Transportation Research Part D 119 (2023) 103748

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Optimal ship lifetime fuel and power system selection under uncertainty

Benjamin Lagemann[a,*], Sotiria Lagouvardou[b], Elizabeth Lindstad[c], Kjetil Fagerholt[d], Harilaos N. Psaraftis[b], Stein Ove Erikstad[a]

[a] Department of Marine Technology, Norwegian University of Science and Technology (NTNU), Norway
[b] Department of Technology, Management and Economics, Technical University of Denmark (DTU), Denmark
[c] SINTEF Ocean AS, Norway
[d] Department of Industrial Economics and Technology Management, Norwegian University of Science and Technology (NTNU), Norway

ARTICLE INFO

Keywords:
Shipping
Greenhouse gas emissions
Alternative fuels
Stochastic optimization
Flexibility
Retrofit

ABSTRACT

Ship designers face increasing pressure to comply with global emission reduction ambitions. Alternative fuels, potentially derived from bio-feedstock or renewable electricity, provide promising solutions to this problem. The main challenge is to identify a suitable ship power system, given not only uncertain emission requirements but also uncertain fuel and carbon emission prices. We develop a two-stage stochastic optimization model that explicitly considers uncertain fuel and carbon emission prices, as well as potential retrofits along the lifetime. The bi-objective setup of the model shows how the choice of optimal power system changes with reduced emission levels. Methanol and LNG configurations appear to be relatively robust initial choices due to their ability to run on fuel derived from different feedstocks, and their better retrofittability towards ammonia or hydrogen. From a policy perspective, our model provides insight into the effect of the different types of carbon pricing mechanisms on a shipowner's decisions.

1. Introduction

In 2015, the Paris Agreement set out to limit global warming by the end of the century to preferably 1.5 °C (United Nations 2015). The International Maritime Organization (IMO), although not regulated under the same agreement, declared ambitions to contribute this goal by reducing absolute greenhouse gas (GHG) emissions from seaborne transport by at least 50% and relative transport work emissions by at least 70% by 2050 (International Maritime Organization 2018) compared to 2008 levels.

The translation of these high-level ambitions to concrete per-ship requirements is currently still under discussion and the IMO (2018) indicates this may take time. Different regions, e.g., EU (European Commission 2019), and industry associations (e.g., European Community Shipowners' Associations 2020) have recognized that the current IMO ambitions are inconsistent with the overarching goal of limiting global warming and have both declared more ambitious emission reduction targets (European Commission 2019, European Community Shipowners' Associations 2020) to exercise increasing pressure on the IMO to substantiate (Psaraftis et al. 2021) and potentially tighten requirements. This process, accompanied by a lack of transparency (Psaraftis and Kontovas 2020), translates into significant uncertainty for shipowners and designers when it comes to emission requirements along a ship's lifetime.

Alternative fuels are by many seen as a promising technology to substantially reduce emissions from shipping and eventually

* Corresponding author at: Department of Marine Technology, Jonsvannsveien 82, 7050 Trondheim, Norway.
E-mail address: benjamin.lagemann@ntnu.no (B. Lagemann).

https://doi.org/10.1016/j.trd.2023.103748
Received 6 December 2022; Received in revised form 24 March 2023; Accepted 17 April 2023
Available online 4 May 2023
1361-9209/

comply with whatever emission target is set (DNV 2021, McKinlay et al. 2021, Nair and Acciaro 2018, CE Delft 2020, DNV GL 2019, Korberg et al. 2021, Lindstad et al. 2021b, Lloyd's Register and UMAS 2020, Wang and Wright 2021, Xing et al. 2021). Each of the fuels comes with its own challenges, be they technical (DNV GL 2019, Wang and Wright 2021), social (Ashrafi et al. 2022), environmental (Lindstad et al. 2021a) or economic (DNV GL 2020, Lloyd's Register and UMAS 2020, Lindstad et al. 2021b). In particular the economic aspects exhibit a high uncertainty, as the long-term costs of the fuels' feedstocks (being fossil, biomass, renewable electricity and captured carbon dioxide) are uncertain (Zwaginga et al. 2022). The aforementioned political negotiations on market-based measures (MBMs), which could potentially map environmental aspects to economic ones, introduce additional economic uncertainty (Psaraftis et al. 2021).

Even reducing the selection of alternative fuels down to techno-economic aspects involves different system complexities (Rhodes and Ross 2010, Gaspar et al. 2012), in particular:

- Structural complexity (the number of fuel and power system options to be studied)
- Contextual complexity (exogenous parameters such as fuel or carbon prices)
- Temporal complexity in combination with the first two complexities (retrofits and development of fuel & carbon prices)

Wang and Wright (2021) have reviewed several studies in this field. These studies, however, either do not consider the whole range of alternative fuel options (Nair and Acciaro 2018, Horvath et al. 2018), do not explicitly consider retrofits (e.g., Lindstad et al. 2021b, Korberg et al. 2021, Zwaginga et al. 2022, Horvath et al. 2018) or employ a deterministic scenario thinking as opposed to across-scenario thinking (DNV 2021, Horvath et al. 2018, Korberg et al. 2021, Lagemann et al. 2022a, Lindstad et al. 2021b, Lloyd's Register and UMAS 2020).

Across-scenario thinking has shown to be useful when dealing with temporal uncertainty, i.e., uncertainty that gradually resolves over time (De Neufville and Scholtes 2019 and King and Wallace 2012 for general engineering systems; Balland et al. 2013 and Pantuso et al. 2016 for ship design). Flexible systems, for example retrofittable ships, are one potential response strategy to handle such uncertainty (De Neufville and Scholtes 2019, Rehn et al. 2018, Parker and Singer 2012). Choi and Erikstad (2017) and Knight and Singer (2012) show how such flexible ships can be evaluated by means of real-options theory in across-scenario thinking.

This article contributes to the existing literature by providing a decision-support model for selecting alternative fuels and power systems that explicitly considers retrofits (similar to Lagemann et al. 2022a) and the prevailing uncertainty with respect to fuel and carbon pricing. Similar to Trivyza (2019), the model considers economic and environmental objectives separately. Uncertainty and across-scenario thinking is accounted for by means of two-stage stochastic programming (e.g., Balland et al. 2013).

The remainder of the article is structured as follows: Section 2 provides a concise description of the problem studied. Section 3 presents the mathematical formulation of the bi-objective two-stage stochastic programming model. Section 4 describes our case study for testing the model and the corresponding results are discussed in Section 5. Section 6 finally concludes our findings.

2. Problem description

This article examines the choice of alternative fuel and power systems from a techno-economic perspective and a shipowner's viewpoint, considering the complexities named in Section 1. Given that the selection among alternative fuels and corresponding systems is a compromise between cost and emission (Trivyza 2019, Lagemann et al. 2022a), the problem can be summarized as: "What are the best ship fuel and power systems today, given significant uncertainty with respect to the development of fuel and carbon prices in the future?". Similar to Balland et al. (2013) we refer to this problem as "ship fuel and power system selection under uncertainty".

Lagemann et al. (2022a) showed that even under an assumed known, deterministic scenario, retrofits can be among the optimal compromises. Considering recourse options (King and Wallace 2012, Pantuso et al. 2016), here in the form of retrofits, may thus be even more important when trying to handle uncertainty. Moreover, fuel switches between compatible fuels, say fossil liquified natural gas (LNG) to its electro counterpart (e-LNG), are recourse options without a switch cost nor option cost, but obviously entailing operational costs for the fuel.

The choice of fuel and respective power system also leads to consequences for the ship's cargo-carrying capacity: Since fuels that are based on different energy carriers, for example very low sulfur fuel oil (VLSFO) and LNG, have different net energy densities (both weight- and volume-wise), a ship with the same engine efficiency needs to be either larger to achieve the same cargo-carrying capacity and increase the installed power or keep the installed power but lose some cargo-carrying capacity. In this article, we choose the second option as we consider this more sensible for retrofits.

The most important decision in the problem outlined is the choice of power system to invest in today. For such urgent here-and-now decisions under uncertainty, two-stage stochastic programming has shown to be a suitable solution technique (King and Wallace 2012, Balland et al. 2013). In two-stage stochastic programming, the uncertainty is accounted for by a set of stochastic scenarios, in the presence of which the program needs to optimize. The next section explains how we map the described problem to a bi-objective two-stage stochastic programming model as well as how the scenario trees unfold.

3. Model formulation

The mathematical formulation of the stochastic programming model is explained in the following subsections. Subsection 3.1 describes the model notation; Subsection 3.2 outlines the mathematical model with objective functions and constraints and Subsection 3.3 aims to visualize the problem formulation by outlining how the here-and-now decisions are connected to the stochastic scenario tree. The model presented herein builds on top of the bi-objective deterministic model presented by Lagemann et al. (2022a) and the single-objective scenario application described by Lagemann et al. (2022b).

3.1. Notation

Sets

Set	Description	Modeling comment
$\mathbb{T}$	set of discrete **time periods**, indexed by t	
$\mathbb{F}$	set of **fuel options**, indexed by f	refers to main chemical composition and physical state
$\mathbb{S}$	set of pre-generated **ship system options** for energy storage and power conversion, indexed by s	refers to a ship with an energy storage of a certain type and size, and a power converter of certain type and size
Ω	set of **scenarios**, indexed by ω	complete realization of random parameters

Parameters

Parameter	Description	Modeling comment
C_s^N	**newbuild cost** of ship with system option s	Static parameter
$C_{s's t}^R$	**retrofit cost** from option s' to option s for period t	Discounted static parameter
$C_{ft\omega}^F$	**fuel cost** of fuel f at time period t in scenario ω	Discounted stochastic parameter
P_ω	**probability of scenario** ω	
C_{st}^{LO}	**lost opportunity cost** of system s per time period t	Discounted static parameter
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	assuming tank-to-wake emissions do not change over time.
K_{fs}	1 if fuel f and system s are **compatible**, 0 otherwise	Required since fuel and power system are modelled as separate decisions
ε	constraint on global warming potential	ε-constraint method, ε iteratively increased

Decision variables

$x_{ft\omega}$	1 if **fuel** f is chosen at time t in scenario ω, 0 otherwise
x_{f1}	1 if **fuel** f is chosen in period 1, 0 otherwise
$y_{st\omega}$	1 if **ship system option** s is chosen at time t in scenario ω, 0 otherwise
y_{s1}	1 if **ship system option** s is chosen in period 1, 0 otherwise
$r_{s'st\omega}$	1 if **retrofit** is to be made from system option s' to system option s at the beginning period t in scenario ω, 0 otherwise

3.2. Mathematical model

Objectives

Our first objective, minimizing the expected total cost of ownership (ETCO), is defined as:

$$\min\ ETCO = \sum_{s\in\mathbb{S}}\left[\underbrace{C_s^N\cdot y_{s1}}_{building\ cost} + \sum_{\omega\in\Omega}P_\omega\left[\sum_{t\in\mathbb{T}}\left(\underbrace{C_{st}^{LO}\cdot y_{st\omega}}_{lost\ opportunity\ costs} + \sum_{s'\in\mathbb{S}}\underbrace{C_{s'st}^R\cdot r_{s'st\omega}}_{retrofit\ cost}\right)\right]\right] + \sum_{\omega\in\Omega}\sum_{t\in\mathbb{T}}\sum_{f\in\mathbb{F}}\underbrace{P_\omega\cdot B\cdot C_{ft\omega}^F\cdot x_{ft\omega}}_{fuel\ cost} \tag{1}$$

Carbon prices can be included implicitly through the fuel prices. The retrofit cost depends on the selected systems in two consecutive time periods. Since our model is meant to capture differences between solutions, we have excluded pure operational expenditures (OPEX), such as port fees or crewing, which would apply to all alternatives. The lost cargo-carrying capacity under alternative fuels is translated into lost opportunity costs and thus an economic penalty in the objective function. The separation of decision variables into fuel ($x_{f1}, x_{ft\omega}$) and power system ($y_{s1}, y_{st\omega}$) enables considering multi-fuel engines in the model.

