Optimal maritime fleet composition under future greenhouse gas emissions restrictions and uncertain fuel prices

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Industrial Economics and Technology Management
June 2023
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PREFACE

This master's thesis is the result of my Master of Science degree in Industrial Economics and Technology Management at the Norwegian University of Science and Technology, Department of Industrial Economics and Technology Management.

The purpose of the master's thesis has been to provide decision support for shipping companies that need to modify their fleets of cargo ships in order to comply with future greenhouse gas emissions restrictions. I would like to express my sincerest gratitude towards my supervisors Professor Magnus Stålhane, Professor Kjetil Fagerholt and Postdoctoral Fellow Benjamin Lagemann for their guidance, interesting discussions and contributions throughout the semester.

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Trondheim, June 2023

ABSTRACT

The shipping industry is a major contributor to global greenhouse gas (GHG) emissions. An important factor for the industry's large emissions, is its reliance on heavy fuels with high carbon content. Thus, in order to reduce the emissions, the utilization of alternative fuels should be considered. Hence, this thesis analyzes how shipping companies can optimally modify their fleets to utilize alternative low- or zero-emission fuels in order to satisfy future GHG emission restrictions.

The analysis takes into account both existing shipping companies that need to modify their fleets, as well as and that need to acquire a fleet of ships in order to become operative. Thus, the fleet modification may involve decisions such as retrofitting ship power systems, acquisition of new ships and scrapping of old ships that have reached their lifetime potential. A retrofit is needed whenever a ship is desired to run on an alternative fuel that is not compatible with the ship's already existing power system. The main cost drivers of the shipowners are fuel costs and costs related to ship acquisitions.

To handle the uncertainty related to future fuel prices, the thesis proposes three two-stage stochastic mixed integer programming (MIP) models that allow shipowners to minimize costs. One model is created for optimal investment of a new fleet of ships with the option to retrofit them in the future. The other two models are applicable to shipowners that need to modify their existing fleets, where one of the models allows for the option to scrap old ships and acquire new ones, while the other model only allows retrofits.

The results from analyzing the model that initially invests in a new fleet of ships show that on average, methanol ships make up nearly 90% of the fleet when GHG emissions are restricted to be less than 50% of a traditional fleet's emissions by 2045. However, higher carbon prices make LNG and ammonia ships constitute a larger share of the fleet due to their ability to utilize fuels that give lower emissions at a slightly higher cost. When emissions are restricted to be less than 90% of a conventional fleet's emissions in 2045, the results indicate that most of the methanol ships are retrofitted to ammonia ships. Similar results are shown in the analysis of the model that allows for scrapping and acquisition of ships. Because the results support the industry's vision of using methanol and LNG ships in the foreseeable future, they seem applicable as decision support for shipowners.

SAMMENDRAG

Shippingindustrien er en stor bidragsyter til globale klimagassutslipp. En viktig faktor for industrien sine store utslipp er dens avhengighet av tung fyringsolje med høyt karboninnhold. For å redusere utslippene, bør dermed bruken av alternative drivstoff vurderes. Følgelig inneholder denne masteroppgaven en analyse av hvordan skipsredere kan endre sammensetningen av flåtene sine for å tilfredsstille fremtidige krav til reduserte klimagassutslipp, samtidig som de minimerer totale kostnader knyttet til drift og endringer av flåtene.

Oppgaven inneholder analyser for både eksisterende rederier som trenger å endre flåtesammensetningen sin for å redusere utslipp, samt de rederiene som nylig har startet opp og som har behov for å investere i en flåte med nye skip for å bli operative. Dermed tar de matematiske modellene hensyn til beslutninger som ettermontering av skipenes fremdriftssystemer, anskaffelse av nye skip og skroting av gamle skip som har nådd sine levetidspotensial. En ettermontering av fremdriftssystemene er nødvendig når et skip skal kjøre på et alternativt drivstoff som ikke er kompatibelt med skipets eksisterende fremdriftssystem. De viktigste kostnadsdriverne til rederiene er drivstoffkostnader og investeringer i nye skip.

For å håndtere usikkerheten knyttet til fremtidige drivstoffpriser, er det i denne oppgaven foreslått tre to-trinns stokastiske matematiske modeller av typen blandet heltallsprogrammering for å bistå skipsredere med å minimere kostnadene sine. Den ene modellen er laget for å foreslå optimal investering i en ny flåte med mulighet for å et-

termontere skipene i fremtiden. De to andre modellene er anvendbare for skipsredere som trenger å modifisere sine eksisterende flåter; den ene modellen tillater skroting og investering av skip, og den andre tillater kun ettermonteringer.

Resultatene fra analysen av modellen som investerer i en ny flåte i starten av planleggingshorisonten viser at metanolskip i gjennomsnitt utgjør nesten 90% av flåten når klimagassutslipp begrenses til mindre enn 50% av en tradisjonell flåtes utslipp innen 2045. Høyere karbonpriser vil imidlertid gjøre at LNG- og ammoniakkskip utgjør en større andel av flåtesammensetningen på grunn av deres evne til å bruke drivstoff som gir lavere utslipp til kun en liten kostnadsøkning. Når utslippene begrenses til mindre enn 90% av en tradisjonell flåtes utslipp innen 2045, indikerer resultatene at de fleste metanolskipene blir ettermontert til ammoniakkskip. Tilsvarende resultater vises i analysen av modellen som tillater skroting og anskaffelse av skip. Fordi resultatene støtter industriens visjon om å bruke metanol- og LNG-skip i overskuelig fremtid, virker det rimelig å bruke de som beslutningsstøtte for skipsredere.

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CHAPTER ONE

INTRODUCTION

The shipping industry is an important sector for the international trade and commerce, enabling the transportation of goods across the world. However, the industry is also a major contributor to rising levels of greenhouse gas (GHG) emissions globally, which are a significant factor of the climate change. According to the International Maritime Organization (IMO), the total annual emissions from the shipping industry amount to 2-3% of global CO_2 emissions, with predictions estimating a potential increase from shipping emissions of 50% to 250% by 2050 if no measures are taken (Lagouvardou et al. 2020). One major cause of the potential rise in emissions is the industry's reliance on heavy fuel oils and marine diesel fuels, which are high in sulfur and carbon content.

In order to comply with the Paris Agreement's ambitions of limiting global warming to 1.5°C by the end of the century, the IMO has set a goal to reduce GHG emissions from international shipping by at least 50% by 2050 compared to 2008 emissions (Decarbonize Shipping - DNV, n.d.). The use of alternative fuels as a means to reduce emissions from the industry in order to comply with future emission targets is supported in the literature (Lindstad et al. 2021b, Wang and Wright 2021, Korberg et al. 2021, DNV GL 2020). However, research into which fuel technology is most suitable for the industry has to be performed, as the different fuels entail their own challenges, being technical (DNV GL 2019; Wang and Wright 2021), environmental (Lindstad et al. 2021a) or economic (DNV GL 2020, Lindstad et al. 2021b). Thus, as the need to slow down the rate at which the climate change develops, the shipping industry should be motivated to invest in research of the utilization of alternative fuels in order to reduce future GHG emissions.

There is a scarcity of studies that consider both the environmental and the economic aspect of changing fleet compositions. Furthermore, the purpose of this thesis is to provide the shipping industry with decision support from a techno-economic perspective by presenting optimization models that are applicable both for new companies that do not yet operate a fleet and for established companies that may wish to renew their existing fleets in order to comply with future emissions restrictions. Consequently, the mathematical models presented in the thesis consider decisions related to acquiring new ships, scrapping of ships that have reached their lifetime potential and the option to retrofit the ship power systems of an existing fleet in order to reduce GHG emissions. Because the future fuel and carbon prices are uncertain, estimations of those prices are provided, including a discussion of different carbon pricing mechanisms.

Additionally, the preference for alternative fuels in the industry seems to shift from LNG- to methanol-fuels (DNV 2023). In a presentation by Rystad Energy AS it is proposed that LNG has been the favoured alternative fuel in the past years due to its price competitiveness and availability (Rystad Talks Industry - Shipping Fuels of the Future, 2023). However, they now see a shift in the preference of alternative fuels towards 2030, with methanol comprising 42% of the current placement of newbuild orders. Furthermore, the trend towards the utilization of methanol as an alternative fuel is supported by a poll performed by DNV, in which 41.75% of 473 companies replied that they would prefer methanol ships when placing a newbuilding order in the next one to two years (DNV 2023). Therefore, the purpose of the thesis is also to investigate whether the shift towards methanol-fuels seems reasonable from a techno-economic perspective.

The mathematical models and computational results of this thesis are to a large degree based on Lagemann et al. (2023a). The paper proposes a two-stage stochastic MIP model for optimal power system and fuel selection on a single-ship problem under uncertain future fuel and carbon prices. Consequently, the main difference between the paper and this thesis is that this thesis extends the scope of the paper such that it becomes a fleet problem, as well as including aspects such as future ship scrapping and ship acquisition.

Furthermore, this thesis contributes to the literature by providing decision support for the selection of alternative fuels and ship power systems for a maritime fleet under uncertain future fuel and carbon prices. The solutions have been found by solving a two-stage stochastic mixed integer programming (MIP) model that accounts for the uncertainties when computing the optimal fleet composition. To provide decision support to shipping companies that are already established, the thesis contains a model that optimizes the future fleet composition of an existing fleet. Additionally, two models that take into account investments to establish an initial fleet are proposed to provide decision support for new shipping companies that do not yet operate a fleet.

The thesis is structured as follows: Chapter 2 gives an overview of the emissions and cost aspects of the alternative fuel technologies that shipping companies may consider. Chapter 3 contains an overview of the existing literature on the same problems. In Chapter 4, a verbal description of both the fleet renewal problems and the fleet size and mix problem is provided. Then, the corresponding mathematical models of the verbal problem descriptions from Chapter 4 are proposed in Chapter 5. The generated test instances and a computational study is presented in Chapter 6. Finally, concluding remarks and a suggestion of future research are provided in Chapter 7 and Chapter 8 respectively.

CHAPTER

TWO

BACKGROUND

This chapter contains a detailed overview of the greenhouse gas (GHG) emissions related to the utilization and consumption of alternative fuels in the operation of cargo ships. The emissions are presented and discussed in Section 2.1. Related costs, such as the annual fuel costs, are presented in Section 2.2 along with the abatement costs of using alternative fuels.

2.1 GHG Emissions From Alternative Fuels

According to Wang and Wright (2021), GHG emissions from ships must be reduced by 75-85% per ton-mile to meet Paris Agreement goals, due to the predicted growth in shipping volumes. To meet the emission reduction ambitions, shipowners should consider the option of using alternative fuels, which in this thesis are defined to be any fuel or source of energy other than the conventional fuel-oils that are currently being used for powering ships. Wang and Wright (2021) present a review of a range of alternative fuels that may be included as a part of the transition to reduced emissions. Additionally, several studies show that alternative fuels are estimated to have the greatest GHG emission reduction potential in the long term (Balcombe et al. 2019; Faber et al.

2020), which is further supported in Lagemann et al. (2023b) where the GHG emission reduction potential among several options is compared, as shown in Figure 2.1. The figure shows that the reduction group "energy", which contains alternative fuel options, may have a 100% GHG emission reduction potential. However, as can also be seen in the figure, there is a possibility that no GHG emission reduction may occur for the energy-option. This could occur if a shipowner for instance were to utilize an alternative fuel that gave lower TTW-emissions, but with higher WTT-emissions than those of a traditional fuel. Thus, it is important to consider the reduction of WTW GHG emissions rather than looking at isolated parts of the emissions supply chain in order to ensure reductions.

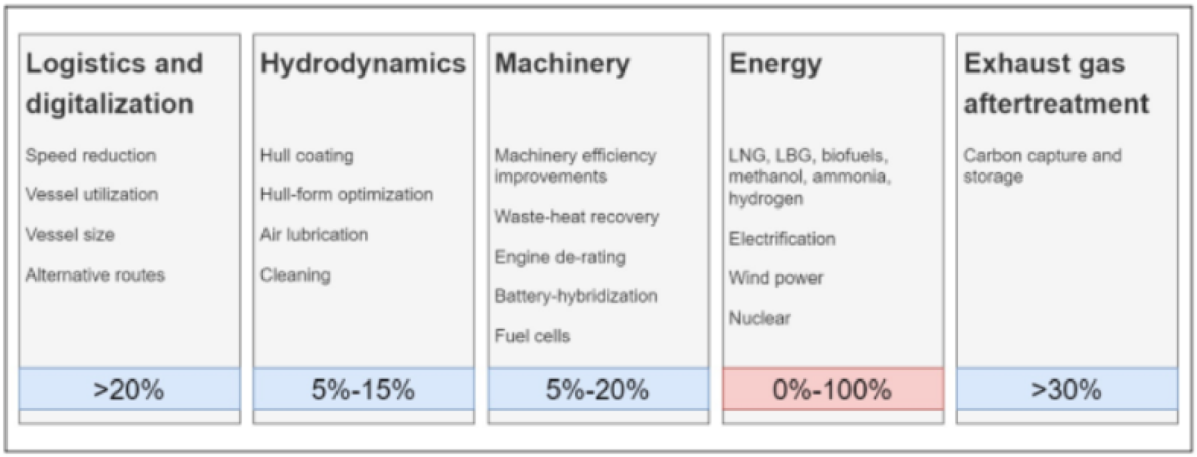

Figure 2.1: GHG emission reduction options in shipping (Lagemann et al. 2023b).

To assess whether conventional fuel should be replaced by alternative fuel to reduce the GHG emissions, one may divide each fuel type's emissions into two stages; the fuel's emissions from Well-to-Tank (WTT) and the fuel's emissions from Tank-to-Wake (TTW). A WTT assessment includes all emissions related to the production of the fuel. According to Lindstad et al. (2021a), emissions from producing a conventional fossil fuel comprise production, processing and transport to the refinery, refining, transport to the ship, and bunkering operations. Aggregated, these factors make up the WTT emissions related to a conventional fossil fuel. On the other hand, a TTW assessment includes the emissions related to the combustion of the fuel as a function of the used engine technology and the fuel (Lindstad et al. 2021a). The Well-to-Wake (WTW) assessment of a fuel's emissions is the sum of WTT and TTW emissions, thus including both the production and the combustion of the fuel. However, the WTW assessment is not to be confused with more advanced life cycle assessment (LCA) methods, as WTW assessments exclude construction and decommissioning of the fuel production chain (Lindstad et al. 2021b).

To investigate how alternative fuels may reduce GHG emissions, Lindstad et al. (2021b) propose a study that analyzes the GHG reduction potential on a WTW basis from using low and zero carbon fuels in comparison with conventional fuels. Both Heavy Fuel Oil (HFO), Very Low Sulphur Fuel Oil (VLSFO) and Marine Gas Oil (MGO) are considered conventional fuels, with HFO and MGO representing close to 80% and 20% of international shipping's fuel consumption in 2020, respectively (Lindstad et al. 2021b). In their report, Lindstad et al. (2021b) use MGO as a reference fuel when comparing the GHG reduction potential of alternative fuels with conventional fuels. Low carbon fuels, including Liquefied Natural Gas (LNG) and Liquefied Petroleum Gas (LPG), are defined as fuels that potentially may reduce GHG emissions by 20% compared to MGO.

One alternative fuel group that is likely to have a large potential to reduce the GHG emissions from shipping is the group of carbon neutral electro fuels (E-fuels). Two of the most utilized E-fuels in shipping are liquid hydrogen and ammonia. The two E-fuels can be created through electrolysis of water into hydrogen and oxygen, and they must be in a liquid state to be feasible fuels for shipping. According to McKinlay et al. (2021) the technology needed for electrolysis is well developed and commercially viable. However, the electrolysis and liquefying processes result in a total energy loss of nearly 50% for liquid hydrogen from electricity and 45% for ammonia. Additionally, the current production of ammonia accounts for 1% of global CO_2 emissions, which an upscaling of the production may significantly increase unless the production is decarbonized.

Additionally, a challenge with hydrogen as an alternative fuel is that it is a scarce resource, and that the current production of hydrogen is to a large extent used in the fertilizing industry, in oil refining and in the steel industry, leading to great competition for the resource. Consequently, switching to E-fuels may be a costly decision. However, despite the large costs associated with the production and use of hydrogen, it is recognized as one of the most promising alternative fuels for transportation due to few harmful byproducts and its high energy-to-weight storage ratio. Additionally, hydrogen may be produced from several renewable sources, such as nuclear power, wind and solar photovoltaics (PV) (Wang and Wright, 2021), which increases the availability of the feedstock.

Another group of alternative fuels that may be considered is the group of synthetic electro-fuels, which are produced from hydrogen and captured carbon from the air using renewable electricity (Lindstad et al. 2021b). Advantages of using synthetic E-fuels are that they have high energy efficiency, and that they easily blend with conventional fuels. An example provided by Lindstad et al. (2021b) is blending E-diesel with MGO. Compared to hydrogen and ammonia, synthetic E-fuels are also advantageous because they do not need the new infrastructure that is needed when fuelling ships with hydrogen or ammonia. Some synthetic E-fuels are E-LNG and E-methanol, both of which are considered in the input to the mathematical models of this thesis.

Lastly, biofuels and biogas may be used as alternative fuels on existing infrastructure (Korberg et al. 2021). However, compared to fossil fuels, these fuels are prone to large variations in WTT emissions due to their varying sources of origin (Lindstad et al. 2021b). Thus, the feedstock and the production processes are important factors to consider when assessing the GHG emissions from biofuels. Lindstad et al. (2021b) contains an example of this, showing that the emissions from biodiesel produced from palm oil more than triples emissions compared to conventional fuels due to the necessary conversion of the rainforest. Additionally, as with hydrogen and ammonia, the demand for biofuels from other industries is large, and thus the competition for small volumes may make the biofuels less accessible than other alternatives.

An illustration of alternative fuels' Well-to-Wake emissions compared to MGO is shown in Figure 2.2. The Well-to-Tank emissions for each fuel are visualized with the solid blue bar, and the striped orange bar indicates the Tank-to-Wake CO_2 emissions. The solid orange bar indicates the combination of methane (CH_4) and nitrous oxide (N_2O) emissions for each fuel. To compare the different fuels' emissions with MGO emissions, the vertical dashed line is shown to indicate the emissions from MGO. For each fuel, the result of the comparison is shown by either a green percentage, which indicates that the fuel has lower emissions than MGO, or by a red percentage, which indicates an increase in WTW emissions compared to MGO.

