

Article

Green Technology Adoption and Fleet Deployment for New and Aged Ships Considering Maritime Decarbonization

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Abstract: Maritime decarbonization and strict international regulations have forced liner companies to find new solutions for reducing fuel consumption and greenhouse gas emissions in recent years. Green technology is regarded as one of the most promising alternatives to achieve environmental benefits despite its high initial investment costs. Therefore, a scientific method is required to assess the possibility of green technology adoption for liner companies. This study formulates a mixed-integer nonlinear programming model to determine whether to retrofit their ship fleets with green technology and how to deploy ships while taking maritime decarbonization into account. To convert the nonlinear model into a linear model that can be solved directly by off-the-shelf solvers, several linearization techniques are applied in this study. Sensitivity analyses involving the influences of the initial investment cost, fuel consumption reduction rate of green technology, unit fuel cost, and fixed operating cost of a ship on operation decisions are conducted. Green technology may become more competitive when modern technology development makes it efficient and economical. As fuel and fixed operating costs increase, more ships retrofitted with green technology will be deployed on all shipping routes.



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1. Introduction

Although the shipping industry is regarded as environmentally friendly transportation, it releases enormous amounts of greenhouse gases and air pollutants [1–5]. For example, greenhouse gases from shipping account for approximately 3% of global greenhouse gases annually [6], and the shipping industry emitted 833 million metric tons of carbon dioxide (CO₂) in 2021 [7]. Large amounts of carbon dioxide released into the atmosphere inevitably affect the global climate. If the shipping industry does not make a green and sustainable transition, it will be more harmful to the climate. Therefore, maritime decarbonization has become a key concern for the public, enterprises, organizations, and countries, and green shipping has drawn much more attention [1,8], which means that the methods of achieving maritime decarbonization in the context of green shipping is very important.

To curb the rise in the average global temperature, the Intergovernmental Panel on Climate Change (IPCC), which is an intergovernmental group of the United Nations (UN) responsible for advancing knowledge on human-induced climate change, says global emissions must be cut in half by 2030 to prevent the earth from global warming by more than 1.5 °C this century [9]. However, the International Maritime Organization (IMO),

which is a UN-specialized agency responsible for shipping, has a more realistic but slower target of cutting shipping emissions in half by 2050 [10]. However, even this goal is prohibitively expensive to achieve, costing an estimated 3.4 trillion USD to achieve [11]. However, at the same time, the global demand for shipping is still growing [12]. Therefore, this study aims to address the question of whether it is possible to grow the shipping industry while reducing its influence on the climate simultaneously.

In order to achieve maritime decarbonization, there are many approaches that the liner companies can take. Specifically, the first method is operational planning. Among all operational measures, speed optimization is one of the most common methods because existing literature believes that the generation of exhaust gas is related to the fuel consumption of ships, and the fuel consumption of ships is approximately a cubic relationship of speed. Hence, liner companies use slow steaming to reduce fuel consumption and exhaust emissions. For example, a container ship consumes 200 and 125 tons of fuel per day at 24 and 21 knots, respectively [13]. However, slow streaming inexorably corresponds to the need to deploy more ships for a weekly service pattern. Moreover, green technology adoption is the second method for maritime decarbonization, such as scrubbers for sulfur dioxide (SO₂) removal of more than 95% [14] and Silverstream for CO₂ removal of 1.6 million tonnes over the ships' lifecycle [15], which means retrofitting ships with green technology can significantly reduce ship exhaust emissions. However, an unavoidable disadvantage of green technology adoption is its very high installation cost. For example, the cost of installing a scrubber could be between 1 million and 5 million USD [16]. Therefore, in terms of strategic-level planning, one must decide whether refitting ships with green technology requires scientific methodologies, such as mathematical programming.

When using mathematical programming to help liner companies scientifically decide whether to refit ships with green technology, a phenomenon that needs to be paid extra attention to is that liner companies often have ships with different service years. However, few studies incorporate ships of different ages into their models while taking green technology adoption and the relationship between speed and fuel consumption into account. New and aged ships have different hull and propeller roughness, which directly affects fuel consumption and exhaust gases [17]. In addition, the cost of retrofitting ships with green technology is also different, and the saving rates of adopted green technology are also different. Therefore, in the face of new and aged ships, green technology adoption decisions may be different, which requires scientific decision making to a higher degree.

This study is motivated by the above-mentioned real-world challenge in green shipping, and it may contribute to liner operations management by proposing a nonlinear mixed-integer programming (MIP) model. This study provides liner companies with a new scientific decision-making method to determine whether to retrofit their ship fleets with new technologies and how to deploy ships while taking maritime decarbonization into account. Numerical experiments with different route compositions are first conducted to evaluate the performance of the proposed model. Moreover, sensitivity analyses with crucial parameters, including the investment cost and fuel consumption saving rate of green technology, unit price of fuel, and weekly fixed operating cost, are carried out to show the influence of these aspects on the results to look for managerial insights.

The remainder of this study is organized as follows. Related works are reviewed in Section 2. Section 3 elaborates on the problem background and proposes a nonlinear MIP model for the integrated problem. Model linearization process is shown in Section 4. Section 5 summarizes the computational experiments, including basic experiments and sensitivity analyses for managerial insights. Conclusions are outlined in the Section 6.