We define our second objective as minimizing the expected global warming potential (EGWP) over the entire ship lifetime and weighted by the probability of each scenario:

$$\min\ EGWP = \sum_{\omega\in\Omega}P_\omega\cdot\sum_{t\in\mathbb{T}}\sum_{f\in\mathbb{F}}B\cdot E_f^{WTW}\cdot x_{ft\omega} \tag{2}$$

subject to:

First stage:

$$\sum_{f\in\mathbb{F}}x_{f1} = 1 \tag{3}$$

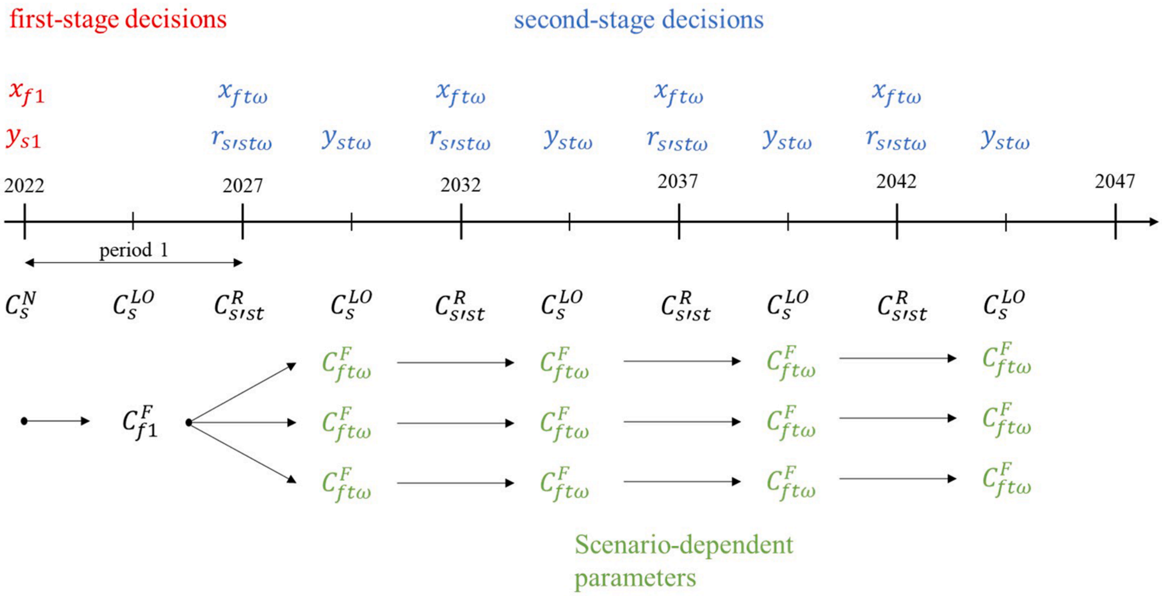

Fig. 1. Connection between decisions and scenario-tree.

$$\sum_{s\in\mathbb{S}} y_{s1} = 1 \tag{4}$$

$$x_{f1} + y_{s1} \le 1 + K_{fs} \quad f \in \mathbb{F}, s \in \mathbb{S} \tag{5}$$

$$y_{s1} \in \{0,1\} \quad s \in \mathbb{S} \tag{6}$$

$$x_{f1} \in \{0,1\} \quad f \in \mathbb{F} \tag{7}$$

Constraint (3) ensures that only one ship system option is selected at the first time step. Likewise, Constraint (4) enforces only one fuel to be selected for the initial period. Constraints (5) ensure compatibility of the selected fuel and power system. Constraints (6) and (7) declare that the decision variables x_{f1} and y_{s1} are of binary type.

Second stage:

$$y_{s1\omega} = y_{s1} \quad s \in \mathbb{S}, \omega \in \Omega \tag{8}$$

$$x_{f1\omega} = x_{f1} \quad f \in \mathbb{F}, \omega \in \Omega \tag{9}$$

$$\sum_{f\in\mathbb{F}} x_{ft\omega} = 1 \quad t \in \mathbb{T}, \omega \in \Omega \tag{10}$$

$$\sum_{s\in\mathbb{S}} y_{st\omega} = 1 \quad t \in \mathbb{T}, \omega \in \Omega \tag{11}$$

$$x_{ft\omega} + y_{st\omega} \le 1 + K_{fs} t \in \mathbb{T}, \quad f \in \mathbb{F}, s \in \mathbb{S}, \omega \in \Omega \tag{12}$$

$$y_{s'(t-1)\omega} + y_{st\omega} - 1 \le r_{s'st\omega} \quad s', s \in \mathbb{S}, t \in \mathbb{T}\backslash\{1\}, \omega \in \Omega \tag{13}$$

$$y_{s'(t-1)\omega} + y_{st\omega} \ge 2 r_{s'st\omega} \quad s', s \in \mathbb{S}, t \in \mathbb{T}\backslash\{1\}, \omega \in \Omega \tag{14}$$

$$r_{s'st\omega} = 0 \quad s', s \in \mathbb{S}, t = 0, \omega \in \Omega \tag{15}$$

$$x_{ft\omega} \in \{0,1\} \quad f \in \mathbb{F}, t \in \mathbb{T}, \omega \in \Omega \tag{16}$$

$$y_{st\omega} \in \{0,1\} \quad s \in \mathbb{S}, t \in \mathbb{T}, \omega \in \Omega \tag{17}$$

$$r_{s'st\omega} \in \{0,1\} \quad s', s \in \mathbb{S}, t \in \mathbb{T}, \omega \in \Omega \tag{18}$$

Constraints (8) and (9) link the first stage decision variable to the second stage. Similar to the first stage, constraints (10) and (11)

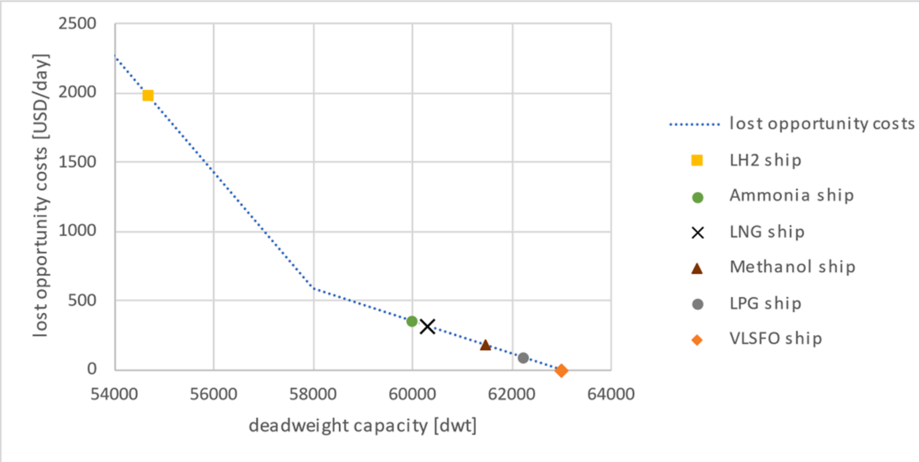

Fig. 2. Daily lost opportunity costs for constant range and energy efficiency.

make sure that exactly one fuel and one ship system option are selected for each time period. Constraints (16) to (18) ensure that also the second stage decision variables are of binary type.

Constraints (12) imply that a fuel and system can only be selected at the same time when compatible. A switch from system s' to another system s in consecutive periods triggers the retrofit variable $r_{s'st\omega}$. This is mathematically defined in constraints (13) to (15).

Additional constraints on emissions, e.g., a Carbon Intensity Indicator (CII), could be added to the problem. This is not done for this paper to maintain simplicity of the model and thus traceability of the results.

The defined model is a two-stage bi-objective binary programming model and can be implemented by means of a commercial solver. The bi-objective nature of the model means that we will obtain Pareto set of non-dominated compromise solutions. To identify this Pareto set, constraint (19) applies the epsilon-constraint method to our second objective:

$$EGWP \leq \varepsilon \tag{19}$$

The parameter ε is iteratively reduced to the EGWP of the cheapest solution found during the previous iteration.

3.3. Scenario trees

We have defined the choice of fuel and power system for the first period as the important here-and-now decisions, because they are most urgent for a shipowner and need to be implemented immediately. The decision variables thus make up the first-stage decisions, as defined in constraints (6) and (7). Fig. 1 aims to explain the relation, in particular the timing, between first-stage decisions to be made and the point when the initial uncertainty resolves. As can be seen in the Figure, this point of resolving uncertainty is after period 1. The main first-stage decision, what ship to invest in, thus needs to be made in the presence of uncertainty, i.e., without knowing which scenario will actually unfold.

As can be seen, the uncertainty resolves after the first time period (period 1), i.e., the further course of fuel prices over time becomes known. The assumption that the fuel prices become known for all consecutive time periods is a modelling feature of two-stage stochastic programming (King and Wallace 2012) and does not affect the outcome of the first-stage decisions. For the first time period, i.e. from 2022 to 2027, fuel prices are assumed to be known, which is certainly a strong assumption. The assumed known price, however, is simply based on the expected value for the stochastic fuel price and likewise is more of a modelling requirement than an additional assumption on top of the probability distributions. The key feature of the model is that is allows accounting for many possible futures, rather than one single deterministic scenario.

4. Case study

This section sketches the case study to which we apply the model developed in Section 3. Subsection 4.1 deals with the general deterministic inputs for our case study, while Subsection 4.2 describes how the uncertainty is accounted for during scenario generation. Again, our goal is not to optimize *within*, but *across* scenarios – we do not know what is going to happen.

4.1. Description of the case

We apply our model to a generic Supramax dry bulk carrier which is to be replaced. The shipowner and designer thus need to select among alternative fuels and power systems for the vessel. Supramax carriers are traditionally designed for maximum cargo-carrying capacity within the beam of the old Panama Canal locks (32.3 m). They typically have a length of about 200 m and a draught around 13.5 m, resulting in 58,000–65,000 tonnes deadweight capacity. Five cargo holds, served by four slewing cranes, accommodate the dry

Table 1
CAPEX and lost opportunity costs.

		Ship power system option, s					
		1	2	3	5	6	7
	parameter	VLSFO ship	LNG ship	LH2 ship	Ammonia ship	LPG ship	Methanol 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

As for the retrofit costs, we use the same system-based cost factors as for newbuilds (Lindstad et al. 2021b), plus an additional penalty of 3.6 mUSD to account for shipyard costs and lost income during retrofitting. The resulting retrofit costs between options are shown in Table 2. Blank fields indicate no retrofit option when the focus is on reducing GHG, computationally modelled by a very large cost penalty.