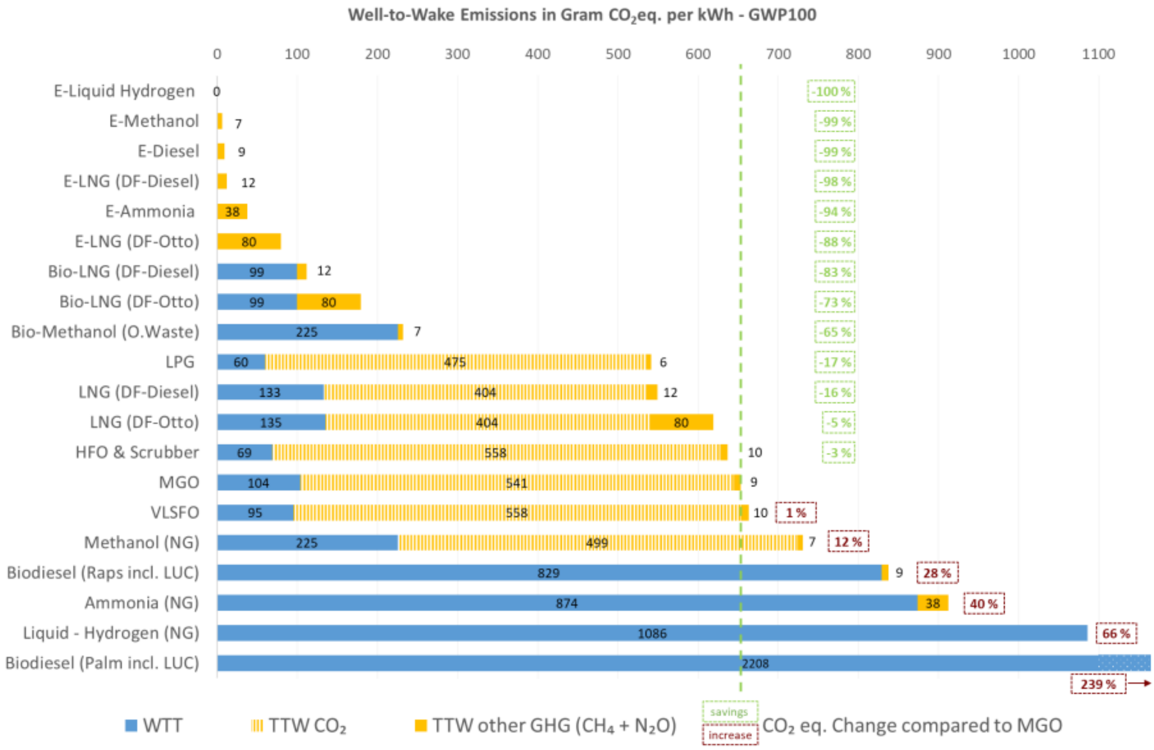

Figure 2.2: Well-to-Wake emissions in gram CO_2-eq. per kWh for the assessed fuels and engine combinations (Lindstad et al. 2021b).

Some observations to be made from Figure 2.2 are that E-fuels may potentially lead to a GHG reduction up to 100%. However, a necessary assumption for such results is that those fuels are made from 100% renewable energy sources (Lindstand et al. 2021b), which is not a realistic assumption to make today. Another observation from Figure 2.2 is that some biofuels, like Bio-LNG combusted in a dual fuel diesel engine, reduce WTW GHG emissions, while others, like Biodiesel made from palm oil, may increase GHG emissions by 239% and therefore be climate negative. That is a consequence of the large WTT emissions associated with producing biodiesel from palm oil, which shows the importance of not only examining the TTW emissions of different fuels.

Finally, the figure shows that ammonia and hydrogen made from natural gas (NG) increase WTW GHG emissions. According to Lindstad et al. (2021b), this is due to the huge energy losses that occur during the process of transforming the natural gas into liquid hydrogen or ammonia.

2.2 Fuel and Engine System Cost

In this section, costs related to the vessel, engine and fuel consumption are provided to help the reader understand the results that are presented and discussed in Chapter 6. Additionally, having a knowledge of the large range of costs that different fuels incur contributes to the understanding of why some fuels that have a low environmental impact are not utilized in an optimal solution.

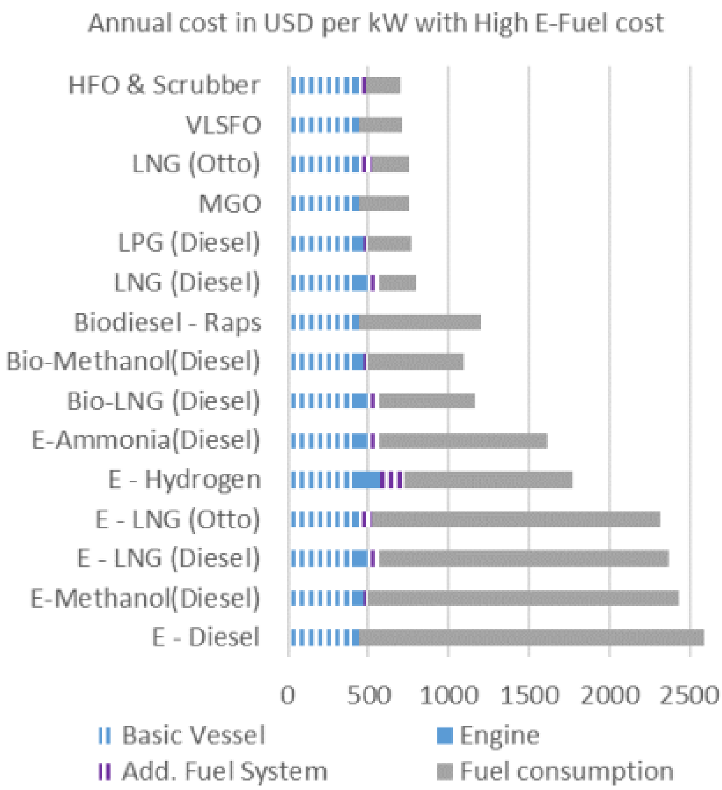

Figure 2.3: Annual cost per kW with high E-fuel cost (Lindstad et al. 2021b).

Figure 2.3 and Figure 2.4 show the cost per kW in USD per annum, for high and low E-fuel costs respectively. The high E-fuel costs are based on a scarcity of renewable electricity and recent high market price of electricity, while the low E-fuel costs are calculated based on the assumption of renewable electricity being a highly available resource and that future prices are far below current prices (Lindstad et al. 2021b). The dashed blue bars represent vessel costs, while the solid blue bars represent engine costs. Next, the dashed purple bars show the cost for advanced fuel-tanks and control systems that are required for LNG, Methanol and ammonia, and the scrubber cost for when HFO is used. A scrubber, also called an exhaust gas cleaning system (EGCS), is an installation that removes harmful components from the exhaust gasses that are created during fuel combustion in marine engines (Sethi, 2021). Finally, the grey bars indicate the cost of fuel consumption.

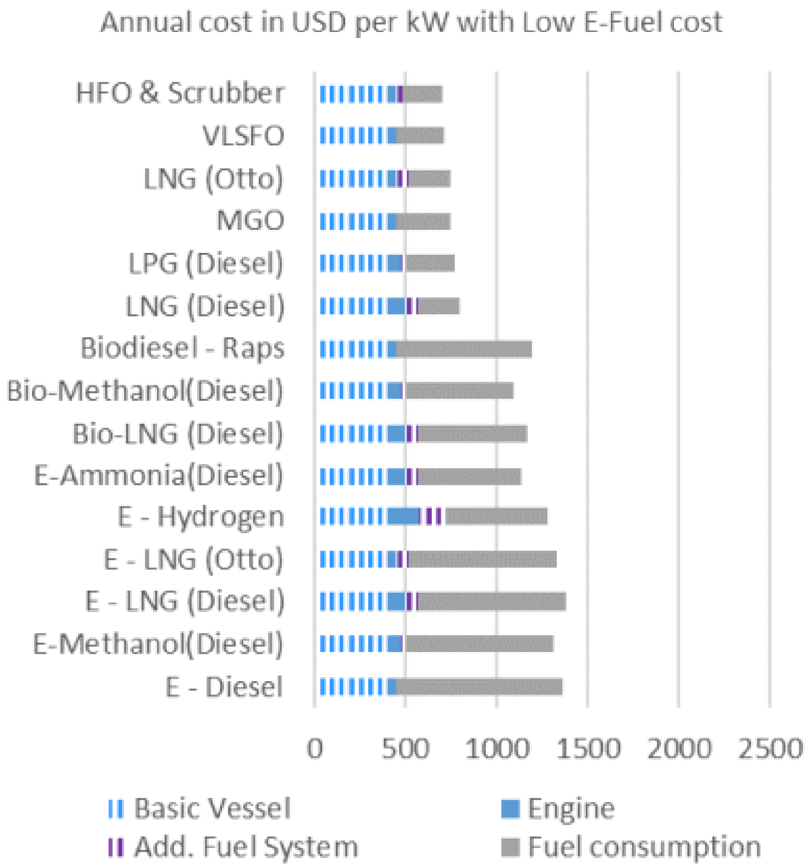

Figure 2.4: Annual cost per kW with low E-fuel cost (Lindstad et al. 2021x).

As can be seen in Figure 2.3, which shows the annual cost in USD per kW with high E-fuel cost, a transition to biofuels will double the cost of fuel consumption compared to conventional fuel cost. A transition to E-hydrogen and E-ammonia will further increase fuel consumption costs and total costs, and the synthetic E-fuels triples the total costs compared to running ships on conventional fuels. With low E-fuel costs, however, the synthetic E-fuels become cost competitive compared to E-hydrogen and E-ammonia, as shown in Figure 2.4. Additionally, keeping in mind that synthetic E-fuels can easily be applied to existing ships and that E-hydrogen and E-ammonia require new infrastructure to be built, shipowners will likely prefer synthetic E-fuels given low E-fuel costs.

Furthermore, Figure 2.5 shows the abatement cost per ton of CO_2-eq. for the alternative fuels that yield a reduction in GHG. The abatement cost is the additional cost of utilizing the alternative fuel as compared to traditional fuel per kW GHG reduction potential from a WTW perspective. The cost is represented as a bar for the E-fuels, because such costs depend on whether the E-fuel price is low or high. The percentages represent the potential GHG reduction for each fuel. An important observation to be made from the figure, is that the E-fuels are very cost competitive given low E-fuel prices. With high E-fuel prices, however, the costs of the E-fuels become significantly larger, and thus the biofuels become more competitive. In any case, the industry may start the transition towards GHG reductions with low-cost alternatives, such as LNG.

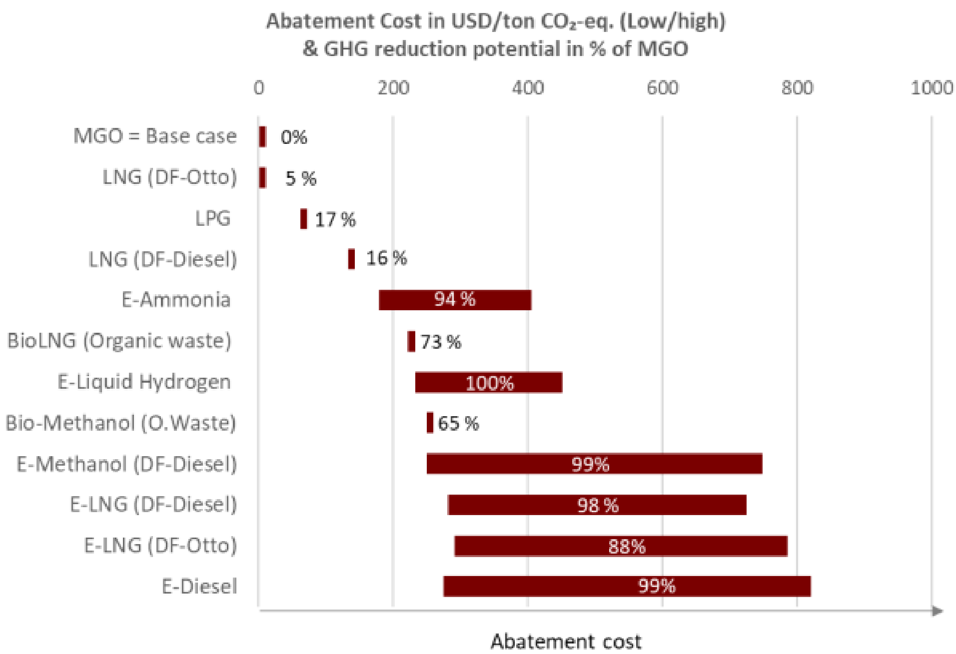

Figure 2.5: Abatement cost as a function of fuel and E-fuel cost (Lindstad et al. 2021b).

Lastly, an illustration of fuel costs where a fixed electricity cost of 33 € /MWh is presented in Figure 2.6. The figure shows that there mainly are three groups of fuels from a cost-perspective; electrofuels, bio-electrofuels and biofuels, though with some outliers. It becomes clear that electrofuels are the most expensive fuel group, and that bio-fuels seem like the cheapest one. Additionally, the figure shows that the cost of infrastructure seems larger whenever there is a need for storage at very low temperatures, also known as cryogenic storage (Korberg et al. 2021); fuels such as LH2, LMG and LBG all have a significantly larger share of infrastructure costs than the fuels that do not need to be cryogenically stored.

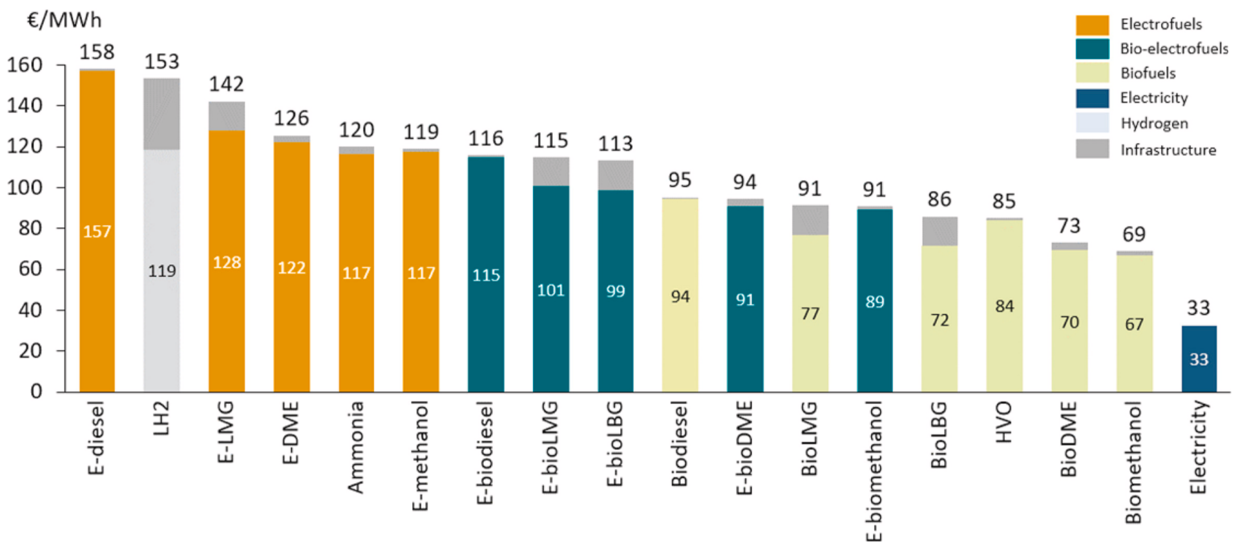

Figure 2.6: Fuel costs, including a fixed cost of electricity(Korberg et al. 2021).

CHAPTER

THREE

LITERATURE REVIEW

The problems studied in this thesis are variants of the Maritime Fleet Renewal Problem (MFRP) and the Maritime Fleet Size and Mix Problem (MFSMP). In this chapter, a review of the literature that is relevant for such maritime fleet adjustment problems is presented. Because the MFRP is an extension of the MFSMP, the literature on MFSMP is introduced in Section 3.2, before the literature on the MFRP is presented in Section 3.3. The literature on the MFSMP refers to only a few studies, due to the main focus of this thesis being on the problem that is characterized as an MFRP. Finally, the contribution of this thesis is presented in Section 3.4, including a table that visualizes a comparison of the key characteristics of the model in this thesis and the models of the studied literature.

3.1 Search Strategy

Due to the scarcity of studies performed on the maritime fleet renewal problem (MFRP) before 2014, a literature survey conducted by Pantuso et al. (2014) is briefly presented to provide an overview of that literature. The survey provides an extensive overview of the literature on both the MFSMP and the MFRP, but as it is almost a decade old, just the most relevant literature is presented in the review of this thesis. To get insight into more recent studies on the MFSMP and the MFRP, Google Scholar has been utilized as a search engine. A summary of the search words used in Google Scholar is presented in Table 3.1. Further, some of the literature that is presented in Lagemann et al. (2023a) is also included in this review, as that paper has greatly influenced this thesis. To limit the literature search to studies that are relevant to this thesis, land-based fleet size and mix problems (FSMPs) are not included. This is supported by Stålhane et al. (2020) who reason that land-based FSMPs lack applicability to the maritime industry. This is explained in more detail in Section 3.2.

MFSMP	**MFRP**
Review	Stochastic
General	Minimization
Shipping	Maximization
Heuristic	Alternative Fuels
	Emissions

Table 3.1: Search words used in conjunction with the terms MFSMP and MFRP for the literature review.

3.2 The Maritime Fleet Size and Mix Problem

Due to the uncertainty and volatility in the maritime shipping environment, an important decision to make for shipowners is how to design their fleet of ships. A simple Maritime Fleet Size and Mix Problem (MFSMP) consists of deciding the number and type of each ship to include in the fleet to meet a demand. The shipowners would typically want to minimize the total costs of designing, building and operating their fleet (Pantuso et al. 2014). While making the decisions that will minimize such costs, there are conditions that need to be satisfied, for instance to keep the consumption of resources that are associated with the fleet within some boundaries.