2. Literature Review and Discussion

In general, this study is mainly related to the general fleet deployment problem, which refers to [18–20] for a systematic overview. The main contribution of this study is to put the fleet deployment problem in the background of green shipping, which has recently drawn much attention in academic fields and ship operating markets. According

to [21], to reduce fuel consumption and greenhouse gas emissions, alternative fuels, optimal operational measures, and green technology maturity, are the primary elements that liner companies consider. However, there are still some barriers to burning alternative fuels, such as hydrogen and liquefied natural gas (LNG). Ref. [22] demonstrated that no readily available fuel option to deliver significant environmental benefits when considering local pollutants and greenhouse gas emissions generated during the fuel life-cycle. Ref. [23] assessed environmental friendliness and economic, technical, and safety factors to evaluate the potential usage of green hydrogen in the shipping industry and found that green hydrogen with high density can pose higher fire and explosion risks when coupled with low temperature. Thus, this study focuses on operational measures and green technologies. This section briefly reviews the related works through two streams: green shipping with optimal operational measures and green shipping with the adoption of green technologies.

In the area of green shipping with optimal operational measures, sailing speed, displacement, and voyage length may significantly impact fuel consumption. Low fuel consumption causes fewer greenhouse gas emissions. Ref. [24] studied a joint optimization problem of service frequency, sailing speed, and ship allocation for a long-haul liner service route. They used a piecewise linear function to approximate the fuel consumption function. Considering a general fuel consumption function associated with the speed and cargo load, Ref. [25] studied a joint optimization problem of fleet deployment, speed optimization, and cargo allocation to maximize the total profit. Under carbon emissions policies, Ref. [26] established a mixed-integer nonlinear programming (MINLP) model to address a joint optimization problem of ship speed and fleet deployment. They also proposed a simulated annealing algorithm to solve the problem. Ref. [27] considered sailing speed and the payload of ships, and they formulated a multi-objective MINLP model to optimize ship allocations in different voyage routes considering multiple ship types. Ref. [28] proposed a joint optimization problem of ship path, sailing speed, and ship allocation to minimize the total cost of ships deployed on all routes, including fuel cost, carbon tax, and fixed operating cost. They also took into account correlations between ship speed and low-sulfur fuel usage in international emission control areas (ECAs) where ships are required to use low-sulfur fuel.

Despite the high initial investment cost, ship operators tend to consider green technology adoption. Firstly, the efficiency of energy-saving devices is evaluated by some scholars. Specifically, Ref. [29] showed a fuel-saving effect of 6.8 percent in an energy-saving device by using simulated data. Ref. [30] used real-time data to assess fuel savings for an oil tanker installed with an energy-saving device. To ensure the possibility of green technology adoption, some scholars consider its merits and demerits together from the point of view of sustainability. Ref. [31] proposed a generalized subjective methodology as a transparent evaluation tool to help ship operators choose their preferred emissions reduction methods. In order to have a comprehensive assessment of technological maturity, investment cost, environmental effects, and social and political support for green technology, Ref. [32] developed a multi-criteria decision-making method on the technology selection for emission reduction. Ref. [33] studied existing risks of scrubber installation in an analytical framework and compared returns and profits between scrubber technologies and other abatement techniques. More and more researchers currently take the green technology adoption into their models in compliance with international regulations. Ref. [34] compared solutions for burning different fuels and scrubber installation based on realistic data from a cruise ship. Ref. [35] investigated a quantitative decision methodology to determine whether to adopt scrubbers and shore power under the background of ECAs. Ref. [36] conducted quantitative case studies of the most important shipping sectors and found that scrubbers are more promising than fuel switching.

To sum up, most existing literature related to green shipping with optimal operational measures focuses on optimizing ship speeds to reduce the daily fuel cost, such as [24,25,28]. With an increasing awareness of maritime decarbonization, green technology adoption draws more attention in academic fields. In practice, liner companies always allocate ships

with different hull conditions to different routes. However, few studies incorporate ships of different ages into their models while taking green technology adoption into account. In addition, fleet deployment and green technology adoption are strategic decisions that pose a further influence on the daily operations of ships, which means that a scientific method needs to be proposed to help liner companies make decisions. Hence, this study aims to fill the research gap and proposes an MINLP model to jointly optimize fleet deployment, green technology adoption, and sailing speeds while considering maritime decarbonization.

3. Problem Description and Model Formulation

New green technologies are proposed to reduce fuel consumption and emissions. However, the initial investment cost for ships is usually high. Hence, this study formulates a non-linear mixed-integer programming (MIP) model to provide liner companies with a scientific decision-making method to determine whether to retrofit their ship fleets with new technologies and how to deploy ships while taking maritime decarbonization into account. This section first introduces the detailed background of the problem in Section 3.1 and then formulates the mathematical model in Section 3.2.

3.1. Use Case Background

We consider a liner company operating on a shipping network containing a set R of ship routes indexed by r . Each ship route consists of a set I_r of ports of call (legs) indexed by i . To carry out container shipping, the liner company owns ships of a set K of ship types indexed by k . Let o_k , m_r , and V represent the number of ships of type k owned by the liner company, the maximum number of ships that can be deployed on ship route r , and a set of all possible sailing speeds indexed by v , respectively. Ships of different types are homogenous in terms of the cost structure and capacity, but are different in hull conditions, which means both new and aged ships are considered in this study. Suppose that a new green technology is proposed, and the technology can help a retrofitted ship save a proportion of g amount of main engine fuel (g denotes the main engine fuel consumption saving rate (%) after retrofitting ships with the new green technology), which means that the weekly main engine fuel consumption of the retrofitted ship is $1 - g$ (%) of that of the ship without retrofit. However, retrofitting ships with the new green technologies is usually expensive. Therefore, the liner company has to determine whether to retrofit new and aged ships with the new green technology and how to deploy ships to the shipping network with the aim of minimizing the total weekly cost.

