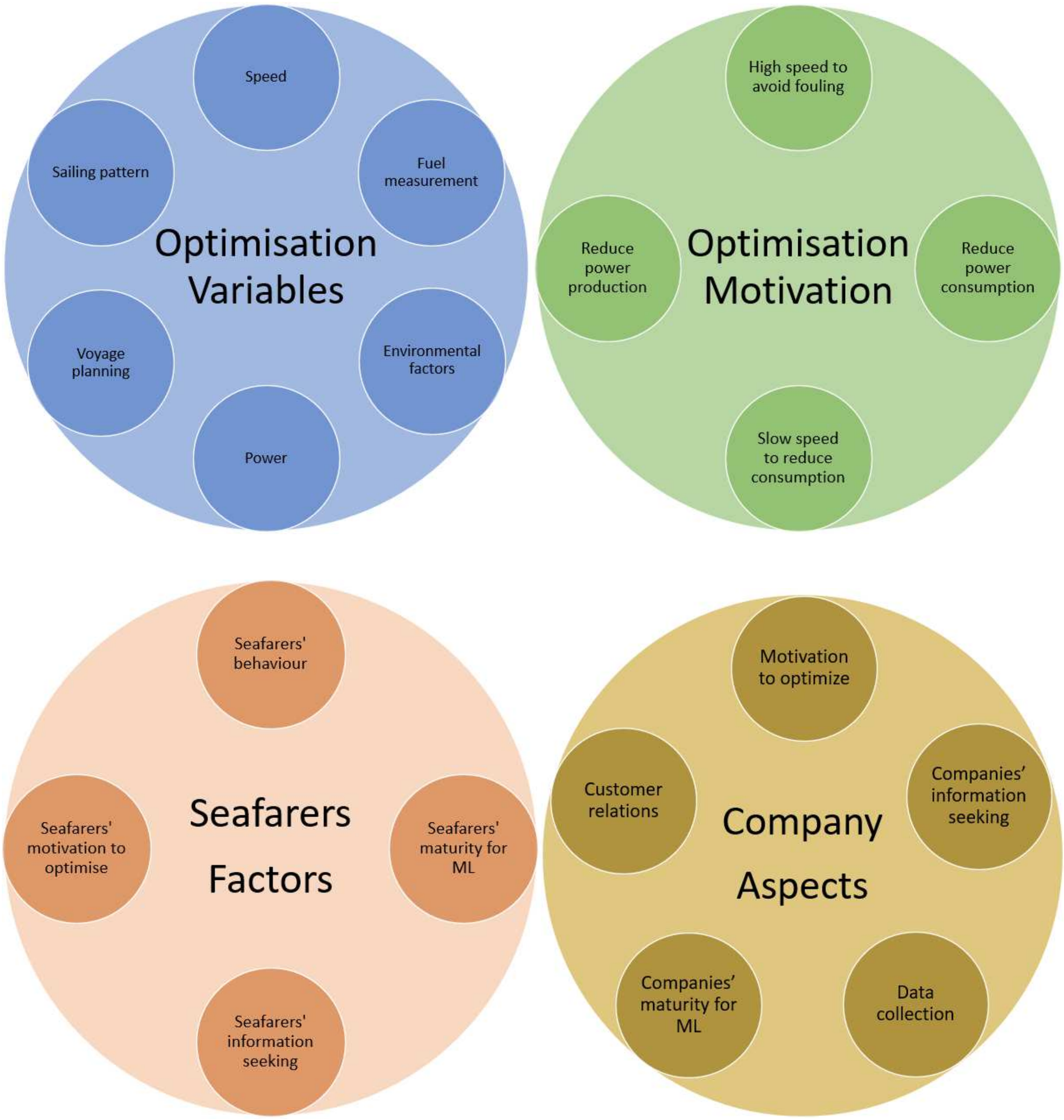

Figure 7 Map of high-level themes affecting optimisation, with categories.

With the data presented and analysed, it was time to reflect on what the findings meant for the research question. In the next chapter, the focus turns to the practical implications of the research exploring how the findings can assess the application of ML within the maritime industry.

5 Discussion

Acknowledging the potential power of machine learning in improving efficiency, reducing costs and optimisation from previous research as presented in the background chapter, it provided a foundation for further discussion. Looking to provide more knowledge into the use of machine learning as a tool for operational optimisation within ship management companies, this discussion will connect the collected data with previous research.

This research aimed to explore to what degree ML was used for optimisation within ship management companies. The data collected from management executives emphasised the importance placed on efficiency and cost-effectiveness in all aspects of the business. The chapter will present several key learnings which may be valuable for practical implementation of ML for optimisation, or when introducing new technology on ships.

The four high-level themes will be discussed in two sections as some categories within them may be looked upon in parallel. First the high-level themes Optimisation Variables and Optimisation Motivation will be discussed, and then the high-level themes Seafarers Factors and Company Aspects will be discussed. Under each of these sections, the related results from the previous chapter will be discussed.