Table 2
Retrofit costs, cheap (green) to more expensive (red).

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					5.9	0.0

bulk cargo. Supramax bulk carriers are a relevant segment in terms of global shipping emissions, as they constitute almost a quarter of the global dry bulk fleet (Bengtsson 2018) and provide about 10% of the global transport work in ton-miles. Due to the generic nature and relatively few ship-specific inputs needed, the model could however easily be applied to other shipping segments.

Conventional Supramax bulk carriers are powered by fuel oil (HFO or VLSFO). We use a VLSFO configuration as a reference for comparison in our case study. As briefly outlined in Section 2, we keep the total displacement constant for all power systems and reduce the cargo-carrying capacity for power systems that require more weight or space than the reference VLSFO configuration. The lost cargo-carrying capacity is accounted for by means of a lost opportunity cost. In order to calculate the lost opportunity cost, we assume an average utilization of 90% for the first 58,000 dwt and 25% utilization for the following 5,000 dwt. We assume a charter rate of 25,000 USD/day (Handybulk 2022), which is split proportionally over the mentioned deadweight ranges weighted with their average utilization. This results in a piecewise linear function for the lost opportunity costs, displayed in Fig. 2. For that figure, we keep the range and energy efficiency constant and only replace the energy carrier.

As compared to Lagemann et al. (2022a), the part of our method for calculating the cargo-carrying capacity has been refined by accounting for potentially lower volumetric power system density. In essence, energy carriers such as methanol that can be integrated into the ship structure are penalized based on excess weight, while energy carriers that cannot be integrated are penalized based on either excess weight or excess volume. Thus, the lost cargo-carrying capacity is now computed by

$$w_s^{lostcargo} = max\left(w_s^{fuelcontained} - w_{VLSFO}^{fuelcontained}; v_s^{excess} \cdot \rho^{cargo}\right) \tag{20}$$

Where $w_s^{fuelcontained}$ is the weight of the contained fuel (including tanks) for each power system s, $w_{VLSFO}^{fuelcontained}$ is the weight of the fuel for the baseline VLSFO configuration and ρ^{cargo} the cargo density, here assumed as simply 1 t/m^3. The required volume for fuel tanks, in excess of what is freely available on the open deck, is calculated as

$$v_s^{fuelexcess} = max\left(0, v_s^{fuelcontained} - v^{free}\right) \tag{21}$$

Where $v_s^{fuelcontained}$ is the contained fuel volume (incl. tanks) and v^{free} the freely available volume, i.e., volume available for fuel storage without any impact on the cargo-carrying capacity. The contained fuel volume $v_s^{fuelcontained}$ is set to zero for integral tanks (e.g., VLSFO, methanol) and the freely available volume is assumed as roughly 1600 m^3, based on the space behind the deckhouse of a typical Supramax carrier.

Over the past years, newbuilding prices for the VLSFO reference configuration have circled around roughly 30 mUSD (Hellenic Shipping News 2022). Deducting the costs of the VLSFO power system yields a cost of roughly 27 mUSD for a vessel without any power system. Using a system-based (Levander 2012) cost estimation approach with cost factors per unit power as proposed by Lindstad et al.

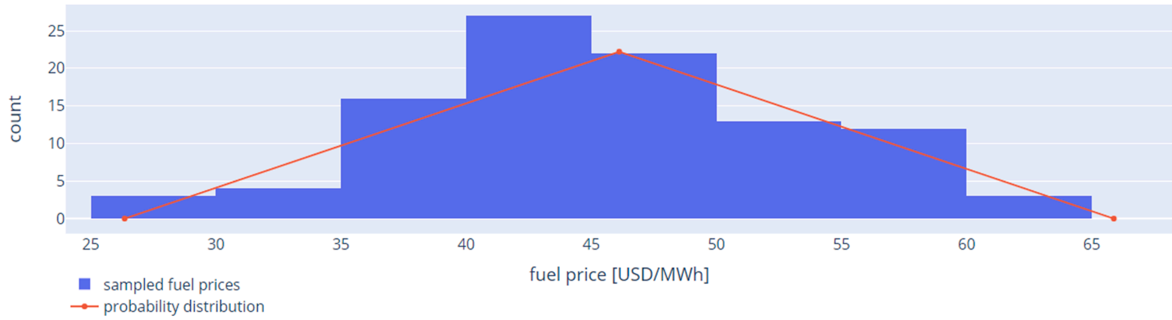

Fig. 3. Sampled and discounted fuel prices for VLSFO in period 1, set with 100 scenarios.

Table 3
Upper and lower bound fuel costs and GWP factors.

			Environmental impact	Economic impact	
Energy carrier	Feed-stock	Fuel label	GWP WTW per fuel energy unit [gCO_{2eq}/kWh]	Upper bound cost [USD/MWh]	Lower bound cost [USD/MWh]
Diesel	Fossil	VLSFO	331.6 [1]	95 [2]	38 [2]
	Bio	bio-Diesel	220.0 [5]	128 [3]	93 [3]
	electro	e-Diesel	4.5 [1]	423 [2]	131 [2]
Methane	Fossil	LNG	305.4 [1]	81 [2]	32 [2]
	Bio	bio-LNG	55.7 [1]	119 [3]	89 [3]
	electro	e-LNG	6.0 [1]	358 [2]	115 [2]
LPG	Fossil	LPG	267.5 [1]	98.3 [2]	39.3 [2]
Methanol	Fossil	Methanol	366.1 [1]	210 [2]	90 [2]
	Bio	bio-Methanol	115.9 [1]	97 [3]	66 [3]
	electro	e-Methanol	3.5 [1]	385 [2]	116 [2]
Ammonia	Fossil	Ammonia	106.1 [1], [4]	220 [2], [6]	56 [2], [6]
	electro	e-Ammonia	19.0 [1]	220 [2]	80 [2]
Hydrogen	Fossil	LH2	108.7 [1], [4]	245 [2], [6]	55 [2], [6]
	electro	e-LH2	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.

(2021b) and an installed power of 7500 kW, we arrive at the newbuilding cost estimations as shown in Table 1.

Decisions and potential costs lying in the future usually have less of an impact on here-and-now investments, particularly when evaluating flexibility (De Neufville and Scholtes 2019). Costs incurring in the future (i.e., lost opportunity costs, retrofit costs and fuel costs) are thus discounted (Benford 1965) and we assume an annual discount rate of 5% over the entire time horizon.

4.2. Scenario generation

Section 1 described that large uncertainty is related to future fuel prices as well as carbon prices. In order to separate and somewhat isolate the impact of these uncertainties, we generate two scenario sets:

1. A scenario set with stochastic fuel prices
2. A scenario set with stochastic fuel prices and stochastic carbon prices

The mathematical model will then be applied to one set of scenarios at a time, and within this set optimizes across scenarios.

Sampling of fuel prices

Most studies estimating future prices for alternative fuels give high- and low-price scenarios (Lloyd's Register and UMAS 2020, DNV GL 2020, Lindstad et al. 2021b), due to the many uncertain parameters involved in such estimates. This approach is certainly helpful for investigating best- and worst-case scenarios for specific fuels and thus assessing the robustness of different options. However, it is more unlikely that all independent parameters in the estimation are unfavorable (or favorable) than that only some of them are unfavorable (or favorable) for the fuel price. Therefore, a probability distribution, that assigns higher probability to

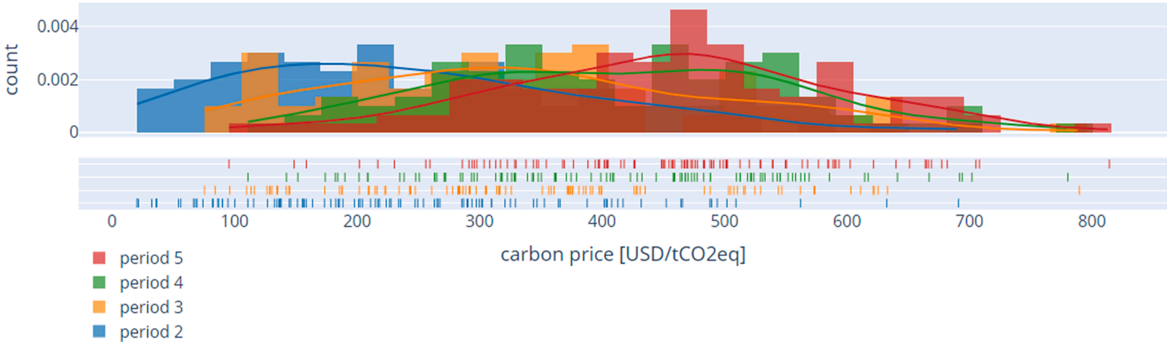

Fig. 4. Sampled carbon prices for 100 scenarios with five time periods.

intermediate values, seems natural. For this study, we assume a simple triangular probability distribution between lower and upper bound fuel prices. This is of course not 100% correct, but we do so on the basis the following argument: It is impossible to accurately know the probability distribution for future, currently non-existing, fuels beforehand. Even in retrospective, this may be hard. One can certainly fit a probability distribution to any historic volatile curve, but it is debatable whether the derived probabilities would be applicable to future developments on the long run. Pantuso et al. (2015), however, argue that it is not always necessary to be right on the probability distribution. It may often be more important that uncertainty is accounted for *at all*.

The main uncertainties affecting fuel costs may have different origins. For example, Lindstad et al. (2021b) show that the cost of electricity is a main determinant for the price of electro-fuels. Similarly, the cost of biomass as a feedstock influences the cost of bio-fuels to a significant extend. Trivyza (2019) finds that prices for conventional fossil fuels have historically been strongly correlated with prices for HFO by around 90%. Keeping in mind that we want to address long-term uncertainty rather than short-term volatility, we take the following approach in this article: We assume that fuel prices within each group of fuels (fossil, bio- and electro-fuels) are perfectly correlated and we draw a random number for each group of fuels and each discrete time period per group of fuel. That is, for generating the first time period for the first scenario, we draw three independent random numbers, based on a triangular probability distribution, which are used to compute the fuel price for fossil, bio- and electro-fuels, respectively. Based on the drawn random number per fuel group, the computation of fuel prices is a simple interpolation between lower and upper bound:

$$C^F_{ft\omega} = C^{F,lower\_bound}_f + (C^{F,upper\_bound}_f - C^{F,lower\_bound}_f) \cdot random\_number\_per\_group_{t\omega} \quad (22)$$

Thus, the numbers are drawn independently per group of fuel, time period and scenario. Fig. 3 visualizes the probability distribution and sampling of scenarios for VLSFO in period 1.

The numbers used as estimates for the lower and upper bound fuel prices are shown in Table 3. The global warming potentials (GWPs) are primarily based on the life cycle assessment by Lindstad et al. (2021a), complemented with data from Korberg et al. (2021) and Sustainable Shipping Initiative (2019) on biofuels. The GWPs are given for a 100-years period. As for the price estimates in Table 3, we refer to Lindstad et al. (2021b) for fossil as well as electro-fuels and Korberg et al. (2021) for bio-fuels, scaled with a biomass price between 5 and 10€/GJ and finally converted to USD.