In order to ensure the daily operation of the liner company, ship deployment and speed optimization must be determined. For the ship deployment problem, let β_{rk}^1 and β_{rk}^2 represent the number of ships of type k retrofitted with the new technology deployed on ship route r and the number of ships of type k without retrofit deployed on ship route r , respectively. Obviously, the total number of deployed ships of type k ($\sum_{r \in R} (\beta_{rk}^1 + \beta_{rk}^2)$) cannot exceed o_k . In addition, the number of ships deployed on ship route r ($\sum_{k \in K} (\beta_{rk}^1 + \beta_{rk}^2)$) must be between 1 and m_r . Finally, ship deployment influences speed optimization because of the weekly arrival pattern. Specifically, the total time (in hours) for a ship finishing its route, including sailing time and duration time, needs to equal 168 times the number of ships deployed on the route. Moreover, the sailing speeds of all deployed ships during each voyage leg should be between the minimum speed denoted by $\underline{v}$ and the maximum speed denoted by $\bar{v}$.

This study aims to minimize the total weekly cost, which consists of three parts: weekly investment cost for retrofitting ships with the new green technology, weekly operating cost, and weekly fuel cost. Let b , c , and a represent the weekly investment cost for retrofitting a ship with the new green technology, weekly operating cost of a deployed ship, and unit price of fuel, respectively. Hence, the weekly investment cost and weekly operating cost can be calculated by $\sum_{k \in K} \sum_{r \in R} b \beta_{rk}^1 + \sum_{r \in R} \sum_{k \in K} c (\beta_{rk}^1 + \beta_{rk}^2)$. The last part of the total weekly cost is the weekly fuel cost, which involves costs of both main and auxiliary engines. Weekly auxiliary engine fuel cost is simple and can be directly

calculated by $\sum_{r \in R} \sum_{k \in K} 7ae_k(\beta_{rk}^1 + \beta_{rk}^2)$, where e_k denotes the amount of fuel consumed by the auxiliary engine of a ship of type k per day. However, weekly main engine fuel cost is more complicated. To make this study closer to reality, both sailing speed and actual displacement of ships are allowed to affect the main engine's fuel consumption. According to [37], the weekly main engine fuel cost without green technology retrofit is $\sum_{r \in R} \sum_{k \in K} \sum_{i \in I_r} \sum_{v \in V} af_{k,1}v^{f_{k,2}}\varepsilon_{riv}n_{ri}f_{k,3}\frac{l_{ri}}{v}$, where n_{ri} , l_{ri} , and ε_{riv} represent the actual displacement of the ship during voyage i on ship route r , length of the i^{th} voyage leg of ship route r , and a binary variable that equals 1 if, and only if, the speed of the ship sailing during voyage i on ship route r is v and 0 otherwise, respectively, and $f_{k,1}$, $f_{k,2}$, and $f_{k,3}$ are coefficients for unit fuel consumption calculation. However, the new green technology can help retrofitted ships save a proportion of g amount of main engine fuel, which means that the weekly main engine fuel consumption of the retrofitted ship is $(1 - g)$ of that of the ship without retrofit. Therefore, the total weekly cost can be calculated by $\sum_{r \in R} \sum_{k \in K} b\beta_{rk}^1 + \sum_{r \in R} \sum_{k \in K} c(\beta_{rk}^1 + \beta_{rk}^2) + \sum_{r \in R} \sum_{k \in K} a[7e_k(\beta_{rk}^1 + \beta_{rk}^2) + \sum_{i \in I_r} \sum_{v \in V} f_{k,1}v^{f_{k,2}}\varepsilon_{riv}n_{ri}f_{k,3}\frac{l_{ri}((1-g)\beta_{rk}^1 + \beta_{rk}^2)}{v\sum_{k' \in K}(\beta_{rk'}^1 + \beta_{rk'}^2)}]$.

In summary, this study aims to help liner companies to determine whether to retrofit new and aged ships with the new green technology and how to deploy ships on ship routes with the consideration of maritime decarbonization. Specifically, this study develops a non-linear MIP model to minimize the total weekly cost consisting of weekly investment cost, weekly operating cost, and weekly fuel cost by determining optimal fleet deployment, speed optimization, and green technology adoption.

3.2. Model Formulation

Based on the above analysis of the problem, this study formulates a non-linear MIP model in this section. Two assumptions are considered in this study: (I) ships of different types are homogenous in terms of the cost structure and capacity; (II) ships' dwell time at all ports of call on a ship route is deterministic.

Before formulating the MIP model for this problem, we list the notation used in this paper as follows.

Indices and sets:

R set of all ship routes, $r \in R$.

I_r set of all ports of call (legs) on ship route r , $i \in I_r$.

K set of all available ship types, $k \in K$.

V set of all possible sailing speeds, $v \in V$, $V = \{\underline{v}, \underline{v} + 1, \dots, \bar{v} - 1, \bar{v}\}$, where $\bar{v}$ and $\underline{v}$ represent the maximum and minimum speeds of ships, respectively.

Z_+ set of all non-negative integers.

Parameters:

a unit price of fuel (USD/ton).

b weekly investment cost for retrofitting a ship with the new green technology (USD).

c weekly fixed operating cost of a deployed ship (USD).

d_r total duration of a ship dwells at all ports of call on ship route r (hour).

e_k amount of fuel consumed by the auxiliary engine of a ship of type k per day (ton/day).

$f_{k,1}$, $f_{k,2}$, $f_{k,3}$ coefficients to calculate the unit fuel consumption of a ship of type k for travelling per hour.

g main engine fuel consumption saving rate (%) after retrofitting ships with the new green technology.

l_{ri} voyage length of the i^{th} leg of ship route r (n mile).

m_r maximum number of ships that can be deployed on ship route r .

n_{ri} actual displacement of the ship during voyage i on ship route r (ton).

o_k number of ships of type k owned by the liner company.

