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Maritime fleet composition under future greenhouse gas emission restrictions and uncertain fuel prices

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ABSTRACT

This paper studies the maritime fleet composition problem with uncertain future fuel and carbon prices under the restriction of complying with future greenhouse gas (GHG) emission restrictions. We propose a two-stage stochastic programming model that can be adapted to two different variants of this problem. The first variant considers the Maritime Fleet Renewal Problem where there is an existing initial fleet to be renewed through scrapping and acquisitions, as well as retrofitting of ships in the current fleet. The second variant considers the Maritime Fleet Size and Mix Problem, where also the initial fleet must be determined. When applying the model to a fleet of Supramax bulk carriers as a case study, we find that LNG- and methanol-based power systems are favorable initial choices. Two different scenario sets, with 50% and 90% reduction restrictions by 2045, are investigated. Depending on the ambition level, retrofits towards ammonia can be cost-effective.

1. Introduction

The shipping industry is a major contributor to rising levels of greenhouse gas (GHG) emissions globally. According to the International Maritime Organization (IMO), the shipping industry's share of the global CO_2 emissions amounts to 2%–3%, and it is estimated that the emissions from this sector will increase by 50% by 2050 if no measures are taken (Faber et al., 2020). This is in heavy contrast to the IMO goals to reduce GHG emissions from international shipping to net zero around 2050 (IMO, 2023). A large share of the emission reductions from the industry should come from the use of alternative fuels (Faber et al., 2020; Wang and Wright, 2021; DNV, 2023). However, research about which fuel technologies that are most suitable for the industry still has to be performed, as the different fuels entail their own challenges, being technical (Wang and Wright, 2021), environmental (Lindstad et al., 2021a), or economical (Lindstad et al., 2021b).

In this paper, we study the planning problem of adapting a shipping fleet over time to comply with future GHG emission restrictions by using alternative low and zero emission technologies and fuels. In contrast to most previous studies, we consider both the environmental and the economic aspects in this transition. Lagemann et al. (2023) studied a somewhat similar problem, although for a single ship only, i.e., they studied how a single ship should be modified (retrofitted) over time to comply with future GHG emission restrictions. However, we extend this by considering the transition to low and zero emission technologies for a whole fleet instead of only a single ship, i.e., we adopt a portfolio perspective instead of a per-ship approach.

We consider two variants of this planning problem. The first is the Maritime Fleet Renewal Problem (MFRP), where it is assumed that there is a given initial fleet (of conventional vessels running on fossil fuels) which is to be renewed with new power systems

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and fuels over time to comply with future emission regulations. The second variant is the Maritime Fleet Size and Mix Problem (MFSMP), where it is assumed that there is no initial fleet and one also has to decide on the fleet composition of the whole fleet, i.e., which power system and fuel each ship in the fleet should have.

This paper contributes to the existing literature by providing a decision-support model for selecting and modifying power systems and fuels to comply with future GHG emission regulations. The proposed model is a two-stage stochastic programming model that takes into account the uncertainty with respect to future fuel and carbon prices, and it can easily be adapted to handle both the MFRP and MFSMP variants of the planning problem. Similar to Lagemann et al. (2023), our model explicitly considers the possibility of retrofitting and the uncertainty with respect to future fuel and carbon prices. However, extending from Lagemann et al. (2023), which considers a single ship, our model has a portfolio or *fleet perspective* so that we can investigate how this affects the solutions, i.e., which *mix of power systems and fuels* should be selected over time as the GHG emission regulations become stricter.

Section 2 provides a review of the relevant literature. Section 3 formally defines the MFRP and MFSMP, while the two-stage stochastic programming models for these problems are described in Section 4. Section 5 presents the case study and our analyses, while concluding remarks are drawn in Section 6.

2. Literature review

Pantuso et al. (2014) present a survey on both the MFRP and the MFSMP. Most recent contributions are on the MFRP, which can be considered as an extension of the MFSMP considering a dynamic adjustment of a given initial fleet. In most studies on the MFRP, the adjustment of the fleet is triggered by changes in market conditions and simply to replace ships that have reached their lifetimes, e.g., Alvarez et al. (2011), Bakkehaug et al. (2014), Pantuso et al. (2016), Arslan and Papageorgiou (2017), Skålnes et al. (2020) and Wang et al. (2023). There are also a few recent studies on the MFSMP in maintenance of offshore wind farms, e.g., Gundegjerde et al. (2015) and Stålhane et al. (2021).

Since the MFRP and MFSMP are both strategic solutions, it is essential to take future uncertainties into account, when making decisions. Most of the studies on the MFRP and MFSMP explicitly address uncertainty through stochastic programming models similar to what we do in this paper. However, none of the previous studies, neither for the MFRP nor the MFSMP, focus on selecting power systems and fuel types for the ships to comply with future emission regulations. A study that incorporates emissions as parameters in the MFRP is the work by Patricksson et al. (2015). However, they focus on how to comply with the stricter emission requirements for sulphur and nitrogen for ships sailing through emission control areas (ECAs), and not on GHG emissions like we do in this paper. Furthermore, most of the above studies on the MFRP and MFSMP do not include the possibility of modifying ships in the fleet through retrofitting, like we do in this paper.

As indicated above, there is a scarcity of studies that consider both the environmental and the economic aspect in the transition of shipping fleets to low and zero emission technologies and fuels. However, there are some studies focusing on this using a per-ship approach instead of a portfolio perspective. Lagemann et al. (2022) propose an optimization model for determining a single ship's power system and fuel over its lifetime, while adhering to future emission regulations. Their model includes both the here-and-now investment decisions and the possibility for retrofitting the ship's power system and change of fuel at a later stage. In a recent study, Lagemann et al. (2023) extend this optimization model by explicitly considering the uncertainty with respect to future fuel and carbon prices. This uncertainty is accounted for by means of stochastic programming in a similar way as Balland et al. (2013), who present a two-stage stochastic programming model for creating a plan for when a single ship should be modified with air emission controls (although not alternative fuels) to comply with emission regulations, taking uncertainty in the reduction effects of the different controls into consideration.

