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Optimal Selection of Multi-Fuel Engines for Ships Considering Fuel Price Uncertainty

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Abstract: Maritime transport serves as the backbone of international trade, accounting for more than 90% of global trade. Although maritime transport is cheaper and safer than other modes of transport, it often means long sailing distances, which often results in substantial fuel consumption and emissions. Liner shipping, a vital component of maritime transport, plays an important role in achieving sustainable maritime operations, necessitating the implementation of green liner shipping practices. Therefore, this study formulates a nonlinear integer programming model for a multi-fuel engine selection optimization problem to optimally determine ship order choice in terms of the fuel engine type, fleet deployment, fuel selection, and speed optimization, with the aim of minimizing the total weekly cost containing the weekly investment cost for ship orders and the weekly fuel cost. Given the complexity of solving nonlinear models, several linearization techniques are applied to transform the nonlinear model into a linear model that can be directly solved by Gurobi. To evaluate the performance of the linear model, 20 sets of numerical instances with, at most, seven routes are conducted. The results show that among 20 numerical instances, 16 sets of numerical instances are solved to optimality within two hours. The average gap value of the remaining four sets of numerical instances that cannot be solved to optimality within two hours is 0.51%. Additionally, sensitivity analyses are performed to examine crucial parameters, such as the weekly investment cost for ordering ships, the ship ordering budget, and the potential application of new fuel engine types, thereby exploring managerial insights. In conclusion, our findings indicate that equipping ships with low-sulfur fuel oil engines proves to be the most economical advantageous option in the selected scenarios. Furthermore, ordering ships with low-sulfur fuel, oil + methanol + liquefied natural gas engines, is beneficial when the weekly investment cost for such engines does not exceed $13,000, under the current parameter value setting.

Keywords: multi-fuel engine selection; fuel price uncertainty; two-stage stochastic programming; green shipping

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1. Introduction

Worldwide trade occurs every day [1]. Maritime transport, as the backbone of international trade, accounted for more than 90% of the cargo volume of global trade in 2019 and has experienced rapid growth in the context of globalization [1,2]. This growth is closely related to the advantages of low cost and high safety associated with maritime transport. Although maritime transport has the advantages mentioned above, its disadvantages cannot be ignored. Long sailing voyages associated with maritime transport often result in significant fuel consumption and the release of numerous emissions by ships [3,4]. For example, shipping is estimated to account for 5–7% of global sulphur oxides (SO_X) emissions [5]. Moreover, the shipping industry contributes 15% of nitrogen oxides, 13% of SO_X, and 2.7% of carbon dioxide emissions produced by human activities [6]. Therefore, green shipping attracts increasing attention from countries, regions, enterprises, and the public [7].

As a major maritime transport mode, liner shipping provides container transport services and serves as an important part of the global logistics system in international trade [8]. Liner shipping, which specifically caters to containerized goods, constitutes approximately 24% of the global shipping industry [9]. It operates on fixed routes with predetermined ports of call, ensuring regular and consistent services, typically on a weekly basis [10]. Prior to the COVID-19 pandemic, the volume of the containerized goods steadily grows by more than 8% per year [11]. Therefore, achieving sustainability in liner shipping is important for the goal of green shipping.

To achieve green liner shipping, many governments and organizations implement several decarbonization policies, such as the European Green Deal and Fit for 55 (European Union; [12,13]), the Clean Energy Plan (United States; [14]), the Clean Fuel Regulations (Canada; [15]), the National Solar Mission (India; [16]), and the Ten Point Plan for a Green Industrial Revolution (United Kingdom; [17]). Liner companies also employ various strategies for decarbonization. One commonly adopted approach is slow steaming, which significantly reduces fuel consumption and air emissions. However, slow steaming necessitates deploying more ships to maintain the weekly visit pattern. As a result, speed optimization and fleet deployment are interconnected aspects of liner companies' operations management. Nevertheless, as stricter emissions regulations come into effect, optimizing speed alone is insufficient for liner companies. Fortunately, advancements in technology reveal significant differences in exhaust emissions per unit of fuel consumption among different types of fuels, which creates an opportunity for research on selection optimization of multi-fuel engines for ships. Moreover, compared to ships equipped with mono-fuel engines, ships with multi-fuel engines have greater flexibility in fuel selection, enabling companies to mitigate the fuel cost in response to fluctuating prices across different fuel options. For example, the fuel price of low sulfur fuel oil (LSFO) increased after the outbreak of the conflict between Russia and Ukraine [18], while the price of methanol fluctuated little and is lower than that of LSFO [19]. In this case, ships equipped with multi-fuel engines, such as a LSFO + methanol engine, can burn methanol. Conversely, when the price of LSFO is lower than that of methanol, the ship may switch to LSFO, resulting in significant fuel cost reductions. However, the investment cost of multi-fuel engines is much higher than that of mono-fuel engines [20]. Moreover, the fleet deployment decision is a strategic decision with long-term impact on liner companies. Therefore, liner companies require scientific and quantitative analyses to support optimal selection of multi-fuel engines for ships considering fuel price uncertainty.

To offer liner companies a scientifically grounded decision support tool, this study investigates an optimization problem of selecting multi-fuel engines for ships and proposes an integer programming (IP) model to optimally determine ship order choice in terms of the fuel engine type, fleet deployment, fuel selection, and speed optimization, with the aim of minimizing the total weekly cost containing the weekly investment cost for ship orders and the weekly fuel cost. To validate the model, numerical approaches with different instance scales are conducted. Sensitivity analyses are also performed to assess the impacts of the weekly investment cost for ordering different types of ships and the budget allocated for ship orders, as well as the potential application of new fuel engine types. Particularly, we evaluate the feasibility of commercially applying ships equipped with LSFO + methanol + liquefied natural gas (LNG) engines from a cost point of view. Through these experiments and analyses, this study aims to provide valuable managerial insights for liner companies seeking to optimize their operations and achieve green shipping practices.

The remainder of this study is organized as follows. Section 2 provides a comprehensive review of the relevant literature. Section 3 describes the problem, formulates a nonlinear IP model for the problem and applies several linearization techniques to linearize the model. In Section 4, computational experiments are conducted to evaluate the proposed model. Section 5 concludes the paper by summarizing the main findings and pointing out further research.

2. Literature Review

Liner shipping, characterized by fixed shipping routes and service frequencies, plays an important role in international trade, particularly in the context of international maritime trade. Interested readers may refer to [21,22] for liner shipping basics. The scheduling of liner shipping involves several operations decisions, including ship sailing speed, fleet deployment, and fuel selection, which are reviewed in the following paragraphs.