It should be noted that different sources can employ different accounting techniques for bio-fuel emissions. Some account for combustion emission already during the production of such fuels. Due to the linear nature of our model though, what matters is only the sum of well-to-tank and tank-to-wake emissions, not the accounting technique. Thus, the GWP factors in Table 3 represent emission per unit energy of the fuel on a well-to-wake basis (WTW). That is, they represent roughly 50% of the GWP factors per unit break power for a large two-stroke engine, with the exact value dependent on the engine's efficiency.

Scenario set generation with and without carbon pricing

To date, there have been multiple discussions on enforcing an MBM in the shipping sector. At the IMO, several member states stand in favor of a carbon levy that will incentivize the stakeholders to opt for low carbon systems onboard their vessels. On the other hand, there have also been proposals in favor of an Emissions Trading System (ETS) that ultimately sets a cap on emissions and lets the market (supply and demand for carbon allowances) to settle on a price for carbon. The implementation of a levy in principle provides certainty on investments as that the level of carbon pricing is pre-decided from the regulators. In this way, stakeholders are able to foresee the increase on their operational expenses and decide whether or not to invest in abatement technology (Lagouvardou et al. 2022). On the other hand, in the case of an ETS, and as indicated from the evolution of carbon pricing from different ETS, the price can be very volatile (Lagouvardou et al. 2020). The certainty on emissions reduction is in practice easily dismissed by grandfathering, e.g., provisions of free allowances, leading to a too low carbon price set by the market to incentivize investments into carbon abatement systems.

Despite the fundamental differences of these two schemes, what is most important for this study is the level of uncertainty that derives from these two most prominent MBMs and the discussion around them. From today's perspective, the carbon price in, say 20 years from now, in practice appears to be uncertain both under an ETS and a levy-based MBM. Our model aims to address this resulting uncertainty on the following three premises: First, the case of no emission pricing can be seen as a special variant with 0 costs for emissions. Second, no matter whether the MBM will be a levy, ETS or any other system, there will be an average price for emissions

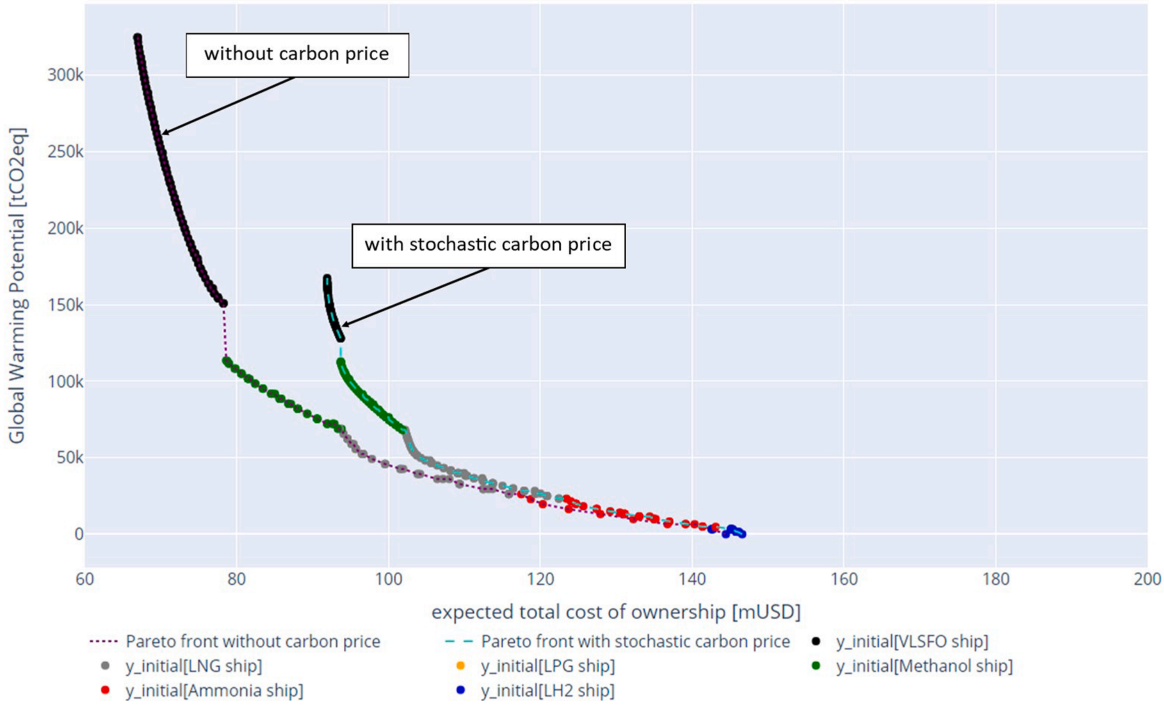

Fig. 5. Pareto front for initial power system configurations with and without carbon price, 100 scenarios.

over any discrete time period. Third, this average long-term development of the emission price level is currently uncertain.

Estimating a long-term probability distribution for carbon prices is thus challenging, as there is currently no global carbon pricing scheme in place and hence a lack of comparative data (Cullinane and Yang 2022). The probability distribution can thus only be based on local carbon pricing systems as well as ongoing discussions and proposals at IMO level (Lagouvardou et al. 2020). The following arguments have led us to apply a beta-variate distribution with alpha = 1.5 and beta = 5, which is scaled to a carbon price range between 0 and 1000 USD/tCO_{2eq}: Currently and historically discussed pricing levels have a large variance, ranging from a few USD/tCO_{2eq} to prices in the order of several hundred USD/tCO_{2eq}. The choice of range is supposed to account for low-probability but high-impact tail effects. The resulting distribution, visualized in Fig. 4, peaks at about 100 USD/tCO_{2eq} which is not far away from current EU ETS levels (Trading Economics 2022) and coincides with a proposal from the Marshall and Salomon Islands (IMO MEPC 2021).

On top of the outlined considerations on ranges and peaks, we apply a path-dependency for carbon prices as follows: Both theory (Center for Climate and Energy Solutions 2013, Mundaca et al. 2021) and historic data for the EU ETS (Trading Economics 2022) suggest that carbon prices should generally increase over time. The same can be said about many proposals discussed at the IMO, which are thought to increase over time (Lagouvardou and Psaraftis 2022). However, effects such as grandfathering have in practice shown to have a lowering effect on carbon prices. We aim to capture both the theoretical and practical considerations in our model, by restricting the carbon price of a consecutive period to not fall below 80% of the previous period. That is, when drawing a random number from the beta-variate probability distribution, the number is simply rejected and a new number drawn, until the carbon price is equal to or higher than 80% of the carbon price of the previous period. Fig. 4 illustrates the resulting sampled carbon prices for the four consecutive time periods. As there is currently now global carbon pricing system in place (zero carbon price for period 1), the random sampling applies from period 2 onwards.

It seems natural and important to question the choice of this probability distribution. It cannot be seen as a probability distribution based on empirical frequency, but rather on belief or expectations (Köhn 2017). Similar to Subsection 4.1 and based on the findings of Pantuso et al. (2015), we deem it more important to account for the uncertainty *at all* – including the mentioned features – than to be absolutely right on the actual distribution. However, in order to separate the effects of random fuel prices from random carbon prices, we use two sets of scenarios, one without carbon price and one with the explained stochastic carbon price features.

Since the stochasticity is dealt with by sampling in the scenario generation, we assign equal probability to each of the generated scenarios:

$$P_\omega = \frac{1}{|\Omega|} \tag{23}$$

Both fuel and carbon prices are discounted with a rate of 5% as in Subsection 4.1. The carbon price is added to the fuel price per unit energy based on the WTW GWP potential. The sampled scenarios with corresponding fuel prices over time are stored as dictionaries in Python.

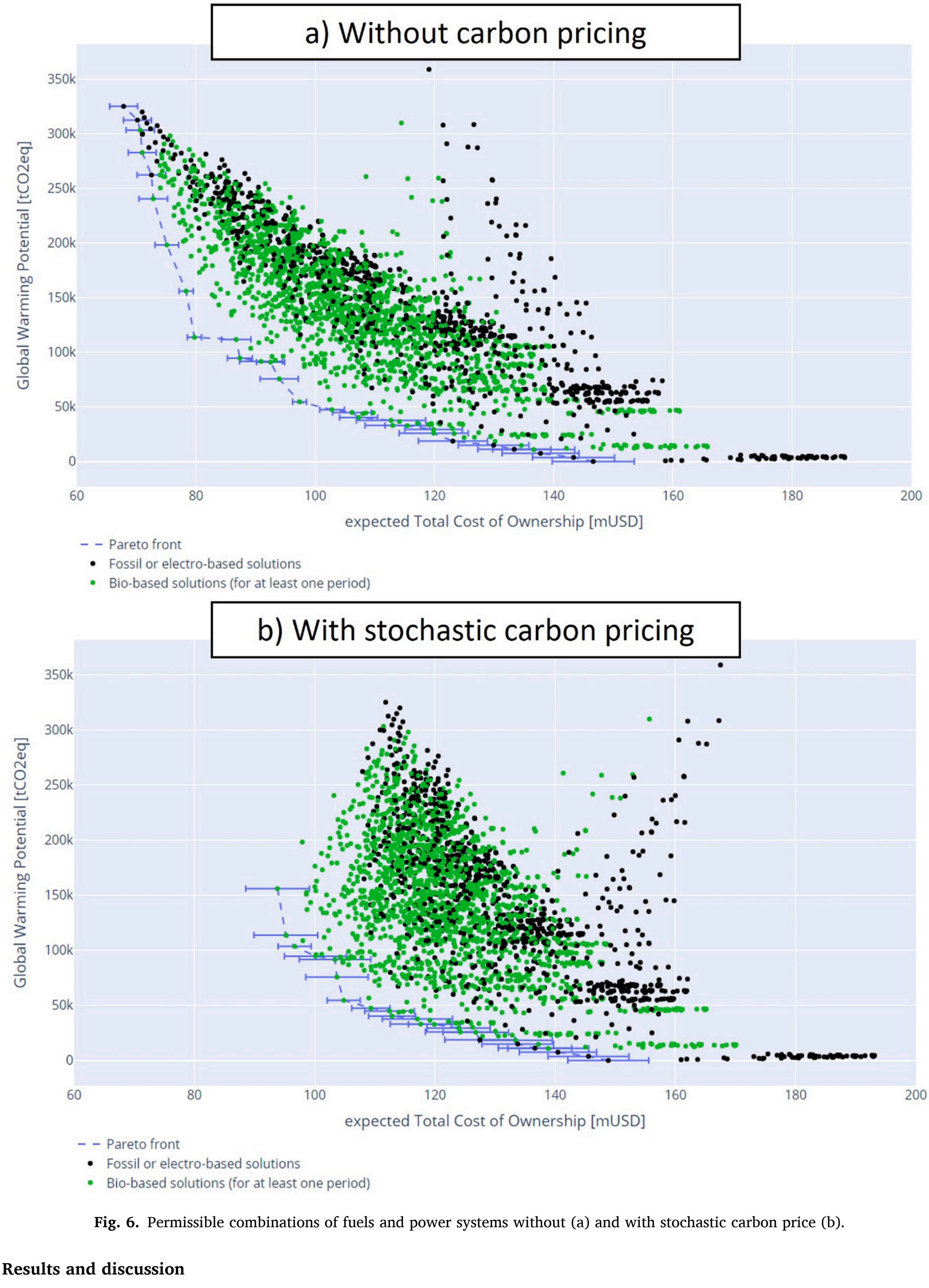

Fig. 6. Permissible combinations of fuels and power systems without (a) and with stochastic carbon price (b).