5.1 Optimisation Variables and Optimisation Motivation.

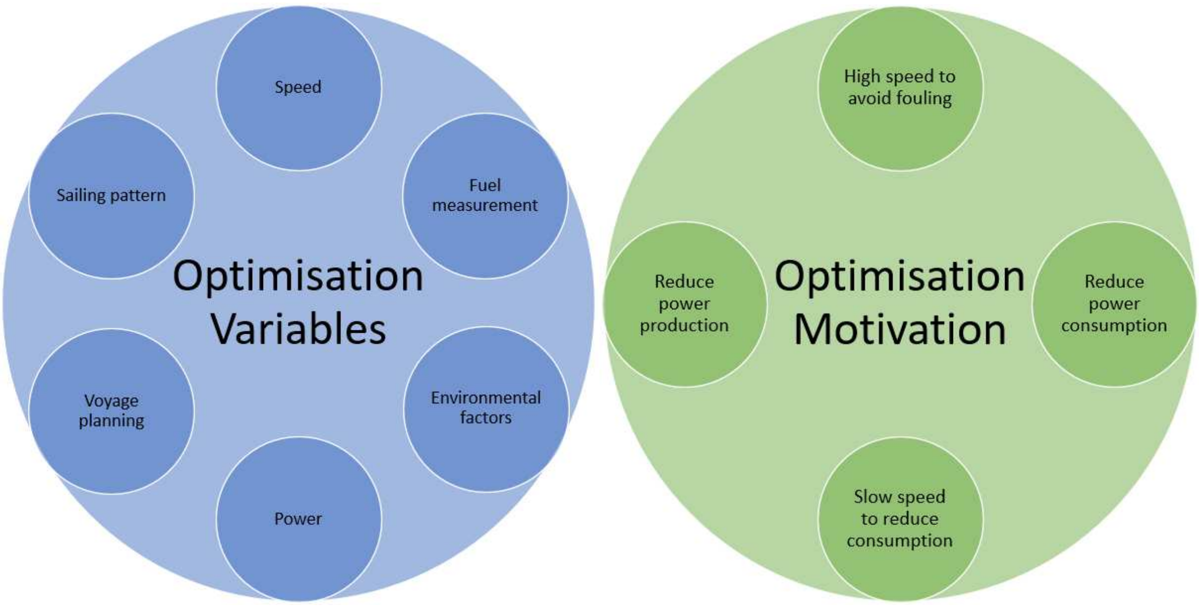

Figure 8 First two high-level themes Optimisation Variables and Optimisation Motivation affecting optimisation, with categories.

Returning the map of the first two high-level themes (see Figure 8) developed in the previous chapter, the attention is first drawn to the first two high-level themes.

5.1.1 Power balance

Optimisation is about balancing multiple factors and conditions across a complex system. Avoid producing more power than needed at any time or reducing the consumption as much as possible was highlighted by several of the participants as one of the most important measures for reducing fuel consumption. This may be regarded as a power balance that needs to be monitored frequently in the changing environment for ships where both the environmental factors such as wind, current and waves are changing continuously along with the changes in types of ship operations and modes. ML has been applied for combining power management with propulsion control systems in research (Perera et al., 2016). Combining information about engine power, ship speed, shaft speed and fuel consumption where ML is based on big data sets, it could advise the ship officers what speed would be optimal (Huang et al., 2022). No evidence was found that this had been applied among the respondents.

Reducing power consumption may also be a driver for the development of technology and inventions that use less energy and are more environmentally friendly. ML could have the potential applications of optimising the power balance, reducing power production and reducing power consumption. Several of the ships had batteries installed, and ML could be used to suggest how the battery could contribute to optimising energy production. Should it be used during DP operations, should it be used during transit, manoeuvring or should it be used during all the different operations or modes? These are all relevant questions if the full potential of the battery installation and the power production should be optimised. Research has shown that a reduction of fuel consumption by up to 8,5% may be achieved when applying ML in a hybrid battery - diesel engine propulsion set up for optimising the energy sources (Planakis et al., 2022). However, several participants indicated that experience and personal preference were the main factors for optimising the energy onboard, and one participant also raised concern that the battery was not optimally used. No indication was found that ML was applied in any way for optimising the power onboard, although several initiatives were taken to optimise without using ML.

Key learnings in this section:

- It is valuable to monitor both power production and power consumption.
- Companies need to make informed decisions about what's right for them to optimise.

5.1.2 Data collection

The technology of ML requires that datasets are available for training the algorithms. We have seen that the companies are collecting data and have been collecting it consistently over long periods of time. Some companies collect the data through reports which are sent daily based on manual readings and recording in the report. In contrast, others have a varying degree of automated collection of performance data from the ships. All in all, companies are collecting a significant amount of relevant information for their ships' performance, which makes it possible to analyse the data for optimisation. But it is a question of whether the data foundation for training the algorithms is ready yet. A key factor for good output from ML models, is that the training data used to produce the model is of good quality. As such, such advancements do depend on the correct data being used for training ML models to maximise their impact.

Some companies reported in their interview that they were considering implementing more automatic data collection from the ships in the future, using the existing sensors or installing additional sensors. Automatic data collection has many benefits over manually collected data, such as more frequent data collection, more accurate data and less risk of human failure. A key requirement to generate good results from ML is to have reliable data – as the algorithms are trained on the existing data, an error may cause the output of the model to suggest non- optimal solutions. More frequent data readings during the collection period may identify variations to a higher degree and thus provide a more reliable data foundation for predicting future aspects. Having the human resources available to collect performance data with the same high frequency as automated sensor collection might be unrealistic, considering the emphasis on cost-effectiveness in the business. Daily reports that are used by several of the companies with a 24-hour report interval, might provide a very rough data foundation for ML, which may not accommodate the full potential of optimisation. Although it became clear that ML was not used on any ships, automated data collection could have provided datasets to train the ML.

Key learnings in this section:

- When assessing the available data, evaluate its quality, consistency and amount.
- Consider if is necessary to collect more data automatically.

5.1.3 Reliable data

The variations in environmental factors, internal factors and operations might change significantly during a 24-hour period, and as these factors might not be taken fully into consideration during the training of the ML algorithms, the algorithms may be trained on the wrong premise causing the quality of the results to be less reliable. Using the existing daily reports for ML training might provide valuable suggestions for optimisation, but to fully benefit from the potential of ML, a more reliable and accurate data foundation would likely add to the quality of the output. More automated data collection might be a solution, which may also reduce the risk of errors in the data material due to typing errors, wrong readings, wrong reporting, or other human errors affecting the ML optimisation output.

Both ML and artificial neural networks computer technology have shown great accuracy in predicting fuel consumption in several research initiatives, as discussed in section 2.5, online and in real-time with as little as 0,8% – 2,8% deviation. ML was the most effective method, producing the best results, and research has indicated that ML may estimate the fuel consumption of each engine without installing a physical fuel flow meter (Ahlgren & Thern, 2018). However, none of the companies interviewed used ML to predict fuel consumption.