Ship speed optimization is a practical and important approach to reducing the total cost in the maritime industry [23]. Ref. [24] developed a speed optimization model aimed at minimizing the sum of fuel and ship operating costs, demonstrating that the established model provides reasonable speed optimization decisions for shipping companies. Similarly, [25] explored the optimal speed determination for shipping companies. The results suggest that slow steaming is beneficial to reducing the total cost when the fuel cost saving outweighs the capital and operating costs. In the field of container liner transportation, [26] focused on the speed optimization problem and propose a mixed-integer nonlinear programming model with the objective of minimizing the sum of operating, capital, and voyage costs. To tackle this complex problem, they designed a probability-based tabu search algorithm. [27] also highlighted that, in response to high fuel prices, shipping companies often resort to implement slow steaming to reduce the total cost.

The second key operations decision of shipping companies is fleet deployment. Refs. [11,28,29] provided a comprehensive overview of this problem. Ref. [30] revisited the liner fleet deployment models in the literature and identified an implicit assumption leading to non-essential redundant ships in fleet deployment. To address this issue, a more realistic liner fleet deployment model was proposed, resulting in cost reductions of up to 15%. Ref. [31] proposed a nonlinear mixed integer programming model for the liner fleet deployment and demand fulfilment problem to minimize the total cost. Two efficient algorithms were developed to solve the model for different scales of numerical instances, and the experimental results demonstrated the effectiveness of the model and algorithms. Ref. [32] investigated a problem of fleet deployment and shipping revenue management in liner shipping networks under demand uncertainty. A two-stage robust optimization model with demand randomness represented by probability-free uncertain sets was proposed. An exact algorithm based on column and constraint generation was designed, and an M-tightening technique was used to accelerate the convergence of the algorithm.

In response to the increasingly severe energy shortage, researchers are shifting their focus towards new energy sources as alternative fuels [33–35]. Refs. [36,37] provided a comprehensive literature review on alternative fuels. According to [38], the fuel cost constitutes a significant portion of shipping operating costs, ranging from 20% to 60%. Hence, the selection of fuels has a direct impact on the fuel consumption of ships. To qualitatively assess the potential of different fuels, including low sulphur heavy fuel oil (LSHFO), hydrogen, ammonia, renewable natural gas (RNG), bioethanol, bio-dimethyl ether (bioDME), and biodiesel, ref. [39] used a multi-dimensional decision-making framework and revealed that the most promising alternative fuel for shipping is methanol, while zero-carbon synthetic fuels such as hydrogen and ammonia prove to be uneconomical choices. Furthermore, ref. [40] proposed a new investment appraisal method to compare the costs of LNG-fueled ships with conventional ships. The results indicate that LNG-fueled ships generally contain lower fuel costs than traditional ships, albeit at the expense of higher initial investment costs for LNG-fueled ships.

In summary, previous studies in the field of liner shipping scheduling primarily focus on individual aspects such as speed optimization, fleet deployment, and the selection of fuels. However, these studies lack a methodology to comprehensively determine ship order choice in terms of the fuel engine type, fleet deployment, fuel selection, and speed optimization, despite the fact that these decisions were interconnected and mutually influenced each other. Specifically, the total shipping cost contains both ship investment costs and fuel costs. Sailing at lower speeds can lead to reduced fuel consumption and potential fuel cost savings. However, this necessitates increasing the number of ships deployed on the routes, consequently increasing ship investment costs. Additionally, with fluctuating fuel prices, ships equipped with multiple-fuel engines have greater flexibility in fuel selection to achieve the optimal fuel costs compared to ships with mono-fuel engines, but the corresponding ship investment cost is higher. To address this research gap and provide comprehensive decision support for shipping companies, this study proposes an IP to optimize the combined factors of ship order choice in terms of the fuel engine type, fleet deployment, fuel selection, and speed optimization in a holistic manner.

3. Problem Description and Model Formulation

The emergence of multi-fuel engines provides shipping companies with increased opportunities for flexible operations. For operational purposes, a shipping company plans to order a group of ships characterized by their fuel engine types with a limited budget, and then deploy existing and ordered ships on its shipping network. As this problem is a two-stage problem, we formulate a two-stage IP model to help the shipping company optimally determine ship order choice in terms of the fuel engine type, fleet deployment, fuel selection, and speed optimization. This section first introduces the detailed background of the problem in Section 3.1, then formulates the mathematical model in Section 3.2, and finally linearizes the proposed model in Section 3.3.

3.1. Problem Background

We consider the shipping company operating on a shipping network containing a set R of ship routes indexed by r. In order to conduct container liner shipping, the shipping company possesses a fleet of ships characterized by their fuel engine types. A set K of fuel engine types (including mono-fuel and multi-fuel engines) indexed by k and a set F of available fuels indexed by f are available in this study. Here, notice that we let F_k represent a subset of fuels available for fuel engine k, $F_k \subset F$. Ships equipped with multi-fuel engines can use any one available fuel while sailing. However, ships with mono-fuel engines can only use the corresponding type of fuel.

Let m_k represent the number of ships with fuel engine type k owned by the shipping company at present. For operational purposes, the company intends to order a group of ships with a budget represented by g. Obviously, ships equipped with multi-fuel engines are much more expensive than ships with mono-fuel engines. However, ships equipped with multi-fuel engines can choose to use the most cost-effective fuel in the future considering price fluctuations of different fuels, resulting in a substantial reduction of operating costs. As is usual in stochastic programming formulations, fuel price uncertainty is represented by a set S of scenarios indexed by s. Our problem is a two-stage stochastic problem that involves a first-stage decision of determining the number of ships with fuel engine type k ordered (represented by α_k), and second-stage decisions of determining under each scenario, the number of ships with fuel engine type k deployed on ship route r (represented by β_{rks}), a binary variable (represented by ε_{rvs}) that describes sailing speeds of ships deployed on each ship route, as well as fuel selection for ships with multi-fuel engine types by minimizing the total fuel cost, because ships equipped with multi-fuel engines always choose the most cost-effective fuel.

