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Joint Maritime Bunker Hedging and Operational Consumption Based on CVaR Optimization

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Abstract: Maritime shipping is an important driver of global economic growth. Efficient green maritime technologies are critical for both the profitability and sustainability of shipping carriers due to the fact that fuel consumption has already made up 45–55% of the total operational cost of a ship. Moreover, the application of green maritime technologies also challenges the input/output of the maritime industry. Currently, there is a lack of coordination between the two strategies of maritime bunker management: one is the bunker procurement, which is faced with the fierce volatility of bunker fuel prices, and the other is the bunker consumption of vessel operation scheduling with applicable maritime technologies. To address the challenge posed by the new sulfur emission regulations, the two isolated strategies are inefficient. This study presents an integrated model that takes both the financial technology (bunker hedging) and the operational bunker cost efficiency (sailing speed and routing optimization under emission regulations) into account. The objective is to maximize the total rate of portfolio return considering the revenue and the cost simultaneously. By analyzing the Conditional Value at Risk (CVaR) risk measure, we examined the effects of the bunker spot, contract, and hedging in futures markets on the optimal joint solution. Numerical results from a real-world case study show that the optimized integrating financial and operational strategies yield the lowest expected total costs as well as the highest revenue with CVaR constraints. The findings provide a prospect for maritime shipping as an effective decision tool for bunker management under environmental regulations. The management insights of our study will benefit the corporate participants, policy makers, and researchers in liner shipping revenue and risk management.

Keywords: maritime shipping; hedging technology; Conditional Value at Risk; sulfur emission regulations; coordination

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1. Introduction

The economic and environmental impacts of shipping have risen considerably in maritime management during the last decade. Bunker fuel is one of the most notable factors among all the impacts [1]. Primarily, the volatility of bunker prices affects operational costs directly via the profits of shipping. Consequently, many measures have been carried out to reduce the bunker cost [2]. For instance, the China Ocean Shipping Company (COSCO) has signed contracts with solid bunker suppliers [3]. Although the contracts are favorable with the amount of bunker consumption, it may not be always feasible due to the uncertain bunker prices, sailing speed, and leg options. In recent years, De et al. [4] proposed different bunker policies under various fuel price scenarios due to the great impacts of bunker price fluctuations as well as the varying vessel speed of bunker consumption. In particular, current environmental regulations from the IMO posed a challenge to all ship companies; it is compulsory to reduce sulfur emission whilst sailing in the sea. Schinas and Ourolidis [5] also investigated key performance factors including new sulfur emission regulations during the COVID-19 pandemic period which affected bunkering in ports. Michail and Melas [6] analyzed the economic turmoil of shipping markets from the new environmental change.

Therefore, it is natural to expect that the maritime bunker management decision should be made considering the fluctuating prices of bunkers and the expected uncertain amount of bunker consumption under the new sulfur emission regulations. Maritime bunker management is involved in two main aspects. The first one is to stabilize the bunker price. The high volatility of bunker prices has a significant impact on the total cost of vessels. Many measures have been taken to reduce the cost because bunker expenditure accounts for a major portion of the operational cost of a liner [7]. On one hand, although contracts fill up most of the supply of the bunker, the higher price sometimes makes shipping companies procure the bunker from spot markets. On the other hand, hedging using derivatives has been proven to be a useful tool to reduce risk. However, the financial strategy is not connected with the operational bunker consumption amount, which makes the financial strategy inefficient. Therefore, controlling bunker prices whilst considering the key operational factor is an essential issue for liners in achieving their cost advantage.

The second aspect is the optimal consumption of bunkers, which includes the choices of routing, legs, and sailing speed under the time limitation. A high speed indicates a short transit time during the sailing which leads to a substantial proportion of fuel consumption. To reduce the total operational bunker cost, many liners have adopted optimal sailing speed and fuel cost minimization [8]. It should be noted that the slowest speed or the shortest leg are not always the optimal choice to reduce bunker expenditure. The sailing speed and leg choices have different levels of sensitivity compared to the bunker prices. Nevertheless, optimal operational routing and speed have not been considered with bunker prices synchronously to minimize the bunker cost until now.