5.1.4 Correct data

ML may demonstrate its power in identifying patterns and relationships in enormous amounts of data. Still, it is critical that the information contained in the data has the actual influencing factors for the area one wishes to optimise. The companies collected data valid for various performance aspects, although all the participating companies collected data about fuel consumption. Fuel consumption alone does not necessarily indicate optimisation, as this may be very dependent on the activity in the period. One ship may have a high fuel consumption in one period during a busy summer month while having a period with low fuel consumption in another period, for example, during autumn when the ship might spend much more time in port. The low fuel consumption may not necessarily indicate that the ship is operating more optimised during the autumn period compared to the summer period. This illustrates that fuel consumption by itself does not indicate a level of optimisation, and if one aims to optimise the fuel consumption, other influencing factors should also be taken into consideration. In the mentioned example, factors such as sailed distance, weather conditions and time in port also impact fuel consumption and should thus be taken into consideration when carrying out the ML training. For some companies, it would mean that more data would have to be collected, and for others the available collected data might contain the necessary information. Although no evidence was found that ML was used for optimisation in the fleet of ships, carefully assessing which data to train the algorithms would be very important for the result of implementing ML.

Key learnings in this section:

- Assess collected data relevance, given company priorities.

5.1.5 Antifouling

Coraddu et al. (2019) found that ML is more accurate and reliable for predicting fouling on the ships' hull compared to traditional ways of estimating fouling, such as using the ISO 19030 "Measurement of changes in hull and propeller performance". However, when asking the participants how they estimate fouling to determine when it is necessary to clean the hull, it was found that they had decided to do this twice every year, by experience or by monitoring the speed of the ship. Usually, it indicated that the ship would have to be taken up into drydock to remove the fouling. However, it may also be possible to use in-water equipment developed during recent years to remove fouling when the ship is afloat. Taking the ship into dry-dock is both expensive due to the cost of using the drydocking facilities and paying for the workers, but also as the ship is taken out of operation for the time transiting to and from the dry-dock and during the time in drydock. The ship may then lose potential revenue as it is out of service, but it may also be on contract without any loss if the contract terms allow for dry-docking.

Having the hull cleaning frequency determined as a regular activity twice a year may not be optimal as the marine growth may not be constant throughout the year. The growth may depend on several factors, such as temperature, trading area or biological factors (Floerl, 2003). It is beyond doubt that marine growth increases when the temperature increases (Floerl, 2003), and the temperature in the North Atlantic Ocean is significantly lower than further south. Some ships are also prone to keeping higher speed than others, and this will affect the growth significantly (Floerl, 2003). The companies' effort to keep the hull free of growth is reflected in the investment into expensive antifouling to reduce growth. Several companies had invested into silicone-based antifouling to reduce marine growth, although it was significantly more expensive than regular antifouling.

ML may have a great potential for optimisation as it could predict more accurately when hull cleaning would be necessary. Taking the ship up into dry-dock at more correct intervals, could possibly save costly dry-dockings or avoid having the ship in operation with much marine growth causing increased fuel consumption. The algorithms used in ML could take into consideration factors such as ships speed, trading area, biological factors, type of antifouling, and hull design to accurately determine when hull cleaning or propeller polishing would be necessary. Despite the potential optimisation that could have been achieved by applying ML in this area, no evidence was found that ML was used for this purpose.

Key learnings in this section:

- ML may be applied for optimising hull cleaning.

5.1.6 Weather routing

Another area where research indicates that ML may have great potential is weather routing. Research indicates up to 9% in timesaving and 28% CO_2 reduction could be achieved with ML software on an intercontinental voyage (Grifoll et al., 2022). But in this research, there was no indication that ML was applied for weather routing or optimising the route. The route planning carried out onboard the ships of the interviewed companies indicated that route planning was carried out based on experience and available information. One should also consider that the ship types PSV and AHTS, normally have a trading area between the offshore fields and the shore cargo bases, leaving intercontinental voyages more rare. However, considering the fast-changing weather in the North Sea, ML may be applied there as well.

Key learnings in this section:

- ML may be applied for optimising weather routing.

Returning to the map from the second two major themes (see Figure 9), it is time to reflect on the last two high-level themes.

5.2 Seafarers' Factors and Company Aspects.

Several categories are overlapping also here, hence it is natural to discuss these together. One of the categories was motivation which will be discussed first.

5.2.1 Motivation

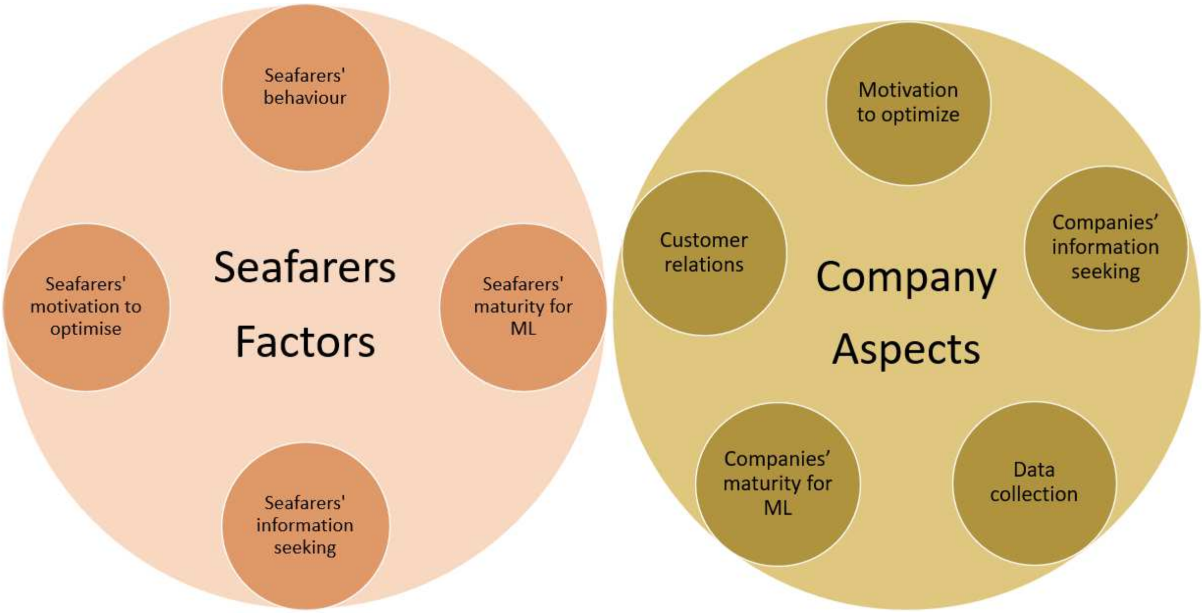

Figure 9 Second two high-level themes Seafarers' Factors and Company Aspects affecting optimisation, with categories.