Let b_k represent the weekly investment cost for ordering a ship with fuel engine type k. In this case, the total weekly ordering cost cannot exceed the total budget for ships ordered. Additionally, for each fuel engine type, the total deployed ships cannot exceed the sum of existing and ordered ships. Moreover, to ensure the smooth operation of each route, at least one ship and, at most, t_r ships can be deployed on each route. Although multiple fuels are acceptable fuels for ships equipped with multi-fuel engines, each ship with the multi-fuel engine can only use one type of fuel under each scenario. Moreover, sailing speeds of deployed ships on all routes under each scenario should satisfy the feasible speed range of ships (i.e., a set V of all feasible sailing speeds). Finally, a weekly visit pattern to each port of call needs to be guaranteed because this shipping company provides liner shipping.

This study aims to minimize the expected total weekly cost, which consists of two parts: weekly investment cost for ship orders, and weekly fuel cost. Recall that b_k represents the weekly investment cost for ordering a ship with fuel engine type k. Hence, the weekly investment cost for ship orders can be calculated by $\sum_{k\in K} b_k\alpha_k$. The calculation of the weekly fuel cost is more complicated because multiple engine types are available in this study. Maritime-related studies find that the fuel consumption of a ship in a unit of time is proportional to the sailing speed [41,42]. Let l_r represent the length of a round trip for route r (n mile). At the same time, for ships with multi-fuel engine types, fuel selection is determined by minimizing the total fuel cost. Hence, the total fuel cost of completing a round trip of ship route r by a ship equipped with fuel engine type k can be calculated by $\sum_{v\in V} \varepsilon_{rvs}\frac{l_r}{v}\min\limits_{f\in F_k} a_{fs}i_{f,1}v^{i_{f,2}}$, where a_{fs}, and $i_{f,1}$ as well as $i_{f,2}$ represent the unit price of fuel f under scenario s (\$/ton), and two coefficients to calculate the unit fuel consumption of a sailing ship using fuel f per hour, respectively. Hence, the expected total weekly cost can be calculated by $\mathrm{Min}[\sum_{k\in K} b_k\alpha_k+\sum_{s\in S} p_s\sum_{r\in R}\sum_{k\in K}\frac{\beta_{rks}}{\sum_{k'\in K}\beta_{r,k',s}}\sum_{v\in V}\varepsilon_{rvs}\frac{l_r}{v}\min\limits_{f\in F_k}(a_{fs}i_{f,1}v^{i_{f,2}})]$, where p_s represents the probability of scenario s. More explanations about the objective function are provided below. The total weekly fuel cost is calculated by adding up the fuel costs of each ship traveling through all routes. Since this study allows ships with different engine types to be deployed on each route, an additional term $\frac{\beta_{rks}}{\sum_{k'\in K}\beta_{r,k',s}}$ is needed to compute the proportion of a specific type of ship. This proportion is then multiplied by the corresponding fuel cost to obtain the total weekly fuel cost of the specific type of ships deployed on the route.

In summary, this study aims to help shipping companies optimally determine ship order choice in terms of the fuel engine type, fleet deployment, fuel selection, and speed optimization. Specifically, this study develops a nonlinear IP model to minimize the expected total weekly cost consisting of the weekly investment cost and the weekly fuel cost.

3.2. Model Formulation

A two-stage IP model is formulated based on the above analysis. One assumption is considered in this study: the ships' dwell time at all ports of call on each ship route is deterministic. Before introducing the mathematical model, the notation used in this study is summarized as follows.

Indices and sets:

R	set of all ship routes, $r \in R$.
K	set of all available fuel engine types, $k \in K$.
F	set of all available fuels, $f \in F$.
F_k	subset of fuels available for fuel engine k, $F_k \subset F$.
V	set of all available sailing speeds, $v \in V$.
S	set of all scenarios, $s \in S$.
Z_+	set of all non-negative integers.

Parameters:

a_{fs}	unit price of fuel f under scenario s (\$/ton).
b_k	weekly investment cos t for ordering a ship with fuel engine type k (\$).
g	budget for ordering ships (\$).
m_k	number of existing ships with fuel engine type k owned by the shipping company.
l_r	length of a round trip for route r (n mile).
d_r	total duration of a ship dwells at all ports of call on ship route r (hour).

t_r	maximum number of ships that can be deployed on ship route r.
p_s	probability of scenario s.
$i_{f,1}$, $i_{f,2}$	coefficients to calculate the unit fuel consumption of a sailing ship using fuel f per hour.

Variables:

α_k	integer, the number of ships with fuel engine type k ordered.
β_{rks}	integer, the number of ships with fuel engine type k deployed on ship route r under scenario s.
ε_{rvs}	binary, equals 1 if and only if the speed of ships deployed on ship route r underscenario s is v; 0 otherwise.

Mathematical model

$$[\mathbf{M1}]\ \mathrm{Min}\left[\sum\nolimits_{k\in K} b_k\alpha_k+\sum\nolimits_{s\in S} p_s\sum\nolimits_{r\in R}\sum\nolimits_{k\in K}\frac{\beta_{rks}}{\sum_{k'\in K}\beta_{r,k',s}}\sum\nolimits_{v\in V}\varepsilon_{rvs}\frac{l_r}{v}\min_{f\in F_k}\left(a_{fs}i_{f,1}v^{i_{f,2}}\right)\right] \tag{1}$$

$$\text{subject to}:\quad \sum\nolimits_{k\in K} b_k\alpha_k \le g \tag{2}$$

$$1 \le \sum\nolimits_{k\in K}\beta_{rks} \le t_r \qquad \forall r\in R, s\in S \tag{3}$$

$$\sum\nolimits_{r\in R}\beta_{rks} \le m_k+\alpha_k \qquad \forall k\in K, s\in S \tag{4}$$

$$\sum\nolimits_{v\in V}\varepsilon_{rvs} = 1 \qquad \forall\, r\in R, s\in S \tag{5}$$

$$\frac{l_r}{\sum_{v\in V} v\varepsilon_{rvs}} + d_r \le 168\sum\nolimits_{k\in K}\beta_{rks} \qquad \forall\, r\in R, s\in S \tag{6}$$

$$\alpha_k \in Z_+ \qquad \forall\, k\in K \tag{7}$$

$$\beta_{rks} \in Z_+ \qquad \forall\, r\in R, k\in K, s\in S \tag{8}$$

$$\varepsilon_{rvs} \in \{0,1\} \qquad \forall\, r\in R, v\in V, s\in S \tag{9}$$

Objective (1) minimizes the total weekly cost, including the weekly investment cost for ship orders and the weekly fuel cost. Constraint (2) states that the total weekly investment cost cannot exceed the total budget for ordering ships. Constraints (3) guarantee that at least one ship and, at most, t_r ships can be deployed on each route. Constraints (4) ensure that for each ship engine type, the total deployed ships cannot exceed the sum of existing and ordered ships under each scenario. Constraints (5) ensure that sailing speeds of deployed ships on all routes under each scenario satisfy the feasible speed range of ships. Constraints (6) guarantee the weekly visit pattern to each port of call. Constraints (7)–(9) define the ranges of the variables.