According to Pantuso et al. (2014), maritime fleet size and mix problems (MFSMPs) have operational characteristics that differ from the fleet size and mix vehicle routing problems (FSMVRP). Additional characteristics that create a difference between maritime and land-based applications are that the maritime sector is affected by a higher level of uncertainty, higher amount of capital involved and a ship's value function. As presented by Pantuso et al. (2014), maritime transportation is more affected by uncertainty in demand, ship costs and freight rates than any other sector. Further, a ship's lifetime of about 20-30 years is much longer than that of road-based vehicles, and the capital involved when acquiring new ships is more comparable with that of new airplanes, i.e., up to hundreds of million US Dollars. Furthermore, the research of land-based FSMPs does not seem relevant to this thesis. Thus, this chapter only reviews maritime FSMPs and maritime FRPs.

While the objective of an MFSMP often is to minimize the total cost of fleet acquisition and operation, there are several papers that suggest maximization of the problem's objective (Alvarez et al. 2011; Meng and Wang 2011; Meng et al. 2015; Mørch et al. 2017; Skålnes et al. 2020). Meng and Wang (2011) and Meng et al. (2015) take a profit maximization approach to provide shipowners with strategic decision support. Through a numerical example, the study by Meng and Wang (2011) found that their profit maximizing model indicated buying ships would be more profitable in the long term than chartering ships, though it was much cheaper to charter in the short term.

However, minimizing the total costs is a more common objective. For instance, cost-parameters related to chartering, acquisitions, electricity, fuel and taxes are commonly seen in MFSMP models. Some studies also present models in which the objective function includes fewer and more industry-specific cost-parameters; Stålhane et al. (2020) present a model for the offshore wind industry that minimizes the total cost of conducting maintenance through the planning horizon, including costs such as vessel chartering costs and offshore station and harbor usage costs. Another example of a study that considers cost minimization is presented by Gundegjerde et al. (2015), who create a model that minimizes the fixed costs of vessels that are acquired or chartered, the expected costs of using the vessels, maintenance costs, penalty costs as well as transportation costs.

As mentioned, uncertainty has a big effect on the decisions made in maritime transportation. Pantuso et al. (2014) state that the focus on methods that consider the uncertainty in maritime transportation should be larger. Supporting this statement, some studies provide numerical results indicating that stochastic modeling may yield significantly better results than those of deterministic modeling. Gundegjerde et al. (2015) present a three-stage stochastic programming model to solve the MFSMP that occurs during maintenance operations of offshore wind farms. Vessel spot rates, weather conditions, electricity prices and system failures are the parameters that represent the uncertainty in the model. By testing the model on real sized problem instances, the results show that the value of the stochastic model is significant compared to solving the model deterministically, and that the model is suitable for application to realistic-sized problem instances. Other parameters such as uncertainty related to electricity subsidy levels and the technology development of the vessel industry may also be considered uncertain, as shown by Stålhane et al. (2020). The stochastic programming model is solved with a customized L-shaped method, and the computational experiments show that the method yields better results than when solving the deterministic equivalent of the model. Other studies that provide results suggesting that stochastic modeling gives better results than deterministic modeling, measured by the resulting objective function values, are presented by Meng et al. (2015) and Wang et al. (2017).

3.3 The Maritime Fleet Renewal Problem

In the Maritime Fleet Renewal Problem (MFRP) it is decided when and how the fleet should be renewed while keeping costs as low as possible. According to Pantuso et al. (2014), the MFRP is an extension of the MFSMP, where the MFSMP is considered a problem where a fleet of ships gets established through ship acquisitions, whereas an MFRP allows a dynamic adjustment of an existing fleet. At a strategic level, such fleet renewal decisions may be related to the acquisition, retrofitting, sales or scrapping of ships. However, the problem may also exist on a tactical or operational level, including decisions regarding ship chartering or the operation of the fleet. It is also often a prerequisite for the MFRP that the shipowner is replacing existing ships mainly to adapt the fleet to new market conditions, and that these may change between periods (Pantuso et al. 2016).

As a consequence of the International Maritime Organization's (IMO) global greenhouse gas reduction ambitions for the seaborne transport industry, there exists an incentive to include emission reduction constraints in models that solve the MFRP, because shipowners may want to comply with these new regulations while minimizing costs. Although the regulations were suggested in 2018, some literature on the MFRP have already studied the effect that emission regulations have on the problem (Balland et al. 2013; Patrickson et al. 2015; Lagemann et al. 2023a). Balland et al. (2013) present a two-stage stochastic model for creating a plan for when a ship should be modified with air emission controls to comply with emission regulations, taking uncertainty in the reduction effects of the different controls into consideration. The model is not intended to solve problems for fleets of ships, and is therefore only applied to a single vessel problem. In a study by Lagemann et al. (2023a), a ship may be retrofitted in the future to adhere to stricter emission regulations, because the retrofit entails that the ship power system is altered in such a way that the ship may run on fuels with lower emissions such as methanol, LNG and ammonia. A study that incorporates emissions as a parameter for a fleet problem, is presented by Patrickson et al. (2015). The paper shows the effect of modifying a fleet in such as way that it can comply with the stricter emission requirements that ships are exposed to when sailing through emission control areas (ECAs). The results show that considering emissions in the model gives a significant cost reduction, as the ships can avoid potential penalty costs for breaking emission requirements of ECAs.

Due to the uncertainty that is related to parameters such as future freight rates, vessel prices, electricity prices and demand, it is common for studies on the MFRP to use stochastic programming models to solve the problem. Such studies are presented by Alvarez et al. (2011), Bakkehaug et al. (2014), Patrickson et al. (2015) and Lagemann et al. (2023a). Alvarez et al. (2011) present a mixed integer programming

(MIP) model of a strategic multi-period fleet planning problem, which is extended into a robust optimization model to take price and demand uncertainty into consideration. Patricksson et al. (2015) present a stochastic MIP model which includes future fuel prices as an uncertain variable. However, the first strategic multi-stage stochastic programming model to solve an MFRP was proposed by Bakkehaug et al. (2014). The model is explicitly designed to handle uncertainty in future demand, ship prices, cargo prices, freight rates and several other uncertain parameters. A common feature of using stochastic programming to solve the MRFP is that the models yield better results than their deterministic equivalents. For instance, Bakkehaug et al. (2014) reported significant improvements, especially for long-term strategic decisions, because the resulting fleet capacities were significantly larger than the ones obtained with deterministic models, thus satisfying higher demands and less chartering.

Due to the stochastic modeling approach that is often made when modeling the MFRP, solution times may increase significantly depending on the model's complexity. Therefore, exact solutions may not be suitable, and several studies have designed more appropriate solution methods by creating heuristics or by utilizing more advanced optimization theory such as decomposing the models (Bakkehaug et al. 2014; Arslan and Papageorgiou, 2017; Pantuso et al. 2015; Stålhane et al. 2020). Stålhane et al. (2020) propose a dual-level stochastic model that is solved using an ad hoc integer L-shaped method with customized optimality cuts. The L-shaped method stems from Benders decomposition, and divides the original model of the problem into a master problem, which is solved first using the first stage variables and restrictions, followed by one subproblem for each second-stage scenario, which are solved using the solution from the master problem. Solving the subproblems will result in cuts that restrict the master problem. Because the problem contains integer variables, Stålhane et al. (2020) designed a variant of the L-shaped method that allowed for generating customized cuts. Due to the low run time of the mathematical models presented in this thesis, however, a heuristic is not needed to solve the models within reasonable time.

3.4 Contribution and Comparison

It is evident that the literature on the MFRP until recent times is scarce, especially on MFRPs that include an emission aspect. However, some studies have incorporated both an emission aspect and uncertainty in their models, and the interest in optimizing the seaborne transport industry with respect to both costs and emission reductions may be increasing in near future due to the demand from the IMO. As a contribution to support shipowners make the shipping industry greener, this thesis suggests three two-stage stochastic MIP models that minimize the total costs of the fleet's lifetime while adhering to future emission reductions - one model that represents an MFSMP, and two models that represent an MFRP. To comply with the emission reduction ambitions, the models consider the fleet to be retrofittable, meaning that the ships of the fleet may change their power systems to allow for consumption of more sustainable fuels. However, while the models share these similarities, they are intended to provide decision support for two different stakeholders. The model that represents an MFSMP takes into account that the shipping company has to invest in a new fleet in the initial period. The two models of the MFRP, however, assume that the shipping company already has an existing fleet in the initial period, and propose solutions for how to optimally modify the composition of such an initial fleet. This has not yet been done on a problem that considers an entire fleet of ships, but Lagemann et al. (2023a) present a model that shows the benefits of retrofitting ship power systems on a single vessel problem. In Table 3.2 some key features of this thesis' problem and the studied literature are visualized to allow for basic comparison.

In Table 3.2 the key characteristics of this thesis' problem and of the problems from the existing literature on MFSMPs and MFRPs are visualized. Each row represents a unique paper, and the columns display the problem characteristics that are most important to position this thesis in the existing literature. All green cells represent a similarity between this thesis and the investigated paper. Thus, the white cells represent differences between this thesis and the papers. As can be seen in the table, there are very few papers that analyze the emissions that are related to the problems. This thesis is the only row that contains just green cells, because no other paper has investigated the exact same problem, at least to the knowledge of the author.

Table 3.2: Key characteristics of this thesis' problem and those of existing literature on MFSMPs and MFRPs

Paper	Problem	Objective	Fleet/ Vessel	Solution Method	Considers Emissions	Green Retrofit	Initial Fleet	Uncertainty
This thesis	MFRP	Minimize	Fleet	MIP	Yes	Yes	Yes	Yes
Lagemann et al. (2023a)	MFRP	Bi-objective	Vessel	MIP	Yes	Yes	No	Yes
Lagemann et al. (2022)	MFRP	Bi-objective	Vessel	MIP	Yes	Yes	No	No
Balland et al. (2013)	MFRP	Minimize	Vessel	MIP	Yes	No	Yes	Yes
Alvarez (2011)	MFRP	Maximize	Fleet	MIP	No	No	Yes	Yes
Patrickson et al. (2015)	MFRP	Minimize	Fleet	MIP	Yes	No	Yes	Yes
Arslan and Papageorgiou (2017)	MFRP	Minimize	Fleet	Heuristic	No	No	Yes	Yes
Bakkehaug et al. (2014)	MFRP	Minimize	Fleet	Metaheuristic	No	No	Yes	Yes
Skålnes et al. (2020)	MFRP	Maximize	Fleet	MIP	No	No	Yes	Yes
Pantuso et al. (2015)	MFRP	Minimize	Fleet	Matheuristic	No	No	Yes	Yes
Mørch et al. (2017)	MFRP	Maximize	Fleet	MIP	No	No	Yes	Yes
Wang et al. (2018)	MFSMP	Minimize	Fleet	MIP	No	No	No	Yes
Meng and Wang (2011)	MFSMP	Maximize	Fleet	MIP	No	No	No	Yes
Meng et al. (2015)	MFSMP	Maximize	Fleet	MIP	No	No	No	Yes
Stålhane et al. (2020)	MFSMP	Minimize	Fleet	L-shaped	No	No	No	Yes
Gundegjerde et al. (2015)	MFSMP	Minimize	Fleet	MIP	No	No	No	Yes
Wang et al. (2017)	MFSMP	Minimize	Fleet	MIP	No	No	No	Yes

CHAPTER

FOUR

PROBLEM DESCRIPTION

Shipping companies own and/or operate fleets of ships that are used to transport goods by sea in order to generate income for the company. In this thesis, an analysis of how shipping companies may modify their fleets of transporting ships to comply with future greenhouse gas (GHG) emissions restrictions while minimizing the total life-cycle costs for the fleet is provided. The analysis is performed both in the context of shipping companies that already own and operate a fleet of ships, as well as in the context of companies that wish to establish a new fleet of shipping vessels. A possible way to modify a fleet of ships may be to retrofit the ships' power systems, i.e., to change the power system of the ships to allow for utilization of fuel types that lead to lower future GHG emissions during fleet operation. The GHG emissions produced by the fleet are measured through both the well-to-tank emissions - the emissions related to the production of the fuel type, and the tank-to-wake emissions - the emissions related to the fuel combustion. For companies that wish to establish a new fleet, acquisition of new ships is necessary, incurring investment costs. Additionally, a ship has a limited lifetime expectancy. Thus, ships that have reached their lifetime potential must be scrapped and replaced by investing in new ships, assuming that the shipping company wants to maintain its fleet size.

The retrofit of a ship's power system is necessary when the shipowner wants to utilize a fuel type that is not compatible with the ship's current system. For instance, if the ship runs on very low sulfur fuel oil (VLSFO) and the company considers to run the ship on liquefied natural gas (LNG), this change in fuel requires a retrofit of the ship's power system because a VLSFO-ship cannot utilize LNG as fuel. However, if the considered change is based on a switch to a fuel type that is compatible with the ship's current power system, such as a transition from fossil LNG to e-LNG, a retrofit of the power system is not necessary. Such a fuel switch would therefore not incur a retrofit cost, but it could lead to both different fuel costs and emissions during fleet operations.

The main drivers of the fleet's total costs are the costs related to the consumption of fuel during operation, as well as the potential retrofit costs related to the choice of power system or the costs related to ship acquisitions. The retrofit costs are assumed to be known. On the other hand, due to fuel cost being an exogenous parameter, its future values are unknown. However, the current fuel prices in the market may be used as an estimate for the decisions that are made during the next few years. Further, because the fuel types have varying net energy densities, both in terms of volume and weight, they affect the cargo-carrying capacity of the ships. This incurs lost opportunity costs associated with the choice of power system, when assuming that the ships need to keep their installed power constant. Next, it is assumed that a ship may utilize only one fuel type and one power system at the same time, and that the fuel type must be compatible with the power system. Additionally, the fleet size is considered constant.

Furthermore, the actions the shipowners may take to change their fleets are to retrofit existing ships to allow for utilization of more sustainable fuel types, to switch between fuel types that are compatible with the same power system, or to invest in the acquisition of new ships whenever old ships need to be scrapped. Additionally, companies that do not yet own a fleet need to acquire ships in the initial time period. All mentioned decisions are made with respect to increasingly stricter fleet emissions restrictions, which need to be satisfied throughout the planning horizon. Because such decisions may incur significant costs, the objective of the shipowners is to minimize the expected total cost of modifying and operating their fleets.

CHAPTER

FIVE

MATHEMATICAL MODELS

This chapter presents the mathematical formulations of the thesis. First, the necessary remarks and assumptions are described in Section 5.1. Further, the mathematical notation that is common to all the formulations is presented in Section 5.2. The mathematical formulation of this thesis' variant of the MFRP, without the option of scrapping old ships, is proposed in Section 5.3. Next, Section 5.4 presents an extension of that problem, in which scrapping of old ships is accounted for. Finally, Section 5.5 contains the mathematical formulation of this thesis' variant of the MFSMP.

5.1 Modeling Assumptions

This section provides a description of the remarks and assumptions that are important to the problem formulation, as well as a description of how the thesis has created scenario trees for modeling the uncertainty of future fuel prices. Note that the assumptions are simplifications of reality, rather than being a true reflection of it. Some additional assumptions are described in later chapters because they should be described in the context in which they are needed.

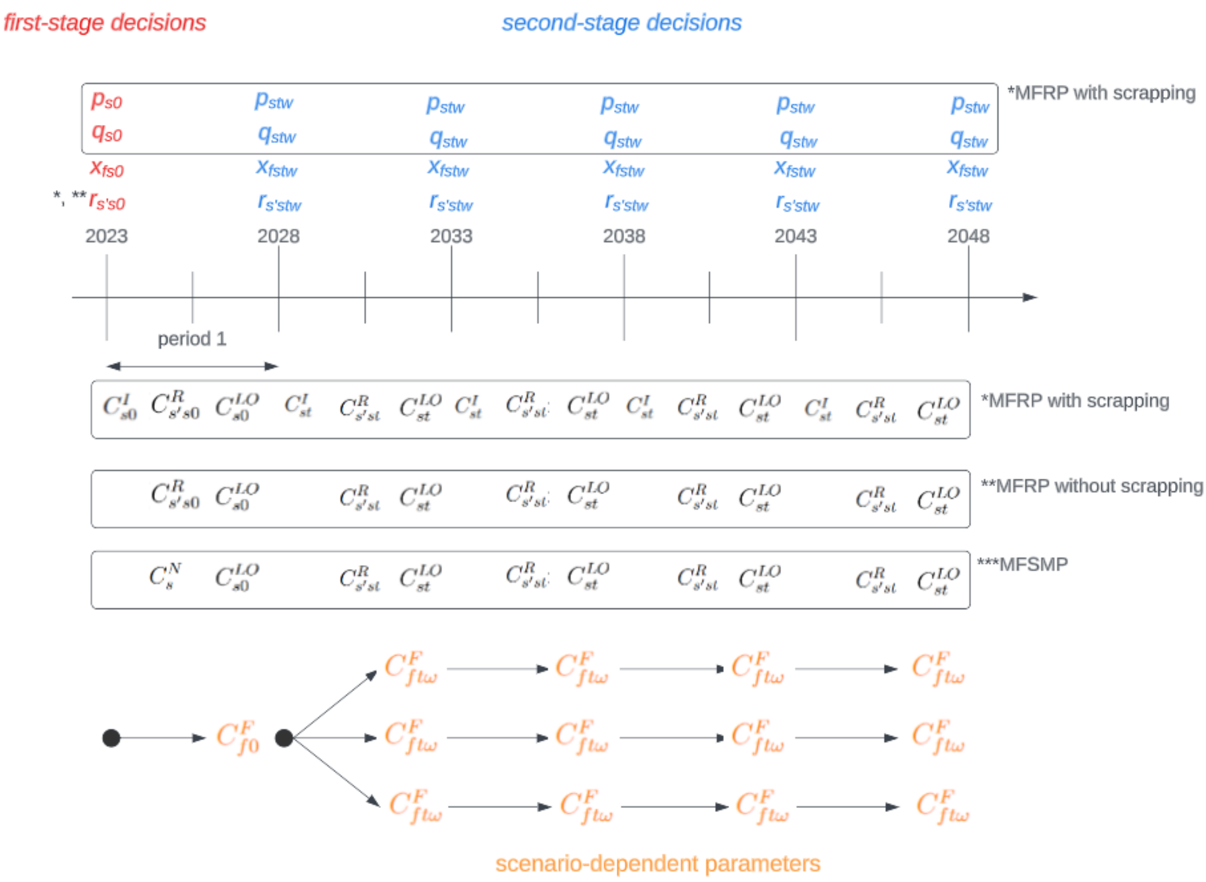

Figure 5.1: Scenario tree for the mathematical models.