Motivation to optimise is a category that was identified both from the seafarers' perspective and the companies' perspective. Considering motivation as the driving force or the underlying cause for performing optimisation, it may be the reason behind initiatives or behaviour to optimise. The company can influence optimisation significantly by their decisions, control and focus, and the driving force behind these decisions is the motivation of the company. The companies decide the design of the ships, they make the decisions on what equipment and possibilities should be available onboard, and they decide the content of the management system specifying how the ships should be operated. The ISM code also requires that the companies set objectives, policies and targets constantly improving the environmental performance of the ships (ISM Code, 2018). Companies have to relate to increasingly stricter restrictions for emissions, and the customers and other interested parties possibly also have expectations for environmental performance, including fuel consumption and emissions. Some companies could also have additional incentives to optimise, especially if they have to pay for the fuel themselves and when focusing on reduced cost due to less running hours and less wear and tear on their ship machines and equipment. Optimisation may contribute to reduced costs for operating the ships, which can create a competitive advantage over other companies with higher costs. Companies' management could also have a genuine incentive in optimisation to create sustainability and reduce emissions, founded on their stated purpose, vision and values. Companies might have a very long history through generations, and a business perspective with the aim of conserving the environment and create a sustainable foundation for future generations. Companies with shorter history could also have the same objective, and external parties such as financial institutions, insurance companies, partners (Poseidon Principles, undated) and the general public expect that all companies aim to have a good environmental performance.

The seafarers can also be motivated to optimise by the media, friends, family and a general focus on reducing carbon emission. The company's management system should address environmental performance together with continuous improvement, and it is the master's responsibility to motivate the crew in complying with this in their daily work (ISM Code, 2018). Controlling the variables and act with the intention of optimising is a key to achieving good optimisation results. Even if ML has not been implemented onboard the ships, motivation to optimise and take ML tools into use is very important for its successful implementation in the future.

Key learnings in this section:

- Employees should be involved to increase motivation.

5.2.2 Information seeking

Information seeking is also a category that appeared in both the interviews for the companies and seafarers. From the company's perspective related to optimisation, they should possess or have access to the competence of technological solutions enabling them to evaluate potential opportunities. Reflecting on available solutions and what type of equipment and measures are available for their ships and ship types, including advantages and disadvantages, is key to making informed decisions about systems to invest in and is essential for the future success of optimisation. For example, the conversion of ships enabling the use of shore power may have little effect if none of the ports it is trading have available shore-power facilities, and thus other solutions could be more beneficial.

Seeking information about own ships' performance can also be considered a form of information seeking. Having reliable performance data may enable the company to identify potential improvements and compare data. A key thing can also be that the collected performance data could form input for ML where the technology might be used to identify patterns and suggest optimised solutions in a more powerful way than human capabilities. The ability to predict performance and data based on powerful algorithms with high accuracy may also compensate for deficiencies in actual measurements or even predicting the data without making actual measurements (Ahlgren & Thern, 2018).

The seafarers operating the ship on a daily basis may have a tremendous impact on the optimisation and being aware of which optimisation solutions are available on their ship, as well as being motivated to optimise are key to achieving good results. This requires the seafarers to seek information about the possibilities on their ship, as all ships depending on ship type are different regarding design, machinery, propulsion, systems and equipment to varying extent. Training and familiarisation, as required by the ISM code (2018), play an important role here, but also the initiative and motivation of each seafarer to seek information about the possibilities on board. The ships operating to support the Norwegian offshore industry are known to be complex and advanced, which provides several opportunities for operating the ship in various ways. Still, to take full advantage of this for optimisation, it is necessary to seafarers have a good understanding how the different systems work individually and in combination. There are a lot of variables that can be controlled, and great flexibility to operate in different modes and settings. As discussed earlier, optimisation is about balancing factors, where adjusting the variables is an important element. Examples include how many engines should be running, how the battery should be integrated as an energy source and for which situations. Based on the research question no evidence indicate implementation of ML on the ships, but for possible future implementation information seeking both from the companies' perspective and seafarers perspective, information seeking plays a significant role.

Key learnings in this section:

- Ensure employees are competent, trained and familiarised.

5.2.3 Maturity for ML

Understanding the technology behind ML combined with fundamentals about optimisation may enable the company to adopt it more easily. Artificial intelligence and ML are fairly new terms in maritime, where, perhaps, the media and the movie industry may have contributed to creating a frightening image of its capabilities and scenarios. This can cause extra scepticism towards the technology and combined with normal human resistance to change (Jacobsen, 2018), It might create challenges for implementation. However, the offshore support ships are often technologically advanced, which can lower the threshold for implementing ML. When the company and seafarers are more accustomed to relating to technology, they may also see the benefits and opportunities more easily when introducing ML. There is an aspect of seafarers age for adopting new digital tools, as indicated during the interviews and this is something that the companies must take into consideration. Older seafarers may be more reluctant to implement the new technology. It may also be a matter of how it is presented, and whether change management principles are used in the process (Jacobsen, 2018). The interviews indicated that the companies regularly updated their software versions used onboard for the various equipment as the existing software was further developed with new functions and new technology. The interviews indicated, however, that even if the technology was made available, it did not necessarily mean that it was implemented and taken into use. If ML is going to be implemented successfully on board in the future and taken into use for optimisation, the companies should ensure that the implementation is carried out properly from the beginning.

Key learnings in this section:

- Employees should be involved to increase motivation.