3. Problem definition

We consider a shipping company (or a ship operator) that must determine and/or modify its fleet of ships to comply with future GHG (we focus here on CO_2) emission restrictions while minimizing the total life-cycle costs for the fleet. We consider this problem both in the context of shipping companies that already own and operate a fleet of ships (currently running on fossil fuels), i.e., the MFRP, as well as in the context of companies that wish to establish a new fleet, i.e., the MFSMP. 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 (at a cost) to allow for utilization of fuel types that lead to reduced GHG emissions during fleet operation. The GHG emissions produced by the fleet are measured through both the well-to-tank (WTT) emissions, i.e., the emissions related to the production of the fuel type, and the tank-to-wake (TTW) emissions, i.e, the emissions related to the fuel combustion. We assume that each ship has a given lifetime. Thus, a ship that has reached its lifetime must be scrapped and replaced by a acquiring new ship (at an investment cost), 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 power system. For example, if the ship runs on very low sulphur fuel oil (VLSFO) and one is considering the switch to 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, e.g., 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 costs for retrofit and new ship acquisitions. The retrofit costs between different power systems are assumed to be known. On the other hand, due to fuel cost being an exogenous parameter, its future values are assumed to be uncertain. Furthermore, because different fuel types have varying net energy densities, both in terms of volume and weight, they affect the cargo-carrying capacity of the ships. Assuming that the ships need to keep their installed power (and sailing speed) constant, a lost opportunity cost associated with the choice of power system might occur. Moreover, 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.

To summarize: The decisions the shipowner can make to change or adjust its fleet are to (1) retrofit existing ships to allow for utilization of more sustainable fuel types; (2) switch between fuel types that are compatible with the same power system; and to (3) acquire new ships with new power systems whenever old ships need to be scrapped. Additionally, companies that do not yet own a fleet (i.e., the MFSMP) need to acquire ships in the initial time period. All above decisions may incur significant costs and are made with respect to increasingly stricter future emission restrictions, which need to be satisfied throughout the planning horizon. The objective of the shipowner is to minimize the expected total cost of modifying, acquiring and operating its fleet.

4. Mathematical model

The problem described in Section 3 can be modeled as a two-stage stochastic program. The *here-and-now* decisions in the first stage account of modifications of the existing fleet at the beginning of the planning horizon for the MFRP variant of the problem, while the first-stage decisions correspond to the initial acquisitions for the MFSMP variant. During this first stage we assume that all costs are known with certainty. As explained in Section 3, it is assumed that this fleet size will stay constant throughout the planning period. The second-stage model evaluates the future costs for a given first stage decision and a given realization of the uncertain future fuel and carbon costs.

We present the first-stage model in Section 4.1, while the second-stage model is shown in Section 4.2. This combined model can easily be adapted to both the MFRP and MFSMP variants of our planning problem by adjusting some input parameter values, as explained in the following.

4.1. The first-stage model

Let S be the set of available ship power systems, and let F_s be the set of fuel types that are compatible with ship power system s. For a fixed fleet size of N ships, we introduce the set $V = \{1, \dots, N\}$ as the set of ships in the fleet. Note that this set contains the set of active ships, and once a ship is scrapped, the new ship acquired inherits the index of the ship it is replacing.

We further let A_{sv} be a binary parameter equal to 1 if $s \in S$ is the initial power system of ship $v \in V$, and 0 otherwise. This allows us to define an initial fleet with any power systems, but in our analyses for the MFRP variant we restrict ourselves to let the initial fleet consist of only conventional ships running on fossil fuels. Note that in the MFSMP, where there is no initial fleet, A_{sv} is equal to 0 for all $s \in S$ for all N ships. In addition, we let C^I_s denote the investment cost of acquiring a new ship with power system $s \in S$, while C^{LO}_s and $C^R_{s's}$ denote the lost opportunity cost of utilizing power system $s \in S$ and the retrofit cost of changing from power system $s' \in S$ to power system $s \in S$, respectively.

The binary variable $r_{s'sv}$ takes the value 1 if ship $v \in V$ in the initial fleet is retrofitted from power system $s' \in S$ to power system $s \in S$, and 0 otherwise. This variable only applies for the MFRP variant of the problem where there is an initial fleet. Similarly, for the MFSMP variant with no initial fleet, the binary variable q_{sv} is equal to 1 if a ship with power system $s \in S$ is acquired and assigned ship index $v \in V$ before the beginning of the planning horizon, and 0 otherwise. The variable x_{fsv} is equal to 1 if ship $v \in V$ is equipped with power system $s \in S$ using fuel $f \in F_s$ in the first-stage problem. Furthermore, we let $\tilde{\xi}$ represent the uncertain parameters of the problem (i.e., the future fuel and carbon prices), and let $\Theta(x, \xi)$ be the *recourse function* which represents the total cost of using and developing the fleet over the planning horizon, given the first stage value of the x-variables, and a given realization ξ of $\tilde{\xi}$.

Using this notation the first-stage model can be formulated as follows:

$$ETCO = \min \sum_{s\in S} \sum_{s'\in S} \sum_{v\in V} (C^R_{s's0} + C^{LO}_{s0}) r_{s's0v} \quad + C^I_s q_s + \mathbb{E}_\xi \left[\Theta(x, \xi)\right] \tag{1}$$

s.t.

$$\sum_{f\in F_s} x_{fsv} = A_{sv} - \sum_{s'\in S} r_{ss'0v} + \sum_{s'\in S} r_{s'sv} + q_{sv}, \qquad s \in S, v \in V, \tag{2}$$

$$\sum_{s\in S} q_{sv} = 1 - \sum_{s\in S} A_{sv}, \qquad v \in V, \tag{3}$$

$$r_{s'sv} \in \{0,1\}, \qquad s', s \in S, v \in V, \tag{4}$$

$$q_{sv} \in \{0,1\}, \qquad s \in S, v \in V, \tag{5}$$

$$x_{fsv} \in \{0,1\}, \qquad f \in F, s \in S, v \in V. \tag{6}$$

The objective function (1) minimizes the expected total cost of ownership (ETCO). The expected total costs consist of the retrofit costs and investment costs done in the first stage, and the expected cost of all subsequent time periods, depending on the outcome of the random parameters ξ. Constraints (2) ensure that each vessel is assigned a power system and fuel type in the first stage of the problem. Thus, the fleet composition at the end of the first time period must be equal to the initial fleet (which is zero in the MFSMP) plus or minus any retrofits that happen at the start of the time period, and any new acquisitions made. Next, constraints (3) state that a new ship may only be acquired and assigned to a given v-index if there is currently not assigned a ship to this index, i.e., $A_{sv} = 0$ for all $s \in S$ (as is the case for the MFSMP variant). Finally, constraints (4)–(6) put binary restrictions on the variables in the model.