Figure 5.1 provides a visualization of the decisions made in the mathematical models, as well as when the uncertainty regarding future fuel prices is resolved. The fuel prices in the initial time period are assumed known, and are based on the expected value of the stochastic fuel price. As can be seen in the figure, the uncertainty resolves after the first time period, which means that the future prices become known from that point in time. Therefore, the decisions made in the initial period are made under uncertain future fuel prices. Note that the differences between the three models are pointed out in the figure. Parameters and variables that are common to all models, are not assigned any box or *. For instance, it is indicated by *,** that the first-stage decisions in the two models of the MFRP is how many ships to retrofit from a traditional power system s' to an alternative power system s, denoted by $r_{s's0}$. Because variables x_{fs0}, $x_{fst\omega}$ and $r_{s'st\omega}$ and parameters C^F_{f0} and $C^F_{ft\omega}$ are common to all models, they are not assigned a * or a box.

Assumptions about cargo-carrying capacity

- Different energy carriers have varying net energy densities. Consequently, shipowners need to decide whether cargo-carrying capacity should be reduced to keep the installed power constant, or if they should make their ships larger and increase the installed power in order to keep the cargo-carrying capacity constant. In this thesis, the first option is assumed to be most sensible with respect to retrofits.

Assumptions about costs and fuel prices

- At the operational level, operational expenditures such as port fees, ship maintenance costs and crew costs occur. However, these costs will not be affected by the considered decisions, and are therefore not included in the costs of the objective function.
- Future costs are discounted at an annual discount rate
- Fuel prices are assumed to be known in the first time period. They are based on the expected value of the stochastic fuel price. Furthermore, the future fuel prices are assumed to become known for the rest of the planning period after the first time period.
- The carbon price is included in the model implicitly through the fuel prices. In the implementation of the models, the price is added to the fuel price per unit energy.

Other assumptions

- All ships of the fleet are assumed to be of the same type and operate in the same segment. In the case study, all ships are assumed to be of the type Supramax dry bulk vessel.
- The well-to-tank and tank-to-wake emissions from each fuel are assumed known
- In reality, shipping regulations usually target emissions per ship. In this thesis however, the emissions are considered for the entire fleet in each time period.
- Retrofits, scrapping, investments and acquisition of ships happen at the start of each time period

5.2 Notation

This section defines the notation that is included in the formulation of all the mathematical models presented in this chapter. Further notation that is specific to each of the models is provided separately when presenting the different models. Because the necessary assumptions are provided in Section 5.1, this section only provides brief comments on the notation to facilitate for good readability.

Table 5.1: Sets

T	Set of discrete time periods, indexed by t
F	Set of fuel types, indexed by f
S	Set of ship power systems, indexed by s
Ω	Set of scenarios, indexed by ω

Table 5.2: Parameters

$C^R_{s'st}$	Retrofit cost from system s' to system s in period t
$C^F_{ft\omega}$	Fuel cost of fuel f in period t in scenario ω
N	Number of ships in the fleet
P_ω	The probability of scenario ω
C^{LO}_{st}	Lost opportunity cost of utilizing system s in period t
B	Energy consumption per time period, assuming the fuel conversion efficiencies do not change over time, equidistant time periods
E^{WTT}_f	Well-to-Tank emissions of fuel f
E^{TTW}_f	Tank-to-Wake emissions of fuel f
E_t	Maximum allowed emissions from each ship in time period t
K_{fs}	1 if fuel f and system s are compatible, 0 otherwise

Table 5.3: Variables

$x_{fst\omega}$	Number of vessels that use fuel f and system s in the end of time period t in scenario ω, where $t > 0$
x_{fs0}	Number of vessels that use fuel f and system s in the end of time period 0
$r_{s'st\omega}$	Number of vessels that make a retrofit from ship system s' to ship system s at the beginning of period t in scenario ω, where $t > 0$

5.3 The Stochastic MFRP Without Scrapping of Ships

This section presents a mathematical formulation of an MFRP without the option to scrap old ships. The formulation is to a large extent based on the formulation provided by Lagemann et al. (2023a). However, while Lagemann et al. (2023a) propose a model for solving an MFRP for a single ship that has to be acquired in the initial time period, this formulation is extended to be able to solve the problem for an existing, initial fleet of ships. Additional differences are that emissions are restricted step-wise in the constraints rather than being minimized in an objective function, and that the objective just is to minimize total costs.

To formulate the mathematical model of the MFRP that is considered in this thesis, some additional notation is required. A parameter that indicates the initial fleet composition is needed. Consequently, parameterN_{fs0} represents the number of vessels with fuel type f and power system s in the initial fleet in the first time period. Furthermore, a variable that allows the model to account for retrofits of the ships in the initial fleet is required. The variable $r_{s's0}$ therefore represents the number of vessels that make a retrofit from ship system s' to ship system s at the beginning of the initial time period. The new parameter and variable are also required for formulating the mathematical model of the extension of this problem, where scrapping of old ships is accounted for. Hence, the notation is not repeated in the next section.

Objective Function

The objective function (5.1) minimizes the ETCO. The expected total costs consist of the retrofit costs and lost opportunity costs that may occur in all periods, as well as the cost related to fuel consumption throughout the planning horizon. Operational expenditures (OPEX) such as port fees and crew costs are not included in the objective, as they would apply to all alternatives considered. Further, a potential carbon tax would affect the objective based on a solution's selected fuel types. In all the models presented in this thesis, the carbon price is included implicitly through the fuel prices.

$$min\ ETCO = \sum_{s \epsilon S} \sum_{s' \epsilon S} (C^{R}_{s's0} + C^{LO}_{s0}) r_{s's0} +$$
$$\sum_{\omega \epsilon \Omega} P_{\omega} (\sum_{f \epsilon F} \sum_{s \epsilon S} \sum_{t \epsilon T} C^{LO}_{st} x_{fst\omega} + \sum_{s' \epsilon S} C^{R}_{s'st} r_{s'st\omega} + BC^{F}_{ft\omega} x_{fst\ omega}) \tag{5.1}$$

Constraints

The objective function is subject to the following constraints:

$$\sum_{f \epsilon F} x_{fs0} = \sum_{f \epsilon F} N_{fs0} + \sum_{s' \epsilon S} r_{s's0} - \sum_{s' \epsilon S} r_{ss'0}, \qquad s \epsilon S, \tag{5.2}$$

$$\sum_{s' \epsilon S} r_{ss'0} \leq \sum_{f \epsilon F} N_{fs0}, \qquad s \epsilon S. \tag{5.3}$$

Constraints (5.2) ensure balance between the number of vessels at the start and end of the first time period. Thus, the fleet composition at the end of the first time period must be equal to the initial fleet plus or minus any retrofits that happen at the start of the time period. Further, Constraints (5.3) ensure that the number of retrofits from a power system can not be greater than the number of vessels that already have power system s in the initial fleet.

$$\sum_{f \epsilon F} x_{fst\omega} = \sum_{f \epsilon F} x_{fs(t-1)\omega} + \sum_{s' \epsilon S} r_{s'st\omega} - \sum_{s' \epsilon S} r_{ss't\omega}, \qquad s \epsilon S, t \epsilon T \backslash \{0\}, \omega \epsilon \Omega, \tag{5.4}$$

$$\sum_{s' \epsilon S} r_{ss't\omega} \leq \sum_{f \epsilon F} x_{fs(t-1)\omega}, \qquad s \epsilon S, t \epsilon T \backslash \{0\}, \omega \epsilon \Omega. \tag{5.5}$$

Constraints (5.4) ensure that the fleet composition at the end of a time period after the initial period is equal to the fleet in the preceding time period plus or minus any retrofits that may have happened in the start of the period. Constraints (5.5) make sure that the number of retrofits from a power system can not be greater than the number of ships that use that power system at the end of the preceding period after the initial period.

$$\sum_{f\epsilon F}\sum_{s\epsilon S} B(E_f^{WTT} + E_f^{TTW})x_{fst\omega} \leq E_t N, \qquad t\epsilon T, \omega\epsilon\Omega, \tag{5.6}$$

$$x_{fst\omega} <= K_{fs}N, \qquad f\epsilon F, s\epsilon S, t\epsilon T, \omega\epsilon\Omega. \tag{5.7}$$

In Constraints (5.6) the total greenhouse gas emissions produced by the fleet in any time period and scenario must be less than or equal to the maximum allowed emissions for each time period. Because the parameter E_t defines the allowed emissions from a single ship, the right hand side (RHS) of the equation is scaled with N, the size of the fleet, to indicate the maximum allowed emissions from the fleet. Constraints (5.7) ensure that the fuel type and power system that a ship utilizes must be compatible.

$$x_{fst\omega} = x_{fs0}, \qquad f\epsilon F, s\epsilon S, t = 0, \omega\epsilon\Omega, \tag{5.8}$$

$$r_{s'st\omega} = r_{s's0}, \qquad s', s\epsilon S, t = 0, \omega\epsilon\Omega, \tag{5.9}$$

$$r_{s's0} \geq 0, integer, \qquad s', s\epsilon S, \tag{5.10}$$

$$r_{s'st\omega} \geq 0, integer, \qquad s', s\epsilon S, t\epsilon T, \omega\epsilon\Omega, \tag{5.11}$$

$$x_{fst\omega} \geq 0, integer, \qquad f\epsilon F, s\epsilon S, t\epsilon T, \omega\epsilon\Omega. \tag{5.12}$$

Constraints (5.8) and (5.9) connect the second-stage decisions to the first stage decisions. Finally, Constraints (5.10) to Constraints (5.12) ensure that all variables are non-negative integers.

5.4 The Stochastic MFRP With Scrapping of Ships

This section provides an extension of the mathematical model that was presented in Section 5.3. This extended formulation accounts for the fact that ships may have different remaining lifetimes, and that ships that have reached their lifetime potential should be scrapped. Because the scrapping of ships would need to be part of all solutions, potential salvage value would not differentiate solutions and it is therefore not included in the mathematical formulation. However, because the fleet size is assumed to be kept constant throughout the planning horizon, this model must include the option to invest in new ships. Furthermore, some additional notation that is specific to this formulation is presented in the next paragraph.

To account for scrapping of old ships, the mathematical model takes the number of ships to be scrapped in each time period as input. This is represented by the new parameter R_t, as presented in Table 5.4. Additionally, the model must include an investment cost that is associated with the acquisition of a new ship of type s in time period t. The investment cost is depreciated with respect to remaining years of the project horizon. Further, because parameter R_t does not specify which ships that need to be scrapped in time period t, the new formulation includes an integer variable $p_{st\omega}$ that represents the number of ships with system s that are to be scrapped in period t in scenario ω. Likewise, the integer variable $q_{st\omega}$ is included to represent the number of ships with system s that are to be acquired in period t in scenario ω. While the extended model yields expected results, it has a potential flaw. There are no constraints that restrict the model from scrapping ships that have already been retrofitted. Thus, there is a possibility that an old ship is being retrofitted and then scrapped in a later time period. However, because the emissions restrictions get stricter each time period and the initial fleet contains just traditional ships, is has, for all practical cases, proven to avoid this potential problem in the test runs. To circumvent the mentioned flaw, one could extend the model to account for which ships that need to be scrapped in each time period rather than just considering the number of ships to scrap. An example of a model that includes such an approach is proposed by Skålnes et al. (2020). However, note that the modification of the model would increase its complexity.

Note that the necessary modifications of the mathematical formulation are rather small. Therefore, only the differences between the model presented in Section 5.3 and the extension are pointed out.

Table 5.4: Additional parameters

R_t	Number of ships to be scrapped in period t
C^I_{st}	Investment cost of acquiring a new ship with system s in period t. Depreciated with respect to remaining years of the project horizon

Table 5.5: Additional Variables

$q_{st\omega}$	Number of ships with system s to be acquired in period t in scenario ω
$p_{st\omega}$	Number of ships with system s to be scrapped in period t in scenario ω

Addition to the objective function

As described, the potential salvage value associated with the scrapping of a ship will not contribute to differentiating solutions, and is therefore not included in the extended formulation. However, the investment cost that occurs when acquiring new ships must be included. This is done by adding the expression in Equation (5.13) to the original objective function that is presented in objective function (5.1).

$$(... + \sum_{\omega \epsilon \Omega} \sum_{s \epsilon S} \sum_{t \epsilon T} C^I_{st} q_{st\omega}) \tag{5.13}$$

Additional constraints

Constraints (5.14) and Constraints (5.15) are added to the mathematical formulation from Section 5.3. The former equation makes sure that the total number of ships of different types s that are scrapped in each time period and scenario is equal to the required number of ships to be scrapped in each time period. The latter equation makes the number of ships that are scrapped equal to the number of acquired ships in each time period and scenario. Note that this specification does not specify which ship types that should be scrapped or invested in, and that this is something the model solves to optimality.

$$\sum_{s \epsilon S} p_{st\omega} = R_t, \qquad t \epsilon T, \omega \epsilon \Omega, \tag{5.14}$$

$$\sum_{s \epsilon S} q_{st\omega} = \sum_{s \epsilon S} p_{st\omega}, \qquad t \epsilon T, \omega \epsilon \Omega. \tag{5.15}$$

Modified constraints

Because the added parameters and variables will affect the balance equations presented in Section 5.3, Constraints (5.2) and Constraints (5.4) need to be modified. The resulting modified constraints are presented in Constraints (5.16) and Constraints (5.17). Constraints (5.2) become:

$$\sum_{f \epsilon F} x_{fs0} = \sum_{f \epsilon F} N_{fs0} + \sum_{s' \epsilon S} r_{s's0} - \sum_{s' \epsilon S} r_{ss'0} - R_0 + q_{s0}, \qquad s \epsilon S, \tag{5.16}$$

Constraints (5.4) become:

$$\sum_{f \epsilon F} x_{fst\omega} = \sum_{f \epsilon F} x_{fs(t-1)\omega} + \sum_{s' \epsilon S} r_{s'st\omega} - \sum_{s' \epsilon S} r_{ss't\omega} - p_{st\omega} + q_{st\omega}, \qquad s \epsilon S, t \epsilon T \backslash \{0\}, \omega \epsilon \Omega. \tag{5.17}$$

The modifications presented in Constraints (5.16) make sure that the number of ships in the fleet at the end of the initial time period is affected by the number of ships that are scrapped and the number of ships that are acquired in that time period. Constraints (5.17) present the same modifications but for the fleet in future time periods. Note that ships in future time periods may use alternative power systems, and therefore the scrapping of ships must be accounted for by the means of the scrapping-variable $p_{st\omega}$. However, in Constraints (5.16), it is the parameter R_0 that represents the number of ships scrapped. This is because scrapping of ships happens at the start of the initial time period, and because all ships in the initial fleet are of the traditional type, it is not necessary to account for ship types in this equation.

5.5 The Stochastic MFSMP

In this section, a variant of the mathematical formulation presented in Section 5.3 is defined to account for the acquisition of an initial fleet. Such a model may provide useful decision support for newly established shipowners that do not yet own a fleet. As this problem has many similar characteristics to the mathematical formulation presented in Section 5.3, only the differences between the models are presented in this section. To see the complete mathematical models, readers are referred to the appendix.

Although not many, there are some changes that need to be made to the notation before the model of the MFSMP can be formulated. No new sets are required to formulate the problem, but because there are no initial ships, the shipowner has to acquire a number of ships at the start of the planning horizon. Thus, the parameter C^N_s, which represents the newbuild cost of a ship with power system s, is introduced. Note that the parameter is only dependent on the type of ship power system, and that it is therefore considered static throughout the planning period. No additional variable is needed to support the decision of ship acquisition, because the variable x_{fs0} can in this problem be interpreted as the number of ships that are acquired in the first period.

Supported by the described changes to the mathematical notation, the necessary changes to the mathematical formulation are presented in Constraints (5.18) - (5.20). First, the objective function needs to be altered, because the costs associated with the acquisition of ships in the initial period need to be considered. Additionally, any potential retrofit and lost opportunity costs in the initial period are no longer needed, and should be removed from the objective function. Furthermore, the resulting objective function becomes:

$$\begin{aligned} min\ ETCO = \sum_{f \epsilon F} \sum_{s \epsilon S} C_s^N x_{fs0} + \\ \sum_{\omega \epsilon \Omega} P_\omega (\sum_{f \epsilon F} \sum_{s \epsilon S} \sum_{t \epsilon T} C_{st}^{LO} x_{fst\omega} + \sum_{s' \epsilon S} C_{s'st}^R r_{s'st\omega} + BC_{ft\omega}^F x_{fst\ omega}) \end{aligned} \tag{5.18}$$

Next, Constraints (5.2) are replaced by Constraint (5.19) and Constraints (5.3) are no longer needed, as the option to perform retrofits in the initial time period is removed. Constraint (5.19) limits the number of initial acquisitions to be equal to the intended fleet size. Because it is not possible to do any new acquisitions after the initial period, this constraint sets the fleet size for the entire planning horizon. Naturally, constraints (5.9) and (5.10) are no longer needed when initial retrofits are no longer an option. Finally, Constraints (5.20) are added to the formulation to make sure that no retrofits are made in the initial period.

$$\sum_{f \epsilon F} \sum_{s \epsilon S} x_{fs0} = N, \tag{5.19}$$

$$r_{s'st\omega} = 0, \qquad s', s \epsilon S, t = 0, \omega \epsilon \Omega. \tag{5.20}$$

CHAPTER

SIX

COMPUTATIONAL STUDY

This chapter contains a computational study of the MFSMP and the MFRP with scrapping that were presented in Chapter 5. Because the MFRP with scrapping seems a more realistic representation of reality than the MFRP without scrapping, the model that represents the latter problem is not included in this chapter. A case description and an overview of the cost parameters is provided in Section 6.1. Section 6.2 contains a discussion of scenario generation, including both the fuel prices and carbon prices. Further, Section 6.3 presents the results from solving the MFSMP. Finally, the results from the MFRP with scrapping is provided in Section 6.4.