5.3 Audience for these themes

Executives representing ship management companies were interviewed during this research as they were the main target group, controlling implementation of new technology onboard. The knowledge provided on the topic could be valuable for ship management companies considering implementing ML and focusing on optimisation on their ships. It might also bring value to other parties, which were not interviewed. It makes the impact of the survey much broader extending also to the related industries, which are affected by the services and cargo transport the ships offer. This could be charterers of ships like companies involved in offshore oil- and gas exploration or transport of cargo, as optimisation could reduce the cost for fuel which may have to be paid by the charterer or the cargo owner. The status of ML implementation and optimisation may provide knowledge for charterers of what to expect from ship optimisation, how ships optimise and the potential effects of ML in addition to using the key outcomes from this research to cooperate with the ship management companies reducing fuel consumption and emissions. Below some of the most relevant parties that may find value from the research will be further discussed.

The high-level themes and categories reflecting the collected data from interviews with the executives, provided valuable information into what was important for the executives and for potential applications of the technology. Several respondents indicated that ML would become more and more relevant to use for optimisation on their ships in various ways. Many interviewees used software solutions that could be further developed to include ML, and some companies were expecting that new software versions from their equipment and system providers would include ML. It indicated that the companies were open to this technology for optimisation on their ships, and that ML may become more widely implemented in the future. The executives are the decision-makers, and for companies aiming to sell or re-sell their products, the considerations of the decision-makers and requirements for the technology to be used on ships are valuable to develop their products, create revenue and make decisions. The ability of the new technology to produce reliable results immediately after implementation, was raised as such a requirement. This means that an if a seller should be able to successfully sell a product or software offering optimisation using ML to a decision-maker, the ML must already be trained and be able to produce results immediately. Several respondents also highlighted the importance of reducing fuel consumption and emissions. Hence this may be a key element for the decision-makers when deciding whether or not to invest in ML for optimisation, or which supplier to select. Based on this, companies offering such solutions should take this into consideration when offering their services in competition with other providers producing similar solutions. Reliable and trust-worthy numbers of how much fuel or emissions the product may save for each ship, may be very important to highlight and prepare for sales presentations held by the suppliers, as the research highlight that this is important for the decision-makers in the ship management companies. Optimising to save fuel may also mean saving costs, which was also highlighted as important for the ship management companies. Hence, when offering their products, suppliers of solutions for optimisation should incorporate expected reduced costs in the information to the decision-makers and maybe also consider offering different solutions for paying for the product, to be able to sell it. These are examples how other parties may find value from this research, and continuing this section, also other possible interested partied will be discussed.

Developers of software solutions for application on ships or in the maritime context could find it valuable to study this research as they may benefit from the results when designing their products. Good design is of vital importance for the success of developed software solutions onboard, and although the companies most likely have knowledge about the requirements and the companies' and seafarers' expectations, this research may supplement their knowledge, help aligning their business goals and create value.

Shipyards and manufacturers of integrated bridge navigation systems where several systems and sensors are connected, might also benefit from this research, differentiating them from competitors in adopting new technology. Ships may be built to last for several decades, and preparing them for integration, or integrating new technology, could make them more attractive in the contest with their competitors.

Also, other manufacturers, such as engine manufacturers, manufacturers of battery-hybrid solutions for ships and manufacturers of marine antifouling- coating and systems, may benefit from this research as ML and optimisation can also be potentially applied for optimisation in these areas. Providing knowledge about application requirements and expectations from the decision-makers of their customers, could enable them to develop their products and services, creating added value and competitive advantages.

There are several interested parties that could use this research for their benefit and even if no other companies apart from ship management companies were interviewed, the results can be used also for others to drive innovations aiming to lower emission of greenhouse gasses. Some applications for ML have been addressed in this research, but it may also be other types of applications that can be relevant for ships reducing emissions. This calls for further innovations, or development of existing solutions. Innovative environments may use this research as background knowledge to find solutions how ML may be applied in different ways for ships, either for the applications identified in this research, or for developing new applications. In this way the research also provide value for innovative purposes. The next section will provide a summary of the main topics discussed in this chapter.

5.4 Discussion Summary

The purpose of this chapter was to discuss the results presented in the previous chapter and provide input to the conclusions chapter. In this chapter the four high-level themes have been discussed and power was a category that appeared in two of the high-level themes, based on the analysis. This reflected the respondents' emphasis on power and its effect on optimisation. ML could have been applied for managing power, and research indicated that it could be used for optimisation.

The chapter considered a series of data-related issues that are relevant to the research question: data collection and reliability, as having available data to train the ML algorithms is a premise for the technology. It varied between the companies how much data they were collecting, and how often they collected it, which should be taken into consideration if evaluating to implement ML for optimisation. Some companies are planning to start collecting data automatically in the future, which might provide better and more reliable data. What type of data to collect should also be carefully considered to ensure the collected data is sufficient in size, and accuracy to train the models well enough to enable accurate optimisation.

The companies' approach to fouling of the ships' hull and propellers was highlighted as one of the most important factors for optimisation. The companies made significant efforts in keeping the hull and propellers clean as this was very important for fuel consumption and speed. The cleaning was based on regular intervals, and no evidence was found that ML was used for this purpose.

Weather routing was also based on experience and available information, and for the two last high-level themes, motivation and information seeking was identified as important categories influencing optimisation both for the seafarer and company. Both regulatory requirements and customer pressure could create motivation to optimise and seeking information about the possibilities to optimise was found as an important factor for optimisation.

Considering the level of technology already onboard the investigated ships, the introduction of ML could be easier than on other types of ships with less technology, but older seafarers would likely be more reluctant to adopt ML than younger seafarers.

No evidence was found that ML was implemented in any areas onboard, but the discussions highlighted a focus on optimisation ML that could be useful for several other parties outside ship management companies.

Having analysed and discussed the results in the last two chapters it is time to draw the final conclusions of the research. The conclusions will be presented in the next chapter.

6 Conclusions and recommendations

The objective of reducing GHG emissions has put the reduction of fuel consumption and fuel optimisation higher on the agenda during the recent years, and the efforts towards a sustainable environment in the coming years will impact the future of the planet. As the requirements for reducing fuel consumption and emission gradually strengthens, new technology can create additional possibilities to save fuel and optimise fuel consumption. The introduction of artificial intelligence and ML has been compared with the industrial revolution, and its powerful ability to find patterns and identify connections may be applied also for fuel optimisation.