Variables:

β_{rk}^1 integer, number of ships of type k retrofitted with the new technology deployed on ship route r .

β_{rk}^2 integer, number of ships of type k without retrofit deployed on ship route r .
 ε_{riv} binary equals 1 if, and only if, the speed of the ship sailing during voyage i on ship route r is v ; it is 0 otherwise.

Mathematical model

Based on the above definition of parameters and variables, a non-linear MIP model is formulated as follows.

$$[\text{M1}] \text{ Min } \sum_{r \in R} \sum_{k \in K} (b\beta_{rk}^1 + c(\beta_{rk}^1 + \beta_{rk}^2)) + \sum_{r \in R} \sum_{k \in K} a[7e_k(\beta_{rk}^1 + \beta_{rk}^2) + \sum_{i \in I_r} \sum_{v \in V} f_{k,1} v^{f_{k,2}} \varepsilon_{riv} n_{ri}^{f_{k,3}} \frac{l_{ri}((1-g)\beta_{rk}^1 + \beta_{rk}^2)}{v \sum_{k' \in K} (\beta_{rk'}^1 + \beta_{rk'}^2)}] \quad (1)$$

subject to:

$$1 \leq \sum_{k \in K} (\beta_{rk}^1 + \beta_{rk}^2) \leq m_r \quad \forall r \in R \quad (2)$$

$$\sum_{v \in V} \sum_{i \in I_r} \frac{l_{ri}}{v} \varepsilon_{riv} + d_r = 168 \sum_{k \in K} (\beta_{rk}^1 + \beta_{rk}^2) \quad \forall r \in R \quad (3)$$

$$\sum_{v \in V} \varepsilon_{riv} = 1 \quad \forall r \in R, i \in I_r \quad (4)$$

$$\sum_{r \in R} (\beta_{rk}^1 + \beta_{rk}^2) \leq o_k \quad \forall k \in K \quad (5)$$

$$\beta_{rk}^1, \beta_{rk}^2 \in \mathbb{Z}_+ \quad \forall r \in R, k \in K \quad (6)$$

$$\varepsilon_{riv} \in \{0, 1\} \quad \forall r \in R, i \in I_r, v \in V. \quad (7)$$

Objective (1) minimizes the total weekly cost. Constraints (2) guarantee that at least one ship and at most m_r ships should be deployed on each route. Constraints (3) ensure that the total number of hours for a ship finishing its route is 168 times the number of ships deployed on the route because of the weekly arrival pattern. Constraints (4) ensure that sailing speeds of the deployed ships during each voyage on all routes satisfy the feasible speed range of ships. Constraints (5) guarantee that the number of ships of type k deployed on all ship routes cannot exceed the number of ships of type k owned by the liner company. Constraints (6)–(7) define the ranges of the decision variables.

4. Model Linearization

It is almost impossible to directly solve the non-linear model [M1], which contains multiple non-linear parts in Objective Function (1). Therefore, this study uses some linearization methods to linearize the non-linear parts. Before introducing our linearization methods, a transformation of Constraints (3) is first introduced. The feasibility of the model might be affected because the sailing speed in Constraints (3) is discretized. Hence, Constraints (3) are replaced by Constraints (8), which replace the equal symbol with a greater than or equal to symbol to ensure the weekly service pattern.

$$\sum_{v \in V} \sum_{i \in I_r} \frac{l_{ri}}{v} \varepsilon_{riv} + d_r \leq 168 \sum_{k \in K} (\beta_{rk}^1 + \beta_{rk}^2) \quad \forall r \in R. \quad (8)$$

The first non-linear part is $\sum_{k' \in K} (\beta_{rk'}^1 + \beta_{rk'}^2)$ in the denominator in Objective (1). To linearize this part, some newly defined variables and constraints are added as follows. In this case, $\frac{1}{\sum_{k' \in K} (\beta_{rk'}^1 + \beta_{rk'}^2)}$ can be replaced with $\sum_{h \in \{1, \dots, m_r\}} \frac{\pi_{rivh}}{h}$, which is obviously linear.

Newly defined parameter:

M refers to the big M for linearization.

Newly defined variable:

π_{rivh} binary, equals 1 if, and only if, the speed of the ship sailing during voyage i on ship route r is v and the number of ships deployed on route r is h ; it is 0 otherwise.

Newly defined constraints:

$$\pi_{rivh} \leq \varepsilon_{riv} \quad \forall r \in R, i \in I_r, v \in V, h \in \{1, \dots, m_r\} \quad (9)$$

$$\sum_{v \in V} \sum_{h \in \{1, \dots, m_r\}} \pi_{rivh} = 1 \quad \forall r \in R, i \in I_r \quad (10)$$

$$\sum_{v \in V} \sum_{h \in \{1, \dots, m_r\}} \pi_{rivh} h = \sum_{k \in K} (\beta_{rk}^1 + \beta_{rk}^2) \quad \forall r \in R, i \in I_r \quad (11)$$

$$\pi_{rivh} \in \{0, 1\} \quad \forall r \in R, i \in I_r, v \in V, h \in \{1, \dots, m_r\}. \quad (12)$$

Hence, Objective (1) is replaced with the following objective.