3.3. Model Linearization

Model [M1], proposed in Section 3.2, contains a nonlinear objective function and nonlinear constraints (6). We linearize them one by one in this section.

First is the linearization process of objective function (1). Nonlinear parts in objective (1) is $\sum_{s\in S} p_s\sum_{r\in R}\sum_{k\in K}\frac{\beta_{rks}}{\sum_{k'\in K}\beta_{r,k',s}}\sum_{v\in V}\varepsilon_{rvs}\frac{l_r}{v}\min_{f\in F_k}\left(a_{fs}i_{f,1}v^{i_{f,2}}\right)$. We first define an auxiliary binary variable δ_{rvns} to deal with $\frac{\varepsilon_{rvs}}{\sum_{k'\in K}\beta_{r,k',s}}$. To that end, some new constraints are defined as follows.

Newly defined parameter:

n_r minimum number of ships that can be deployed on ship route r, $n_r = \left\lceil \left(\frac{l_r}{\overline{v}} + d_r\right)/168 \right\rceil$, where $\overline{v}$ represents the maximum sailing speed.

Newly defined variable:

δ_{rvns} binary, equals 1 if, and only if, the number of ships with all fuel engine types deployed on ship route r and the sailing speed of these ships under scenario s are n and v, respectively, 0 otherwise.

Newly defined constraints:

$$\sum_{v\in V}\sum_{n\in\{n_r,\cdots,t_r\}}\delta_{rvns} = 1 \qquad \forall r\in R, s\in S \tag{10}$$

$$\sum_{n\in\{n_r,\cdots,t_r\}}\delta_{rvns} = \varepsilon_{rvs} \qquad \forall r\in R, v\in V, s\in S \tag{11}$$

$$\sum_{v\in V}\sum_{n\in\{n_r,\cdots,t_r\}} n\delta_{rvns} = \sum_{k\in K}\beta_{r,k,s} \qquad \forall r\in R, s\in S \tag{12}$$

$$\delta_{rvns}\in\{0,\ 1\} \qquad \forall r\in R, v\in V, n\in\{n_r,\cdots,t_r\}, s\in S \tag{13}$$

Then, $\sum_{s\in S} p_s \sum_{r\in R}\sum_{k\in K}\frac{\beta_{rks}}{\sum_{k'\in K}\beta_{r,k',s}}\sum_{v\in V}\varepsilon_{rvs}\frac{l_r}{v}\min\limits_{f\in F_k}(a_{fs}i_{f,1}v^{i_{f,2}})$ is transformed to $\sum_{s\in S} p_s \sum_{r\in R}\sum_{k\in K}\sum_{v\in V}\sum_{n\in\{n_r,\cdots,t_r\}}\beta_{rks}\delta_{rvns}\frac{l_r}{nv}\min\limits_{f\in F_k}(a_{fs}i_{f,1}v^{i_{f,2}})$. Then, we address the nonlinear part of the product of β_{rks} and δ_{rvns} by defining an auxiliary variable φ_{rkvns} to replace it.

Newly defined parameter:

M_r big m for linearization; maximum value of β_{rks}, which is equal to the value of t_r.

Newly defined variable:

φ_{rkvns} integer, equals β_{rks} if and only if the value of δ_{rvns} is equal to 1, 0 otherwise.

Newly defined constraints:

$$\varphi_{rkvns} \geq \beta_{rks} + (\delta_{rvns} - 1)M_r \qquad \forall r\in R, k\in K, v\in V, n\in\{n_r,\cdots,t_r\}, s\in S \tag{14}$$

$$\varphi_{rkvns} \leq \beta_{rks} \qquad \forall r\in R, k\in K, v\in V, n\in\{n_r,\cdots,t_r\}, s\in S \tag{15}$$

$$\varphi_{rkvns} \leq \delta_{rvns}M_r \qquad \forall r\in R, k\in K, v\in V, n\in\{n_r,\cdots,t_r\}, s\in S \tag{16}$$

$$\varphi_{rkvns}\in Z_+ \qquad \forall r\in R, k\in K, v\in V, n\in\{n_r,\cdots,t_r\}, s\in S. \tag{17}$$

The final version of the objective is provided below.

$$\text{Min}\left[\sum_{k\in K} b_k\alpha_k + \sum_{s\in S} p_s\sum_{r\in R}\sum_{k\in K}\sum_{v\in V}\sum_{n\in\{n_r,\cdots,t_r\}}\frac{l_r}{nv}\varphi_{rkvns}\min_{f\in F_k}(a_{fs}i_{f,1}v^{i_{f,2}})\right] \tag{18}$$

In terms of nonlinear constraints, constraints (6) can be directly transformed to linear constraints (19) because 0 does not belong to the feasible speed range of ships.

$$\sum_{v\in V}\frac{l_r}{v}\varepsilon_{rvs} + d_r \leq 168\sum_{k\in K}\beta_{rks} \qquad \forall\, r\in R, s\in S \tag{19}$$

Finally, nonlinear model [M1] is transformed to the following model [M2]:

[M2] objective (18) subject to: constraints (2)–(5), (7)–(17), (19).

4. Computational Experiments

A large number of computational experiments are conducted on a PC (14 cores of CPUs, 2.5 GHz, Memory 64 GB) to evaluate the performance of the model which is implemented in Gurobi 10.0.0 (Anaconda, Python). This section first introduces the value setting in Section 4.1, shows experimental results in Section 4.2, and summarizes managerial insights in Section 4.3.

4.1. Experimental Setting

Nine ship routes with different ports of call and round-trip sailing distances are used in this study, which are in line with the setting in [4]. Details of each route, including the ports of call and the round-trip sailing distances (l_r), are shown in Table 1. LSFO, methanol, and LNG are three available fuels in the computational experiments, denoted by $f = 1$, $f = 2$, and $f = 3$, respectively. A total of six fuel engine types are available, including LSFO engine, methanol engine, LNG engine, LSFO + methanol engine, LSFO + LNG engine, and methanol + LNG engine. Ref. [43] indicate that the life span of ships is 30 years; according to [44], the total investment cost of a LSFO engine ship with 1638 deadweight ton (around 170 TEUs) is \$312,100; the weekly investment cost of the LSFO engine ship is set to \$6242 ($\frac{312{,}100\times 0.02\times 1.02^{30\times 52}}{1.02^{30\times 52}-1} = 6242$). The weekly investment costs (b_k) for ordering a ship with each fuel engine type k are summarized in Table 2. The budget for ordering ships (g) is set to \$100,000.