4.2. The second-stage model

The second-stage model evaluates the future costs of the shipping company for a given first stage decision and a given realization of the uncertain parameter ξ. This problem considers the development over a set of future time periods T. In each time period $t \in T$, the shipping company faces a fuel price $C^F_{ft}(\xi)$ for each fuel type $f \in F$, which is dependent on the realization ξ of the random parameter $\tilde{\xi}$. The costs C^I_{st}, C^{LO}_{st}, and $C^R_{s'st}$ all have the same interpretations as in the first-stage model, but with a t-index added to account for the fact that these values can change over time.

In addition, the shipping company must take into account the maximum allowed GHG emissions per ship in time period $t \in T$, E_t, and the fact that some ships have to be scrapped due to their age. Let the binary parameter R_{tv} be equal to 1 for the time period t ship v must be scrapped, and 0 otherwise. We assume that the number of time periods $|T|$ is sufficiently short so that no new ships acquired during the planning period need to be scrapped and replaced.

To calculate the emissions of each ship for a given fuel type we introduce E^{WTT}_f and E^{TTW}_f as the WTT, and TTW emissions of fuel $f \in F$, respectively, and B_t as the total energy consumption of the fleet during time period t, assuming the fuel conversion efficiencies do not change over time.

The x-, r-, and q-variables have the same meaning as in the first-stage model, but with a t-index added, since we allow changes to the fleet in each time period. In addition, we introduce the binary variable p_{stv}, which takes the value 1 if ship $v \in V$ with power system $s \in S$ is scrapped in time period $t \in T$.

Now, the second-stage model can be written as follows:

$$\Theta(x,\xi) = min \sum_{s\in S}\sum_{t\in T}\sum_{v\in V}\left(\sum_{f\in F_s} C^{LO}_{st} x_{fstv} + \sum_{s'\in S} C^R_{s'st} r_{s'stv} + \sum_{f\in F_s} B_t C^F_{ft}(\xi) x_{fstv} + C^I_{st} q_{stv}\right) \tag{7}$$

s.t.

$$\sum_{f\in F_s}(x_{fstv} - x_{fs(t-1)v}) = \sum_{s'\in S}(r_{s'stv} - r_{ss'tv}) - p_{stv} + q_{stv}, s \in S, t \in T \setminus \{0\}, v \in V, \tag{8}$$

$$\sum_{s\in S} q_{stv} = \sum_{s\in S} p_{stv}, \qquad t \in T, v \in V, \tag{9}$$

$$\sum_{s'\in S} r_{ss'tv} + p_{stv} \le \sum_{f\in F_s} x_{fs(t-1)v}, \qquad s \in S, t \in T \setminus \{0\}, v \in V, \tag{10}$$

$$\sum_{s\in S} p_{stv} = R_{tv}, \qquad s \in S, t \in T, \tag{11}$$

$$\sum_{s\in S}\sum_{f\in F_s}\sum_{v\in V} B_t(E^{WTT}_f + E^{TTW}_f) x_{fstv} \le |V| E_t, \qquad t \in T, \tag{12}$$

$$x_{fstv} = x^*_{fsv}, \qquad s \in S, f \in F_s, t = 0, \tag{13}$$

$$r_{s'stv} \in \{0,1\}, \qquad s', s \in S, t \in T, v \in V, \tag{14}$$

$$q_{stv} \in \{0,1\}, \qquad s \in S, t \in T, v \in V, \tag{15}$$

$$x_{fstv} \in \{0,1\}, \qquad s \in S, f \in F_s, t \in T, v \in V. \tag{16}$$

The objective function of the second stage problem has four terms. The first and second term take into account the loss in revenue from using fuels with less energy density and the cost of retrofitting ships, respectively. The third term takes into account the total fuel costs of the fleet, while the fourth term adds the cost of acquiring new ships. The objective function is minimized subject to the following constraints: Constraints (8) ensure that the power system stays the same for each vessel, unless a retrofit is made, or the vessel is scrapped and a newbuilt has taken over its v-index. Next, constraints (9) state that a new ship may only be acquired if one is scrapped in the same time period (i.e., to maintain a constant fleet size). Constraints (10) make sure a ship $v \in V$ with power system $s \in S$ can only be scrapped or retrofitted if it had that power system in the previous time period. Constraints (11) ensure that a ship is scrapped in the correct time period, while constraints (12) state that the total GHG 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 of the equation is scaled with the size of the fleet $|V|$. Constraints (13) fix the x-variables in time period 0 to be equal to the first stage decisions and act also as non-anticipativity constraints that connect the first and the second stages of the model. Finally, constraints (14)–(16) put binary requirements on the variables.

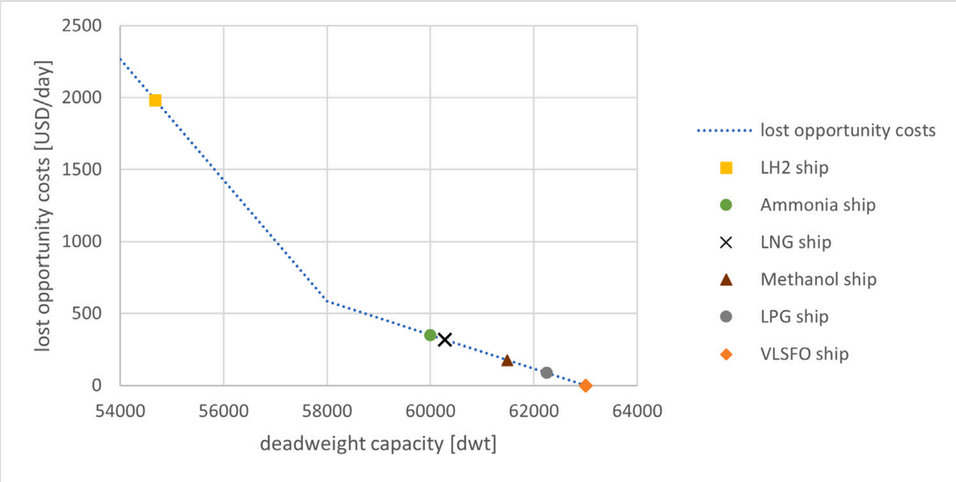

Fig. 1. Daily lost opportunity costs for constant range and energy efficiency (Lagemann et al., 2023).