$$\begin{aligned} \text{Min} \sum_{r \in R} \sum_{k \in K} (b\beta_{rk}^1 + c(\beta_{rk}^1 + \beta_{rk}^2)) + \sum_{r \in R} \sum_{k \in K} a[7e_k(\beta_{rk}^1 + \beta_{rk}^2) + \\ \sum_{i \in I_r} \sum_{v \in V} \sum_{h \in \{1, \dots, m_r\}} f_{k,1} v^{f_{k,2}} \pi_{rivh} n_{ri}^{f_{k,3}} l_{ri} ((1-g)\beta_{rk}^1 + \beta_{rk}^2) / vh] \end{aligned} \quad (13)$$

Notice that Objective (14) still contains a non-linear part $\sum_{r \in R} \sum_{k \in K} \sum_{i \in I_r} \sum_{v \in V} \sum_{h \in \{1, \dots, m_r\}} a f_{k,1} v^{f_{k,2}} \pi_{rivh} n_{ri}^{f_{k,3}} l_{ri} ((1-g)\beta_{rk}^1 + \beta_{rk}^2) / vh$. We first redefine β_{rk}^1 and β_{rk}^2 as a new binary variable δ_{rkpq} , which equals 1 if, and only if, the number of ships of type k with retrofit deployed on route r are p and the number of ships of type k without retrofit deployed on route r are q , and it equals 0 otherwise. Some newly defined variables and constraints are added as follows.

Newly defined variable:

δ_{rkpq} binary equals 1 if, and only if, the number of ships of type k with retrofit deployed on route r are p and the number of ships of type k without retrofit deployed on route r are q ; it is 0 otherwise.

Newly defined constraints:

$$\sum_{p \in \{0, \dots, m_r\}} \sum_{q \in \{0, \dots, m_r\}} \delta_{rkpq} = 1 \quad \forall r \in R, k \in K \quad (14)$$

$$\sum_{p \in \{0, \dots, m_r\}} \sum_{q \in \{0, \dots, m_r\}} \delta_{rkpq} p = \beta_{rk}^1 \quad \forall r \in R, k \in K \quad (15)$$

$$\sum_{p \in \{0, \dots, m_r\}} \sum_{q \in \{0, \dots, m_r\}} \delta_{rkpq} q = \beta_{rk}^2 \quad \forall r \in R, k \in K \quad (16)$$

$$\delta_{rkpq} \in \{0, 1\} \quad \forall r \in R, k \in K, p \in \{0, \dots, m_r\}, q \in \{0, \dots, m_r\}. \quad (17)$$

Then, Objective (14) becomes:

$$\begin{aligned} \text{Min} \sum_{r \in R} \sum_{k \in K} (b\beta_{rk}^1 + c(\beta_{rk}^1 + \beta_{rk}^2)) + \sum_{r \in R} \sum_{k \in K} a[7e_k(\beta_{rk}^1 + \beta_{rk}^2) + \\ \sum_{i \in I_r} \sum_{v \in V} \sum_{h \in \{1, \dots, m_r\}} \sum_{p \in \{0, \dots, m_r\}} \sum_{q \in \{0, \dots, m_r\}} f_{k,1} v^{f_{k,2}} \pi_{rivh} n_{ri}^{f_{k,3}} l_{ri} \delta_{rkpq} ((1-g)p + q) / vh]. \end{aligned} \quad (18)$$

However, Objective (19) still contains a non-linear part, which is a product of two binary variables. Therefore, some newly variables and constraints are added as follows to linearize this part.

Newly defined variable:

$\theta_{rivhkpq}$ binary equals 1 if, and only if, both π_{rivh} and δ_{rkpq} are equal to 1; it is 0 otherwise.

Newly defined constraints:

$$\theta_{rivhkpq} \geq \pi_{rivh} + \delta_{rkpq} - 1$$

$$\forall r \in R, i \in I_r, v \in V, h \in \{1, \dots, m_r\}, k \in K, p \in \{0, \dots, m_r\}, q \in \{0, \dots, m_r\} \quad (19)$$

$$\theta_{rivhkpq} \leq \pi_{rivh}$$

$$\forall r \in R, i \in I_r, v \in V, h \in \{1, \dots, m_r\}, k \in K, p \in \{0, \dots, m_r\}, q \in \{0, \dots, m_r\} \quad (20)$$

$$\theta_{rivhkpq} \leq \delta_{rkpq}$$

$$\forall r \in R, i \in I_r, v \in V, h \in \{1, \dots, m_r\}, k \in K, p \in \{0, \dots, m_r\}, q \in \{0, \dots, m_r\} \quad (21)$$

$$\theta_{rivhkpq} \in \{0, 1\}$$

$$\forall r \in R, i \in I_r, v \in V, h \in \{1, \dots, m_r\}, k \in K, p \in \{0, \dots, m_r\}, q \in \{0, \dots, m_r\}. \quad (22)$$

As a result, the final linear version of the model [M1] becomes:

$$\begin{aligned}
 \text{[M2] Min } & \sum_{r \in R} \sum_{k \in K} (b\beta_{rk}^1 + c(\beta_{rk}^1 + \beta_{rk}^2)) + \sum_{r \in R} \sum_{k \in K} a[7e_k(\beta_{rk}^1 + \beta_{rk}^2) + \\
 & \sum_{i \in I_r} \sum_{v \in V} \sum_{h \in \{1, \dots, m_r\}} \sum_{p \in \{0, \dots, m_r\}} \sum_{q \in \{0, \dots, m_r\}} f_{k,1} v^{f_{k,2}} \theta_{rvhkpq} n_{ri}^{f_{k,3}} l_{ri}((1-g)p+q)/vh] \\
 & \text{subject to: Constraints (2), (4)–(12), (14)–(17), and (19)–(22).}
 \end{aligned} \tag{23}$$

5. Computational Experiments

In order to evaluate the proposed model, we perform numerous computational experiments on a PC (4 cores of CPUs, 1.6 GHz, Memory 8 GB). The mathematical model proposed in this study is implemented in off-the-shelf solver Gurobi 9.0.1 (Anaconda 3 5.3.0, Anaconda Inc., Austin, TX, USA; Python 3.6.6, which can be found in <https://repo.anaconda.com/archive/>, accessed on 27 September 2018). This section first summarizes the value setting of used parameters in Section 5.1, reports experimental results in Section 5.2, and conducts sensitivity analyses to look for some managerial insights in Section 5.3.