The aim of this research was to understand the current use of machine learning as a tool for operational optimisation within ship management companies. Acknowledging the majority of the world fleet use marine fuel oil as the primary source of energy through combustion engines, fuel consumption generates both energy and emissions. Fuel consumption is the main contributor for emissions onboard ships, and ML may have an impact on optimising usage to minimise emissions. Therefore, to understand how the current maturity level in the industry for optimising this energy source the following research question was posed:

To which degree is machine learning used for fuel optimisation in major ship management companies today?

This final chapter reflects on what has been achieved, the contributions made into the field, and provides a conclusion to the story told in the preceding chapters. First the main findings of the research will be presented before the limitations and suggestion for further research is addressed last.

6.1 Contribution to the field

The interviews and subsequent analysis did not indicate any degree of implementation of ML for fuel optimisation in major shipping companies today. However, it revealed focus and interest in optimisation and produced knowledge of the current practise in the industry. First and foremost, this thesis produced a map of high-level themes (see Figure 7 overpage) with categories that are relevant when discussing optimisation, current practise and possible application of ML.

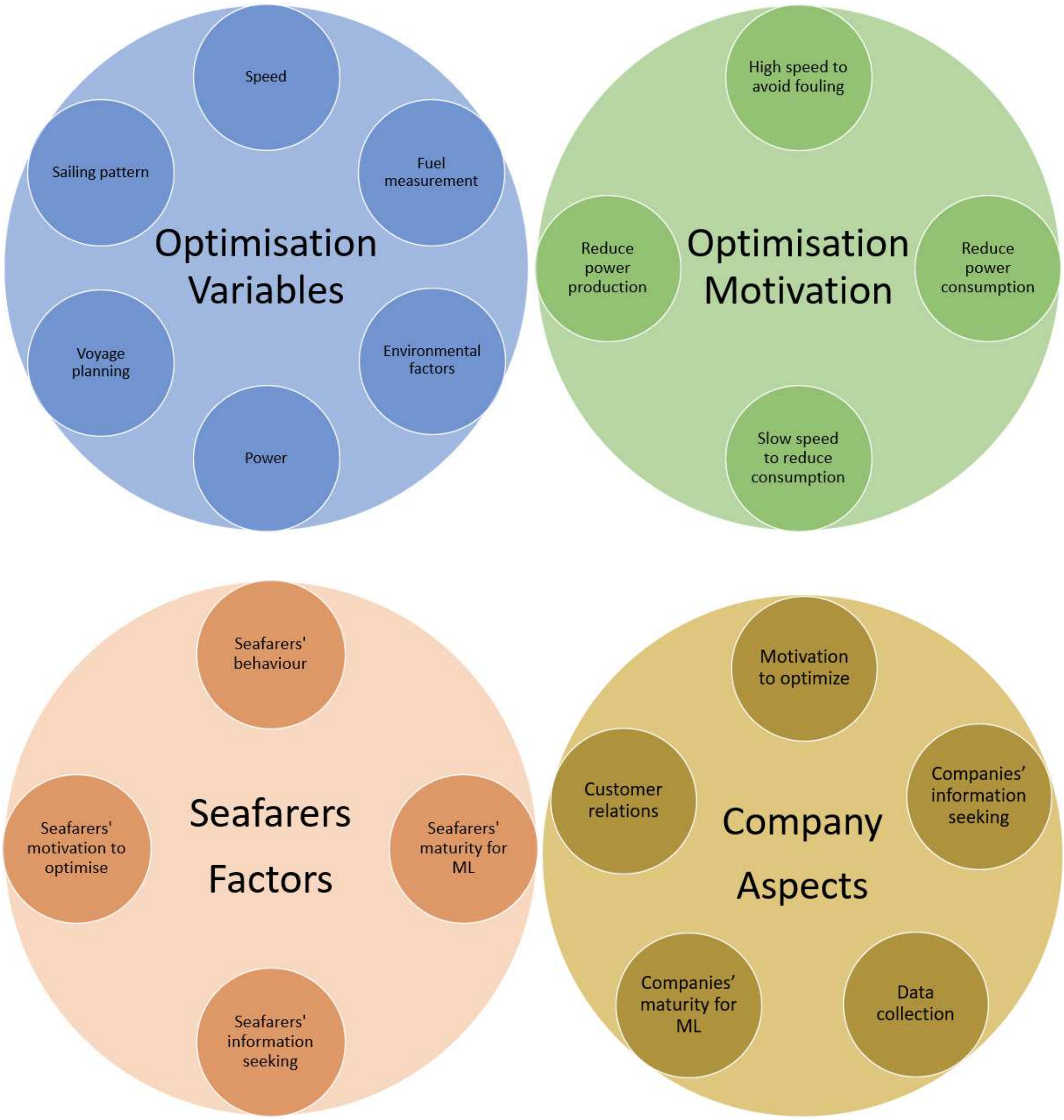

Figure 7 Map of high-level themes affecting optimisation, with categories.

The high-level theme of Optimisation Variables has considerable potential for implementing ML, where the technology may be applied in several identified categories. It became clear that experience is the prevailing principle seafarers use to save fuel and optimise. However, the complexity of a moving ship in a dynamic element, including external and internal forces that can very quickly become complex, proving challenging for the capabilities of the human brain. ML can analyse and identify patterns from large data sets and may be of great assistance in undertaking the analysis and to predict and suggest solutions. Implementing ML for optimisation has shown significant optimisation improvements in research projects carried out for maritime application (Yuan and Wei, 2018; Huang et al., 2022; Soner et al., 2019; Coraddu et al., 2017; Coraddu et al., 2019; Ahlgren and Thern, 2018; Yang et al., 2018; Pena et al., 2020; Wang et al., 2018; Uyanik et al., 2020; Raptodimos and Lazakis, 2018; Perera et al., 2016; Huang et al., 2022; Planakis et al., 2022; Wu and Bucknall, 2020; Wu et al., 2021; Yuan et al., 2021; Li et al., 2021; Grifoll et al., 2022).