5. Computational analyses

In the following, we describe our case study with its estimation of input parameter values in Section 5.1, while Section 5.2 explains the generation of the scenarios representing the realizations of the uncertain future fuel and carbon costs. Then, Sections 5.3 and 5.4 present and discuss the results of running the MFRP and MFSMP variants of the model, respectively. Both model variants are solved as a so-called *deterministic equivalent*, which combines the two model stages into a single mixed-integer programming (MIP) model, similarly e.g., to Pantuso et al. (2014) and Lagemann et al. (2023). The resulting MIP models are implemented in Python and solved with the commercial optimization solver Gurobi 10.0.1. The times to obtain optimal solutions were only a few minutes.

5.1. Case study: Supramax

Measured in tons transported, the global dry bulk fleet accounts for about 50% of the global sea transport and more than 40% of the freight work measured in ton-miles. Because the fleet consists of close to 12 000 vessels, with Supramax carriers amounting to nearly 25% and being responsible for providing nearly 10% of the global transport work in ton-miles, we use this segment in our case study. This makes it possible to use the same data as Lagemann et al. (2023), which also consider the same shipping segment in their analyses. However, it should be noted that the model and analyses easily can be adapted also to other shipping segments.

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 m, a draft of about 13.5 meters and a beam width up to 32.3 m, which is the old restrictions of the Panama Canal locks. A ship in this segment typically has 58–65 000 deadweight tonnes (dwt) capacity, which is a measure of the total aggregated weight/capacity of cargo, fuel, gear, crew and other factors, disregarding the weight of the ship and its machinery.

Lost opportunity costs

We assume that all ships in the initial fleet of the MFRP case are configured with the same fuel and power system options, i.e., we have a homogeneous fleet. Even though both heavy fuel oil (HFO) and very low sulphur fuel oil (VLSFO) are considered conventional fuels, we use just VLSFO as a reference fuel for comparison with alternative fuel selections. Using VLSFO as a reference fuel, selection of alternative fuels that have reduced net energy densities 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 58 000 tonnes. Additionally, ship charter rates of 25 000 USD/day for the Supramax carrier are included in the cost by weighting the daily charter rate with the ship's average utilization. To calculate the lost opportunity cost, we follow the approach by Lagemann et al. (2023), which gives the results summarized in Fig. 1. We refer to Lagemann et al. (2023) for further details about the calculation of the lost opportunity costs.

Newbuild costs

The estimated costs of building a new Supramax carrier with different power system options are also gathered from Lagemann et al. (2023) and are summarized in Table 1. This table also shows the estimated lost opportunity costs for the different power systems, as well as the compatibility among the different power systems and fuel types.

Table 1
Building costs, lost opportunity costs, and compatibility among power systems and fuel types (Lagemann et al., 2023).

Power system	Engine costs [USD/kW]	Tanks & add-ons [USD/kW]	Newbuilding price [mUSD]	Lost opportunity costs per 5 years [mUSD]	Compatible fuels
VLSFO	400	0	30	0	VLSFO, Bio-Diesel, E-Diesel,
LNG	800	600	37.5	0.5	Bio-LNG, E-LNG, fossil LNG
LH2	1500	1200	47.5	3.0	Liquid E-Hydrogen, Liquid NG-Hydrogen
Ammonia	1000	400	37.5	0.5	E-Ammonia, NG-Ammonia
LPG	600	200	33	0.1	Fossil LPG
Methanol	600	200	33	0.3	Bio-methanol wood, Bio-methanol waste stream, E-methanol

The costs of building a new Supramax carrier with a VLSFO system configuration is approximately 30 mUSD (Hellenic Shipping News, 2022). Furthermore, Lindstad et al. (2021b) present cost estimations in USD per kW main engine power installed for engines that are utilized for alternative fuels (shown in Table 1). We use these estimations assuming that each ship has 7500 kW installed power.

Retrofit cost
Similar to the newbuild costs of ships with alternative power systems, the retrofit costs incurred when changing the power system of an existing ship are based on the system based cost factors provided by Lindstad et al. (2021b). Furthermore, the retrofit costs account for the time spent in dock when retrofitting, which results in lost income, as well as additional shipyard costs. These additional costs are assumed to be 3.6 mUSD, following Lagemann et al. (2023).

Discounting costs and time periods
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%. We consider a planning horizon of 20 years from 2025 to 2045, divided into time periods of five years.

5.2. Scenario generation

To solve the model presented in Section 4 we describe the random variables $\tilde{\xi}$ using a set of representative scenarios, where each scenario is a collection of fuel prices $C^F_{ft}(\xi)$. It should be noted that we include the carbon prices in this fuel cost parameter. We then solve the extensive form of the deterministic equivalent of the two-stage stochastic program presented in Section 4 as a mixed integer program. We use the approach proposed by Lagemann et al. (2023) to generate the scenarios for these uncertain parameters, which is summarized in the following.

Sampling of fuel prices
While Lagemann et al. (2023) 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 in the middle parts between the lower and upper bounds than closer to the low and high price estimates. Hence, it is more realistic 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 for each fuel type.

The fuels considered relevant in this study can be grouped into fossil, bio- and electro-fuels. The uncertainty of a fuel price is to a large degree dependent on the fuel group to which the 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) assume that future bio-fuel prices are sensitive to the cost of the biomass on which the fuel is based. Here, following Lagemann et al. (2023), we assume that fuel prices within each of the fuel groups are perfectly correlated, and we compute the fuel price for each fuel in each time period by interpolating the lower and upper bound for the fuel. 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, while we use the calculations by Korberg et al. (2021) for bio-fuels. The bounds are presented in Table 2 along with each fuel's global warming potential (GWP) (split into WTT and TTW emissions), which represents emission per unit energy of the fuel. The GWP factors are mainly based on Lindstad et al. (2021a) for fossil and electro-fuels and Korberg et al. (2021) for bio-fuels. As in Lagemann et al. (2023), the GWP factors in the table represent approximately 50% of the GWP factors per unit break power for a large two-stroke engine.