In addition, the emission regulations in the Emission Control Areas (ECA) including the Baltic, North, North American, and Caribbean Sea Areas have been coming into effect since 1 January 2015. From 1 January 2019, the whole of China's territorial sea became an ECA. Zis and Cullinane [9] discussed the three available strategies related to changes in fuel from economic and applicable aspects. (1) Under the global sulfur limit from 2020, the very low sulfur fuel oil (VLSFO, 0.5% sulfur content) is used outside ECAs. (2) Use marine gas oil (MGO, 0.1% sulfur content) within ECAs. (3) Use liquefied natural gas (LNG). This means that shipping companies are very sensitive to the price differences between them. The original viable bunker prices make this situation sophisticated. Hence, it is imperative for liner shipping to take the uncertain bunker price into account while determining the operational schedule synchronously to meet the environmental regulations.

To fill the gap between the two current separated problems of bunker procurement and the operational choice facing the new environmental restrictions, this study provides a joint model to analyze the coordination of both operational bunker cost efficiency and financial risk control, which is lacking in the existing literature. Among the very limited integrated models, some researchers proposed minimizing the total cost model in the field of bunker risk aversion and consumption. Wang and Teo [10] utilized a decision tree analysis to prove the benefits of integrating shipping network planning with bunker risk management. The decision tree analysis of forwarding two-stage bunker hedging includes three numerical examples: an upward price movement, a downward price movement, and a high uncertain market. In addition, Gu et al. [11] examined the relationship between sulfur emission and risk aversion levels under ECA regulations. They minimized the expected total bunker cost with a Conditional Value at Risk constraint. In this paper, we propose a joint portfolio return maximized model taking bunker futures hedging and operational consumption into account with different risk aversion attitudes. Our objective of the model is to maximize the total rate of portfolio return, which considers the revenue and the cost simultaneously during the whole process [12–14]. Our model establishes a financial incentive-based program, which offers shipping companies more essential and comprehensive information to make decisions, compared with the current minimizing cost model. To the best of our knowledge, this is the first attempt to consider the applicability of the revenue and cost in one model in liner shipping services.

Furthermore, by analyzing a series of downside algorithms including Value at Risk (VaR), CVaR, and Maximum Loss (MaxL), we examine the effects of bunker spot, contract, and hedging in futures markets of the optimal procurement strategy. Due to the persistent differences among the three categories of procurement resources, the advantage of our model is that both the magnitude of the rate of portfolio return and the corresponding risk aversion attitude are evaluated during the in-sample and out-of-sample periods.

Numerical experiments are conducted for the south and east regions of the Asia route served by China Ocean Shipping Company (COSCO) to assess the performance of our joint model and reveal relevant managerial insights. The empirical results show that the bunkering hedging strategy not only stabilizes the volatility of bunker prices efficiently but also has impacts on the optimal routing and speed via bunker consumption. This is due to the lower bunker prices after hedging. Vice versa, the operational decision also has impacts on the optimal procurement amounts and hedging amounts. Therefore, the two isolated models are not comparable with our joint model.

Additionally, we systematically analyze the impacts of three different options including the shortest routes, the least usage of MGO due to its high price, and the optimized joint hedging and operation strategies in ECA and non-ECA districts. The numerical results show that the optimized integration of financial and operational strategies yields the lowest expected total costs and lower risk. Specifically, through the change ratios of ECA vs. non-ECA distances during the service routes, the optimal solution of the U-type total cost is subject to the composition of the price and consumption of the two bunkers suitable for ECA and non-ECA, respectively. The findings from the real-world case study confirm the superiority of risk control and the profitability of our proposed model. This study provides insights for shipping companies, practitioners, and researchers into an effective decision mechanism from a joint perspective regarding emission regulations.

The remaining parts of our paper are as follows. Section 2 reviews the literature. Then, Section 3 entails problem formulation and Section 4 discusses the performance of our proposed model through a real Chinese liner case study. In Section 5 some relevant conclusions are provided.

2. A Literature Review

The problem of bunker hedging and shipping routing in liner shipping with risk control has been publicized in recent decades. There are three classification schemes being applied generally: (a) bunker hedging strategy and risk management based on minimum-CVaR; (b) shipping routing decisions which are related to the bunker consumption, sailing speed, and other factors; and (c) the emission control regulations. This section provides a review of the recent research on bunker management in liner shipping.