The high-level theme Optimisation Motivation addresses both speed and power, where both a high speed and a slow speed may be beneficial for optimisation purposes. Regular periods with high speed determined by ML estimating hull growth may help reduce fouling on the ships' hull and propeller. At the same time, a low speed during normal operations, also optimised by ML, may contribute to overall speed optimisation. Reducing power production and power consumption may also be regarded in combination, as reduced power consumption may allow for reduced power production. Power is very important when discussing fuel optimisation, and research indicates that ML may have a considerable impact in this area also.

The high-level theme Seafarers Factors highlights the importance of the seafarers' contribution to optimisation. Their actions, motivations, and willingness to find information and adopt new technology are critical for the successful optimisation and implementation of ML. Without the support of the seafarers, there is a risk that both optimisation and ML will fail, or that technology will not be used effectively.

The high-level theme Company Aspects also acknowledges that the ship management company has an essential role in optimising and implementing ML. If the company does not support optimisation or ML, it is unlikely that it will be implemented. The company's motivation may be influenced by customer pressure and regulatory pressure to reduce emissions, and it is important that the company stays updated on technological developments to understand its potential. Having implemented other technological solutions earlier may contribute to implementing ML when it becomes available. The ability to predict values and variables may also contribute to cost savings in some areas where sensors may be replaced with ML technology that has proven accuracy and reliability in research.

This research also has an impact across the maritime industry, as discussed in the previous chapter, including for ship management companies, developers of software solutions, shipyards, manufacturers of integrated bridge navigation systems and other manufacturers such as engine manufacturers, manufacturers of battery-hybrid solutions for ships and manufacturers of marine antifouling- coating and systems. All of these are able to guide their own decision-making processes using the insights gained from the analysis conducted within this research.

6.2 Key learnings from this research

Through the discussion, a range of key learnings emerged from this research which may be useful in a practical way for companies considering implementing optimisation or new technology. The key learnings, when considered across the different thematic areas, are able to be further summarised in into the following:

- It is valuable to monitor both power production and power consumption (5.1.1).
- Companies need to make informed decisions about what's right for them to optimise (5.1.1).
- When assessing the available data, evaluate its quality and consistency to ensure it is relevant given the company priorities and consider if is necessary to collect more data automatically (5.1.2 & 5.1.4).
- ML may be applied for optimising hull cleaning and weather routing (5.1.5 & 5.1.6).
- Employees should be involved to ensure motivation (5.2.1 & 5.2.3).
- Ensure employees are competent, trained and familiarised (5.2.2).

These learnings can be considered and applied by a range of industry stakeholders who have a current interest in optimisation of shipping. These include shipping companies, shipyards and equipment- and engine manufacturers. However, they are also valuable to many stakeholders who do not currently have an interest in ship optimisation – such a technology and software vendors. They may see a future role for their business in enabling the shipping industry to optimise its processes to meet the broader societal goals relating to climate change.

6.3 Limitations

Acknowledging that this research has some limitations is important when reading this thesis. The research is based on interviews with six persons from six companies, and generalising to a bigger group may impact the validity of the results for other contexts. Although there is no indication of research errors, also it should be noted that the data is collected only from interviews, and a design triangulation is considered an ideal within research. Combining the qualitative method with a quantitative method would maybe have produced more and more accurate data. The interviews were conducted with companies within Norway. However, ship operations is an international business and ship management companies often operates ships worldwide. Interviewing companies in other countries might have produced different results.

6.4 Suggestion for further research

Previous research and mapping of the high-level themes indicated a significant potential for using ML to optimise ship operations. It may be just a matter of time until ML is applied in the maritime ship operation context, and more research could be carried out to decide where it should be implemented first. This could provide valuable information for ship management companies wanting to implement it, especially if the research could provide a road map and principles for the implementation process.

Further research could also include ship management companies operating ships in other ship segments as this could support the findings of this research or disclose also other perspectives affecting ML and optimisation. Other ship types transporting other types of cargoes for other customers may face other expectations, and the focus of optimisation and ML comparing e.g. a cruise ship or a tanker ship with offshore support ships may be different. Future research could investigate how this is approach in different segments, and this applies for ship management companies in other countries as well. By researching ship management companies in other countries, the results could be compared with this research to look for similarities.

This research has been focused on data and technology, but none of the software providers were interviewed. Their input on the development of ML for optimisation applications on ships could bring additional data from a new perspective. Software providers need to be in the forefront of the technological development to be continuously relevant, improving their products and services and releasing new versions with the latest technology. It is possible that software developers have integrated ML in their new software versions or solutions, and that this will be made available soon. However, software developers were not interviewed during this research, so the status of this is not clear, and further investigation could be carried out.

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Appendix I:

Invitation letter to company:

Høgskulen på Vestlandet

Forespørsel om deltakelse i masterprosjekt

I forbindelse med masterprosjekt ved fakultet for økonomi og samfunnsvitenskap og lærerutdanning ved Høgsulen på Vestlandet (HVL) har deres bedrift blitt valgt ut for å delta på en undersøkelse.

Masterprosjektet er en del av masterprogrammet i maritime teknologi og ledelse, og gjennomføres av student Arne Skarstein. Ansvarlig veileder er Professor Joel Scanlan og HVL er behandlingsansvarlig for prosjektet.

Masterprosjektet har som formål å undersøke optimalisering av skipenes fuel-forbruk og potensiale for maskinlæring. Deres bedrift har blitt valgt ut til undersøkelsen basert på informasjon om næringskode fra Brønnøysundregisteret, antall ansatte, og postadresse. Det bes derfor om at rederiet velger ut én ansatt som har best tilgang til informasjon om fuel-optimalisering som jobber på land ved deres kontor(er) i Norge.

Hvordan gjennomføres spørreundersøkelsen?

Undersøkelsen vil bestå av et individuelt intervju, det er estimert til å ta 30-40 min, og krever ingen forberedelser.

Personopplysninger

Alle svar vil bli anonymisert, alle opplysninger vil bli behandlet konfidensielt og alle personopplysninger vil bli behandlet anonymisert når resultatene skal publiseres. Kun studenten og veilederne vil ha tilgang til personopplysningene. Prosjektet skal etter planen avsluttes 02.06.2023, og på oppdrag fra HVL har NSD – Norsk senter for forskningsdata AS vurdert at behandlingen av personopplysninger i dette prosjektet er i samsvar med personvernregelverket.