Table 1. Summary of nine ship routes.

Route ID	Port Rotation (City)	l_r (n mile)
1	Trincomalee → Tuticorin → Trincomalee	490
2	Singapore → Ho Chi Minh → Singapore	1298
3	Singapore → Laem Chabang → Singapore	1518
4	Singapore → Kochi → Singapore	3706
5	Singapore → Mormugao → Singapore	4434
6	Kaohsiung → Bagui Bay/San Fernando → Manila → Kaohsiung	1126
7	Chennai → Singapore → Port Klang → Chennai	3344
8	Singapore → General Santos → Manila → Singapore	3485
9	Hai Phong → Zhanjiang → Hong Kong → Cam Ranh → Hai Phong	1868

Table 2. Summary of weekly ship investment costs.

Fuel Engine k	F_k	b_k
1 (LSFO engine)	LSFO	6242
2 (methanol engine)	methanol	6678
3 (LNG engine)	LNG	6532
4 (LSFO + methanol engine)	LSFO, methanol	10,462
5 (LSFO + LNG engine)	LSFO, LNG	10,172
6 (methanol + LNG engine)	methanol, LNG	10,752

The minimum and maximum sailing speeds are set to 12 and 18 (knot), respectively. Twenty scenarios are used and each scenario s is with a probability (p_s) of $1/|S|$. Based on the realistic fuel prices of LSFO, methanol, and LNG from January 2021 to August 2022 [18,19], the unit fuel prices of LSFO, methanol and LNG are set, as shown in Table 3. The numbers of existing ships with fuel engine type $k = 1$, $k = 2$, $\cdots$, $k = 6$ owned by the shipping company (m_k) are set to 1, 1, 1, 0, 0 and 0, respectively. The port time in each port of call is set to 24 h [20], and the total duration of a ship dwells at all ports of call on ship route r (d_r) is the sum of the time spent in all ports of call. The maximum number of ships that can be deployed on each ship route (t_r) is set to 8. Values of $i_{1,1}$, $i_{1,2}$, $i_{3,1}$, and $i_{3,2}$ are set to 0.00085, 2, 0.000765, and 2, respectively, which is in line with the setting in [45]. According to [46], methanol has about the same density as LSFO, but only half the heating value. Compared to LSFO, twice the amount of methanol is required to generate the same amount of heat and travel the same distance. Therefore, values of $i_{2,1}$, and $i_{2,2}$ are set to 0.0017, and 2, respectively.

Table 3. Summary of the unit prices of LSFO, methanol and LNG.

s	a_{1s} ($/ton)	a_{2s} ($/ton)	a_{3s} ($/ton)	s	a_{1s} ($/ton)	a_{2s} ($/ton)	a_{3s} ($/ton)
1	354	408	370	11	537	588	1187
2	376	416	475	12	479	556	1590
3	439	425	428	13	510	520	1616
4	421	445	417	14	601	518	1486
5	438	472	491	15	674	516	1785
6	458	470	548	16	792	562	1690
7	484	468	628	17	757	543	1548
8	489	466	822	18	812	520	1477
9	469	503	914	19	814	512	2024
10	504	515	1293	20	686	504	2953

Note: a_{1s}, a_{2s}, and a_{3s} represent the unit prices of LSFO, methanol, and LNG under scenario s, respectively.

4.2. Experimental Results

The model [M2] is solved by the Gurobi solver. The numerical experiment includes 20 sets of instances with different shipping network composition. Table 4 records the computation results, including the objective function values denoted by “Objective Value”, the central processing unit (CPU) running time denoted by “Time”, and the relative difference between the current best solution and the current best dual bound denoted by “Gap”. The solution time for each computational instance is limited to two hours. As shown in Table 4, among 20 numerical instances, 16 sets of numerical instances are solved to optimality within two hours. The average GAP value of the remaining four sets of numerical instances that cannot be solved to optimality within two hours is 0.51%.

Table 4. Experimental results of the cases.

Case ID	Route ID	Distance	Objective Value	Time (s)	GAP
1	1, 2	1788	12,549.44	3.68	–
2	3, 4	5224	47,509.35	27.93	–
3	5, 6	5560	48,747.80	5.49	–
4	7, 8	6829	63,070.01	5.15	–
5	1, 2, 3	3306	30,161.99	869.49	–
6	1, 3, 4	5714	53,182.03	45.16	–
7	5, 6, 9	7428	71,386.09	9.05	–
8	2, 3, 6, 9	5810	60,044.34	143.66	–
9	1, 2, 3, 4	7012	67,991.94	46.17	–
10	6, 7, 8, 9	9823	99,146.92	7203.12	0.78%
11	2, 3, 5, 7, 9	12,462	123,771.46	441.26	–
12	1, 3, 5, 7, 8	13,271	130,119.60	103.52	–
13	5, 6, 7, 8, 9	14,257	142,960.23	95.12	–
14	1, 3, 5, 6, 8, 9	12,921	132,548.92	349.45	–
15	2, 3, 5, 6, 7, 8	15,205	152,898.80	7204.91	0.62%
16	4, 5, 6, 7, 8, 9	17,963	181,552.62	7204.13	0.14%
17	1, 2, 3, 4, 5, 6, 7	15,916	161,099.31	705.27	–
18	1, 3, 4, 5, 7, 8, 9	18,845	191,055.90	100.40	–
19	2, 4, 5, 6, 7, 8, 9	19,261	196,362.63	6763.78	–
20	3, 4, 5, 6, 7, 8, 9	19,481	199,246.29	7206.53	0.51%

Note: The en-dash in the “GAP” column indicates that this set of numerical instance can be solved to optimality within two hours.

4.3. Sensitivity Analyses

The budget for ordering ships (g) is adjusted according to the company’s financial situation in real life. Additionally, the weekly investment cost for ordering a ship (b_k) also decreases as the shipbuilding technology matures. However, in the above numerical instances, values of b_k and g are set to be deterministic. Therefore, case 18 is selected as an example to conduct sensitivity analyses on these parameters to find their influences on the operation decisions. In addition, with the continuous development of technology, ships with LSFO + methanol + LNG engines may also be manufactured. This section also discusses whether such ships are worthy of mass production and market application in terms of economic cost.