5.1. Experimental Setting

Voyage length (l_{ri}) is obtained from the standard instances LINER-LIB (Brouer et al., 2013). The value of the weekly fixed operating cost of a deployed ship (c) is set to 180,000 USD, which is consistent with the setting in [38]. Since the average price of very low sulfur fuel oil (VLSFO) in 20 global ports from the beginning of September 2021 to the end of August 2022 is 790.5 USD/ton [39], and the unit fuel price (a) is set to 790.5 USD/ton. The average value of actual displacement during voyage i on ship route r (n_{ri}) is set to 200,000 tons (normal distribution with standard deviation 3000). The maximum number of ships that can be deployed on a ship route (m_r) is set to 10. The value of the number of ships of each type owned by the liner company (o_k) is set to 8. The value of the total duration (d_r) of a ship on route r is randomly selected from $[24 \times |I_r|, 48 \times |I_r|]$. The average value of daily fuel consumption of the auxiliary engines of type k (e_k) is set to 3 ton/day (normal distribution with standard deviation 0.5). The minimum and maximum values of sailing speed ($\underline{v}$ and $\bar{v}$) are set to 8 and 22 knots, respectively, which are in line with the setting in [35]. Six types of ships, including brand new ships and aged ships of different ages, are available in the computational experiments. Specifically, let ships of the ship type 1 represent brand new ships, and let ships with larger ship type numbers represent older ships. Therefore, the values of $f_{1,1}$, $f_{1,2}$, and $f_{1,3}$ are set to 0.000220, 2.5506, and 0.2072, respectively, which are consistent with the setting in related studies [37,40]; values of $f_{k,2}$ and $f_{k,3}$, $k \in K/\{1\}$, are set to 2.5506 and 0.2072, respectively; values of $f_{2,1}$, $f_{3,1}$, $f_{4,1}$, $f_{5,1}$, and $f_{6,1}$ are set to 0.000225, 0.000230, 0.000235, 0.000240, and 0.000245, respectively. The main engine fuel consumption saving rate (g) (%) after retrofitting ships with the new green technology is set to 5%, which is in line with the realistic data from a new green technology [41]. Since the new green technology can last the lifetime of the ship, the weekly investment cost (b) for retrofitting a ship with the new green technology is set to 40,000 USD, which is consistent with the realistic data [42]. Finally, the experimental setting of the parameters is summarized in Table 1.

Table 1. Summary of the value setting.

Parameters	Value Setting
c	180,000 USD
a	790.5 USD/ton
n_{ri}	200,000 tons (normal distribution with standard deviation 3000)
m_r	10
o_k	8
d_r	$[24 \times I_r , 48 \times I_r]$
e_k	3 ton/day (normal distribution with standard deviation 0.5)
$\underline{v}$ and $\bar{v}$	8 and 22 knots, respectively
$f_{1,1}, f_{1,2},$ and $f_{1,3}$	0.000220, 2.5506, and 0.2072, respectively
$f_{k,2}$ and $f_{k,3}$ ($k \in K/\{1\}$)	2.5506 and 0.2072, respectively
$f_{2,1}, f_{3,1}, f_{4,1}, f_{5,1},$ and $f_{6,1}$	0.000225, 0.000230, 0.000235, 0.000240, and 0.000245, respectively
g	5%
b	40,000 USD

5.2. Basic Analysis

To investigate the performance of the proposed linearized model [M2], we select nine routes with different port rotations to conduct the basic analysis, which can be seen in Table 2. We then conduct ten sets of numerical experiments with different route networks whose total route distances are represented by “Distance” in Table 3. Due to the large scale of computation, the central processing unit (CPU) time is limited to one hour. Computation results are recorded in Table 3, where the objective function value obtained by Gurobi is represented by “OBJ”, CPU running time is represented by “Time”, and the optimality gap within one hour is represented by “Gap”. From Table 3, the objective function value increases with increasing route distance, which is intuitive because more ships are needed for a longer route to maintain the weekly service frequency, and ships need more fuel to reach corresponding destinations. Moreover, CPU running time also increases with larger computing scale. Jointly considering the number of legs, route lengths, and optimality gaps within one hour for all computational instances, Case ID 6 is selected as a computational instance for the following sensitivity analyses.

Table 2. Summary of ten routes.

Route ID	Port Rotation (City)
1	Singapore → Ho Chi Minh → Singapore
2	Singapore → Laem Chabang → Singapore
3	Trincomalee → Tuticorin → Trincomalee
4	Singapore → Kochi → Singapore
5	Kaohsiung → Bagui Bay/San Fernando → Manila → Kaohsiung
6	Chennai → Singapore → Port Klang → Chennai
7	Singapore → Mormugao → Singapore
8	Singapore → General Santos → Manila → Singapore
9	Hai Phong → Zhanjiang → Hong Kong → Cam Ranh → Hai Phong

Table 3. Computational results of the basic analysis.