Note that Sections 6.1 and 6.2 are significantly based on Lagemann et al. (2023a). Section 6.1 provides a case description, as well as a discussion on the data used in the analysis of the implemented mathematical models. All calculations and data, including the lost opportunity costs, newbuild costs and retrofit costs, are retrieved from the research presented in Lagemann et al. (2023a). Because this thesis may be seen as an extension of Lagemann et al. (2023a), the same data and calculations have been used to perform analysis. In Section 6.2, a discussion on the scenario generation, as well as the future fuel and carbon prices, is presented.

6.1 Case description

Measured in tons transported, the global dry bulk fleet accounts for about 50% of the global sea transport, and it provides more than 40% of the freight work measured in ton-miles (Bengtsson, 2018). Because the fleet consists of close to 12000 vessels, with Supramax carriers amounting to nearly 25% and being responsible for providing nearly 10% of the global transport work in ton-miles, the mathematical models in this thesis are applied to a numerical case study in which a fleet of Supramax dry bulk carriers is considered. Additionally, Supramax dry bulk carriers are used in the computational study because this thesis is largely based on Lagemann et al. (2023a), which is based on the dimensions of such vessels. Except for the option to utilize different power systems and fuels, the ships of the fleet are considered homogeneous, and the fleet size is kept constant throughout the planning horizon. However, there are few ship specific inputs needed to run the models, and they may therefore be applied to other shipping segments that utilize other ship types.

The Supramax dry bulk carriers are typically built with five cargo holds which are serviced by four slewing cranes that allow for handling cargo without the use of quay cranes in port. Common dimensions for such ships are a length of about 200 meters, a draught of about 13.5 meters and a beam width up to 32.3 meters, which is the old restrictions of the Panama Canal locks. A ship typically has 58000 - 65000 tonnes deadweight (dwt) capacity, which is a measure of the total aggregated weight of cargo, fuel, gear, crew and other factors, disregarding the weight of the ship and its machinery.

Lost Opportunity Costs

Due to the consideration of the fleet being homogeneous, all ships in the initial fleet of the MFRP case are configured with the same fuel and power system options. Even though both heavy fuel oil (HFO) and very low sulphur fuel oil (VLSFO) are considered conventional fuels, this thesis uses just VLSFO as a reference fuel for comparison with alternative fuel selections. Using VLSFO as a reference fuel, selection of alternative fuels that have other net energy densities than those of VLSFO, meaning they require more weight or space, leads to reduced cargo carrying capacity, as the ship size is assumed constant. The reduced cargo carrying capacity is accounted for in the mathematical models through the inclusion of a lost opportunity cost. To calculate the lost opportunity cost, it is assumed that there is an average utilization of 90% of the dwt until 58000 tonnes, followed by a 25% utilization of the potential remaining capacity of the ship. Additionally, ship charter rates of the Supramax carrier are included in the cost by weighting the daily charter rate with the ship's average utilization. The charter rate is assumed to be 25,000 USD/day, based on data provided by Handybulk (2022). To calculate the lost opportunity cost, it is first necessary to compute the lost cargo carrying capacity that results from the selection of alternative power systems. The calculations are provided in Equations (6.1) and (6.2), while the resulting lost opportunity costs are presented in Figure 6.1. The figure is provided by Lagemann et al. (2023a), and is presented here because this computational study utilizes the same data as Lagemann et al. (2023a). Lagemann et al. (2023a) provides further insight into the calculations of lost opportunity costs in an appendix.

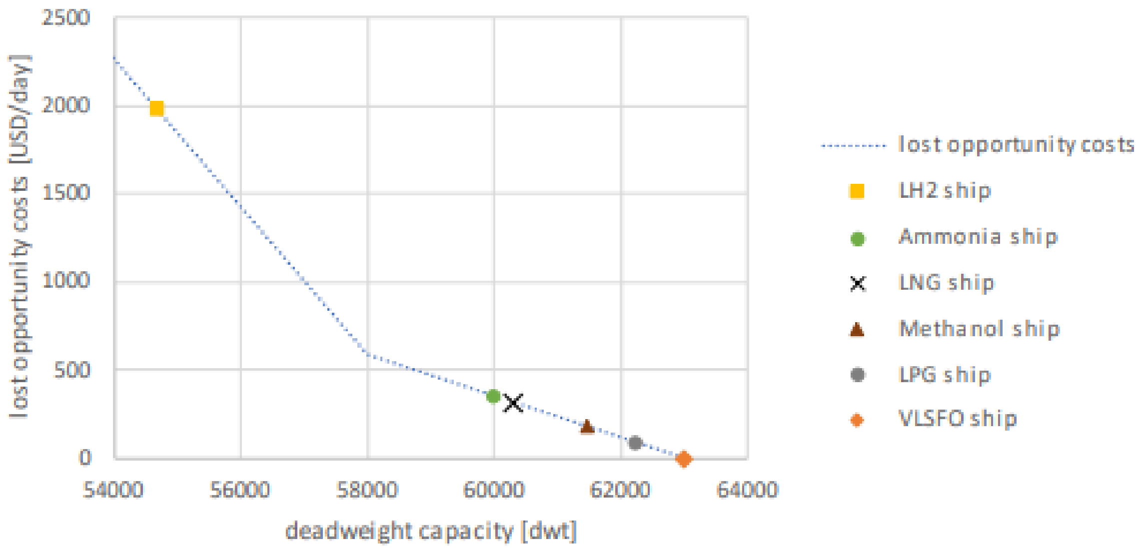

Figure 6.1: Daily lost opportunity costs for constant range and energy efficiency (Lagemann et al. 2023a)

The calculations for computing the cargo-carrying capacity of ship power system s is provided in Equation (6.1). $w_s^{fuel\ contained}$ represents the weight of the contained fuel when power system s is utilized. The traditional VLSFO configuration is what the capacity is being compared against, and thus the weight of the fuel for for the VLSFO power system is included as $w_{VLSFO}^{fuel\ contained}$. Additionally, the cargo density must be accounted for when comparing volumetric measures. It is represented by p^{cargo}, and is assumed to be 1 t/m^3.

$$w_s^{lost\ cargo} = max\{w_s^{fuel\ contained} - w_{VLSFO}^{fuel\ contained}; v_s^{excess} * p^{cargo}\} \tag{6.1}$$

Because the model accounts for both different net energy densities both weight- and volume-wise, the required volume for fuel tanks of the different ship power systems that exceeds the freely available volume must be calculated. The calculation is provided in Equation (6.2), where $v_s^{fuel\ contained}$ represents the required volume for fuel and tanks for power system s, and v^{free} is the available volume on deck. It is assumed that $v_s^{fuel\ contained}$ is zero for VLSFO and methanol ships, and that the freely available volume is approximately $1600m^3$. Whether the penalty cost is derived from excess weight or volume, depends on whether the ship's energy carrier can be integrated into the ship structure or not. Methanol is such an energy carrier, and thus does not require extra space.

$$v_s^{excess} = max\{0; v_s^{fuel\ contained} - v^{free}\} \tag{6.2}$$

Newbuild Costs

The estimated costs of building a new Supramax carrier with different power system options are provided in Table 6.1. To calculate the newbuild prices of a ship that is configured with power system s, one has to look at the cost of building a traditional Supramax carrier than runs on VLSFO, then deduct the cost of the traditional power system and add the estimated cost of the new power system.

The costs of building a new Supramax carrier with a VLSFO system configuration is approximately 30 mUSD (Hellenic Shipping News 2022). Further, Lindstad et al. (2021b) present cost estimations for engines that are utilized for alternative fuels. The cost estimations are presented in USD per kW main engine power installed on the ship.

Table 6.1: CAPEX and lost opportunity costs (Lagemann et al. 2023a)

	parameter	VLSFO ship	LNG ship	LPG ship	Methanol ship	Ammonia ship	LH2 ship
	Engine costs [USD/kW]	400	800	1500	1000	600	600
	Tanks and add-ons [USD/kW]	0	600	1200	400	200	200
C_s^N	newbuilding price [mUSD]	30	37.5	47.5	37.5	33	33
C_{st}^{LO}	lost opportunity costs per 5 years [mUSD]	0	0.5	3.0	0.5	0.1	0.3
K_{fs}	compatible fuels	VLSFO, Bio-Diesel, E-Diesel	Bio-LNG, E-LNG, fossil LNG	Liquid E-Hydrogen, Liquid NG-Hydrogen	E-Ammonia, NG-Ammonia	fossil LPG	Bio-methanol wood, Bio-methanol waste stream, E-methanol

Thus, the cost estimations for a ship are calculated by taking a system-based (Levander 2012) approach combined with the estimations provided by Linstad et al. (2021b) and the assumption that each ship has 7500 kW installed power. As observed in Table 6.1 the engine costs of a conventional VLSFO ship approximates to 400 USD/kW, resulting in engine costs of 3 mUSD. Deducting the engine costs from the VLSFO newbuild price of 30 mUSD, thus gives a ship cost of 27 mUSD for building a new Supramax carrier. Finally, the newbuild prices for the ships with alternative power system configurations are calculated by adding the ship cost of 27 mUSD to the estimated engine costs. The same calculations and resulting data is presented in Lagemann et al. (2023a).

Retrofit Cost

Similar to the newbuild costs of ships with alternative power systems, the retrofit costs that incur when changing the power system of an existing ship are based on the system based cost factors provided by Lindstad et al. (2021b). Further, the retrofit costs need to account for the time spent in dock when retrofitting, which results in lost income, as well as additional shipyard costs. The mentioned extra cost factors result in an additional penalty cost of 3.6 mUSD. A visual representation of retrofit costs between all power systems is provided in Table 6.2. Note that because a retrofit increases the total costs for the shipowner, only retrofits between systems that will result in reduced

GHG emissions during operations are considered, leaving blank cells whenever a retrofit will yield an increase in potential GHG emissions. In the implemented computations, the values that represent these fields are set to very large penalty costs so that a retrofit will not occur.

Table 6.2: Retrofit Costs - green represents low costs, yellow and orange medium costs, and red represents high costs (Lagemann et al. 2023a)

from/to	VLSFO ship	LNG ship	LPG ship	Methanol ship	Ammonia ship	LH2 ship
VLSFO ship	0.0	12.6	7.4	7.4	12.6	25.0
LNG ship	3.6	0.0	5.1	5.1	8.1	20.5
LPG ship	3.6	10.4	0.0	10.7	8.9	22.7
Methanol ship				0.0	10.4	22.7
Ammonia ship					0.0	18.2
LH2 ship						0.0

Discounting costs

To be able to more accurately predict the impact that future decisions will have on the total cost over the fleet's lifetime, all retrofit costs, fuel costs, lost opportunity costs and investment costs that occur after the first time period are discounted at an annual discount rate of 5%.

6.2 Scenario Generation

Future fuel prices and carbon prices are uncertain. Because there are several ways to compute the values of these uncertain prices, this section therefore provides a discussion of how the prices are calculated in this thesis. The calculations and discussions are based on Lagemann et al. (2023a).

6.2.1 Sampling of fuel prices

To solve the stochastic programming models presented in Chapter 5, a discrete representation of the uncertain parameters is required (Pantuso et al. 2015). According to (King and Wallace, 2012), the goal of the discretization is to create a scenario tree such that the error that is caused by that discretization is minimized, while making sure that the model is solvable. However, to predict an accurate probability distribution for uncertain parameters is complex. Even when fitting a probability distribution perfectly to a set of historical data, it is not likely that the distribution would be as fitting for uncertain future data in the long run. Further, Pantuso et al. (2015) argue that taking uncertainty into account is more important than finding the best way to account for uncertainty. Thus, to solve the models presented in Chapter 5, a probability distribution for the uncertain fuel prices is needed.

While Lagemann et al. (2023a) found that most studies that estimate the future prices for alternative fuels give low- and high-price estimates, they argue that the probability is higher for prices lying between the lower and upper bound, than lying on the bounds. Further, they argue that a more realistic way to estimate the future fuel prices is to assume a probability distribution that assigns higher probability to intermediate values than to lower and upper bounds. Consequently, a triangular probability distribution between the lower and upper bound fuel prices is assumed. As the mathematical models in this thesis are based on Lagemann et al. (2023a), which proved to have very good in-sample stability, it is natural to assume the same triangular probability distribution in this thesis. In-sample stability is referred to as a test of the internal consistency of a mathematical model. A model has in-sample stability if the optimal objective values from running the model an equal number of times on each scenario tree from a set of different scenario trees are approximately the same (King and Wallace, 2012). Hence, due to the internal consistency of the model, the choice of scenario tree is no longer important. Consequently, the results from the model may be analyzed based on just one of the generated scenario trees, as the optimal objective values from running the models on different scenario trees would be nearly the same.

The fuels accounted for in this thesis may be grouped into fossil, bio- and electro-fuels. The uncertainty of a fuel is to a large degree dependent on the fuel group to which that fuel belongs. The future price of electro-fuels is highly dependent on the future development of the cost of electricity (Lindstad et al. 2021b). Likewise, Korberg et al. (2021) present that future bio-fuel prices are sensitive to the cost of the biomass on which the fuel is based. Lagemann et al. (2023a) assumes that fuel prices within each of the fuel groups are perfectly correlated, and computes the fuel price for each fuel in each time period by interpolating the lower and upper bound for the fuel. To perform an interpolation, a random number for each fuel group in each time period is drawn for each scenario. Thus, to calculate the fuel prices for a fuel in a given time period, three independent random numbers are drawn based on a triangular probability distribution. The interpolation is presented in Equation (6.3).

$$C^{F}_{ft\omega} = C^{F,lower\ bound}_{f} + (C^{F,upper\ bound}_{f} - C^{F,lower\ bound}_{f}) * random\ number_{t\omega} \qquad (6.3)$$

Figure 6.2 is a visualization of the sampling of fuel prices for VLSFO from a set of 100 scenarios in period 1. As can be seen, the triangular probability distribution makes the fuel price more likely to be in the middle range of the price interval between the lower and upper bound.

Figure 6.2: Sampled and discounted fuel prices for VLSFO in period 1, set with 100 scenarios (Lagemann et al. 2023a)

The estimates for the lower and upper bounds of the different fuel prices are based on the calculations performed by Lindstad et al. (2021b) for fossil and electro-fuels and Korberg et al. (2021), scaled with a biomass price between five and ten €/GJ and converted to USD, for bio-fuels. The bounds are presented in Table 6.3, along with each fuel's global warming potential (GWP), which represents emission per unit energy of the fuel.

Table 6.3: Upper and lower bound fuel costs and GWP factors (Lagemann et al. 2023a)

			Environmental impact		Economic impact	
Energy carrier	Feedstock	Fuel label	GWP WTT per fuel energy unit [gCO_2eq/kWh]	GWP TTW per fuel energy unit [gCO_2eq/kWh]	Upper bound cost [USD/MWh]	Lower bound cost [USD/MWh]
Diesel	Fossil	VLSFO	47.5 [1]	284.1 [1]	95 [2]	38 [2]
	Bio	bio-Diesel	70.0 [5]	150 [5]	128 [3]	93 [3]
	Electro	e-Diesel	0.0 [1]	4.5 [1]	423 [2]	131 [2]
Methane	Fossil	LNG	66.6 [1]	238.8 [1]	81 [3]	32 [3]
	Bio	bio-LNG	49.7 [1]	6.0 [1]	119 [2]	89 [2]
	Electro	e-LNG	0.0 [1]	6.0 [1]	358 [2]	115 [2]
LPG	Fossil	LPG	30.0 [1]	237.5 [1]	98.3 [2]	39.3 [2]
Methanol	Fossil	Methanol	112.7 [1]	253.4 [1]	210 [2]	90 [2]
	Bio	bio-Methanol	112.68 [1]	3.24 [1]	97 [3]	66 [3]
	Electro	e-Methanol	0.0 [1]	3.5 [1]	385 [2]	116 [2]
Ammonia	Fossil	Ammonia	87.1 [1],[4]	19.0 [1]	220 [2],[6]	56 [2],[6]
	Electro	e-Ammonia	0.0 [1]	19.0 [1]	220 [2]	80 [2]
Hydrogen	Fossil	LH2	108.7 [1],[4]	0.0 [1]	245 [2],[6]	55 [2],[6]
	Electro	e-LH2	0.0 [1]	0.0 [1]	245 [2]	79 [2]

Sources and comments: [1] Lindstad et al. (2021a), [2] Lindstad et al. (2021b), [3] Korberg et al. (2021), [4] assuming 80% CCS efficiency, [5] Sustainable Shipping Initiative (2019), [6] Upper bound 100% of electricity-based pendant, lower bound 70% of electricity-based pendant

The GWP factors are mainly based on Lindstad et al. (2021a) for fossil and electro-fuels, and Korberg et al. (2021) and Sustainable Shipping Initiative (2019) for bio-fuels. As in Lagemann et al. (2023a), the GWP factors in the table represent approximately 50% of the GWP factors per unit break power for a large two-stroke engine. Due to differing efficiency among engine types, the exact value depends on the engine type that is being utilized.

6.2.2 Carbon pricing

To incentivize shipowners to reduce the GHG emissions from their fleets, appropriate regulatory tools are needed. The two main approaches to realize such reductions are the "command and control" and the Market-based measures (MBMs) approaches. The former approach implies that authorities regulate emissions by setting benchmarks that restrict the factors that lead to GHG emissions, such as vessel speed, power and fuel consumption (Lagouvardou et al. 2020). However, this would prove very difficult due to the high variability in ship specifications and operating practices, and it would require a significant amount of resources and knowledge. Additionally, a "command and control" approach would leave little incentive for the shipowners to invest in emission reducing technology - if ships are forced to sail at the same speed, then there would be no incentive to invest in technology that would make ships more energy efficient. Hence, we focus on MBMs which are discussed in the following paragraphs.

An MBM is an environmental policy that internalizes the negative external environmental cost of GHG emissions by forcing the polluting company to compensate for the emissions by imposing monetary measures such as environmental taxes (Lagouvardou et al. 2020). Consequently, the introduction of MBMs would incentivize the shipowners to reduce their emissions in a cost-minimizing way. This would further create an incentive to pursue innovation to find the cheapest way to comply with emissions regulations. The responses may be that the shipowners reduce the fleet's sailing speed or that they invest in emission reducing technology such as ships that utilize alternative fuels.