Table 2
Upper and lower bound fuel costs and GWP factors (Lagemann et al., 2023).

Energy carrier	Feedstock	Fuel label	Environmental impact		Economic impact	
			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[a]	284.1[a]	95[b]	38[b]
	Bio	bio-Diesel	70.0[e]	150[e]	128[c]	93[c]
	Electro	e-Diesel	0.0[a]	4.5[a]	423[b]	131[b]
Methane	Fossil	LNG	66.6[a]	238.8[a]	81[c]	32[c]
	Bio	bio-LNG	49.7[a]	6.0[a]	119[b]	89[b]
	Electro	e-LNG	0.0[a]	6.0[a]	358[b]	115[b]
LPG	Fossil	LPG	30.0[a]	237.5[a]	98.3[b]	39.3[b]
Methanol	Fossil	Methanol	112.7[a]	253.4[a]	210[b]	90[b]
	Bio	bio-Methanol	112.68[a]	3.24[a]	97[c]	66[c]
	Electro	e-Methanol	0.0[a]	3.5[a]	385[b]	116[b]
Ammonia	Fossil	Ammonia	87.1[a,d]	19.0[a]	220[b,f]	56[b,f]
	Electro	e-Ammonia	0.0[a]	19.0[a]	220[b]	80[b]
Hydrogen	Fossil	LH2	108.7[a,d]	0.0[a]	245[b,f]	55[b,f]
	Electro	e-LH2	0.0[a]	0.0[a]	245[b]	79[b]

Sources and comments:
[a] Lindstad et al. (2021a).
[b] Lindstad et al. (2021b).
[c] Korberg et al. (2021).
[d] Assuming 80% CCS efficiency.
[e] Sustainable Shipping Initiative (2019).
[f] Upper bound 100% of electricity-based pendant, lower bound 70% of electricity-based pendant.

Carbon pricing

The future price of carbon emissions is also uncertain and the choice of a suitable probability distribution for the uncertain carbon price is a complex task as there is no such global price for the shipping sector today, and thus there is a lack of historical data. We use the same probability distribution as Lagemann et al. (2023), which use 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. Hence, a beta distribution with a relatively large beta-parameter compared to the alpha-parameter seems appropriate to reflect this.

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. Considering both these empirical data and a theoretical perspective, it seems likely that carbon prices will increase in the coming years. Therefore, the sampled carbon price in one time period 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 this requirement is satisfied. An example of the resulting sampling from 100 scenarios in the five different time period in presented in Fig. 2. 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 in that time period.

As shown by the blue colored line and columns in Fig. 2, the distribution results in that approximately 100 USD/tCO_2eq being the most common carbon price in period 2, which corresponds to around the year 2030. 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).

5.3. Results from the MFRP model

As explained in Section 4, the model for the Maritime Fleet Renewal Problem (MFRP) takes as input the initial fleet composition (represented by the binary A_{sv} parameter), as well as which ships that must be replaced due to their age in each time period (represented by the binary parameter R_{tv}). The results that are presented here are based on an initial fleet of 10 ships, where it is assumed that two and eight of these are to be scrapped 2035 and 2040, respectively. We ran the model with 500 scenarios, sampled as presented in Section 5.2, which gave very stable results with an in-sample stability of 0.30%.

In the following, we present results when there is a requirement for both 50% and 90% emission reduction by 2045. These two scenario sets are closely aligned with IMO's initial and revised GHG strategy, respectively. The reduction requirements are assumed

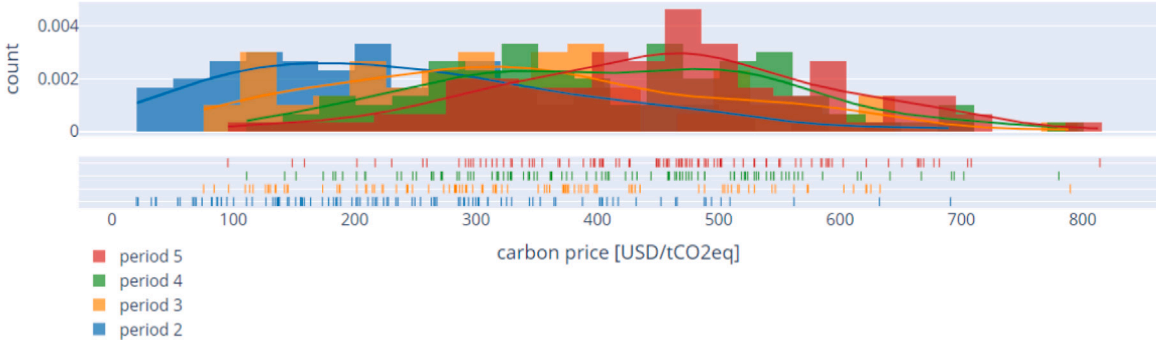

Fig. 2. Sampled carbon prices for 100 scenarios with five time periods (Lagemann et al., 2023).