5. Results and discussion

We present and discuss the results of our case study in Subsection 5.1. Subsection 5.2 touches on the effect of alternative carbon price trajectories, which can be relevant from a policy perspective.

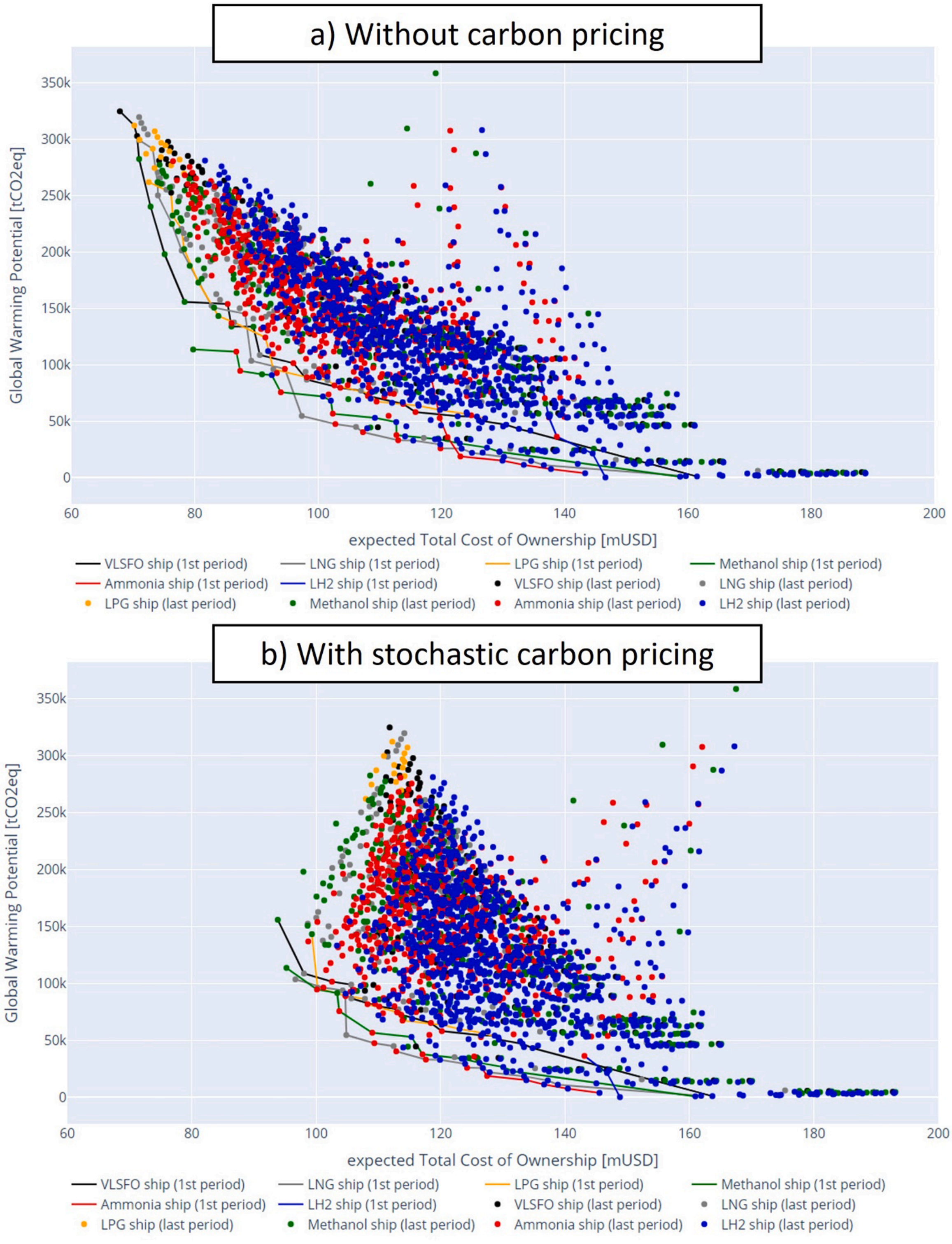

Fig. 7. Permissible combinations showing power system transitions, without (a) and with stochastic carbon price (b). Lines indicating Pareto solution departing from initial power system, dots indicating the power system in the last period.

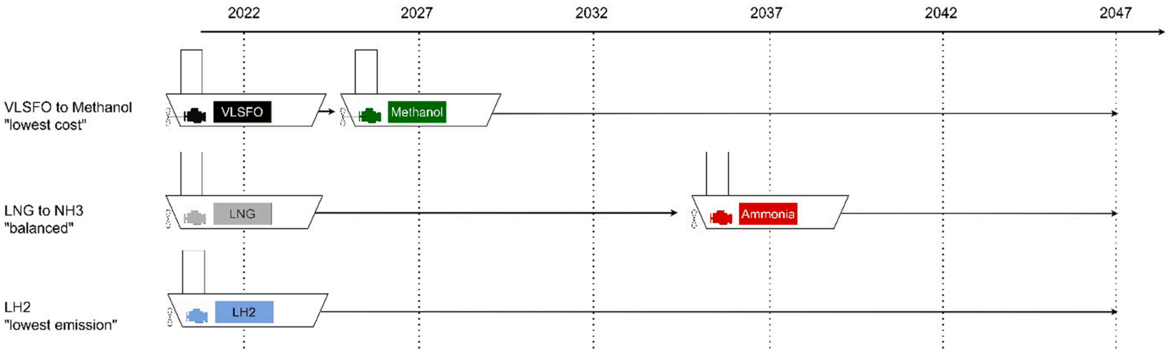

Fig. 8. Lifetime illustration of three Pareto-optimal configurations under stochastic carbon pricing.

5.1. Case study results

The stochastic model is implemented in Python and solved with the commercial optimizer Gurobi 9.5. We have investigated the in-sample stability of our stochastic model by tracing the objective values of Pareto-optimal fuel-system combinations over 10 sampled scenario sets with a size of 20, 100 and 500 scenarios respectively. The results showed a decrease in the objective functions' relative standard deviation from 1.0% (20 scenarios) to 0.2% (500 scenarios). Recall that one scenario represents one complete realization of uncertain external parameters, i.e., fuel and carbon prices. In order to avoid excessive runtime, we have selected 100 as an appropriate scenario set size throughout this paper. On an ordinary laptop computer it takes approximately 70 min to solve the model for 100 scenarios.

Fig. 5 shows the Pareto-optimal solutions for both a scenario set without and with carbon pricing, as described in the previous section. We focus on the first-stage decisions. Therefore, the color of each dot denotes the identified optimal power system.

The commercial optimizer helps finding solutions on the Pareto front, but does not provide much insight beyond the Pareto front. For this particular problem - and in contrast to many other cases - we can also use brute force to generate all feasible solutions in order to obtain additional insight. We therefore implement the model in way that it computes the costs and emissions within each and finally across all scenarios for all permissible combinations of power systems and fuels, similar to Lagemann et al. (2022a). This results in a cloud of points, which allows viewing solutions that might be interesting albeit not directly on the Pareto front. Fig. 6 displays the results of this brute force approach, again for a scenario set without (6a) and with (6b) carbon pricing. Each dot denotes a specific combination of fuel and power system for each period, and the dot's color signals whether a bio-fuel is used in one or more periods (green) or not (black). In addition, we show the standard deviation for the Pareto-optimal combinations.

We see that without carbon pricing, fossil fuels are among the Pareto-optimal combinations in the upper left corner. For reduced lifetime GHG emissions, bio-fuels become Pareto-optimal due to their lower cost compared to electro-fuels at only slightly higher emissions on average. For the very low end of lifetime emissions, bio-fuels do not seem suitable. Comparing these general findings with the scenario set for a stochastic carbon price, we observe that high-emission combinations with fossil fuels are penalized to an extent which makes them roughly equally expensive as low-emission combinations with electro-fuels. With stochastic carbon prices, the cheapest solution with bio-fuels reduces emission by 50%. Most Pareto-optimal solutions make use of bio-fuels at one or more periods. The question around availability of bio-fuels thus is important as it affects a shipowner's decision-making.

The brute force computation also allows tracing the specific power systems, see Fig. 7. The dot's color now denotes the system in the last period, while a line is generated for all Pareto-optimal combinations that start from a specific power system configuration. Both lines and dots have the same color for a specific power system (e.g., red = ammonia). This plot thus allows tracing power system transitions, i.e., potential retrofits after the first-stage decision for the initial power system is made. This can be valuable information for designer who aims to design an "future-energy-carrier-ready" ship. What energy carrier to be ready for thus becomes a relevant question.

Fig. 7 shows that the low-emission combinations on the Pareto front in many cases involve retrofits to ammonia or hydrogen. When comparing the sets without and with carbon pricing, we observe that methanol and LNG power systems remain in the absolute Pareto front, while LPG and VLSFO are rendered inferior by the stochastic carbon pricing for lower emission targets. This is an important observation and, if today's baseline is VLSFO, would signal a departure from status quo. We also note that the cheapest combination with methanol or LNG in the initial period does not include any retrofit, while Pareto-optimal combinations with lower GHG impact do. This could potentially mean that even if shipowners depart from status quo and invest in methanol or LNG, they may be required to retrofit. This depends on the development of future emission reduction legislation.

Although both the two-stage optimization and the brute force model are applied to exactly the same sets of scenarios, we recall their slight difference in perspective: While the two-stage optimization model solely focuses on the first-stage decisions, the brute force implementation traces fixed combinations of fuel and systems over time and across all scenarios. Both these perspectives suggest flexible solutions that enable low-cost retrofits (i.e., methanol and LNG power systems) along large portions of the Pareto front, which shows the value of flexibility under the current uncertainty. Fig. 8 illustrates three Pareto-optimal configurations under stochastic carbon pricing. The solutions displayed are the cheapest, the one with lowest emissions, as well as an intermediate one.