According to Lagouvardou et al. (2020), technical and operational measures do not prove sufficient in order to meet the GHG reduction ambitions of a 50% reduction in 2050 compared to the 2008 levels, unless the fuel prices of carbon neutral or low carbon fuel become cost competitive with those of fossil fuel. Thus, an MBM that would penalize companies based on the quantity of carbon that their fleet emits seems like a useful tool. This is supported by France, who in 2018 argumented that an MBM that provides a carbon pricing based on vessel emissions would enhance technological advancement towards the utilization of low/zero-carbon fuels and technologies (Lagouvardou et al. 2020). An example of such an MBM is the introduction of a bunker levy that increases the cost of using carbon-intensive technology and fuel. The measure would make low-carbon technology attractive, which in turn would increase emissions reductions by providing an incentive to reduce speed and fuel consumption (Lagouvardou et al. 2020). Additionally, the pre-decided carbon pricing would provide certainty on investment for the stakeholders, as they would be able to predict operational expenses from different technical alternatives (Lagemann et al. 2023a).

Another MBM that has recently received attention is the revision of the EU Emissions Trading System (ETS) to include GHG emissions from the maritime sector as part of the goal of reaching net-zero GHG emissions by 2050 (Lagouvardou and Psaraftis, 2022). Such a measure sets a cap on emissions, and lets the market decide a carbon price (Lagemann et al. 2023a). However, basing the price on the market makes it very volatile (Lagouvardou et al. 2022) - the carbon cap may be avoided by large actors being given free allowances, thus making the market price too low to make carbon abatement systems becoming attractive investments to the shipowners. Additionally, Lagouvardou et al. (2020) argue that regulating international sectors like shipping on a regional level proves challenging, and that it may cause countereffects inside the region being regulated.

The choice of an optimal MBM to facilitate for GHG reductions is therefore a challenging task. However, neither of the two MBMs can predict the carbon price in two to three decades. Therefore, in this thesis, the choice of MBM is not what is most important, but rather to focus on the uncertainty that follows from them. As in Lagemann et al. (2023a), the mathematical models of this thesis are based on the following assumptions: First, the case where no carbon price is imposed on the shipowners is accounted for by including a carbon price of zero. Second, independent of the choice of MBM, an average price for emissions is accounted for over any discrete time period. Third, the average future carbon price is assumed uncertain. Consequently, the choice of a fitting probability distribution is a complex task - there is no global MBM for the shipping sector today, and thus there is a lack of historical data. However, as specified, it is more important to account for uncertainty at all rather than choosing the optimal distribution.

The resulting probability distribution is a beta distribution that is scaled between the lower and upper carbon prices, 0 and 1000 USD/tCO_2eq respectively. The parameters are set to alpha = 1.5 and beta = 5, which yields a distribution that entails a higher probability for carbon prices that are in the lower half of the price range. The large range of carbon prices is based on the significant variance in recorded carbon prices, as well as the fact that there is no official carbon taxation in the US. A large variance must therefore be accounted for by including the prices that are either very low or very high.

However, it is important that the probabilities assigned to such values are lower than those assigned to more intermediate values. Furthermore, a beta distribution with a relatively large beta-parameter compared to the alpha-parameter seems appropriate to reflect this. As shown by the blue colored line and columns in Figure 6.3, the distribution results in 100 USD/tCO_2eq being the most common carbon price. This matches the current EU ETS levels rather accurately, as they have been fluctuating around 90 to 100 EUR/tCO_2eq since January 1, 2023 (Statista, 2023).

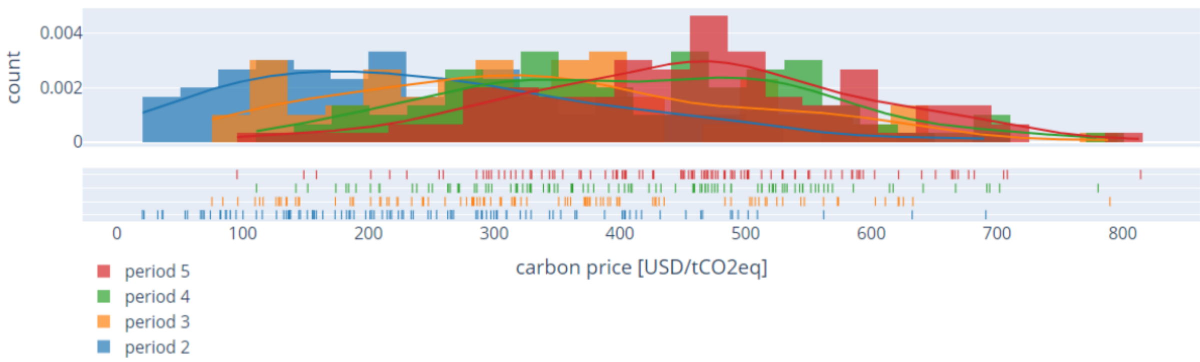

Figure 6.3: Sampled carbon prices for 100 scenarios with five time periods (Lagemann et al. 2023a)

Since January 2020 the carbon price set by the EU ETS has increased from approximately 26 EUR/tCO_2eq to nearly 100 EUR/tCO_2eq, reflecting a clear trend that the carbon prices are increasing (TRADING ECONOMICS, n.d.). Considering both these empirical data and a theoretical perspective (Center for Climate and Energy Solutions

2013) , it seems appropriate to assume that carbon prices will increase in the coming years. However, as mentioned, effects such as grandfathering may reduce the carbon prices. Therefore, to reflect the prediction that future carbon prices are likely to increase, the sampled carbon price in two consecutive periods in this thesis is restricted to not fall below 80% of the previous period. Consequently, the sampling of random carbon prices from the beta distribution will work as follows: a drawn number that is lower than 80% of the carbon price in the previous period will be discarded, and a new number will be drawn until the constraint is satisfied. The resulting sampling from 100 scenarios in the five different time period in presented in Figure 6.3. Note that the figure only visualizes periods two to five. This is due the fact that no global carbon pricing system is yet established in the first period, and the carbon price is therefore considered to be zero.

6.3 Results from the MFSMP Model

The mathematical model of the MFSMP presented in Chapter 5 is implemented in Python and solved with the commercial optimization solver Gurobi 10.0.1. To get insight into the internal consistency of the model, an analysis of the in-sample stability has been performed by comparing the optimal objective values from scenarios sets of different sizes. The scenario set sizes were either 1, 20, 100 or 500 scenarios, and for each size the model was run on ten different sets. The emission restrictions were gradually increased to reach a 50% reduction in GHG emissions in 2045 when compared to the emissions from a fleet of traditional ships. The emissions were restricted to be less than were 95%, 85%, 70%, 60% and 50% than traditional fleet emissions in 2025, 2030, 2035, 2040 and 2045, respectively. Then, the 95% confidence interval, as well as the relative standard deviation, were calculated based on the optimal objective values from each run of the model. The measures are presented in Table 6.4.

Table 6.4: In-sample Stability of Optimal Objective Values [mUSD]

Scenario Set Size	95% Confidence Interval	Relative Standard Deviaton
1	963.0226 ± 20.132	3.37%
20	981.4061 ± 4.468	0.74%
100	974.3527 ± 2.824	0.47%
500	976.8019 ± 1.501	0.25%

Even though the in-sample stabilities of the scenario sets that are of sizes 20 and 100 scenarios are promising, a scenario set size of 500 is used for presenting and analyzing the results from the model due to the optimal solution being found in less than two minutes. Because the relative standard deviation for 500 scenarios is very low, larger scenario set sizes are not analyzed.

Optimal fleet composition when the emissions are reduced by 50% within 2045

Figure 6.4 shows the average number of ships of each power system option that the optimal fleet consists of in each time period. The results are based on a scenario set of 500 scenarios, in which one scenario represents a realization of the stochastic parameters - fuel price and carbon price. The fleet's total GHG emissions are restricted to be less than 50% of those of a traditional fleet in 2045, and the stochastic carbon price is generated from a range of 0 to 1000 USD/tCO_2. Note that the figure only includes the power system options that occur at least once in the optimal solution. This applies to all the figures that illustrate results in this chapter. For an overview of the different power systems, the viewer is advised to go back to Figure 6.2.

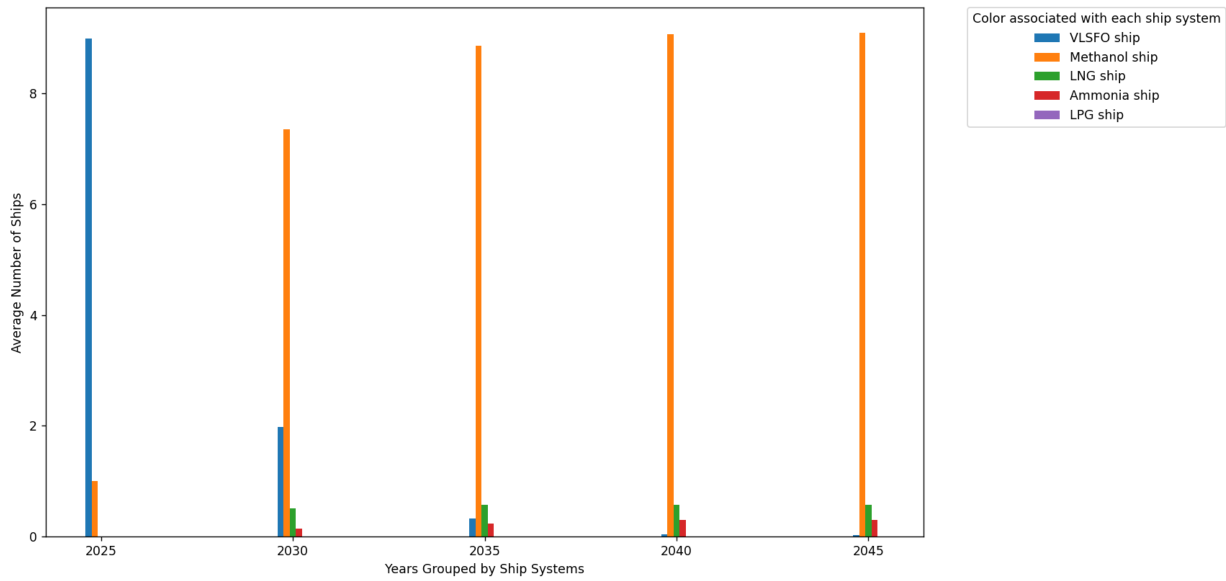

Figure 6.4: Average Number of Ships of Each Power System in Each Period. In 2045 the fleet's GHG emissions are restricted to be less than 50% than those of a traditional fleet.

In 2025, the total fleet emissions are restricted to be less than 95% of a traditional fleet's emissions, and it is therefore optimal to almost exclusively acquire ships that utilize traditional VLSFO power systems. As time passes, however, the allowed fleet emissions get more restricted. In 2030, the relative GHG emissions compared to a traditional fleet are restricted to be less than 85%. Consequently, methanol becomes the optimal power system and nearly 70% of the initial fleet's ships are retrofitted from VLSFO systems to methanol systems. Throughout the remaining periods of the planning horizon, methanol remains the optimal power system and clearly dominates the fleet composition. The figure also shows that about 6% - 8% of the fleet consists of alternative power systems such as LNG and ammonia, which have even lower GHG emissions than methanol from a bio-fuel perspective. However, as LNG and ammonia have higher fuel costs and lower well-to-wake emissions, they will almost exclusively be considered in scenarios where the carbon tax becomes large enough to make them cheaper than methanol, which according to the figure happens quite rarely when emission restrictions are not stricter.

Because Figure 6.4 does not visualize the number of times that a solution occurs across the 500 scenarios, Figure 6.5 is included. The figure is a scatter plot of the exact same solutions that are used to present the bar plot in Figure 6.4. A dot represents the number of ships of each power system that is included in the fleet in each time period. The size of a dot represents how many times that exact dot occurs across all scenarios in the applied scenario set. Therefore, because the fleet has zero ships with the power systems LNG, ammonia and LPG in 2025 in all scenarios, the sizes of the green, red and purple dots in 2025 are the same. This corresponds with Figure 6.4, where there are no columns for these power systems in 2025. Note that even though the dots that represent different power systems are shifted slightly on the horizontal axis, this does not imply that time is accounted for on a yearly basis. The time periods are still 2025, 2030, 2035, 2040 and 2045, and the horizontal shifts are just made to make the figure easier to interpret.

Examining the smaller dots in the scatter plot, one may observe that there are several scenarios in which LNG and ammonia power systems account for a large share of the optimal fleet. This is visualized by the dots of green and red color at the height that indicates that nine ships of these power systems are being utilized. The main reason for these solutions being obtained in some of the scenarios, is that in some cases the carbon prices are so high that it becomes optimal to utilize more expensive fuels to reduce fleet emissions because they allow for less emissions. However, the dots for these solutions are relatively small compared to the larger dots that represent the use of methanol ships, indicating that the solutions only occur in a few scenarios. Consequently, the average number of ships of those power systems becomes very small in 2045, corresponding to the column heights of LNG and ammonia in 2045 in Figure 6.4. This analysis can not be performed with the same accuracy when observing the bar

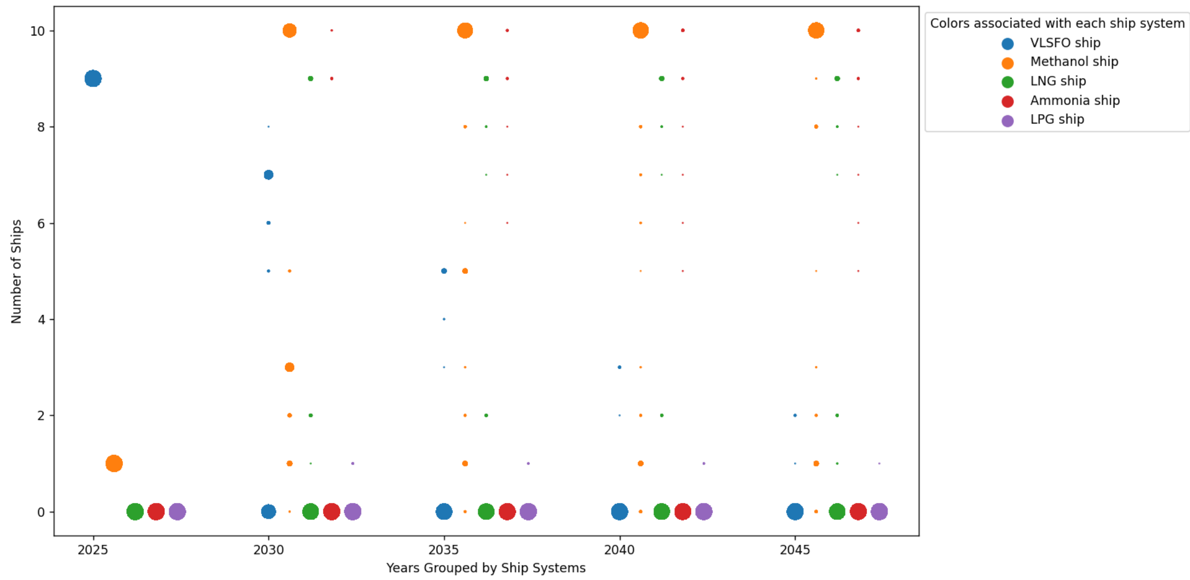

Figure 6.5: Number of ships of each power system in each period. In 2045 the fleet's GHG emissions are restricted to be less than 50% than those of a traditional fleet. The size of a dot visualizes the frequency of occurrences.

plot in Figure 6.4, which shows the benefit of visualizing the optimal solution with a the scatter plot.

Optimal fleet composition when the emissions are reduced by 90% within 2045

The optimal solution that is visualized in Figures 6.4 and 6.5 is based on a gradual reduction in total GHG emissions, with a 50% reduction being realized in 2045. However, because the global shipping industry accounts for significant GHG emissions yearly, this thesis also analyzes the fleet changes that are needed to pursue a zero-emission fleet. Thus, the solution that is obtained by restricting fleet emissions to be less than 10% of the traditional fleet emissions in 2045 is shown in Figures 6.6 and 6.7.

As described in the context of Figure 6.4, the bar plot shows the average number of ships of each power system option in every time period. Figure 6.6 visualizes the results based on an emission reduction of ultimately 90% in 2045 compared to a traditional fleet. The emissions were restricted to be less than were 90%, 75%, 55%, 30% and 10% than traditional fleet emissions in 2025, 2030, 2035, 2040 and 2045, respectively. Comparing the results to those presented in Figure 6.4, the number of VLSFO ships

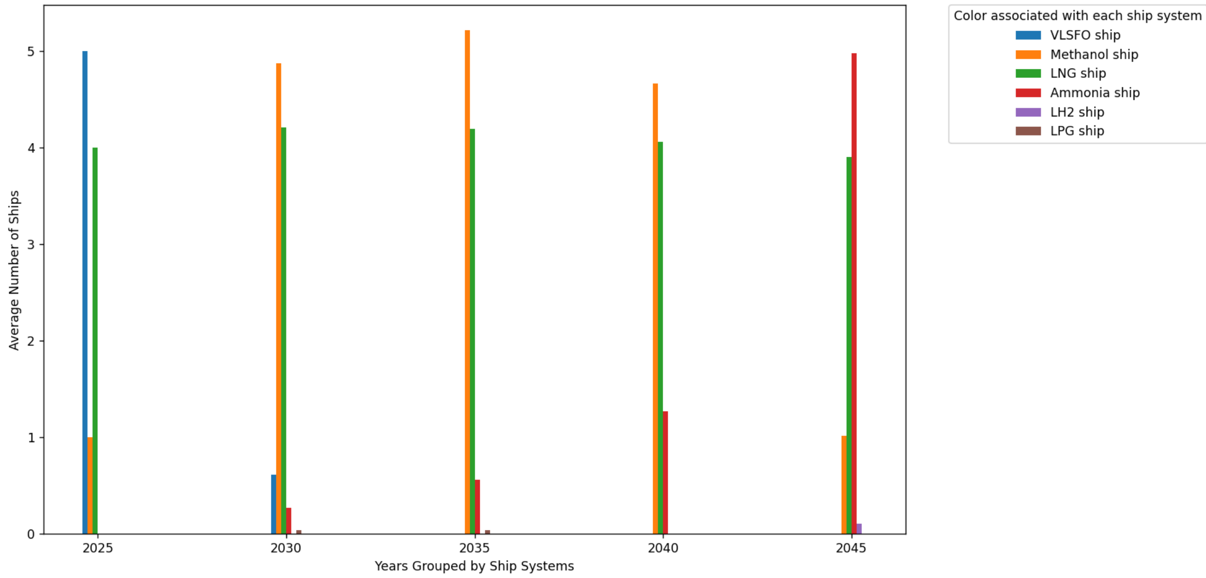

Figure 6.6: Average Number of Ships of Each Power System in Each Period. In 2045 the fleet's GHG emissions are restricted to be less than 90% than those of a traditional fleet.

in the initial fleet is significantly reduced. On average, the acquisition of VLSFO ships has decreased from nine to four, while the acquisition of LNG ships has increased from zero to four in the first time period. The number of LNG ships lies consistently around four ships in the remaining time periods. This is a big difference from Figure 6.4, where LNG ships in the last four time periods amount to nearly 0.5 ships on average. The increase in the use of LNG ships has consequently lead to a decrease in the number of methanol ships in the fleet, as the fleet size must be kept constant throughout the planning period. The main reason for LNG ships taking the place of many of the methanol ships is that utilization of LNG ships results in a reduction in total fleet emissions with an average cost increase that lies beneath the additional costs that occur with other alternative fuels, such as ammonia. However, as the fleet emissions become more restricted, many of the methanol ships are retrofitted to ammonia ships, as can be seen in 2040 and 2045.