Frivillig deltakelse

Det er frivillig å delta i studien, og deltakerne kan når som helst trekke seg uten å oppgi noen grunn.

Dersom du har spørsmål til studien, ta gjerne kontakt på e-post eller telefon.

Med vennlig hilsen,

Arne Skarstein, Masterstudent ved HVL

213473@stud.hvl.no Tlf: 924 39 884

Appendix II:

Invitation letter to interviewees:

Høgskulen på Vestlandet

Vil du delta i forskningsprosjektet
"To which degree is machine learning used for optimisation in shipping companies? "

Dette er et spørsmål til deg om å delta i et forskningsprosjekt hvor formålet er å undersøke i hvilken grad maskinlæring brukes for optimalisering i rederier. I dette skrivet gir vi deg informasjon om målene for prosjektet og hva deltakelse vil innebære for deg.

Formål
Masterprosjektet har som formål å undersøke optimalisering av skipenes fuel-forbruk og potensiale for maskinlæring. Forskningen inngår i en masteroppgave for å belyse i hvilken grad maskinlæring blir bruk til optimalisering av drivstoff-forbruk på skip. Forskningsspørsmålet er i hvilken grad maskinlæring blir brukt i dag i rederiorganisasjoner.

Forskningen skal kun danne grunnlag for denne masteroppgaven og skal ikke brukes til andre formål.

Hvem er ansvarlig for forskningsprosjektet?
Høgskulen på Vestlandet er ansvarlig for prosjektet.

Hvorfor får du spørsmål om å delta?
Deres bedrift har blitt trukket ut til undersøkelsen basert på at den er registrert med næringskode 50.204 og at bedriften har mer enn 50 ansatte, innhentet fra Brønnøysundregisteret. Av alle tilsvarende bedrifter, har fem bedrifter blitt tilfeldig trukket ut og fått henvendelse om å delta. Bedriften har blitt bedt om å velge ut en ansatt som har best mulig tilgang til informasjon om fuel-optimalisering og som jobber på land ved deres

kontor(er) i Norge. Kontaktopplysningene har jeg derfor fått fra bedriften. I undersøkelsen vil fem personer bli intervjuet.

Hva innebærer det for deg å delta?

Hvis du velger å delta i prosjektet, innebærer det at jeg intervjuer deg. Intervjuet vil ta deg ca. 30-40 minutter. Intervjuet inneholder spørsmål om skipenes drivstoff, optimalisering av drivstofforbruket og bruk av dataverktøy for optimalisering. Det blir gjort lyd-opptak av intervjuet for å kunne bruke dette videre i min forskning.

Det er frivillig å delta

Det er frivillig å delta i prosjektet. Hvis du velger å delta, kan du når som helst trekke samtykket tilbake uten å oppgi noen grunn. Alle dine personopplysninger vil da bli slettet. Det vil ikke ha noen negative konsekvenser for deg hvis du ikke vil delta eller senere velger å trekke deg.

Ditt personvern – hvordan vi oppbevarer og bruker dine opplysninger

Vi vil bare bruke opplysningene om deg til formålene vi har fortalt om i dette skrivet. Vi behandler opplysningene konfidensielt og i samsvar med personvernregelverket.

Kun studenten og veiledere ved Høgsulen på Vestlandet vil ha tilgang til intervjuopptaket og transkripsjon.

Navnet og kontaktopplysningene dine vil jeg erstatte med en kode som lagres på egen navneliste adskilt fra øvrige data. Datamaterialet vil oppbevares passord beskyttet på Høgsulen på Vestlandets server. Deltakerne vil ikke kunne gjenkjennes i den publisert masteroppgaven, eller annet materiale.

Hva skjer med personopplysningene dine når forskningsprosjektet avsluttes?

Prosjektet vil etter planen avsluttes 16. juni. Etter prosjektslutt vil datamaterialet med dine personopplysninger slettes fra alle lagringsmedier.

Hva gir oss rett til å behandle personopplysninger om deg?

Vi behandler opplysninger om deg basert på ditt samtykke.

På oppdrag fra Høgsulen på Vestlandet har Sikt – Kunnskapssektorens tjenesteleverandør vurdert at behandlingen av personopplysninger i dette prosjektet er i samsvar med personvernregelverket.

Dine rettigheter

Så lenge du kan identifiseres i datamaterialet, har du rett til:

- innsyn i hvilke opplysninger vi behandler om deg, og å få utlevert en kopi av opplysningene
- å få rettet opplysninger om deg som er feil eller misvisende
- å få slettet personopplysninger om deg
- å sende klage til Datatilsynet om behandlingen av dine personopplysninger

Hvis du har spørsmål til studien, eller ønsker å vite mer om eller benytte deg av dine rettigheter, ta kontakt med:

- Høgsulen på Vestlandet ved student Arne Skarstein, e-post: 213473@stud.hvl.no, tlf: 924 39 884
- Veileder professor Joel Scanlan, e-post: Joel.Scanlan@hvl.no
- Veileder professor Margareta Lützhöft, e-post: Margareta.Holtensdotter.Luetzhoeft@hvl.no, tlf: 947 937 96.
- Vårt personvernombud: Trine Anikken Larsen, Trine.Anikken.Larsen@hvl.no Tlf: 55 58 76 82

Hvis du har spørsmål knyttet til vurderingen som er gjort av personverntjenestene fra Sikt, kan du ta kontakt via:

- Epost: personverntjenester@sikt.no eller telefon: 73 98 40 40.

Med vennlig hilsen

Prof. Joel Scanlan	*Prof. Margareta Lützhöft*	*Arne Skarstein*
(veileder)	(veileder)	(student)

Dersom du ønsker å delta, svarer du på denne e-posten der du skriver:

Samtykkeerklæring:

Jeg ________________________________(navn) har mottatt informasjon om studien om å belyse i hvilken grad maskinlæring blir bruk til optimalisering av drivstoff-forbruk på skip, og jeg ønsker å stille til intervju.

Har du spørsmål eller ønsker mer informasjon kan jeg kontaktes på telefonnummer +47 924 39 884 eller e-post 213473@stud.hvl.no.