2.1. Bunker Hedging Strategy and Risk Management Based on Minimum CVaR

At a tactical level, shipping companies purchase bunker derivatives in the future or forward markets to control the volatile spot fuel prices [15,16]. However, many big losses in the shipping industry occurred, making their strategies inefficient. Thus, there have been good reasons for the management layer's judgement and the perception of risk. From a theoretical perspective, the traditional objective of hedging is minimizing variance [17]. However, variance penalizes the risk and gain equally which exhibits inferior behavior when the distribution of returns is not symmetrical. This leads to the exploration of new measures of risk and investors' motivation.

In risk management, VaR and CVaR are two dominant quantile downside risk measures. For some given confidence level α, VaR refers to the values of the $(1-\alpha)$ quantile of the distribution while CVaR refers to the average value-at-risk (VaR) which is a coherent measure to capture the distribution of risk effectively and a more robust check than VaR [18]. Harris and Shen [19] developed the minimum Value at Risk and the Minimum Conditional Value at Risk hedge models. They found that the historical data are non-normal and minimum variance hedging can augment negative skewness and kurtosis. Hence, the portfolios obtained by minimum variance hedging are risker than those obtained by the minimum VaR and CVaR hedges. Kavussanos and Dimitrakopoulos [20] investigated the medium-term market risk of tanker vessel freight rates based on VaR. They found that the nonparametric approach estimates VaR values best. In this paper, we investigate the optimal bunker hedging strategy based on minimum CVaR. It is due to the fact that CVaR focuses on the expected loss and it can capture the high moment features such as skewness and kurtosis efficiently.

2.2. Bunker Consumption Considering the Shipping Route, Sailing Speed, and Other Factors

There is extensive literature on reducing bunker consumption and shipping operational strategies in maritime transportation. Wang et al. [21] concluded that recent studies have focused on routing, speed optimization, and the environmental impact of vessels. For instance, Notterboom and Vernimmen [22] examined the optimal speed on one ship route. They also designed a cost model simulating the impact of bunker cost charges on the operational costs of liner services. Ronen [2] studied the minimization of operation costs by reducing vessels' speed, refueling bunker times, and expanding the fleet size. Wang and Meng [23] put forward the speed optimization to combine transshipment with routing determinants. Wang and Meng [24] also developed a nonlinear optimization methodology to obtain the minimum cost including the ship, bunker, and inventory costs. Aydin et al. [7] proposed an optimized bunker and speed model with an uncertain port time. Gu et al. [25] proposed a stochastic optimization model including bunker procurement and operational routing to minimize the total bunker costs within a liner service loop. They found that the bunker procurement and operational decisions have mutual effects and that integrating both are necessary, especially the introduction of the latest regulation of the ECAs. Zhen et al. [26] proposed an integrated planning model including the container routing, vessel deployment, and schedule. They found the profitability of incorporating multiple information variables simultaneously.

2.3. The Sulfur Emission Regulations

Recently, the Emission Control Area (ECA) regulations proposed by the International Maritime Organization (IMO) have had significant impacts on shipping companies' strategies and operations due to the closed relationship with bunker consumption [27]. Brynolf et al. [28] illustrated that the evaluation of the alternative strategies under the new regulations may become complicated when considering the cost difference between two fuels, the investment, installation, and operational costs. Specifically, Jiang et al. [29] provided a cost–benefit analysis of the two strategies including switching from heavy fuel oil (HFO, 5% sulfur content) to MGO and using scrubbers. Fagerholt et al. [30] found that a reduction in sulfur within the ECA may lead to a considerable increase in bunker consumption and CO_2 emissions due to the long distance outside of the ECAs. Dulebenets [31] summarized that liner shipping companies face conflicting objectives including the total operational cost and the emission cost. Hence, he developed an optimization model including several objectives and provided a Pareto frontier analysis taking the operational cost and the emission cost into account. In the current literature, the majority of the above study on bunker dynamics, consumption, and procurement has not explicitly considered the integrated impacts of the bunker hedging strategy and the corresponding operational adjustment under the emission regulations specifically. This paper attempts to fill the gap of a lack of coordination between bunker fuel prices and applicable maritime technologies under sulfur emission regulations. More specifically, this research focuses on designing an optimal bunker purchasing model including the spot, contract, and hedging in bunker futures markets. Meanwhile, by considering the price difference in VLSFO and MGO, we are able to design an optimal vessel loop with reasonably high service levels.