To get a more detailed view on the optimal fleet composition in the different scenarios that are generated, a scatter plot of the same solution is shown in Figure 6.7. The scatter plot provides a foundation for better understanding of how the fleet composition varies under uncertain carbon and fuel prices. It can be observed that in some scenarios

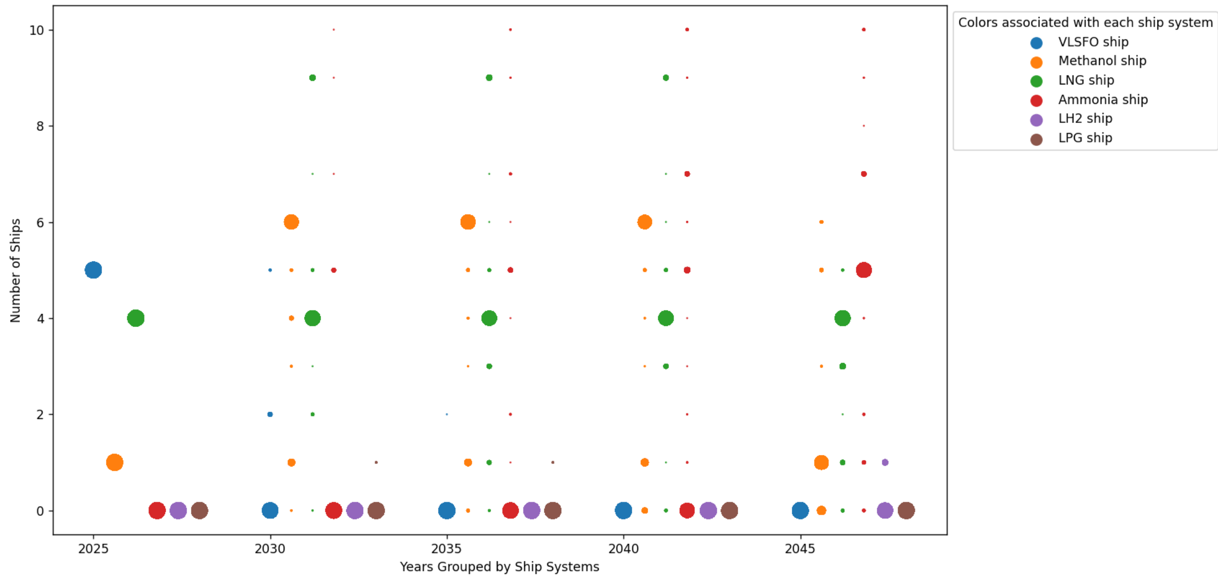

Figure 6.7: Number of Ships of Each Power System in Each Period. In 2045 the fleet's GHG emissions are restricted to be less than 90% than those of a traditional fleet. The size of a dot visualizes the frequency of occurrences.

LNG ships account for about 90% of the fleet in the time periods between 2030 and 2040. This is likely to happen in the scenarios where the realized carbon price is high enough, and the fuel price is low enough, to make LNG ships favourable over methanol ships, even though the utilization of LNG ships leads to higher fuel costs. In scenarios with even higher carbon prices, ammonia ships become optimal because it enables the fleet to have lower emissions than when using LNG ships. Also LH2 ships occur in the optimal solution in the last period, where the emission restrictions are strictest. However, utilization of LH2 ships leads to significantly higher retrofit and fuel costs than any of the aforementioned alternative fuels. Therefore, only one LH2 ship is included in a few scenarios where alternative fuel prices are low and carbon prices are high. Finally, the scatter plot also shows that a few VLSFO ships are included in periods 2030 and 2035 in some of the scenarios. Opposite to the reasoning for the fleet being composed of mainly LNG ships and ammonia ships, the solutions where VLSFO ships are included to a greater extent will mainly occur when carbon prices and VLSFO fuel prices are low enough to make these ships optimal despite their significant GHG emissions.

6.4 Results from the MFRP Model with scrapping

As with the mathematical model for the MFSMP, the mathematical model for the MFRP with scrapping is also implemented in Python and solved with Gurobi 10.0.1. The exact same scenario set was used for the numerical experiments, but this model takes some additional input values - the initial fleet composition, as well as the number of ships to scrap in each time period. The results that are presented in this section are based on scrapping two ships in 2035 and eight ships in 2040. The in-sample stability of the model is presented in Table 6.5. Recall the optimal objective values from the last section, where the 95% confidence interval for a scenario set of 500 scenarios was 976.8019 ± 1.501 [mUSD]. Comparing the 95% confidence interval for the optimal objective values from running the MFRP model with scrapping, it becomes clear that the acquisition of a new fleet leads to a greater total cost than retrofitting an existing traditional fleet - it is approximately 20% more expensive. The main reason for the cost difference not being larger, is that the fuel cost of the fleet, which both models account for, is the main cost driver.

Table 6.5: In-sample Stability of Optimal Objective Values

Scenario Set Size	95% Confidence Interval	Relative Standard Deviaton
1	807.1107 ± 22.718	4.54%
20	818.2427 ± 4.477	0.88%
100	811.1639 ± 2.955	0.59%
500	813.6783 ± 1.545	0.30%

Optimal fleet composition when the emissions are reduced by 50% within 2045

Figure 6.8 is a visualization of the average number of ships of each power system option that comprise the optimal fleet in each time period. The total GHG emissions from the fleet are restricted to be less than 50% of those of a traditional fleet in 2045. There exists no solution in the 500 scenarios that implies the use of LH2 ships, and therefore no color is representing the LH2 power system. According to the figure, the allowed

GHG emissions from the fleet are high enough to allow the shipowner to retrofit only 10% of the traditional ships to methanol ships in the initial time period. As time passes however, the emissions restrictions get stricter. Consequently, about 90% of the initial fleet is retrofitted to ships than run on alternative fuels in 2035, with methanol ships comprising more than 80% of the fleet. Further, in 2040, the emissions from the fleet must be so low that no VLSFO ships can be part of the fleet. Because methanol ships allow for utilization of the cheapest alternative fuel that can satisfy the GHG emission restrictions, they make up almost the entire fleet at the end of the planning horizon. For the fleet to utilize more ships with even more sustainable power systems, the emissions should be restricted to be lower than 50% of the traditional fleet's emissions.

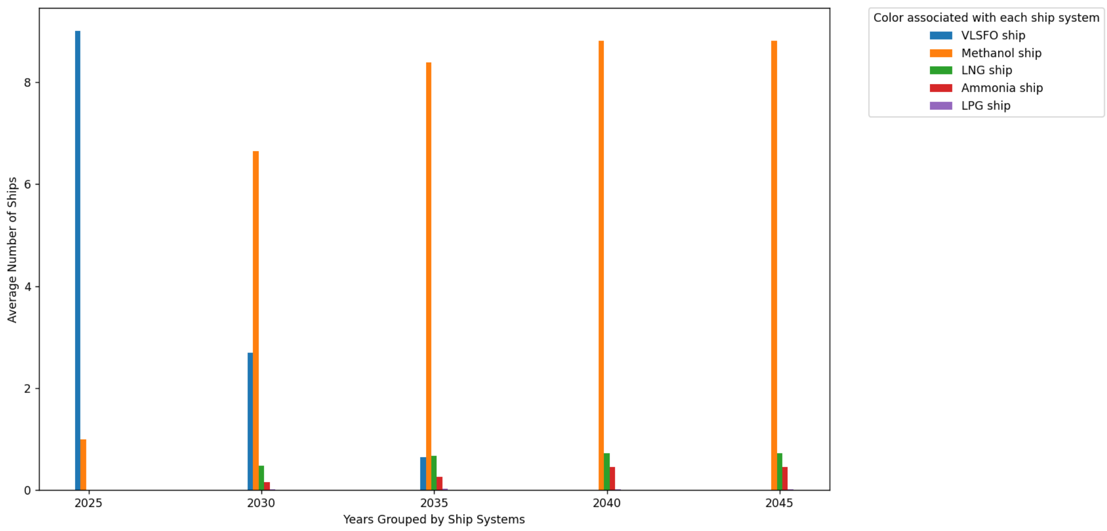

Figure 6.8: Average Number of Ships of Each Power System in Each Period. In 2045 the fleet's GHG emissions are restricted to be less than 50% than those of a traditional fleet.

The shipowner would also have an incentive to use greener alternative fuels if the carbon prices were high enough, and the alternative fuel prices were low enough, to make methanol ships sub-optimal. This can be seen in Figure 6.9. In periods 2035-2045 there are small green and red dots that indicate that it is optimal for the fleet to consist of eight to ten LNG or ammonia ships in a few scenarios. However, the average number of LNG and ammonia ships is greatly reduced due to the high number of scenarios in which no LNG or ammonia ships are used.

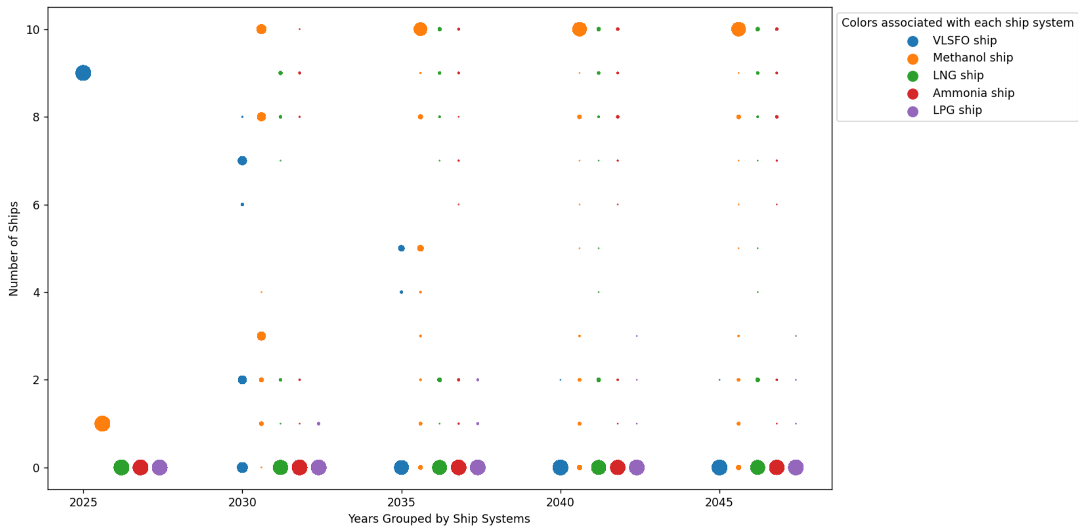

Figure 6.9: Number of Ships of Each Power System in Each Period. In 2045 the fleet's GHG emissions are restricted to be less than 50% than those of a traditional fleet. The size of a dot visualizes the frequency of occurrences.

Optimal fleet composition when the emissions are reduced by 90% within 2045

To assess the effect that very strict emission restrictions have on the fleet, Figure 6.10 is included. It visualizes the average fleet composition when the fleet emissions must be lower than 10% of a traditional fleet's emissions in 2045. When transitioning from 2035 to 2040, the allowed emissions are reduced from 55% to 30% compared to a traditional fleet. This is reflected by the decrease in the number of methanol ships, and the increase in LNG and ammonia ships, which allow for the utilization of fuels that have lower well-to-wake (WTW) emissions than fuels that are compatible with methanol ships. The changes to the fleet composition are made by retrofitting methanol and VLSFO ships to LNG and ammonia ships, incurring retrofit costs and lost opportunity costs. When the emissions are restricted to be less than 10% of the traditional fleet, methanol ships will no longer allow for use of fuels that have low enough WTW emissions. However, note that there is a slight decrease in the use of LNG ships. Thus, almost all the methanol ships in 2040 are retrofitted to ammonia ships for the fleet to comply with the strict emission regulations. Finally, there is a minor introduction of LH2 ships to the fleet in 2045. On average, the number of LH2 ships may seem insignificant. This is because the LH2 ships run on fuels that have significantly higher fuel costs than fuels that are compatible with ammonia ships, and therefore the shipowner will just have an incentive to use LH2 ships if the emission regulations are approaching a zero-emission demand, combined with low LH2-compatible fuel prices and high carbon prices.

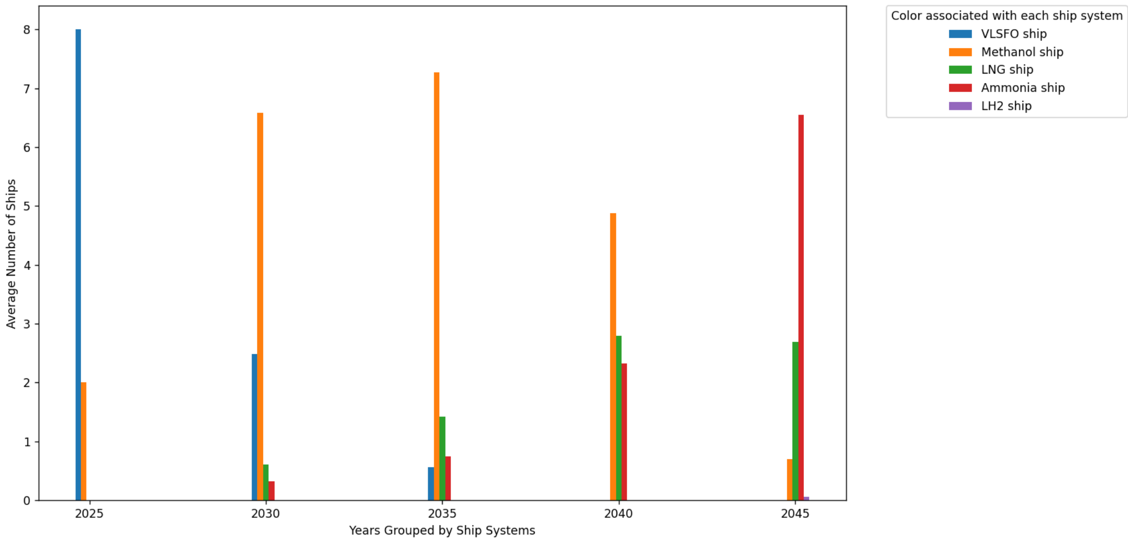

Figure 6.10: Average Number of Ships of Each Power System in Each Period. In 2045 the fleet's GHG emissions are restricted to be less than 90% than those of a traditional fleet.

To gain additional insight into how the fleet composition depends on the uncertain fuel prices and carbon price, a scatter plot is visualized in Figure 6.11.

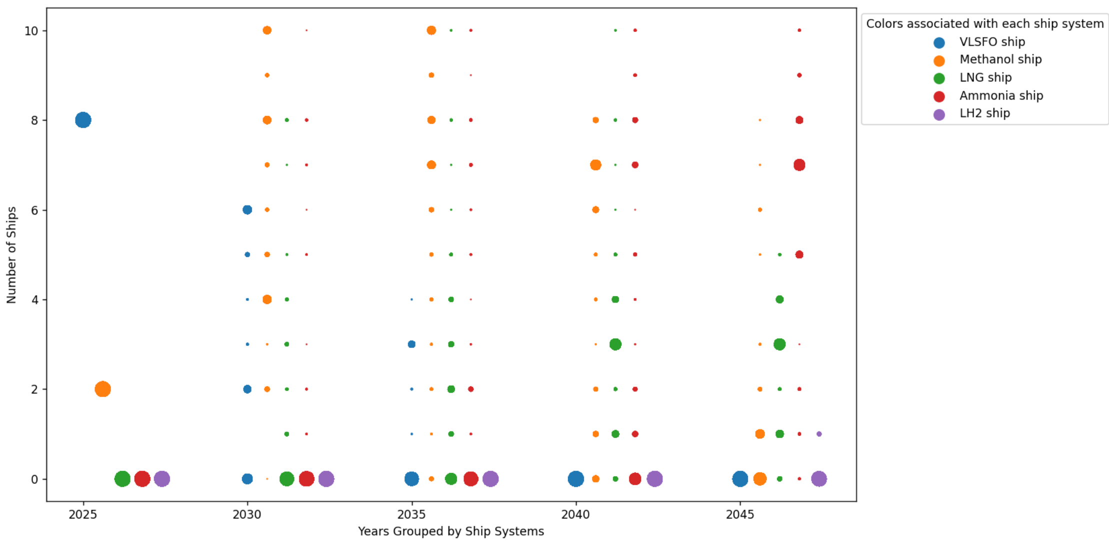

Figure 6.11: Number of Ships of Each Power System in Each Period. In 2045 the fleet's GHG emissions are restricted to be less than 90% than those of a traditional fleet. The size of a dot visualizes the frequency of occurrences.

As observed in Figure 6.10, one sees that LH2 ships will be included in a few scenarios in 2045, when emissions are restricted to be less than 10% of a traditional fleet's emissions. Additionally, the scatter plot shows that at most one LH2 ship is included in the fleet in those scenarios. This matches the reflections that were made based on the bar plot in Figure 6.10, and indicates that LH2 ships will not be attractive until LH2 fuel prices become competitive, or the emissions are even more restricted. In 2040, the bar plot indicates that ammonia ships comprise about 20% of the fleet on average. Looking at the scatter plot, however, it can be seen that ammonia ships will make up a large share of the fleet in a relatively many scenarios. What draws the average down, is that many scenarios will contain zero ammonia ships in the fleet. Again, this depends on the future fuel and carbon prices. Thus, the scatter plot reveals that the fleet composition is volatile to changes in the future pricing of fuels and carbon, and shows that regulating institutions should decide not only on the emission restrictions.