Case ID	Route ID	Distance (n Mile)	OBJ	Time (s)	Gap
1	1, 2	2816	792,315.16	715.92	0.00%
2	3, 4	4196	1,037,293.47	805.80	0.00%
3	5, 6	4470	1,120,442.39	2920.35	0.00%
4	7, 8	7919	1,700,707.68	3651.80	27.99%
5	1, 2, 3	3306	1,003,645.12	857.12	0.00%
6	1, 3, 4	5494	1,375,231.25	1411.20	0.00%
7	5, 6, 9	6338	1,731,652.32	3702.36	37.21%
8	1, 2, 7	7250	1,743,557.05	3667.23	12.31%
9	5, 7, 8	9045	2,145,864.20	3693.32	39.95%
10	1, 2, 3, 4	7012	1,792,859.55	3695.99	12.85%

Notes: “OBJ”, “Time”, and “Gap” represent the objective function value, CPU running time, and the optimality gap within one hour, respectively.

5.3. Sensitivity Analyses

Retrofitting investment cost and fuel consumption saving rate of the green technology may change as the technology develops. In addition, in the basic analysis, some important parameters, such as the unit fuel price and the weekly fixed operating cost, are set to be deterministic; however, these parameters are often fluctuated in real life. Hence, sensitivity analyses on these parameters are conducted to investigate the influences of these parameters on the operation decisions.

5.3.1. Impact of the Investment Cost and Fuel Consumption Saving Rate

This study first investigates the impact of the investment cost and fuel consumption saving rate on the operation decisions. Values of the main engine fuel consumption saving rate (g) (%) after retrofitting ships with the new green technology and the weekly investment cost (b) for retrofitting a ship with the new green technology are set to 5% and 40,000 USD, respectively, which is in line with the realistic data from a new green technology [41,42]. As the technology maturity develops, the initial investment cost may decrease and more green technologies with more effective environmental emission reduction effects may be adopted in the shipping markets in the long run, which means that in the future, as green technologies mature, b may decrease and g may increase. Thus, the value of b is set to vary from 1000 to 40,000, and the value of g is set to vary from 5% to 50%. Computational results are summarized in Table 4, where “Y” and “N” represent green technology retrofit in deployed ships and no green technology retrofit in deployed ships, respectively. The two numbers in parentheses after “Y” represent the total number of ships retrofitted with the green technology deployed on all ship routes and the total number of ships without retrofit deployed on all ship routes, respectively. From Table 4, we can find that more ships will be retrofitted with the green technology when the investment cost of green technology becomes lower. The same trend can be found when the green technology can bring more fuel consumption savings. However, if the investment cost of green technology keeps high or the fuel consumption saving rate keeps low, such as 40,000 USD/week weekly investment cost or 5% consumption saving rate, respectively, there is no need to adopt green technology because the high retrofitting investment cost outweighs the advantages brought by green technology retrofit. Moreover, when the value of g is large enough, green technology is preferred. On the one hand, to ensure the weekly service pattern, fewer ships with faster sailing speeds are needed, and fuel consumption brought by faster sailing speeds can be reduced due to the adoption of green technology. On the other hand, the operating cost of total deployed ships is reduced. In summary, the fleet deployment of liner companies is influenced by green technology adoption.

Table 4. Impact of the investment cost and fuel consumption saving rate on the operation decisions.

b (USD)		1000	5000	10,000	20,000	30,000	40,000
g (%)							
5		Y (5,0)	Y (1,4)	N	N	N	N
10		Y (5,0)	Y (4,1)	Y (1,4)	N	N	N
20		Y (5,0)	Y (5,0)	Y (4,1)	Y (1,4)	N	N
30		Y (5,0)	Y (5,0)	Y (4,1)	Y (3,1)	Y (1,4)	N
40		Y (4,0)	Y (4,0)	Y (4,0)	Y (3,1)	Y (3,1)	Y (3,1)
50		Y (4,0)	Y (4,0)	Y (4,0)	Y (3,1)	Y (3,1)	Y (3,1)

Notes: “Y”, and “N” represent green technology retrofit in deployed ships, and no green technology retrofit in deployed ships, respectively; Two numbers in parentheses after “Y” represent the total number of ships retrofitted with the green technology deployed on all ship routes and the total number of ships without retrofit deployed on all ship routes, respectively.

5.3.2. Impact of the Fuel Price

Considering the case where the weekly investment cost (b) for retrofitting a ship with the new green technology is equal to 10,000 USD, and the main engine fuel consumption saving rate (g) (%) after retrofitting ships with the new green technology is equal to 10%, this study then investigates the impact of the fuel cost on the operation decisions because fuel cost accounts for more than 50% of the total operating cost [43]. In the basic analysis, the unit price of fuel (a) is set to 790.5 USD/ton. Therefore, the value of a in this sensitivity analysis varies from 550 to 1200 USD/ton because the minimum and maximum fuel prices from the beginning of September 2021 to the end of August 2022 are 544.5 and 1125.5 USD/ton, respectively [39]. Relevant results are summarized in Table 5, which records the objective value represented by “OBJ”, the total number of ships retrofitted with the green technology deployed on all ship routes represented by “ $\sum_{r \in R} \sum_{k \in K} \beta_{rk}^1$ ”, and the total number of ships without retrofit deployed on all ship routes represented by “ $\sum_{r \in R} \sum_{k \in K} \beta_{rk}^2$ ”. From Table 5, it can be seen that as the price of fuel increases, the objective value increases because the weekly fuel cost increases. In addition, when the fuel price increases, more deployed ships are retrofitted with green technology because liner companies can benefit from green technology adoption while reducing fuel consumption.