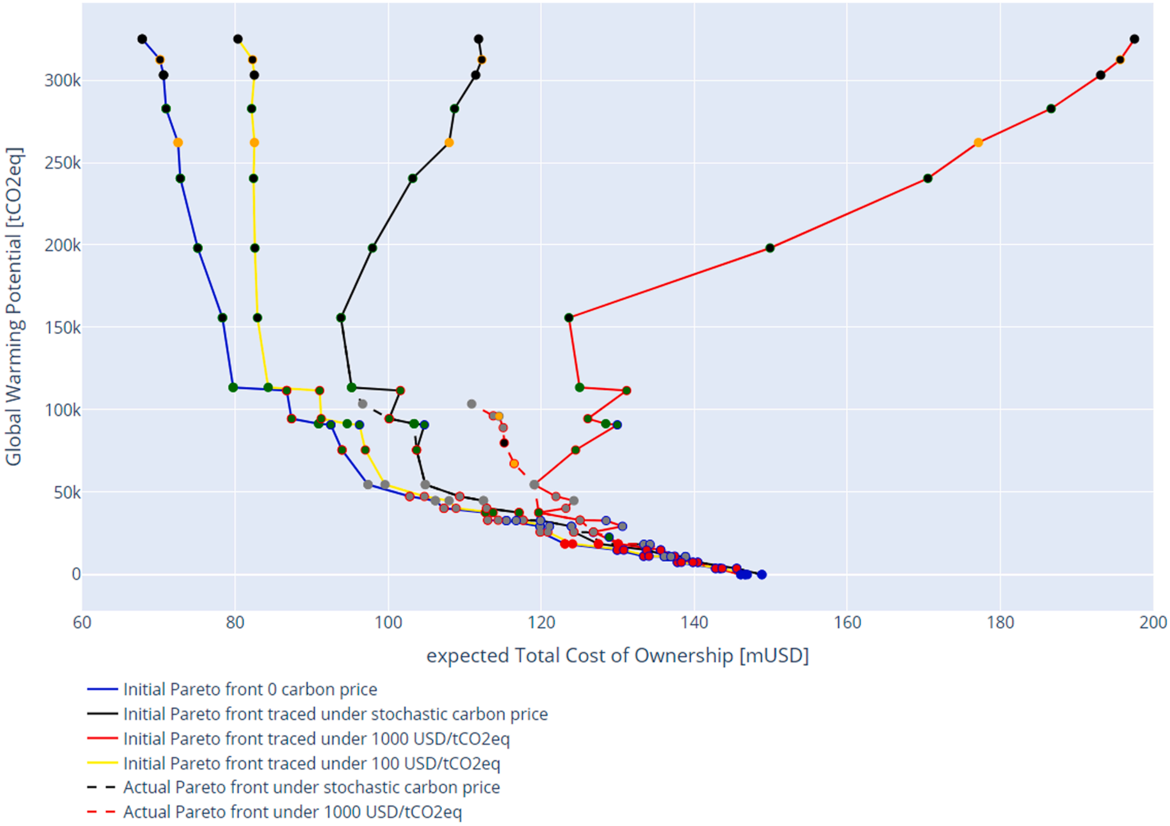

Fig. 9. Tracing the Pareto solutions for 0 carbon pricing (blue) under different conditions (yellow = 100 USD/tCO_{2eq}, black = beta-variate distribution for carbon prices, red = 1000 USD/tCO_{2eq}). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Pareto set of initial power system configurations.

	a) without carbon pricing		b) with stochastic carbon pricing	
Initial power system	TCO, relative to VLSFO without carbon pricing	GWP, relative to VLSFO in all periods	TCO, relative to VLSFO without carbon pricing	GWP, relative to VLSFO in all periods
VLSFO	**100%** – 115%	**100%** – 48%	138%	48%
Methanol	117% – 138%	35% – 23%	140% – 153%	35% – 23%
LNG	143% – 176%	17% – 8%	143% – 182%	32% – 8%
Ammonia	182% – 212%	6% – 1%	187% – 215%	6% – 1%
LH2	216%	0%	219%	0%

Figs. 6 to 8 only present an excerpt of insight that can be gained from looking at solutions beyond the general Pareto front. The brute force computation technique thus not only helps to trace optimal solutions, but even more to identify the bad ones. The latter is particularly relevant for shipowners who simply aim to stay in business. Additional insight, among others from a policy-maker perspective, can be gained by plots such as Fig. 9 in Subsection 5.2. We supplement the online version of this article with interactive graphs, such that for each dot the combination of power system and fuel can be viewed on hovering. Additionally, Table 4 summarizes the Pareto set of initial power systems as shown in Fig. 9.

All TCO and GWP values in Table 4 are normalized by a ship running on VLSFO for all periods and without carbon pricing, such that relative GHG reductions and additional expenditures can be read.

For stochastic programs, it is common to compute the value of stochastic solution (VSS, Birge 1982). For our case study, the monetary VSS is generally found to be low. The value of solving the more complex stochastic program instead of a simpler deterministic expected value program, lies mainly in the clearer insight provided by the stochastic model. For the interested reader we have enclosed more information in the appendix.

Table 5
Alternative carbon price trajectories.

Scenario set label	Sampled scenarios	Fuel prices	Carbon prices	Color in Figure 9
0 carbon price	100	Stochastic	Deterministic 0 USD/tCO_{2eq}	Blue
100 USD/tCO_{2eq}	100	Stochastic	Deterministic 100 USD/tCO_{2eq}	Yellow
Stochastic carbon price	100	Stochastic	Stochastic beta-variate distribution	Black
1000 USD/tCO_{2eq}	100	Stochastic	Deterministic 1000 USD/tCO_{2eq}	Red

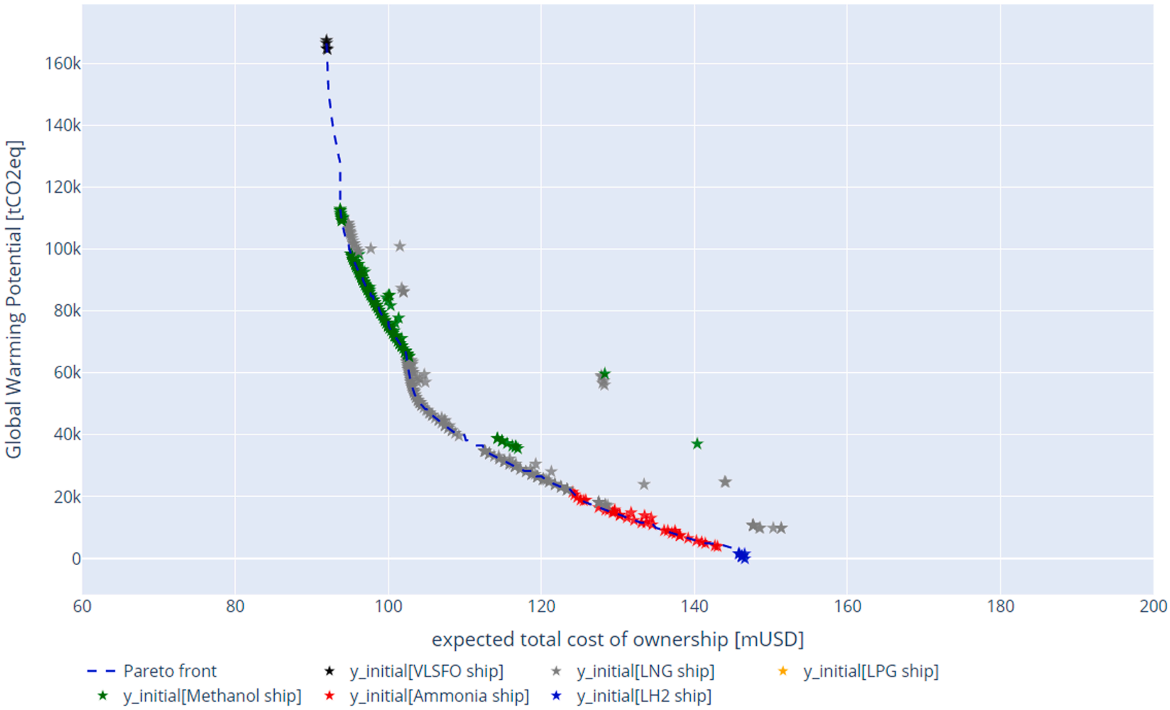

Fig. A1. Value of stochastic solution. Graphical comparison of first-stage solutions from deterministic and stochastic problem.

5.2. *Alternative carbon pricing policies*

In the previous sections, we have examined the effect the assumed carbon price distribution has on the problem of fuel selection. This distribution is based on expectations, grounded in anecdotal empirical support. For a shipowner, however, it may be sensible to investigate the effects of alternative carbon price trajectories on the choice of fuel and power system. From a policy perspective, this can provide additional insight into the incentive that a certain carbon price trajectory may have on a shipowner's decisions and thus the expectable emission reductions.

The generic formulation of the model enables a simple replacement of the scenarios and thus carbon prices. In order to assess the effect of different carbon price trajectories, we test the model with the scenario sets as shown in Table 5.

We use the brute force computation for tracing specific solutions. Fig. 8 shows the results of these computations. The blue continuous line indicates the Pareto front in the absence of any carbon price. The remaining continuous lines trace these so-derived Pareto-optimal combinations under different carbon price policies. The stippled lines indicate the actual Pareto front under the alternative carbon price policies as opposed to the initial Pareto front evaluated under the same scenario.

Besides of the different Pareto-optimal power system configurations, Fig. 9 shows that a fixed carbon price of 100 USD/tCO_{2eq} (yellow line) can render 60% emission reductions cost-competitive with fossil fuels. This may be interesting input from a policy-

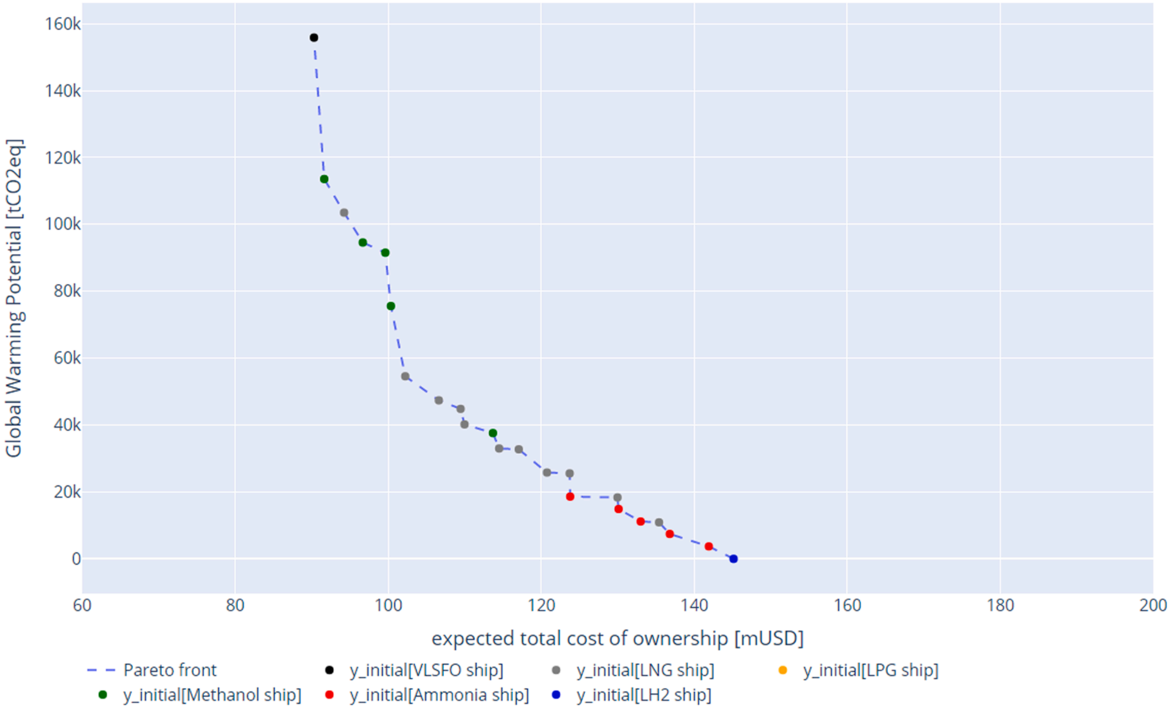

Fig. A2. Pareto front of the expected value-problem, one scenario.

perspective and shows that the model may be used to simulate a single shipowner's behavior, as far as techno-economic aspects are concerned, under different policy-schemes. Also, the actual Pareto front for the stochastic carbon price (black line) does not differ significantly from the initial Pareto front traced under the same conditions. This indicates that the introduction of a carbon price mechanism does not necessarily render completely different solutions optimal. Indeed, the Pareto-optimal solutions may be almost the same, except for the higher end of the emission spectrum. This point is underpinned by the actual Pareto front for the very high carbon price (red line), which coincides with the initial Pareto front in the very low end of the lifetime emission spectrum. Thus, low-emission configurations appear to be robust with respect to carbon prices, but this comes at cost penalty.