3. Problem Formulation

This section presents the problem statement for the joint model for the CVaR framework. First, we elaborate on the details in the definition of the terms for liner operations. Then, we build the bunker procurement model with the hedging strategy. In addition, the assumptions and constraints of the joint model of bunker consumption are given, including operations and procurement. Then, the risk function of the CVaR framework used for modeling the joint problem is given. The selection of the input parameters used in the joint model is also based on bunker procurement from spot markets and contracts, bunker hedging in future markets, and liner operations with choices of legs in ECA and non-ECA districts. Given the time, operation, and CVaR constraints, the objective of the joint model is the maximum rate of portfolio return, which considers the revenue and cost of the whole loop synchronously. Thus, the decision variables are consumption amounts of two different kinds of bunkers and the corresponding hedging amounts according to the optimized speed and leg choices.

3.1. Definition of the Terms

A liner shipping company that serves a group of ports is considered in our paper. Loop refers to a given sequence of ports calls which form a round trip. A leg is, by definition, a trip between two sequent ports in a loop. In this context, options are several alternative paths between any two ports or for one leg, which are considered different sailing distances, as shown in Figure 1. The different options make a distinction between the ECA and non-ECA zones. For instance, within one leg between ports A and B, there are three options. Option 1 denotes that the strategy is sailing the shortest possible distance which implies that the leg only uses MGO since all the sailing is in the ECA zone. Whereas, Option 2 and Option 3 should use MGO inside ECA and VLSFO outside ECA with different distances, respectively. Option 3 represents the strategy involving the lowest possible ECAs without any consideration of reducing the total sailing distance. Option 2 denotes the strategy of the parameter adjustment integrating the prices of VLSFO and MGO, as well as the sailing distance and fuel consumption in ECA and non-ECA.

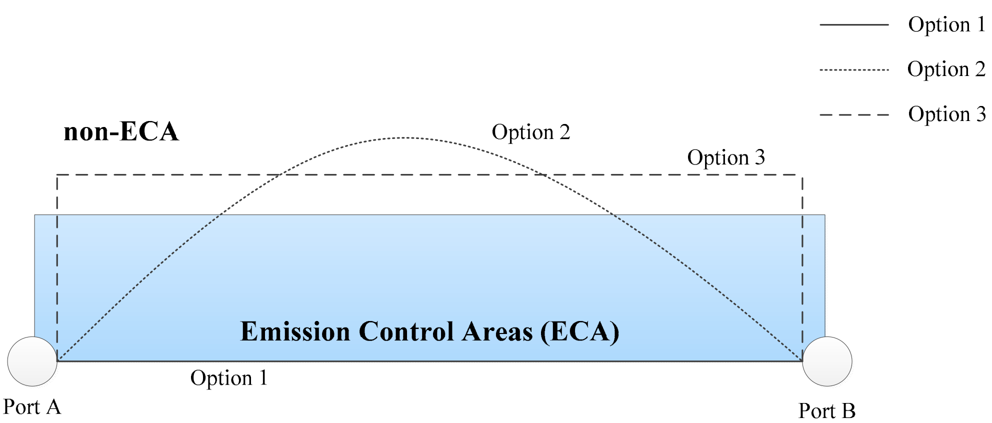

Figure 1. Illustrated leg options in ECA and non-ECA.

3.2. Bunker Procurement with the Hedging Strategy

We present a downside risk-based measure for the portfolio optimization of the shipping company in regard to three trading sources. Physical supply sources contain a procurement contract with terms and bunkering in spot markets. Due to the relatively stable consumption of VLSFO, the shipping companies tend to sign a contract with a bunker supplier which will supply a refill service with the qualified and available bunker at the ports. The bunker cost from contracts $\sum_{i=1,n} C_{i,con}(x_{i,con})$ is related to the procurement amount of bunker $x_{i,con}$ and the price $C_{i,con}$ at each port i. According to Wang and Meng [24], the bunker cost of contracts can be expressed by a piecewise linear function of refilled amount with different discounts. Hence, it can be expressed as follows in Equation (1):

$$C_{i,con}(x_{i,con}) = \begin{cases} w_0 x_{i,con} & if\ x_{con} \leq X^1_{con}, 1 \leq x_{i,con} \leq n \\ C^1_{con} + w_1\left(x_{i,con} - X^1_{con}\right) & if\ X^1_{con} \leq x_{i,con} \leq X^2_{con}, 1 \leq x_{i,con} \leq n \\ C^2_{con} + w_2\left(x_{i,con} - X^2_{con}\right) & if\ x_{i,con} \geq X^2_{con}, 1 \leq x_{i,con} \leq n \end{cases} \quad (1)$$

where $x_{i,con}$ is the amount of bunker procurement from contracts at port i; the consumption upper limits X^1_{con}, X^2_{con}, the cost coefficients C^1_{con}, C^2_{con}, and the bunker price coefficients w_0, w_1, w_2 are parameters satisfying $0 \leq X^1_{con} \leq X^2_{con}$, $0 \leq C^1_{con} \leq C^2_{con}$, and $0 \leq w_2 \leq w_1 \leq w_0$.