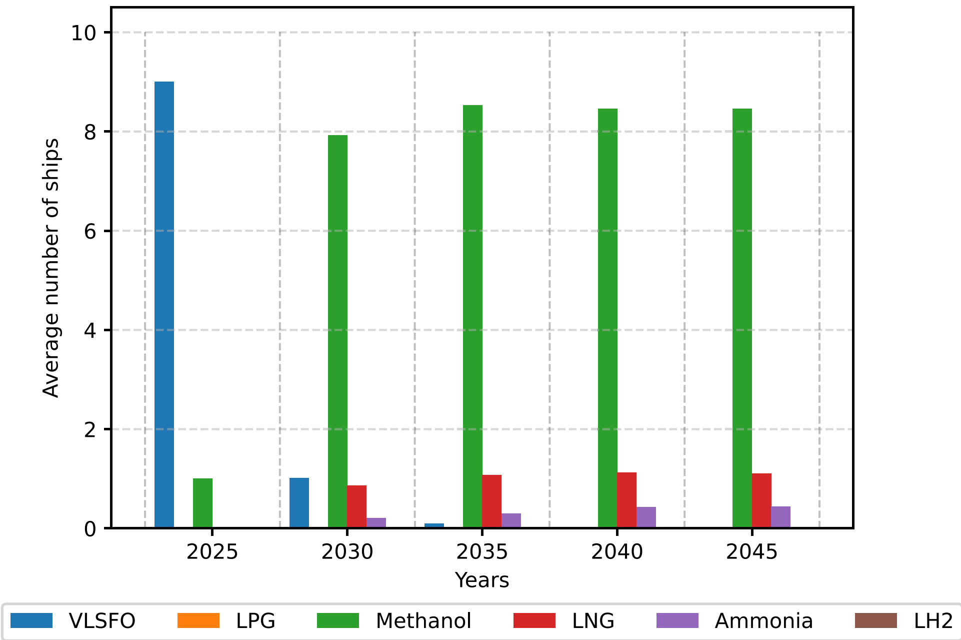

Fig. 3. Average number of ships of each power system in each period (across all 500 scenarios) for the MFRP model results when the emission reduction requirement in 2045 is 50%.

to be increasingly stricter over time. In the case of 50% reductions by 2045, the reduction requirements are 5%, 15%, 30%, 40% and 50% by 2025, 2030, 2035, 2040 and 2045, respectively, while in the case of 90% reductions by 2045, these values are 10%, 25%, 45%, 70% and 90%, respectively.

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

Fig. 3 shows the average number of ships of each power system option that comprise the optimal fleet in each time period (represented by the bars for each power system in each time period). As such, this figure shows the transition of the fleet as the GHG emission restrictions get stricter over time. It should be noted that the bars not necessarily show an integer number of ships, which might seem strange. However, this is because fleets might look different in different scenarios, and the bars show the average numbers of each power system in each time period across all 500 scenarios used when running the model.

It can be noted that there exists no solution in any of the 500 scenarios including the use of LPG and LH2 ships. Hence, there are no visible bars for these ship types because they are selected in none (for LH2) or only in few numbers in a very few of the 500 scenarios (for LPG). (This is illustrated in more detail in Fig. 4.) According to the figure, the allowed emissions from the fleet are high enough to allow the shipowner to retrofit only 10% of the traditional (VLSFO) ships to methanol ships in the initial time period of 2025. However, since the emission restrictions get stricter over time, about 90% of the initial fleet has retrofitted to ships that run on alternative fuels by 2035, with methanol ships comprising more than 80% of the fleet. Furthermore, in 2040, the emission reductions are so strict that no VLSFO ships are included in the fleet. Because methanol ships allow for utilization of the cheapest

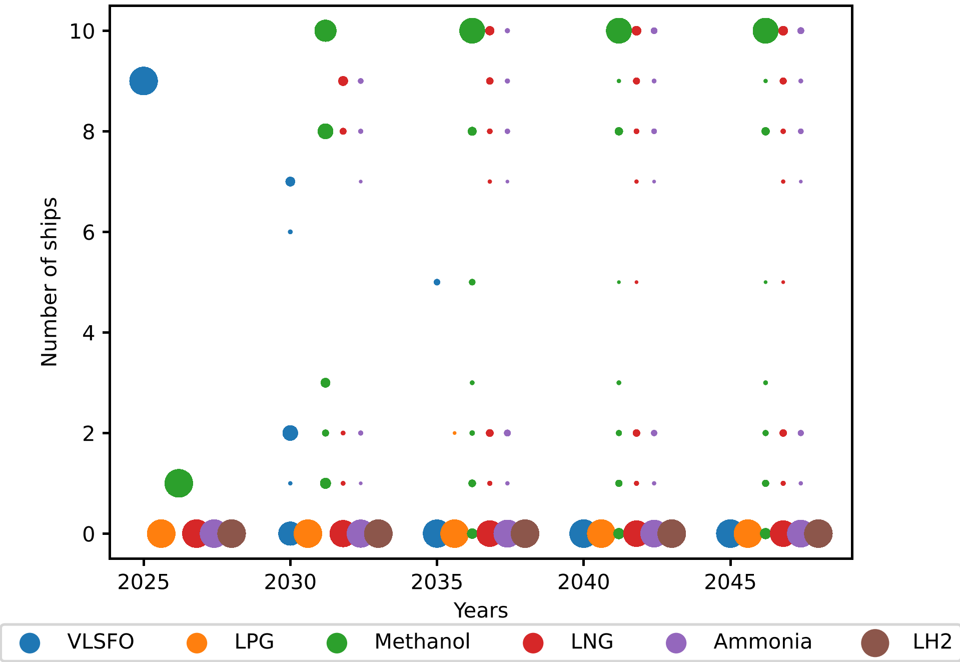

Fig. 4. Number of ships of each power system in each period when the emission reduction requirement in 2045 is 50%. The size of a dot visualizes the frequency of occurrences across the 500 scenarios.

alternative fuel that can satisfy the GHG emission restrictions (bio-methanol in this case), they make up almost the entire fleet at the end of the planning horizon.

Fig. 4 shows the number of ships of each power system in each period, where the size of the dots visualize the frequency of occurrences across all 500 scenarios. The figure shows that greener alternative fuels are preferred in some scenarios where the carbon prices are high and the alternative fuel prices are low, which would make methanol ships sub-optimal. In periods 2035–2045 there are small red and purple dots, which indicate that it is optimal to have eight to ten LNG or ammonia ships in a few scenarios. However, the average number of LNG and ammonia ships, shown in Fig. 3, is very low compared to the high number of scenarios in which no LNG or ammonia ships are preferred.

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

Figs. 5 and 6 show the same results in the case when emissions must be reduced by 90% by 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 reductions are 90% in 2045, methanol ships turn out to be more expensive when running on e-methanol. 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 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.

5.4. Results from the MFSMP model

As discussed in Section 4, the main difference between the MFRP and MFSMP is that we do not have an initial fleet in the latter, i.e., $A_{sv} = 0$ for all $s \in S$ and $v \in V$. This means that in these tests, the initial fleet, which we also here set to consist of 10 ships, need to be determined within the optimization. In the following, we summarize the main results when running the MFSMP model for the same two cases as we used for the MFRP model in the previous subsection, i.e., when there is a requirement for both 50% and 90% emission reduction by 2045. We use 500 scenarios when solving the model also in these tests.