The strong similarity of Pareto fronts for 0, 100 and a stochastic carbon price also implies that, as long as the WTW scope is concerned, the optimal decisions are little dependent on whether the IMO opts for any market-based or a command-and-control policy: Both policies incentivize low-emission solutions, for which our Pareto fronts show little difference. From a practical perspective, it is thus almost indifferent which of these policies will be adopted as long as their ultimate reduction ambition is roughly 50% or more. The optimal solutions in that case will be in the lower end of the target emission spectrum, for which there is little difference in terms of here-and-now decisions. This does not apply to the scenarios with 1000 USD/tCO_{2eq} carbon price, for which the Pareto-optimal solutions contain a higher share of LNG ships and in addition LPG configurations with subsequent retrofits.

We have already pointed out that our model as is can provide additional insight from a policy perspective. Specific command-and-control trajectories, i.e., the effect of specific annual reduction goals, could easily be added to the model as hard constraints.

6. Conclusion

In this paper, we have outlined the use of a bi-objective stochastic programming model for the techno-economic selection of ship fuel and power systems. The model is meant to support the requirements elucidation phase (Andrews 2003), i.e., the working out of a new design's requirements specification.

The proposed model gave insight as to how the targeted lifetime global warming potential affects the choice of initial system configurations and the expected total cost of ownership both with and without carbon pricing and considering potential retrofits and fuel switches. The brute force implementation gave additional insight by showing that retrofits are not unlikely for Pareto-optimal solutions. From a shipowner perspective, both methanol and LNG appear to be relatively robust initial power system choices for a broad range of emission reduction ambitions. Both power systems enable low-cost fuel switches to bio- or electro-fuels, while LNG potentially also enables low-cost retrofits to, e.g., ammonia. These findings coincide with the current orderbook indicating that LNG and lately methanol engines are preferred options by shipowners (Chryssakis et al. 2023). From a policy perspective, our model can provide additional insight into a shipowner's decision-making under either uncertainty or specific carbon pricing policies. Our model can thus be used to inform about expected emission reductions under different policies.

The conclusions drawn from this case study are tightly connected to the input parameters and distributions used. Recent years have shown a decoupling of gas prices from oil prices. The fuel price distributions have been compiled from several sources based on available knowledge on production costs. However, they do not account for market effects which, as exemplified by the spiking gas price.

Using fuel production cost data, as opposed to market-pricing data, thus represents a weakness of the current study. This weakness however is not easy to come by from a general standpoint: Adjusting the distribution range for LNG based on hindsight does not prevent such foresight prediction errors from happening for other fuels in the future. The model thus enforces discussing one's expectations on the future explicitly. Combined with the ability to consider uncertainty by means of stochastic distributions, we see this as a significant advantage over ignoring uncertainty and just optimizing for one future scenario. That is, even though the model does not capture so-called Knightian uncertainty (Knight 1921) with unknown probabilities and sometimes even possibilities ("Black Swans", Taleb 2010), it represents an improvement over just using one scenario. Pantuso et al. (2015) show that considering uncertainty can lead to more robust decisions, even though exact probability distributions may be uncertain. After all, "one cannot change what can be predicted perfectly" (Ackoff 1979).

Andersson et al. (2020) and Ashrafi et al. (2022) suggest that factors beyond cost-efficiency play a significant role in the decision-making process. Further studies could thus aim to account for these factors in a consistent and quantifiable way. In addition to continuously updating the cost and emission data set, an expansion of the fuels used by bio-e-fuels (Grahn et al. 2022) could be interesting. As an expansion of real-options theory as used in this article, Knight (2014) suggests prospect theory (Kahneman and Tversky 1979) or game theory (see e.g., DNV 2022) for a better alignment of quantifiable metrics and risk perception.

CRediT authorship contribution statement

Benjamin Lagemann: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Sotiria Lagouvardou:** Conceptualization, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft. **Elizabeth Lindstad:** Conceptualization, Validation, Investigation, Resources, Writing – review & editing. **Kjetil Fagerholt:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – review & editing. **Harilaos N. Psaraftis:** Investigation, Writing – review & editing, Supervision. **Stein Ove Erikstad:** Conceptualization, Methodology, Investigation, Writing – review & editing, Supervision.

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.

Data availability

We would like to share our data as interactive plots. The files are attached to this submission.

Acknowledgements

We are grateful for the funding from the Research Council of Norway under the SFI Smart Maritime, project number 237917, and for the funding from both the Orients Fund and DTU under the MBM SUSHI project. Also, we would like to thank our anonymous reviewers for their comments and suggestions that helped improving this manuscript.

Appendix A

The following section on the value of stochastic solution (VSS) may provide additional insight, but is not necessary for the understanding of the paper.

The stochasticity adds significant complexity to the problem, compared to its deterministic counterpart (Lagemann et al., 2022a). It may be appropriate to ask: "Is it worth adding this complexity? What is the value of implementing the stochastic solution compared to the deterministic one?" In order to compute the VSS, the same input data as for the stochastic model is used, except for the fact that we only optimize for one scenario which is based on the expected value of each stochastic parameter. For the fuel prices, this is therefore the mean fuel price, discounted for each period. For the stochastic carbon price, which is dependent on the previous time-period, these prices become 200, 300, 360 and 390 USD/tCO_{2eq} for the second to fifth time period respectively.

As we have set up a bi-objective problem, the value of stochastic solution could be expressed in terms of either objective. We choose to compare the cost difference of a solution to achieve a given GWP. This corresponds to our formulation of the epsilon constraint degradation (Eq. (19)). We thus ask: "If we compare solutions that are supposed to achieve the same target GWP, what is the cost difference between implementing the deterministic solution for the first stage vs the stochastic one?" Implementing the deterministic solution hence fixes the first stage decision, but leaves open all further recourse options. Due to the bi-objective nature of the problem as well as for better clarity, we compare the solutions and show the VSS graphically in Fig. A1. The blue line indicates the Pareto front of the stochastic model, while the stars in different colors indicate the initial solutions suggested by the deterministic expected value-problem.

As can be seen, the value of the stochastic solution is generally low as most solutions suggested by the deterministic program coincide with the stochastic program. However, while the stochastic program provides relatively clear ranges in terms EGWP for the optimal systems, the deterministic solution alternates more often. LNG and methanol power systems for example alternate, which is shown by the sudden deviations/spikes in the Pareto front. Thus, the deterministic problem suggests an alternation and thereby chaos of optimal solution that is not present in the stochastic solution. Fig. A2 shows the Pareto front for the deterministic expected value-problem only, which illustrates the alternations of Pareto-optimal solutions.

It can be seen that with decreasing global warming potential, the Pareto-optimal solutions frequently alternate between different initial configurations. This effect is not seen in the corresponding stochastic model (Fig. 5). Possibly, these alterations are due to the sparsity of the problem and discreteness of solutions: The stochastic program has a much higher option density and therefore much smoother Pareto fronts. Although the monetary VSS may not be large, we see substantial value in the stochastic program as it avoids artificial alternation of solution and thereby ultimately contributes to a better understanding and clarity.

References

Andersson, K., Brynolf, S., Hansson, J., Grahn, M., 2020. Criteria and Decision Support for A Sustainable Choice of Alternative Marine Fuels. Sustainability 12, 3623. https://doi.org/10.3390/su12093623. Available at:

Andrews, D., 2003. Marine design - requirements elucidation rather than requirement engineering. In: IMDC 2003: the Eight[h] International Marine Design Conference. National Technical University of Athens, School of Naval Architecture & Marine Engineering, Athens, Greece, pp. 3–20.

Ashrafi, M., Lister, J., Gillen, D., 2022. Toward a harmonization of sustainability criteria for alternative marine fuels. Maritime Transport Research 3, 100052. https://doi.org/10.1016/j.martra.2022.100052.

Balland, O., Erikstad, S.O., Fagerholt, K., Wallace, S.W., 2013. Planning vessel air emission regulations compliance under uncertainty. J. Mar. Sci. Technol. 18, 349–357. https://doi.org/10.1007/s00773-013-0212-7.

Benford, H., 1965. Fundamentals of ship design economics: lecture notes. University of Michigan, Department of Naval Architecture and Marine Engineering, Ann Arbor.

Bengtsson, N., 2018. “Shipping Market Round Up.” In Proceedings of the International Maritime Statistics Forum. Hamburg, Germany: Lloyd’s List Intelligence. Available at: http://www.imsf.info/media/1347/1shipping-market-round-up.pdf.

Birge, J.R., 1982. The value of the stochastic solution in stochastic linear programs with fixed recourse. Math. Program. 24, 314–325. https://doi.org/10.1007/BF01585113.

Center for Climate and Energy Solutions, 2013. Options and Considerations for Federal Carbon Tax. https://www.c2es.org/wp-content/uploads/2013/02/options-considerations-federal-carbon-tax.pdf.

Choi, M., Erikstad, S.O., 2017. A module configuration and valuation model for operational flexibility in ship design using contract scenarios. Ships Offshore Struct. 12 (8), 1127–1135. https://doi.org/10.1080/17445302.2017.1316559.

Chryssakis, C., Sekkesæter, Ø., Skåra, Ø., Adams, S., 2023. Alternative ship fuels - focus on biofuels & methanol. Høvik, Norway. Available at: https://www.dnv.com/events/emerging-alternative-ship-fuels-focus-on-methanol-and-biofuels-238876.

Cullinane, K., Yang, J., 2022. Evaluating the Costs of Decarbonizing the Shipping Industry: A Review of the Literature. J. Marine Sci. Eng. 10 https://doi.org/10.3390/jmse10070946.

De Neufville, R., Scholtes, S., 2019. Flexibility in Engineering Design. The MIT Press, Cambridge, Massachusetts. Available at: http://search.ebscohost.com/login.aspx?direct=true&db=e230xww&AN=421824&site=ehost-live.

DNV, 2021. Maritime Forecast to 2050. Høvik, Norway. Available at: https://www.dnv.com/maritime/webinars-and-videos/videos/maritime-forecast-2050.html.