We should also note that despite the discounts for a large contract, the contract price is not competitive with the spot price all the time. Shipping companies still purchase bunkers from the spot market as a main channel due to its flexibility and availability. Thus, the bunker cost from spot markets $\sum\limits_{i=1,n} C_{i,spot}\left(x_{i,spot}\right)$ is expressed as:

$$\sum_{i=1,n} C_{i,spot}\left(x_{i,spot}\right) = \sum_{i=1,n} P_i x_{i,spot} \quad (2)$$

where P_i denotes the spot price of bunkers at port i. However, the fierce volatility of spot bunker prices weakens the companies' profits heavily. To stabilize the price swings, companies utilize new techniques and instruments such as derivatives to reduce procurement costs. Bunker futures are agreements to deal a standard quantity of some specified asset at a confirmed time at an agreed price. In the deterministic hedging case, we establish the portfolio revenue h_i which denotes that the positive value is revenue and the negative value is loss of the hedging strategy. It is given by:

$$h_{i+m} = (P_{i+m,spot} - P_{i,spot}) - \gamma_i(F_{i+m} - F_i) \quad (3)$$

where $P_{i,spot}$ and $P_{i+m,spot}$ are the spot bunker prices at the time stage of port i and port $i+m$ and $F_{i,t}$ and F_{i+m} are the corresponding futures prices. Here, $m \in \{1, n-i\}$ and we assume that at stage i, the liner company signs bunker futures at strike price of $F_{i,t}$, delivers at port $i+m$, and γ_i is the determined viable of the hedging ratio.

In this study, upon the minimum CVaR measure, the downside value of the hedged portfolio revenue with confidence level $\alpha \in (0,1)$ is:

$$\text{CVaR}_\alpha(h_{i+m}) = \min\left\{ z \,\middle|\, F_{h_{i+m}}(z) \geq \alpha \right\} \quad (4)$$

where $F_{h_{i+m}}(z)$ is the cumulative distribution of h_{i+m}. Eventually, we obtain the following optimization problem:

$$\gamma^*_{\text{CVaR},i+m} = \text{argminCVaR}_\alpha(h_{i+m}) \quad (5)$$

Hence, the bunker hedging strategy may create profit as follows:

$$\sum_{i=1,n-m} R_i(\gamma_i) = \sum_{i=1,n-m} \gamma_i^* x_{i,spot}(F_{i+m} - F_i) \quad (6)$$

Therefore, the key decision in the bunkering problem is how much the shipping company will procure bunker from spot markets and how much from contracts, respectively. In addition, the number of futures is determined by the amount of spot bunkers using the minimum CVaR method.

3.3. Assumptions and Constraints of the Joint Model

A liner shipping company providing a transport service over a given sequence of ports denoted by set $i = \{1, \ldots, n\}$ is considered. Port 0 is the starting node and the voyage from port i to port $i+1$ is denoted by leg i, $i = \{1, \ldots, n\}$.

The assumptions of this research of bunker consumption of operations and procurement are given below:

(1) We only study one ship in a specific loop for a liner shipping company and the fleet size is also given;
(2) The spot prices, the contract prices, and the futures prices are transparent and exogenous;
(3) The bunker demand in each leg should be satisfied, while the remaining bunker will be carried forward to the following leg. Thus, a sufficient amount is necessary to guarantee operations and the last remaining bunker will be refunded at the end of the loop;
(4) Different operational leg choices determine different bunker demands which lead to different procurement amounts and thus different total costs. In this assumption, the bunker consumption is linear with the voyage speed and the optimal vessel speed is constant for each choice on each leg;
(5) All related parameters are known for modeling and calculations.