Firstly, this study investigates the impact of the weekly investment cost for ordering a ship with fuel engine type k on ship order choice. In the experiments in Section 4.2, the weekly investment costs for ordering a ship with fuel engine type LSFO engine, methanol engine, LNG engine, LSFO + methanol engine, LSFO + LNG engine, and methanol + LNG engine are set to 6242, 6678, 6532, 10,462, 10,172, and 10,752, respectively. As shown in Table 5, the objective value decreases as the weekly investment cost decreases. This is obvious because the weekly investment cost for ship orders is an important part of the total weekly cost, namely the objective value. Here, notice that when the values of $b_1, b_2, \cdots, b_6$ is lower than 5800, 6200, 6100, 10,000, 9800 and 10,300, respectively, the number of ordering ships begins to increase. This is because if the number of ships ordered increases, ships can implement slow steaming to save the fuel cost while maintaining the liner frequency. When the weekly fuel savings in fuel costs outweigh the additional weekly ordering costs, increasing the number of ships may achieve a reduction in the total weekly cost.

Table 5. Impact of the weekly investment cost for ordering a ship with fuel engine type k.

b_1 (\$)	b_2 (\$)	b_3 (\$)	b_4 (\$)	b_5 (\$)	b_6 (\$)	Objective Value
7000	7400	7300	11,200	11,000	11,500	198,636
6800	7200	7100	11,000	10,800	11,300	196,636
6600	7000	6900	10,800	10,600	11,100	194,636
6400	6800	6700	10,600	10,400	10,900	192,636
6200	6600	6500	10,400	10,200	10,700	190,636
6000	6400	6300	10,200	10,000	10,500	188,636
5800	6200	6100	10,000	9800	10,300	186,619
5600	6000	5900	9800	9600	10,100	184,419
5400	5800	5700	9600	9400	9900	182,219
5200	5600	5500	9400	9200	9700	180,019

The impact of the budget for ordering ships on ship order choice is then investigated. The value of the budget for ordering ships (g) is set to \$100,000 in previous experiments. However, the value of g may become larger or smaller according to the company's financial situation in real life. Therefore, the value of the budget for ordering ships (g) in this sensitivity analysis varies between 60,000 and 150,000. From Table 6, we can see that the objective value decreases as the budget for ordering ships increases. However, when the value of g exceeds 70,000, the objective value keeps the same. This makes sense because the lower the budget for ordering ships, the fewer ships can be ordered. In order to ensure liner service frequency, ships need to sail faster, leading to higher fuel cost. The increase in the weekly fuel cost outweighs the saving in the weekly investment cost for ship orders, resulting in an increase in the objective value. When the budget for ordering ships increases to a certain level where the increased weekly investment cost is balanced with the saving in the weekly fuel cost, the objective value remains unchanged.

Common multi-fuel engines used in ships today are primarily dual-fuel engines, such as LSFO + methanol engines and LSFO + LNG engines, while ships with tri-fuel engines are rarely produced. To explore the potential application of tri-fuel engines, we use the LSFO + methanol + LNG engine as an example to conduct a sensitivity analysis. For this analysis, let the index of this type of engine be 7, and value of parameters b_7 and m_7 for such ships are set to 14,000 and 0, respectively. We find from Table 7, in this case, that the presence of the LSFO + methanol + LNG engine does not lead to any changes in the decisions made by the shipping company, that is, the total cost remains unchanged. This result is reasonable, as the current price of the LSFO + methanol + LNG engine is not sufficiently attractive to shipping companies. However, given the fluctuations in fuel prices, ships equipped with tri-fuel engines, particularly those with the LSFO + methanol + LNG engine, may have the opportunity to take full advantage of flexible operations when the fuel cost saving is substantial enough to offset the investment cost gap between ships with different engines. Therefore, we next investigate the viability of the LSFO + methanol + LNG engine under the fuel price fluctuation by exploring how much the weekly investment cost of this engine needs to decrease to become advantageous. From Table 8, we find that when the weekly investment cost for ordering a ship with the LSFO + methanol + LNG engine (b_7) does not exceed $13,000, ordering such a ship becomes advantageous based on the adjusted fuel prices in Table 7. Moreover, the lower the weekly investment cost for ordering a ship with the LSFO + methanol + LNG engine, the more such ships can be ordered to achieve the optimal total cost.

Table 6. Impact of the budget for ordering ships on ship order choice.

g	Objective Value	g	Objective Value
150,000	191,056	100,000	191,056
140,000	191,056	90,000	191,056
130,000	191,056	80,000	191,056
120,000	191,056	70,000	191,056
110,000	191,056	60,000	195,216

Table 7. Summary of the adjusted unit prices of LSFO, methanol and LNG.

s	a_{1s} ($/ton)	a_{2s} ($/ton)	a_{3s} ($/ton)	s	a_{1s} ($/ton)	a_{2s} ($/ton)	a_{3s} ($/ton)
1	837	552	326	11	489	579	915
2	888	564	418	12	437	547	1224
3	1038	576	377	13	465	513	1244
4	1155	603	367	14	548	509	1144
5	1036	640	432	15	1062	267	1375
6	1083	637	482	16	1247	292	1301
7	1143	633	553	17	1192	281	1192
8	994	631	958	18	1279	270	1138
9	427	681	946	19	1283	265	1096
10	460	736	996	20	1081	261	1043

Table 8. Impact of the new LSFO + methanol + LNG engine.

b_7	Objective Value	α_1	α_2	α_3	α_4	α_5	α_6	α_7	Time (s)	GAP
12,000	229,493	1	0	4	0	0	0	5	7209.65	0.15%
12,500	231,473	3	0	7	0	0	0	1	7204.87	0.64%
13,000	231,973	3	0	7	0	0	0	1	7212.76	0.82%
13,500	232,025	3	0	9	0	0	0	0	7223.55	0.80%
14,000	231,913	3	0	9	0	0	0	0	7205.52	0.91%
14,500	231,913	3	0	9	0	0	0	0	7204.55	0.83%
15,000	232,112	3	1	8	0	0	0	0	7208.17	0.87%
15,500	231,913	3	0	9	0	0	0	0	7204.80	0.90%
16,000	231,913	3	0	9	0	0	0	0	7205.48	0.93%