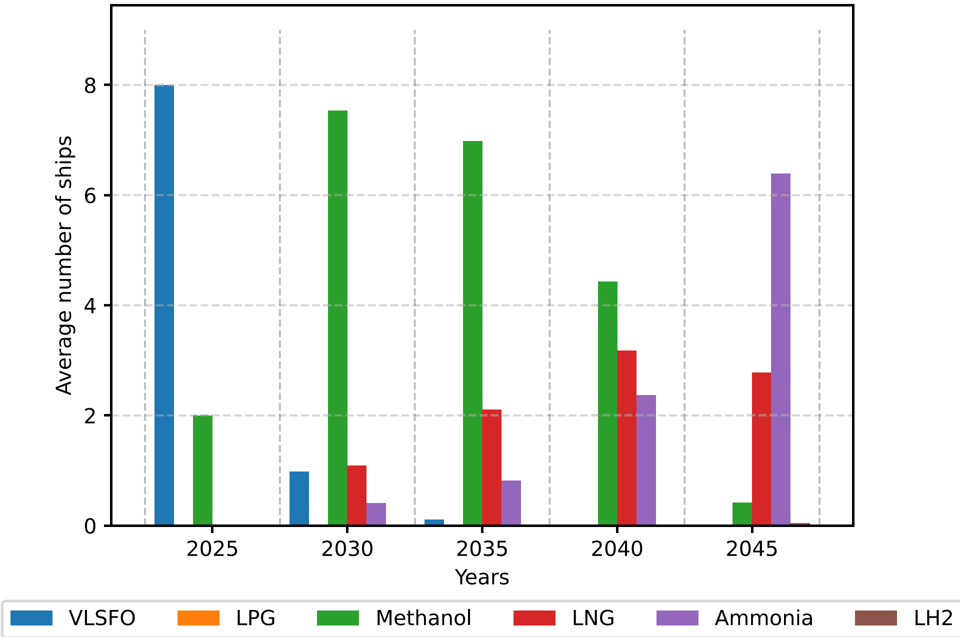

Fig. 5. Average number of ships of each power system in each period (across all 500 scenarios) for the MFRP model results when the emission reduction requirement in 2045 is 90%.

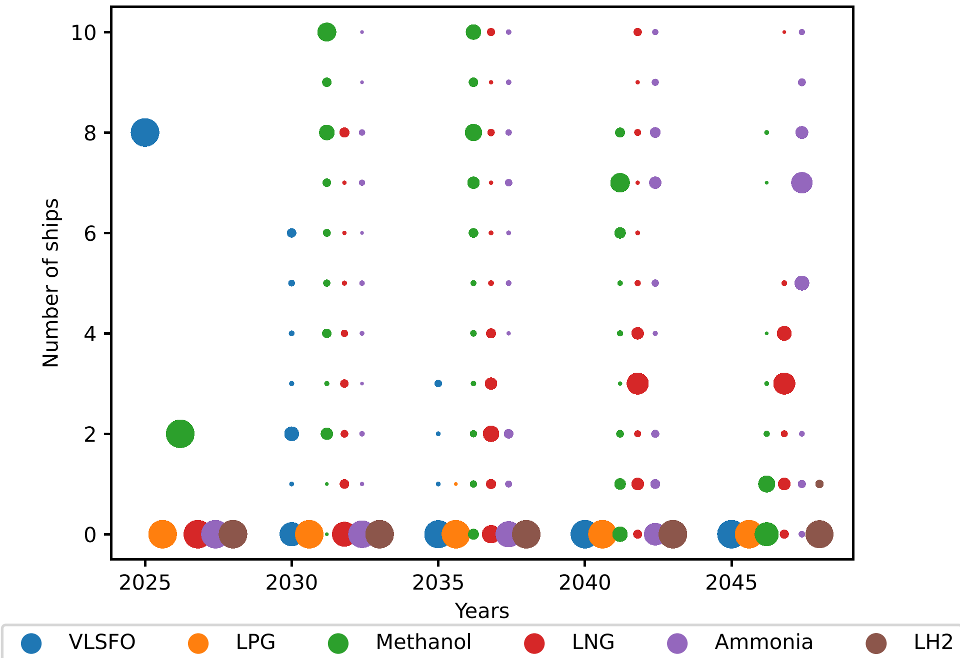

Fig. 6. Number of ships of each power system in each period when the emission reduction requirement in 2045 is 90%. The size of a dot visualizes the frequency of occurrences across the 500 scenarios.

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

Fig. 7 shows the average number of ships of each power system option (across all 500 scenarios) that the optimal fleet consists of in each time period. In 2025, the emission reduction requirements are only 5% compared to a traditional fossil fleet's emissions,

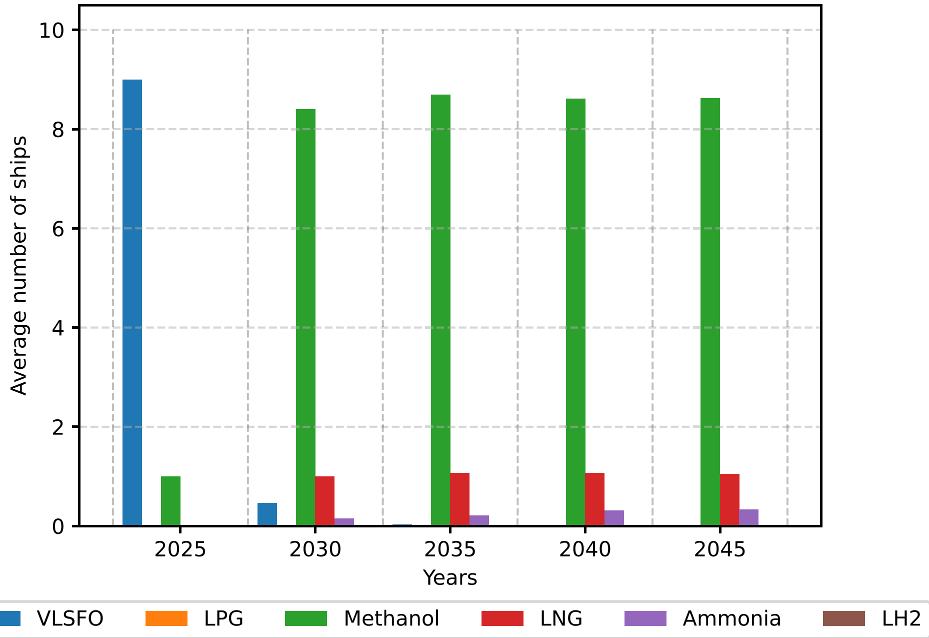

Fig. 7. Average number of ships of each power system in each period (across all 500 scenarios) for the MFSMP model results when the emission reduction requirement in 2045 is 50%.