The decision variables of the bunker procurement, hedging, and consumption should be optimized. Thus, the whole process is separated into N stages according to each leg between two ports. With the above assumptions, the integrated optimization problem can be formulated as multi-stage bunker procurement and operation decisions, which is shown in Figure 2. During stays at Port 1, with the former operational information, the expected sailing speed for different options for each leg should be optimized, taking into account the different bunker procurement prices. Thus, the liner purchases bunker from contracts and spot markets and also signs bunker futures from derivative markets. The number of bunker futures can be calculated based on the available spot and its corresponding derivative prices at Port 1. At Port $i(i = 1, \ldots, n)$ when the vessel arrives, the bunker amounts of procurement corresponding to different ship speed choices are optimized and fulfilled accordingly. Moreover, the shipping liner may rebalance the futures amounts by signing more futures from derivative markets based on the updated price at Port i. Then, at a particular Port $i+m$, the shipping company receives the gains or loss delivered from futures markets. At the end of Port n, the possible excess bunker can be returned to the supplier.

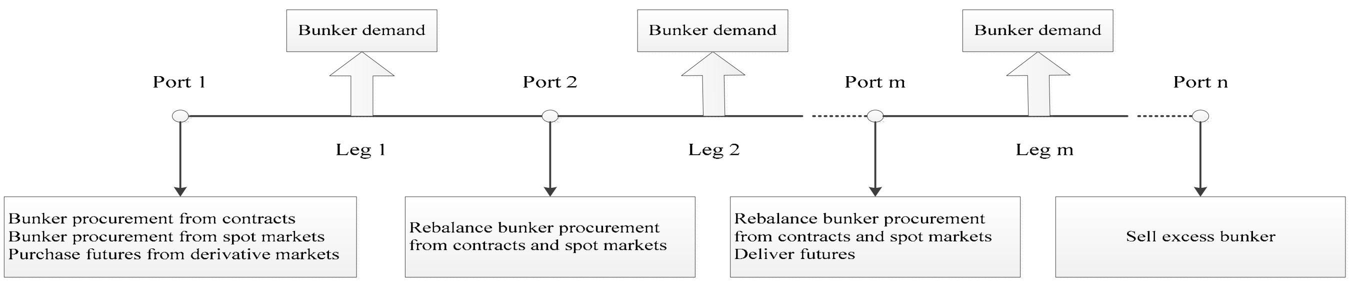

Figure 2. Illustrate bunker procurement from contracts and spot markets, hedging futures, and operational process.

The joint problem illustrated in Figure 2 examines how to initialize and rebalance the bunker procurement and futures to satisfy the operations demand for the whole loop. This model is maximized by the rate of portfolio return which contains the revenue of hedging and operations as well as the cost of procurement and operations at each stage. For example, at Port 1 the company purchases bunkers from contracts and the spot market according to the current prices of contracts and spot markets and also determines the amounts according to the former operation. Then, at Port 2, the company rebalances the bunker procurement according to the new price and optimizes the operational choice including the choice of three options and the vessel speed. From Port m to $m+1$, the company also needs to deliver the futures according to the hedging strategy, while at the end of the loop, the excess bunker should be sold. To control the risk, the joint modeling framework can guarantee low purchasing and operational costs as well as control the price fluctuation risk. The optimal procurement amounts from contracts, spot markets, and the corresponding hedge amounts from derivative markets are determined at each stage. We will use the following notation throughout this paper (Table 1).

Table 1. Notations in the model.