5. Conclusions

Even though maritime transport offers the advantages of cost-effectiveness and safety, the long sailing distance results in significant fuel consumption and exhaust emissions. As liner shipping plays a vital role in maritime transport, achieving green liner shipping becomes crucial for promoting green shipping. Although existing studies related to liner shipping scheduling focus on speed optimization, fleet deployment, and fuel selection separately, they do not comprehensively investigate the interconnected decisions of fuel selection, fleet deployment, fuel selection, and speed optimization. To fill this research gap, this study investigates a multi-fuel engine selection optimization problem and proposes a two-stage IP model to provide the optimal selection of multi-fuel engines for ships considering fuel price uncertainty. Contributions of this paper are summarized in the following two aspects: First, the proposed model [M1] may help liner companies to optimally determine ship order choice in terms of the fuel engine type, fleet deployment, fuel selection, and speed optimization with the aim of minimizing the total weekly cost containing the weekly investment cost for ship orders and the weekly fuel cost. Due to the difficulty of solving the nonlinear model, several linearization techniques are applied to transform the nonlinear model [M1] into a simpler linear model [M2] that can then be directly solved by Gurobi. By providing shipping companies with scientific support for their decision-making process, this study contributes to the advancement of green liner shipping practices. Second, sensitivity analyses are conducted on crucial parameters, including the weekly investment cost for ordering a ship with different fuel engine types, the budget for ordering ships, and the potential application of the new fuel engine type. These analyses provide useful insights for managerial decision-making.

Future research is summarized as follows. First, incorporating realistic data for numerical approaches would enhance the practicality and usefulness of the results, yielding more realistic managerial insights. Moreover, more life cycle factors, such as income, loan repayment, interest payments, maintenance and repair costs, can be incorporated into the problem. Additionally, new policies and requirements for decarbonization, such as a carbon tax [47], energy efficiency existing ships index (EEXI), and carbon intensity indicator (CII), can be considered. Lastly, future studies may explore the impact of potential government subsidies on the investment cost for ships with multi-fuel engines, as such incentives play a vital role in promoting the adoption of new green technologies [6].

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References

1. Stavroulakis, P.J.; Papadimitriou, S. Total cost of ownership in shipping: A framework for sustainability. *J. Shipp. Trade* **2022**, *7*, 14. [CrossRef]
2. Lin, D.Y.; Juan, C.J.; Ng, M.W. Evaluation of green strategies in maritime liner shipping using evolutionary game theory. *J. Clean. Prod.* **2021**, *279*, 123268. [CrossRef]
3. Seddiek, I.S.; Elgohary, M.M. Eco-friendly selection of ship emissions reduction strategies with emphasis on SO_X and NO_X emissions. *Int. J. Nav. Archit. Ocean Eng.* **2014**, *6*, 737–748. [CrossRef]
4. Wu, Y.; Huang, Y.; Wang, H.; Zhen, L.; Shao, W. Green technology adoption and fleet deployment for new and aged ships considering maritime decarbonization. *J. Mar. Sci. Eng.* **2023**, *11*, 36. [CrossRef]
5. Zhen, L.; Wu, Y.; Wang, S.; Laporte, G. Green technology adoption for fleet deployment in a shipping network. *Transp. Res. Part B Methodol.* **2020**, *139*, 388–410. [CrossRef]
6. Wang, S.; Qi, J.; Laporte, G. Governmental subsidy plan modeling and optimization for liquefied natural gas as fuel for maritime transportation. *Transp. Res. Part B Methodol.* **2022**, *155*, 304–321. [CrossRef]
7. Song, J.Y.; Xu, C.Y.; Wang, C.X. Impacts of the carbon tax on green shipping supply chain under the port competition. *Expert Syst.* **2023**, e13229. [CrossRef]
8. Wang, Y.; Wang, S. Deploying, scheduling, and sequencing heterogeneous vessels in a liner container shipping route. *Transp. Res. Part E Logist. Transp. Rev.* **2021**, *151*, 102365. [CrossRef]
9. Elmi, Z.; Singh, P.; Meriga, V.K.; Goniewicz, K.; Borowska-Stefańska, M.; Wiśniewski, S.; Dulebenets, M.A. Uncertainties in Liner Shipping and Ship Schedule Recovery: A State-of-the-Art Review. *J. Mar. Sci. Eng.* **2022**, *10*, 563. [CrossRef]
10. Agarwal, R.; Ergun, O. Ship scheduling and network design for cargo routing in liner shipping. *Transp. Sci.* **2008**, *42*, 175–196. [CrossRef]