Table 5. Impact of the fuel price on the operation decisions.

a (USD/ton)	OBJ	$\sum_{r \in R} \sum_{k \in K} \beta_{rk}^1$	$\sum_{r \in R} \sum_{k \in K} \beta_{rk}^2$
550	1,230,647.85	0	5
600	1,260,706.41	0	5
650	1,290,278.00	1	4
700	1,319,530.17	1	4
750	1,348,782.57	1	4
800	1,378,034.74	1	4
850	1,407,286.91	1	4
900	1,436,539.04	1	4
950	1,465,791.31	1	4
1000	1,493,564.26	4	1
1050	1,521,242.47	4	1
1100	1,548,920.63	4	1
1150	1,576,598.92	4	1
1200	1,604,276.43	4	1

Notes: “OBJ”, “ $\sum_{r \in R} \sum_{k \in K} \beta_{rk}^1$ ”, and “ $\sum_{r \in R} \sum_{k \in K} \beta_{rk}^2$ ” record the objective function value of model, the total number of ships retrofitted with the green technology deployed on all ship routes, and the total number of ships without retrofit deployed on all ship routes, respectively.

5.3.3. Impact of the Weekly Fixed Operating Cost

Finally, this study investigates the impact of the weekly fixed operating cost on the operation decisions. The value of the weekly fixed operating cost of a deployed ship (c) is set to 180,000 USD, which is consistent with the setting in [38]. However, the value of

c may become much larger due to the impact of the pandemic or other factors [44], or it could become much smaller due to technological updates. Therefore, the value range of c is 60,000 to 300,000, and relevant results are recorded in Table 6, which records the objective value represented by “OBJ”, the total number of ships retrofitted with the green technology deployed on all ship routes represented by “ $\sum_{r \in R} \sum_{k \in K} \beta_{rk}^1$ ”, and the total number of ships without retrofit deployed on all ship routes represented by “ $\sum_{r \in R} \sum_{k \in K} \beta_{rk}^2$ ”. From Table 6, we can find objective value increases with the higher weekly fixed operating cost of a deployed ship because the weekly fixed operating cost increases. When the weekly fixed operating cost of a deployed ship increases up to 260,000 USD, fewer deployed ships sail on the route networks in order to reduce the total operating cost. Due to the fixed service frequency, liner ships need to sail to their destination at higher speeds. Green technology may become more competitive because it can reduce the fuel consumption of ships sailing along routes, leading to a corresponding increase in the number of deployed ships retrofitted with green technology.

Table 6. Impact of weekly fixed operating cost on the operation decisions.

c (USD)	OBJ	$\sum_{r \in R} \sum_{k \in K} \beta_{rk}^1$	$\sum_{r \in R} \sum_{k \in K} \beta_{rk}^2$
60,000	772,476.72	1	4
70,000	822,476.46	1	4
80,000	872,476.85	1	4
90,000	922,476.51	1	4
100,000	972,476.73	1	4
120,000	1,072,476.68	1	4
140,000	1,172,476.88	1	4
160,000	1,272,476.72	1	4
180,000	1,372,476.72	1	4
200,000	1,472,476.76	1	4
220,000	1,572,476.49	1	4
240,000	1,672,476.83	1	4
260,000	1,763,638.77	3	1
280,000	1,843,638.06	3	1
300,000	1,923,638.88	3	1

Notes: “OBJ”, “ $\sum_{r \in R} \sum_{k \in K} \beta_{rk}^1$ ”, and “ $\sum_{r \in R} \sum_{k \in K} \beta_{rk}^2$ ” record the objective function value of model, the total number of ships retrofitted with the green technology deployed on all ship routes, and the total number of ships without retrofit deployed on all ship routes, respectively.

6. Conclusions

Growing environmental awareness of maritime decarbonization and strict international regulations in the field of maritime are forcing shipping liners to find new directions, such as alternative fuels, optimal operational measures, and green technology adoption, to reduce fuel consumption and greenhouse gas emissions. Due to the existing barriers to the adoption of alternative fuels, this study focuses on the last two measures. The majority of literature on green shipping with optimal operational measures focuses on optimizing ship speeds to reduce the daily fuel cost. In the area of green shipping, few studies incorporate ships of different ages into their models while taking the adoption of green technologies into account. To fill this research gap, this study considers ships with different hull conditions deployed on different routes and proposes a mixed-integer nonlinear programming model to jointly optimize green technology adoption and sailing speeds considering maritime decarbonization. Contributions of this paper are summarized in the following two aspects: first, since fleet deployment and green technology adoption are strategic decisions, a mixed-integer nonlinear programming model is proposed to determine whether to retrofit their ship fleets with new technologies and how to deploy ships while taking maritime decarbonization into account. To deal with non-linear parts of the model, some linearization methods are introduced, and the proposed linearized model can be directly solved by Gurobi, which can provide liner companies with a scientific decision-making method to determine ships allocation and green technology adoption

before daily operations. Second, sensitivity analyses are conducted to obtain managerial insights.

Limitations and Prospects for Further Green Technology Adoption and Maritime Decarbonization

This paper still has limitations and potential extensions. First, government subsidies may be introduced because investment costs of green technologies are extremely high, and government subsidies may stimulate liner companies to adopt green technologies [45,46]. Second, the adoption of multiple available new technologies can be investigated to give liner companies more options [35,47–49]. Third, uncertain information [50,51] may also be integrated into the problem in the future. Finally, the combination of prediction and optimization in shipping management [52–55] and the combination of land and sea operations [56–59] can be considered in the future.

In summary, the information in this study may help decision makers of liner companies assess existing green technology and design future solutions for green shipping.

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