Sets	Illustration
i	Set of sailing legs along the route from Port i to $i+1$
j	Set of options, $j \in 1,2,3$ as illustrated in Figure 1
L_{ij}^{ECA}	The ECA length of Leg i, Option j
$L_{ij}^{Non-ECA}$	The non-ECA length of Leg i, Option j
T_L	The total time limitation of the loop
Parameters	
v_k	The vessel speed of choice k, in this model it is a discrete point from 17 to 21 knots during one leg
t_{ijk}^{ECA}	The sailing time of ECA of Leg i, Option j with vessel speed of v_k
$t_{ijk}^{Non-ECA}$	The sailing time of non-ECA of Leg i, Option j at vessel speed of v_k
t_i^{star}	Scheduled starting time for Leg i
t_i^{serv}	Service time at Port i
ρ_{v_k}	The coefficient of speed and gasoline consumption
P_i^{MGO}	The spot price of MGO at Port i
P_i^{HFO}	The spot price of VLSFO at Port i
F_i^{MGO}	The futures price of MGO at the time stage of Port i
F_i^{HFO}	The futures price of VLSFO at the time stage of Port i
Q_{ijk}^{MGO}	Amount of MGO consuming of Leg i, Option j at vessel speed of v_k
Q_{ijk}^{HFO}	Amount of VLSFO consuming of Leg i, Option j at vessel speed of v_k
d_i	The revenue coefficient related to the sailing distance via different options
λ	The risk tolerance level for CVaR measure
Decision variables	
$x_{i,con}^{MGO}$	Purchasing amount of MGO from contracts at Port i
$x_{i,con}^{HFO}$	Purchasing amount of VLSFO purchasing from contracts at Port i
$x_{i,spot}^{MGO}$	Purchasing amount of MGO from spot markets at Port i
$x_{i,spot}^{HFO}$	Purchasing amount of VLSFO from spot markets at Port i
γ_i^{MGO}	The hedging ratios of MGO futures at the time stage of Port i
γ_i^{HFO}	The hedging ratios of VLSFO futures at the time stage of Port i
Functions	
$C(x_i)$	The total cost of procurement and operation for Leg i
$R(x_i)$	The revenue of hedging and operation for Leg i
$r_i(x_i)$	The rate of portfolio return for Leg i
$VaR(x_i)$	The downside function by VaR measurement for Leg i
$CVaR(x_i)$	The downside function by CVaR measurement for Leg i
$Loss(x_i)$	The expected loss of the portfolio return for Leg i
$F_{Loss(x_i)}(x_i)$	The cumulative Distributions Function of the variable
ROR	The total rate of portfolio return from Leg 1 to n

The mathematical formulation is as follows. The expected total cost is the sum cost over a whole loop. Its function includes the following terms: (1) the cost of contract trading of VLSFO and MGO and (2) the cost of spot trading of VLSFO and MGO.

$$\sum_{i=1,n} C_i(x_i) = \sum_{i=1,n} P_{i,con}^{HFO} x_{i,con}^{HFO} + \sum_{i=1,n} P_{i,con}^{MGO} x_{i,con}^{MGO} + \sum_{i=1,n} P_{i,spot}^{HFO} x_{i,spot}^{HFO} + \sum_{i=1,n} P_{i,spot}^{MGO} x_{i,spot}^{MGO} \quad (7)$$

Accordingly, the expected total revenue of the loop includes two parts: (1) the operational revenue from each sailing leg and (2) the revenue of hedging bunker futures of VLSFO and MGO, respectively. Hence, we can conclude that the hedging strategy as a part of revenue has impacts on the total revenue, and it also affects the bunker procurement cost. For calculation simplicity, the operational revenue R_i in each leg is only involved in the linear relationship with the cost of VLSFO and MGO, respectively. The simple process is due to the fact that only this part has significant impacts on the rate of portfolio return.

$$\sum_{i=1,n} R_i = d_1 \Big(\sum_{i=1,n} P_{i,con}^{HFO} x_{i,con}^{HFO} + \sum_{i=1,n} P_{i,spot}^{HFO} x_{i,spot}^{HFO} \Big) + d_2 \Big(\sum_{i=1,n} P_{i,con}^{MGO} x_{i,con}^{MGO} + \sum_{i=1,n} P_{i,spot}^{MGO} x_{i,spot}^{MGO} \Big) \quad (8)$$

where d_1 and d_2 are parameters related to the consumption of VLSFO and MGO. Then, the total revenue is specified as

$$R_i(x_i) = \sum_{i=1,n} R_i + \sum_{i=1,n-m} \gamma_i^* x_{i,spot} (F_{i+m} - F_i) \quad (9)$$

Constraints that meet the shipping time and operation requirements are as follows:

1. Time constraint

$$\begin{array}{l} t_{ijk}^{ECA} = L_{ij}^{ECA} / v_k \\ t_{ijk}^{Non-ECA} = L_{ij}^{Non-ECA} / v_k \\ t_{i+1}^{star} \geq t_i^{star} + t_i^{serv} + t_{ijk}^{ECA} + t_{ijk}^{Non-ECA} \\ \sum\limits_{i=1,n} \left(t_{ijk}^{ECA} + t_{ijk}^{Non-ECA} + t_i^{star} + t_i^{serv} \right) \leq T_L \end{array} \quad (10)$$