and it is therefore optimal to almost exclusively acquire ships that utilize traditional VLSFO power systems. However, as the allowed fleet emissions get more restricted as time passes, we see that methanol becomes the most chosen power system and a large share of the initial fleet's ships are retrofitted from VLSFO systems to methanol systems. Fig. 7 also shows that a significant share 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.

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

Figs. 8 shows the same results for the scenario with 90% emission reduction requirement by 2045. Comparing the results to those presented in Fig. 7, the number of VLSFO ships in the initial fleet is significantly reduced. On average, the number of VLSFO ships has decreased from nine to five, 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 Fig. 7, where the number of LNG ships in the last four time periods is approximately only one ship 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 we assume that the fleet size should 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.

6. Concluding remarks

We have presented a two-stage stochastic programming model for the Maritime Fleet Renewal Problem (MFRP) and the Maritime Fleet Size and Mix Problem (MFSMP) under the restriction of complying with future greenhouse gas (GHG) emission restrictions. Both model variants consider uncertainty with respect to alternative fuel costs and carbon prices. Importantly, the model assumes a fleet perspective to emission reduction options. Thus, we adopt a portfolio perspective instead of single-ship approach.

The model has been applied to a fleet of Supramax bulk carriers. We have investigated two scenario sets with different fleet-wide emission reduction ambitions: The first scenario set involves a 50% reduction by 2050 — corresponding to IMO's initial GHG strategy. The second one encompasses a 90% reduction by 2050, closely aligned with IMO's revised strategy. We find that methanol, LNG/methane and e-ammonia are favorable abatement options, in particular when these fuels are produced from biomass or renewable electricity. When comparing the selected abatement options across the two scenario sets, we see that the optimal choice differ. Thus, IMO's revision of the GHG strategy has injected additional uncertainty in the sense that previously cost-effective, but technically ambitious and challenging fuel options may not be the most cost-effective choices under the new strategy. In short,

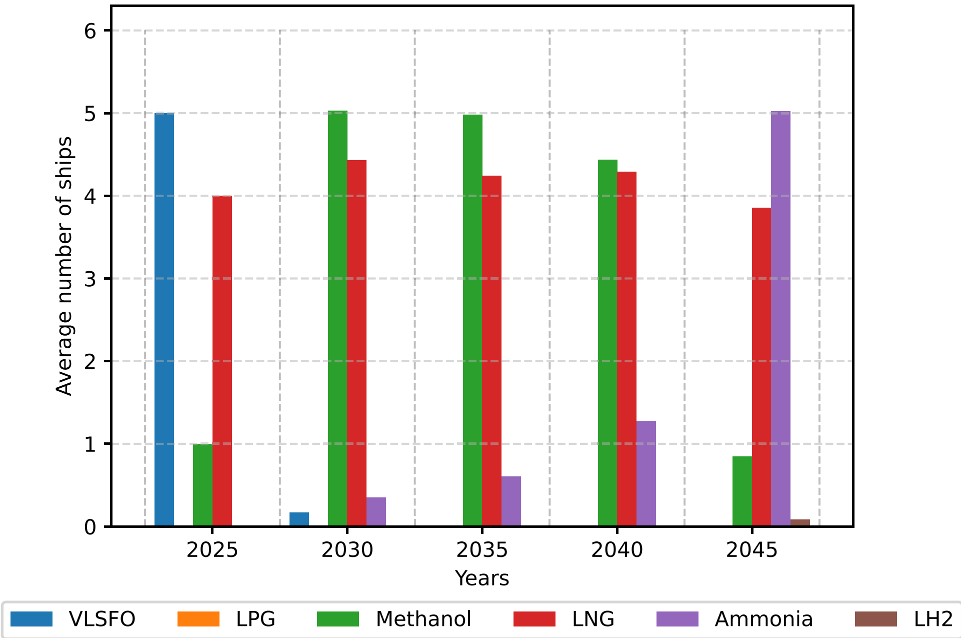

Fig. 8. Average number of ships of each power system in each period (across all 500 scenarios) for the MFSMP model results when the emission reduction requirement in 2045 is 90%.

the revision of the IMO GHG strategy alters the choice of alternative marine fuels (again). From a cost-effectiveness viewpoint, the change in requirements induces a preference towards commercially less mature solutions (ammonia). While these findings are case-specific for our case study, the proposed model is relatively generic and can be applied to other ship types and fleets.

Our model has been developed to identify cost-effective GHG emission reduction plans for a fleet. So far, a number of fossil, bio- and electro-fuels have been considered. Potential extensions could include other fuels such as bio-e-fuels (Grahn et al., 2022). Considering the costs and required energy magnitudes for producing electro-fuels in particular, the combination with other abatement options such as wind power or carbon capture and storage would be interesting to consider (DNV, 2023). Last but not least, existing GHG regulations generally apply on a per-ship basis. It seems relevant to investigate whether the continuation of a per-ship regulative approach has a significant disturbing impact in terms of cost as well as fuels and systems selected compared to a portfolio approach comprising multiple vessels. The implications and practical implementation of such profound change of the regulatory concept warrant further research.

CRediT authorship contribution statement

Olav Loennechen: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – review & editing. **Kjetil Fagerholt:** Conceptualization, Methodology, Supervision, Writing – original draft. **Benjamin Lagemann:** Conceptualization, Resources, Supervision, Validation, Writing – review & editing. **Magnus Stålhane:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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