European Commission, 2019. The European Green Deal. Belgium, Brussels Available at: https://ec.europa.eu/info/sites/default/files/european-green-deal-communication_en.pdf.

CE Delft, 2020. Fourth IMO GHG Study. Available, Delft, the Netherlands at: https://safety4sea.com/wp-content/uploads/2020/08/MEPC-75-7-15-Fourth-IMO-GHG-Study-2020-Final-report-Secretariat.pdf.

DNV GL, 2019. Assessment of Selected Alternative Fuels and Technologies. Høvik, Norway. Available at: https://www.dnv.com/maritime/publications/alternative-fuel-assessment-download.html.

DNV GL, 2020. Maritime Forecast to 2050. Høvik, Norway.

Trading Economics, 2022. EU Carbon Permits. https://tradingeconomics.com/commodity/carbon accessed on August 28, 2022.

DNV, 2022. Energy transition simulator. Høvik, Norway. Available at: https://www.dnv.com/Publications/energy-transition-simulator-137892.

Gaspar, H.M., Rhodes, D.H., Ross, A.M., Erikstad, S.O., 2012. Addressing Complexity Aspects in Conceptual Ship Design: A Systems Engineering Approach. Journal of Ship Production And Design 28 (4), 145–159. https://doi.org/10.5957/jspd.2012.28.4.145.

Grahn, M., Malmgren, E., Korberg, A., Taljegard, M., Anderson, J., Brynolf, S., Hansson, J., Skov, I., Wallington, T., 2022. “Review of electrofuel feasibility - Cost and environmental impact”, Progress. Energy 4, 32010. https://doi.org/10.1088/2516-1083/ac7937.

Handybulk, 2022. Ship Charter Rates https://www.handybulk.com/ship-charter-rates/ accessed on 02.06.2022.

Hellenic Shipping News, 2022. Newbuilding Orders on Positive Ground. Available at: https://www.hellenicshippingnews.com/newbuilding-orders-on-positive-ground/.

Horvath, S., Fasihi, M., Breyer, C., 2018. Techno-economic analysis of a decarbonized shipping sector: Technology suggestions for a fleet in 2030 and 2040. Energ. Conver. Manage. 164, 230–241. https://doi.org/10.1016/j.enconman.2018.02.098.

IMO MEPC 76/7/12, 2021. Reduction of GHG emissions from ships: Proposal for IMO to establish a universal mandatory greenhouse gas levy. Submitted by the Marshall Islands and Solomon Islands. Available at: https://docs.imo.org.

International Maritime Organization, 2018. Resolution MEPC.304(72). International Maritime Organization.

Kahneman, D., Tversky, A., 1979. Prospect Theory: An Analysis of Decision under Risk. Econometrica 47, 263–291. https://doi.org/10.2307/1914185.

King, A.J., Wallace, S.W., 2012. Modeling with Stochastic Programming. New York: Springer (Springer Series in Operations Research and Financial Engineering). Available at: https://doi.org/10.1007/978-0-387-87817-1.

Knight, J., 2014. A Prospect Theory-Based Real Option Analogy for Evaluating Flexible Systems and Architectures in Naval Ship Design. University of Michigan https://www.researchgate.net/publication/272165209_A_Prospect_Theory-Based_Real_Option_Analogy_for_Evaluating_Flexible_Systems_and_Architectures_in_Naval_Ship_Design.

Knight, J., Singer, D., 2012 “A Real Options Approach to Evaluating Flexible Architectures in Ship Design,” in IMDC 2012: 11th International Marine Design Conference. Glasgow, Scotland: International Marine Design Conference, pp. 153–161. Available at: https://doi.org/10.13140/2.1.3999.8243.

Ackoff, R. L., 1979. The Future of Operational Research is Past The Journal of the Operational Research Society 30 (2) pp. 93-104 Available at: http://www.jstor.org/stable/3009290.

Knight, F.H., 1921. Risk, uncertainty and profit. Boston and New York: Houghton Mifflin Company. Available at: https://fraser.stlouisfed.org/files/docs/publications/books/risk/riskuncertaintyprofit.pdf.

Köhn, J., 2017. Uncertainty in Economics: A New Approach. Springer International Publishing AG (Contributions to Economics), Cham, Switzerland.

Korberg, A. D., Brynolf, S., Grahn, M., Skov, I. R., 2021. Techno-economic assessment of advanced fuels and propulsion systems in future fossil-free ships, Renewable and Sustainable Energy Reviews, 142, p. 110861. Available at: https://doi.org/10.1016/j.rser.2021.110861.
Lagemann, B., Lindstad, E., Fagerholt, K., Rialland, A., Erikstad, S.O., 2022. Optimal ship lifetime fuel and power system selection. Transport. Res. Part D: Transport Environ. 102, p. 103145. Available at: https://doi.org/10.1016/j.trd.2021.103145.
Lagemann, B., Erikstad, S.O., Brett, P.O., Garcia Agis, J.J., 2022. Understanding agility as a parameter for fuel-flexible ships. In: International Marine Design Conference 2022. Vancouver, Canada. Available at: https://doi.org/10.5957/IMDC-2022-259.
Lagouvardou, S., Psaraftis, H. N., 2022. Implications of the EU Emissions Trading System (ETS) on European container routes: A carbon leakage case study. Maritime Transport Research, 3(February):100059. Available at: https://doi.org/10.1016/j.martra.2022.100059.
Lagouvardou, S., Psaraftis, H.N., Zis, T., 2020. A Literature Survey on Market-Based Measures for the Decarbonization of Shipping. Sustainability 12. https://doi.org/10.3390/su12103953.
Lagouvardou, S., Psaraftis, H.N., Zis, T., 2022. Impacts of a bunker levy on decarbonizing shipping: A tanker case study. Transp. Res. Part D: Transp. Environ. 106, 103257 https://doi.org/10.1016/j.trd.2022.103257.
Levander, K., 2012. System based ship design. Compendium, Trondheim, Norway.
Lindstad, E., Gamlem, G., Rialland, A., Valland, A., 2021a. Assessment of Alternative Fuels and Engine Technologies to Reduce GHG. In: SNAME Maritime Convention. Rhode Island, USA. Available at: https://doi.org/10.5957/SMC-2021-099.
Lindstad, E., Lagemann, B., Rialland, A., Gamlem, G.M., Valland, A., 2021b. Reduction of maritime GHG emissions and the potential role of E-fuels. Transport. Res. Part D: Transport Environ. 101, p. 103075. Available at: https://doi.org/10.1016/j.trd.2021.103075.
Lloyd's Register and UMAS, 2020. "Techno-economic assessment of zero-carbon fuels." Research report. Available at: https://www.lr.org/en/insights/global-marine-trends-2030/techno-economic-assessment-of-zero-carbon-fuels/.
McKinlay, C.J., Turnock, S.R., Hudson, D.A., 2021. Route to zero emission shipping: Hydrogen, ammonia or methanol? Int. J. Hydrogen Energy. https://doi.org/10.1016/j.ijhydene.2021.06.066.
Mundaca, G., Strand, J., Young, I.R., 2021. Carbon pricing of international transport fuels: Impacts on carbon emissions and trade activity. J. Environ. Econ. Manag. 110 (102517) https://doi.org/10.1016/j.jeem.2021.102517.
Nair, A., Acciaro, M., 2018. Alternative fuels for shipping: optimising fleet composition under environmental and economic constraints. Int. J. Transport Econ. 45, 439–460. https://doi.org/10.19272/201806703005.
European Community Shipowners' Associations, 2020. "Position paper: A Green Deal for the European shipping industry." Available at: https://safety4sea.com/wp-content/uploads/2020/02/ECSA-Position-Paper-A-Green-Deal-for-the-European-shipping-industry-2020_02.pdf.
Pantuso, G., Fagerholt, K., Wallace, S.W., 2015. Which uncertainty is important in multistage stochastic programmes? A case from maritime transportation. IMA J. Manage. Math. 28, 5–17. Available at: https://doi.org/10.1093/imaman/dpu026.
Pantuso, G., Fagerholt, K., Wallace, S.W., 2016. Uncertainty in Fleet Renewal: A Case from Maritime Transportation. Transport. Sci. 50, 390–407. https://doi.org/10.1287/trsc.2014.0566.
Parker, M.C., Singer, D.J., 2012. Flexibility and modularity in ship design: an analytical approach. In IMDC 2012: 11th International Marine Design Conference. Glasgow, Scotland: International Marine Design Conference, pp. 385–396.
Psaraftis, H.N., Zis, T., Lagouvardou, S., 2021. A comparative evaluation of market based measures for shipping decarbonisation. Maritime Transport Res. 2, p. 100019. Available at: https://doi.org/10.1016/j.martra.2021.100019.
Psaraftis, H.N., Kontovas, C.A., 2020. Influence and transparency at the IMO: the name of the game. Maritime Econ. Logist. 22, 151–172. https://doi.org/10.1057/s41278-020-00149-4.
Rehn, C.F., Garcia Agis, J.J., Erikstad, S.O., de Neufville, R., 2018. Versatility vs. retrofittability tradeoff in design of non-transport vessels. Ocean Eng. 167, pp. 229–238. Available at: https://doi.org/10.1016/j.oceaneng.2018.08.057.
Rhodes, D.H., Ross, A.M., 2010. Five aspects of engineering complex systems emerging constructs and methods. In: 2010 IEEE International Systems Conference. San Diego, California, pp. 190–195. Available at: https://doi.org/10.1109/SYSTEMS.2010.5482431.
Sustainable Shipping Initiative, 2019. The role of sustainable biofuels in the decarbonization of shipping: the findings of an inquiry into the sustainability and availability of biofuels for shipping. Presented at 2019 United Nations Climate Change Conference, COP25 (Madrid, 11 December 2019). Available at https://www.sustainableshipping.org/news/ssi-report-on-the-role-of-sustainable-biofuels-in-shippings-decarbonisation/.
Taleb, N.N., 2010. The Black Swan, 2nd ed. Random House, New York. Available at: https://www.bibsonomy.org/bibtex/256bae40afc974c4a84a13925cf425898/flint63.
Trivyza, N.L., 2019. Decision support method for ship energy systems synthesis with environmental and economic sustainability objectives. University of Strathclyde https://doi.org/10.48730/s0g5-8698.
United Nations, 2015. Paris Agreement. Available at: https://unfccc.int/sites/default/files/english_paris_agreement.pdf.
Wang, Y., Wright, L.A., 2021. A Comparative Review of Alternative Fuels for the Maritime Sector: Economic, Technology, and Policy Challenges for Clean Energy Implementation. World, 2, pp. 456–481. Available at: https://doi.org/10.3390/world2040029.
Xing, H., Stuart, C., Spence, S., Chen, H., 2021. Alternative fuel options for low carbon maritime transportation: Pathways to 2050. J. Clean. Prod. 297, p. 126651. Available at: https://doi.org/10.1016/j.jclepro.2021.126651.
Zwaginga, J.J., Pruyn, J.F.J., 2022. An evaluation of suitable methods to deal with deep uncertainty caused by the energy transition in ship design. In: International Marine Design Conference 2022. Vancouver, Canada. Available at: https://doi.org/10.5957/IMDC-2022-252.