CHAPTER

SEVEN

CONCLUDING REMARKS

In this master's thesis, the selection of alternative fuels and power systems under uncertain future fuel and carbon prices as a means to reduce the greenhouse gas emissions from the global shipping sector has been discussed. The main focus of the thesis has been the mathematical formulation of minimizing total costs when modifying an existing fleet of ships in order to reduce fleet emissions, as this is the problem that will be faced by established shipping companies in the coming years. However, because new companies get established too, a mathematical model that accounts for acquisition of new ships in the next five years in addition to the option to retrofit ship power systems in the future is formulated.

The existing literature on such maritime fleet modification problems is scarce, and few papers contain analysis of both the environmental and the economic aspect of modifying a fleet of ships. However, Lagemann et al. (2023a) present a two-stage mixed integer programming (MIP) model for the selection of alternative fuels and power systems for a single ship. Therefore, this thesis contributes to the literature by extending the scope of Lagemann et al. (2023a) to include fuel and power system selection for a fleet of ships. Additionally, this thesis contains formulations for both a Maritime Fleet Size and Mix Problem and a Maritime Fleet Renewal Problem, allowing shipping companies that own a fleet, as well as the ones that don't yet own a fleet, to optimally invest in ship acquisitions or retrofits.

The results from the model of the MFSMP show that methanol ships constitute around 90% of the fleet on average when the fleet's GHG emissions are restricted to be less than 50% of a traditional fleet's emissions in 2045. However, the results also show that LNG ships and ammonia ships may constitute almost the entire fleet in some scenarios. Such scenarios may occur when carbon prices are high, making those ships more optimal than methanol ships because they allow for the utilization of fuels that give lower well-to-wake (WTW) emissions than methanol-fuels at a slightly higher fuel cost. When emissions are restricted to be less than 90% of the emissions from a traditional fleet in 2045, the results show that almost half of the methanol ships from the previous case are replaced by LNG ships. Additionally, almost all methanol ships in 2040 are retrofitted to ammonia ships in 2045 due to the strict restrictions. Lagemann et al. (2023a) shows that methanol-ships and LNG-ships often are included in the optimal solution for a single ship problem, and that LNG-ships tend to be more optimal when the emission restrictions get stricter. Those results are supported by the results from this thesis, although LNG-ships are slightly more represented in the solutions in the paper than in this thesis.

The results from the model of the MFRP with the option to scrap old ships and acquire new ones are very similar to the results from the model of the MFSMP. In fact, when the emissions are restricted to be less than 50% of a traditional fleet's emissions in 2045, the average number of ships of each power system in each period is almost identical to those of the MFSMP model. Furthermore, given those emissions restrictions, investing heavily in acquisitions of and retrofits to methanol ships seems like the optimal decision. However, when emissions are restricted to be less than 90% of the traditional fleet's emissions in 2045, the results differ from those of the MFSMP model. Whereas the results from the MFSMP model show that the average number of LNG ships in the fleet lies around 40% in the entire planning period, LNG ships constitute about 15% in 2035 and 28% in 2040 and 2045 in the MFRP model with scrapping of old ships. The significant decrease in the utilization of LNG ships has been replaced by an increase in the use of methanol and ammonia ships. However, the clear trend from the results from both models are that methanol ships and LNG ships should comprise the majority of the fleet, and that most of the methanol ships should be retrofitted to ammonia ships when emissions are restricted to be less than 90% of a traditional fleet's emissions.

The recommendation of utilizing methanol and LNG ships is also supported by the industry, with players such as Rystad Energy and DNV reporting that the industry is currently in a shift towards the preference of methanol as an alternative fuel. Furthermore, the results from the mathematical models of this thesis seem applicable to real life use, and it seems appropriate to use the results to argue that, from a techno-economic perspective, the utilization of methanol-fuels seems like an appropriate approach in foreseeable future.

CHAPTER

EIGHT

FUTURE RESEARCH

Due to the increasing importance of slowing down the rate at which climate change is developing, further research should be done to reduce the emissions from the global shipping industry. Building on the mathematical models and results of this thesis, several paths may be taken. One path is to extend the models to account for future emission restrictions to be uncertain, rather than modelling them to be deterministic as in this thesis.

Another area of future research that may have a potential to influence the shipping industry, is the analysis of the resulting abatement cost when transitioning from traditional ship power systems and fuels to alternative ones. This may be done by modifying the mathematical models of this thesis in such a way that one can analyze the cost per ton CO_2 that is saved when using alternative fuels, and compare those numbers with the potential future carbon price. If the future carbon price is expected to be higher than the cost of transitioning to the use of alternative fuels and power systems, then the shipping industry may be more motivated to invest in such technology. Lastly, future research may want to account for the limited access of alternative fuels such that the optimal solutions would make the fleets consist of several fuel types in order to make the solution scalable despite the limited resource access.

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APPENDIX

Model of the MFRP without scrapping

Notation

Table 1: Sets - Model of the MFRP without scrapping

T	Set of discrete time periods, indexed by t
F	Set of fuel types, indexed by f
S	Set of ship power systems, indexed by s
Ω	Set of scenarios, indexed by ω

Table 2: Parameters - Model of the MFRP without scrapping

$C^R_{s'st}$	Retrofit cost from system s' to system s in period t
$C^F_{ft\omega}$	Fuel cost of fuel f in period t in scenario ω
N	Number of ships in the fleet
P_ω	The probability of scenario ω
C^{LO}_{st}	Lost opportunity cost of utilizing system s in period t
B	Energy consumption per time period, assuming the fuel conversion efficiencies do not change over time, equidistant time periods
E^{WTT}_f	Well-to-Tank emissions of fuel f
E^{TTW}_f	Tank-to-Wake emissions of fuel f
E_t	Maximum allowed emissions from each ship in time period t
K_{fs}	1 if fuel f and system s are compatible, 0 otherwise

Table 3: Variables - Model of the MFRP without scrapping

$x_{fst\omega}$	Number of vessels that use fuel f and system s in the end of time period t in scenario ω, where $t > 0$
x_{fs0}	Number of vessels that use fuel f and system s in the end of time period 0
$r_{s'st\omega}$	Number of vessels that make a retrofit from ship system s' to ship system s at the beginning of period t in scenario ω, where $t > 0$

Mathematical model

$$min\ ETCO = \sum_{s\epsilon S}\sum_{s'\epsilon S}(C^{R}_{s's0} + C^{LO}_{s0})r_{s's0} + \sum_{\omega\epsilon\Omega} P_{\omega}(\sum_{f\epsilon F}\sum_{s\epsilon S}\sum_{t\epsilon T} C^{LO}_{st} x_{fst\omega} + \sum_{s'\epsilon S} C^{R}_{s'st} r_{s'st\omega} + BC^{F}_{ft\omega} x_{fst\ omega}) \tag{1}$$

Constraints

The objective function is subject to the following constraints:

$$\sum_{f\epsilon F} x_{fs0} = \sum_{f\epsilon F} N_{fs0} + \sum_{s'\epsilon S} r_{s's0} - \sum_{s'\epsilon S} r_{ss'0}, \qquad s\epsilon S, \tag{2}$$

$$\sum_{s'\epsilon S} r_{ss'0} \leq \sum_{f\epsilon F} N_{fs0}, \qquad s\epsilon S. \tag{3}$$

$$\sum_{f\epsilon F} x_{fst\omega} = \sum_{f\epsilon F} x_{fs(t-1)\omega} + \sum_{s'\epsilon S} r_{s'st\omega} - \sum_{s'\epsilon S} r_{ss't\omega}, \qquad s\epsilon S, t\epsilon T\backslash\{0\}, \omega\epsilon\Omega, \tag{4}$$

$$\sum_{s'\epsilon S} r_{ss't\omega} \leq \sum_{f\epsilon F} x_{fs(t-1)\omega}, \qquad s\epsilon S, t\epsilon T\backslash\{0\}, \omega\epsilon\Omega. \tag{5}$$

$$\sum_{f\epsilon F}\sum_{s\epsilon S} B(E^{WTT}_{f} + E^{TTW}_{f}) x_{fst\omega} \leq E_t N, \qquad t\epsilon T, \omega\epsilon\Omega, \tag{6}$$

$$x_{fst\omega} <= K_{fs}N, \qquad f\epsilon F, s\epsilon S, t\epsilon T, \omega\epsilon\Omega. \tag{7}$$

$$x_{fst\omega} = x_{fs0}, \qquad f\epsilon F, s\epsilon S, t = 0, \omega\epsilon\Omega, \tag{8}$$

$$r_{s'st\omega} = r_{s's0}, \qquad s', s\epsilon S, t = 0, \omega\epsilon\Omega, \tag{9}$$

$$r_{s's0} \geq 0, integer, \qquad s', s\epsilon S, \tag{10}$$

$$r_{s'st\omega} \geq 0, integer, \qquad s', s\epsilon S, t\epsilon T, \omega\epsilon\Omega, \tag{11}$$

$$x_{fst\omega} \geq 0, integer, \qquad f\epsilon F, s\epsilon S, t\epsilon T, \omega\epsilon\Omega. \tag{12}$$

Model of the MFRP with scrapping of ships

Notation

Table 4: Sets - Model of the MFRP with scrapping of ships

T	Set of discrete time periods, indexed by t
F	Set of fuel types, indexed by f
S	Set of ship power systems, indexed by s
Ω	Set of scenarios, indexed by ω

Table 5: Parameters - Model of the MFRP with scrapping of ships

$C^R_{s'st}$	Retrofit cost from system s' to system s in period t
$C^F_{ft\omega}$	Fuel cost of fuel f in period t in scenario ω
N	Number of ships in the fleet
P_ω	The probability of scenario ω
C^{LO}_{st}	Lost opportunity cost of utilizing system s in period t
B	Energy consumption per time period, assuming the fuel conversion efficiencies do not change over time, equidistant time periods
E^{WTT}_f	Well-to-Tank emissions of fuel f
E^{TTW}_f	Tank-to-Wake emissions of fuel f
E_t	Maximum allowed emissions from each ship in time period t
K_{fs}	1 if fuel f and system s are compatible, 0 otherwise
R_t	Number of ships to be scrapped in period t
C^I_{st}	Investment cost of acquiring a new ship with system s in period t. Depreciated with respect to remaining years of the project horizon

Table 6: Variables - Model of the MFRP with scrapping of ships

$x_{fst\omega}$	Number of vessels that use fuel f and system s in the end of time period t in scenario ω, where $t > 0$
x_{fs0}	Number of vessels that use fuel f and system s in the end of time period 0
$r_{s'st\omega}$	Number of vessels that make a retrofit from ship system s' to ship system s at the beginning of period t in scenario ω, where $t > 0$
$q_{st\omega}$	Number of ships with system s to be acquired in period t in scenario ω
$p_{st\omega}$	Number of ships with system s to be scrapped in period t in scenario ω

$$min\ ETCO = \sum_{s\epsilon S}\sum_{s'\epsilon S}(C^R_{s's0} + C^{LO}_{s0})r_{s's0} +$$

$$\sum_{\omega\epsilon\Omega} P_\omega(\sum_{f\epsilon F}\sum_{s\epsilon S}\sum_{t\epsilon T} C^{LO}_{st}x_{fst\omega} + \sum_{s'\epsilon S} C^R_{s'st}r_{s'st\omega} + BC^F_{ft\omega}x_{fst\ omega} + \sum_{s\epsilon S}\sum_{t\epsilon T} C^I_{st}q_{st\omega}) \tag{13}$$

Constraints

The objective function is subject to the following constraints:

$$\sum_{s\epsilon S} p_{st\omega} = R_t, \qquad t\epsilon T, \omega\epsilon\Omega, \tag{14}$$

$$\sum_{s\epsilon S} q_{st\omega} = \sum_{s\epsilon S} p_{st\omega}, \qquad t\epsilon T, \omega\epsilon\Omega. \tag{15}$$

$$\sum_{f\epsilon F} x_{fs0} = \sum_{f\epsilon F} N_{fs0} + \sum_{s'\epsilon S} r_{s's0} - \sum_{s'\epsilon S} r_{ss'0} - R_0 + q_{s0}, \qquad s\epsilon S, \tag{16}$$

$$\sum_{f\epsilon F} x_{fst\omega} = \sum_{f\epsilon F} x_{fs(t-1)\omega} + \sum_{s'\epsilon S} r_{s'st\omega} - \sum_{s'\epsilon S} r_{ss't\omega} - p_{st\omega} + q_{st\omega}, \qquad s\epsilon S, t\epsilon T\backslash\{0\}, \omega\epsilon\Omega. \tag{17}$$

$$\sum_{f\epsilon F} x_{fs0} = \sum_{f\epsilon F} N_{fs0} + \sum_{s'\epsilon S} r_{s's0} - \sum_{s'\epsilon S} r_{ss'0}, \qquad s\epsilon S, \tag{18}$$

$$\sum_{s'\epsilon S} r_{ss't\omega} \leq \sum_{f\epsilon F} x_{fs(t-1)\omega}, \qquad s\epsilon S, t\epsilon T\backslash\{0\}, \omega\epsilon\Omega. \tag{19}$$

$$\sum_{f\epsilon F}\sum_{s\epsilon S} B(E^{WTT}_f + E^{TTW}_f)x_{fst\omega} \leq E_t N, \qquad t\epsilon T, \omega\epsilon\Omega, \tag{20}$$

$$x_{fst\omega} <= K_{fs}N, \qquad f\epsilon F, s\epsilon S, t\epsilon T, \omega\epsilon\Omega. \tag{21}$$

$$x_{fst\omega} = x_{fs0}, \qquad f\epsilon F, s\epsilon S, t = 0, \omega\epsilon\Omega, \tag{22}$$

$$r_{s'st\omega} = r_{s's0}, \qquad s', s\epsilon S, t = 0, \omega\epsilon\Omega, \tag{23}$$

$$r_{s's0} \geq 0, integer, \qquad s', s\epsilon S, \tag{24}$$

$$r_{s'st\omega} \geq 0, integer, \qquad s', s\epsilon S, t\epsilon T, \omega\epsilon\Omega, \tag{25}$$

$$x_{fst\omega} \geq 0, integer, \qquad f\epsilon F, s\epsilon S, t\epsilon T, \omega\epsilon\Omega. \tag{26}$$

Model of the MFSMP

Notation

Table 7: Sets - Model of the MFSMP

T	Set of discrete time periods, indexed by t
F	Set of fuel types, indexed by f
S	Set of ship power systems, indexed by s
Ω	Set of scenarios, indexed by ω

Table 8: Parameters - Model of the MFSMP

C_s^N	Newbuild cost of a ship with power system s
$C_{s'st}^R$	Retrofit cost from system s' to system s in period t
$C_{ft\omega}^F$	Fuel cost of fuel f in period t in scenario ω
N	Number of ships in the fleet
P_ω	The probability of scenario ω
C_{st}^{LO}	Lost opportunity cost of utilizing system s in period t
B	Energy consumption per time period, assuming the fuel conversion efficiencies do not change over time, equidistant time periods
E_f^{WTT}	Well-to-Tank emissions of fuel f
E_f^{TTW}	Tank-to-Wake emissions of fuel f
E_t	Maximum allowed emissions from each ship in time period t
K_{fs}	1 if fuel f and system s are compatible, 0 otherwise

Table 9: Variables - Model of the MFSMP

$x_{fst\omega}$	Number of vessels that use fuel f and system s in the end of time period t in scenario ω, where $t > 0$
x_{fs0}	Number of ships with fuel f and system s that are acquired in time period 0
$r_{s'st\omega}$	Number of vessels that make a retrofit from ship system s' to ship system s at the beginning of period t in scenario ω, where $t > 0$

$$\begin{aligned} min\ ETCO = \sum_{f\epsilon F}\sum_{s\epsilon S} C_s^N x_{fs0} + \\ \sum_{\omega\epsilon\Omega} P_\omega(\sum_{f\epsilon F}\sum_{s\epsilon S}\sum_{t\epsilon T} C_{st}^{LO} x_{fst\omega} + \sum_{s'\epsilon S} C_{s'st}^{R} r_{s'st\omega} + BC_{ft\omega}^{F} x_{fst\ omega}) \end{aligned} \tag{27}$$

Constraints

The objective function is subject to the following constraints:

$$\sum_{f\epsilon F}\sum_{s\epsilon S} x_{fs0} = N, \tag{28}$$

$$\sum_{f\epsilon F} x_{fst\omega} = \sum_{f\epsilon F} x_{fs(t-1)\omega} + \sum_{s'\epsilon S} r_{s'st\omega} - \sum_{s'\epsilon S} r_{ss't\omega}, \qquad s\epsilon S, t\epsilon T\backslash\{0\}, \omega\epsilon\Omega, \tag{29}$$

$$\sum_{s'\epsilon S} r_{ss't\omega} \leq \sum_{f\epsilon F} x_{fs(t-1)\omega}, \qquad s\epsilon S, t\epsilon T\backslash\{0\}, \omega\epsilon\Omega. \tag{30}$$

$$\sum_{f\epsilon F}\sum_{s\epsilon S} B(E_f^{WTT} + E_f^{TTW}) x_{fst\omega} \leq E_t N, \qquad t\epsilon T, \omega\epsilon\Omega, \tag{31}$$

$$x_{fst\omega} <= K_{fs}N, \qquad f\epsilon F, s\epsilon S, t\epsilon T, \omega\epsilon\Omega. \tag{32}$$

$$x_{fst\omega} = x_{fs0}, \qquad f\epsilon F, s\epsilon S, t = 0, \omega\epsilon\Omega, \tag{33}$$

$$r_{s'st\omega} = 0, \qquad s', s\epsilon S, t = 0, \omega\epsilon\Omega. \tag{34}$$

$$r_{s'st\omega} \geq 0, integer, \qquad s', s\epsilon S, t\epsilon T, \omega\epsilon\Omega, \tag{35}$$

$$x_{fst\omega} \geq 0, integer, \qquad f\epsilon F, s\epsilon S, t\epsilon T, \omega\epsilon\Omega. \tag{36}$$