11. Christiansen, M.; Hellsten, E.; Pisinger, D.; Sacramento, D.; Vilhelmsen, C. Liner shipping network design. *Eur. J. Oper. Res.* **2020**, *286*, 1–20. [CrossRef]
12. European Commission (EC) A European Green Deal–Striving to Be the First Climate-Neutral Continent. 2023. Available online: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en (accessed on 5 August 2023).
13. European Commission (EC) Fit for 55. 2023. Available online: https://www.consilium.europa.eu/en/policies/green-deal/fit-for-55-the-eu-plan-for-a-green-transition/ (accessed on 5 August 2023).
14. Department of Energy (DoE). Biden Clean Energy Plan Update: March 2023. 2023. Available online: https://www.energy.gov/articles/biden-clean-energy-plan-update-march-2023 (accessed on 5 August 2023).
15. Environment and Climate Change Canada (ECCC). What Are the Clean Fuel Regulations? 2022. Available online: https://www.canada.ca/en/environment-climate-change/services/managing-pollution/energy-production/fuel-regulations/clean-fuel-regulations/about.html (accessed on 5 August 2023).
16. Ministry of New and Renewable Energy (MNRE). Solar Energy. 2023. Available online: https://mnre.gov.in/solar/current-status/ (accessed on 5 August 2023).
17. UKGov. Policy Paper—The Ten Point Plan for a Green Industrial Revolution. 2020. Available online: https://www.gov.uk/government/publications/the-ten-point-plan-for-a-green-industrial-revolution (accessed on 5 August 2023).
18. Ship and Bunker (S&B). Rotterdam Bunker Prices. 2023. Available online: https://shipandbunker.com/prices/emea/nwe/nl-rtm-rotterdam (accessed on 25 April 2023).
19. Marine Methanol (M&M). Fuel Price Comparison. 2023. Available online: http://marinemethanol.com/?nav=meohp (accessed on 25 April 2023).
20. Tan, R.; Psaraftis, H.N.; Wang, D.Z.W. The speed limit debate: Optimal speed concepts revisited under a multi-fuel regime. *Transp. Res. Part D Transp. Environ.* **2022**, *111*, 103445. [CrossRef]
21. Dulebenets, M.A.; Pasha, J.; Abioye, O.F.; Kavoosi, M. Vessel scheduling in liner shipping: A critical literature review and future research needs. *Flex. Serv. Manuf. J.* **2021**, *33*, 43–106. [CrossRef]
22. Meng, Q.; Zhao, H.; Wang, Y.D. Revenue management for container liner shipping services: Critical review and future research directions. *Transp. Res. Part E Logist. Transp. Rev.* **2019**, *128*, 280–292. [CrossRef]
23. Ng, M. Vessel speed optimisation in container shipping: A new look. *J. Oper. Res. Soc.* **2019**, *70*, 541–547. [CrossRef]
24. Li, X.H.; Sun, B.Z.; Guo, C.Y.; Du, W.; Li, Y.J. Speed optimization of a container ship on a given route considering voluntary speed loss and emissions. *Appl. Ocean Res.* **2020**, *94*, 101995. [CrossRef]
25. Wu, W.M. The optimal speed in container shipping: Theory and empirical evidence. *Transp. Res. Part E Logist. Transp. Rev.* **2020**, *136*, 101903. [CrossRef]
26. Wang, S.; Zhao, Q. Probabilistic tabu search algorithm for container liner shipping problem with speed optimisation. *Int. J. Prod. Res.* **2022**, *60*, 3651–3668. [CrossRef]
27. Wang, S.; Liu, Z.; Meng, Q. Segment-based alteration for container liner shipping network design. *Transp. Res. Part B Methodol.* **2015**, *72*, 128–145. [CrossRef]
28. Meng, Q.; Wang, S.; Andersson, H.; Thun, K. Containership routing and scheduling in liner shipping: Overview and future research directions. *Transp. Sci.* **2014**, *48*, 265–280. [CrossRef]
29. Wang, S.; Meng, Q. Container liner fleet deployment: A systematic overview. *Transp. Res. Part C Emerg. Technol.* **2017**, *77*, 389–404. [CrossRef]
30. Ng, M. Revisiting a class of liner fleet deployment models. *Eur. J. Oper. Res.* **2017**, *257*, 773–776. [CrossRef]
31. Zhen, L.; Hu, Y.; Wang, S.; Laporte, G.; Wu, Y. Fleet deployment and demand fulfillment for container shipping liners. *Transp. Res. Part B Methodol.* **2019**, *120*, 15–32. [CrossRef]
32. Lai, X.F.; Wu, L.X.; Wang, K.; Wang, F. Robust ship fleet deployment with shipping revenue management. *Transp. Res. Part B Methodol.* **2022**, *161*, 169–196. [CrossRef]
33. Perčić, M.; Frković, L.; Pukšec, T.; Ćosić, B.; Li, O.L.; Vladimir, N. Life-cycle assessment and life-cycle cost assessment of power batteries for all-electric vessels for short-sea navigation. *Energy* **2022**, *251*, 123895. [CrossRef]
34. Perčić, M.; Vladimir, N.; Fan, A. Techno-economic assessment of alternative marine fuels for inland shipping in Croatia. *Renew. Sustain. Energy Rev.* **2021**, *148*, 111363. [CrossRef]
35. Perčić, M.; Vladimir, N.; Jovanović, I.; Koričan, M. Application of fuel cells with zero-carbon fuels in short-sea shipping. *Appl. Energy* **2022**, *309*, 118463. [CrossRef]
36. Moshiul, A.M.; Mohammad, R.; Hira, F.A.; Maarop, N. Alternative marine fuel research advances and future trends: A bibliometric knowledge mapping approach. *Sustainability* **2022**, *14*, 4947. [CrossRef]
37. Yuan, Y.P.; Wang, J.X.; Yan, X.P.; Shen, B.Y.; Long, T. A review of multi-energy hybrid power system for ships. *Renew. Sustain. Energy Rev.* **2020**, *132*, 110081. [CrossRef]
38. Tan, R.; Duru, O.; Thepsithar, P. Assessment of relative fuel cost for dual fuel marine engines along major Asian container shipping routes. *Transp. Res. Part E Logist. Transp. Rev.* **2020**, *140*, 102004. [CrossRef]
39. Xing, H.; Stuart, C.; Spence, S.; Chen, H. Alternative fuel options for low carbon maritime transportation: Pathways to 2050. *J. Clean. Prod.* **2021**, *297*, 126651. [CrossRef]
40. Fokkema, J.E.; Buijs, P.; Vis, I.F.A. An investment appraisal method to compare LNG-fueled and conventional vessels. *Transp. Res. Part D Transp. Environ.* **2017**, *56*, 229–240. [CrossRef]

41. Fagerholt, K.; Gausel, N.T.; Rakke, J.G.; Psaraftis, H.N. Maritime routing and speed optimization with emission control areas. *Transp. Res. Part C Emerg. Technol.* **2015**, *52*, 57–73. [CrossRef]
42. Xia, J.; Li, K.X.; Ma, H.; Xu, Z. Joint planning of fleet deployment, speed optimization, and cargo allocation for liner shipping. *Transp. Sci.* **2015**, *49*, 922–938. [CrossRef]
43. Wang, H.; Oguz, E.; Jeong, B.; Zhou, P. Life cycle cost and environmental impact analysis of ship hull maintenance strategies for a short route hybrid ferry. *Ocean Eng.* **2018**, *161*, 20–28. [CrossRef]
44. CN-ESHIP. Information Reporting, 2022. Available online: https://www.cn-eship.com (accessed on 19 April 2023).
45. Wu, Y.; Huang, Y.; Wang, H.; Zhen, L. Joint planning of fleet deployment, ship refueling, and speed optimization for dual-fuel ships considering methane slip. *J. Mar. Sci. Eng.* **2022**, *10*, 1690. [CrossRef]
46. Deniz, C.; Zincir, B. Environmental and economical assessment of alternative marine fuels. *J. Clean. Prod.* **2016**, *113*, 438–449. [CrossRef]
47. Jovanović, I.; Perčić, M.; Koričan, M.; Vladimir, N.; Fan, A. Investigation of the viability of unmanned autonomous container ships under different carbon pricing scenarios. *J. Mar. Sci. Eng.* **2022**, *10*, 1991. [CrossRef]