2. Operation constraint

$$\begin{array}{l} \sum\limits_{i=1,d} (x_{i+1,con}^{HFO} + x_{i+1,spot}^{HFO}) - \sum\limits_{i=1,d-1} Q_{ijk}^{Non-ECA} \geq Q_{i+1,jk}^{Non-ECA} \\ \sum\limits_{i=1,d} (x_{i+1,con}^{MGO} + x_{i+1,spot}^{MGO}) - \sum\limits_{i=1,d-1} Q_{ijk}^{ECA} \geq Q_{i+1,jk}^{ECA} \\ \sum\limits_{i=1,n} Q_{ijk}^{ECA} = \sum\limits_{i=1,n} v_k \rho_v L_{ij}^{ECA} \\ \sum\limits_{i=1,n} Q_{ijk}^{Non-ECA} = \sum\limits_{i=1,n} v_k \rho_v L_{ij}^{Non-ECA} \end{array} \quad (11)$$

3.4. The Maximum Rate of Portfolio Return Based on the CVaR Framework

By definition of downside risk measure, the rate of portfolio return for Leg i from the above procurement and operational practice is considered as:

$$r_i(x_i) = \frac{R_i(x_i)}{C_i(x_i)} - 1 \quad (12)$$

where $Loss(x_i)$ is represented by the expected loss of the portfolio return which is the negative part of the $\sum\limits_{i=1,n} r_i(x_i)$. The value at Risk (VaR) at level α can been defined as the α-quantile of $Loss(x_i)$:

$$VaR_\alpha[Loss(x_i)] = \inf\{x_i | F_{Loss}\ (x_i) > \alpha\} \quad (13)$$

where $F_{Loss(x_i)}(x_i)$ represents the Cumulative Distributions Function of the variable $Loss(x_i)$. CVaR is calculated by the expected loss exceeding VaR [18],

$$CVaR_\alpha[Loss(x_i)] = E[Loss(x_i)|Loss(x_i) \geq VaR_\alpha[Loss(x_i)] \tag{14}$$

The objective of our model is maximizing the total rate of portfolio return (ROR), which is involved in the revenue and cost during the whole legs from Equations (7)–(9). This optimization model with CVaR constraints can be expressed by:

$$\max ROR = \max \sum_{i=1,n} r_i(x_i) \tag{15}$$

which is subject to a time constraint (10), operational constraint (11), and CVaR constraint (16)

$$\sum_{i=1,n} CVaR(x_i) < \lambda \tag{16}$$

Here, the risk tolerance level λ denotes some proportion of the total portfolio values, which is the shipping companies' attitude to risk exposure. Thus, the proposed problem can be changed to linear programming using the solver Portfolio Safeguard [32].

4. Case Analyses

The procedures to adopt the joint framework for applications are described in this section. We conducted a case study on account of a south and east service route of Asia from the China Ocean Shipping Company (COSCO) to assess the estimation performance of our proposed model.

4.1. Data Collection of the CASE

In this section, Figure 3 shows the route of the service, which contains 10 legs. In our case, we ignore the port of call in Xingang due to the very limited usage of this loop.

Figure 3. COSCO shipping liner routes in the south and east of Asia [33].

Furthermore, Table 2 provides the sailing distance in ECA and non-ECA for every option between different ports. These data are either real data or estimated from real data. There are three options for each leg of our case. Option 1 denotes that the strategy is sailing the shortest possible distance despite the involvement of ECA, which implies that the leg will consume the most MGO. Option 2 denotes the strategy of the parameter adjustment integrating the prices of VLSFO and MGO, as well as the sailing distance and fuel consumption in ECA and non-ECA. While Option 3 represents the strategy involving the lowest possible ECAs without any consideration of reducing the total sailing distance.

Table 2. The route distances in ECAs and non-ECAs for each option between different ports.

Ports of Call		Option 1		Option2		Option3	
		ECA	Non-ECA	ECA	Non-ECA	ECA	Non-ECA
Leg 1	Shanghai–Dalian	224	233	196	282	101	427
Leg 2	Dalian–Qingdao	467	135	467	135	467	135
Leg 3	Qingdao–Ningbo	231	158	164	247	113	291
Leg 4	Ningbo–Shekou	273	480	188	556	70	705
Leg 5	Shekou–Jakarta	184	1792	76	1877	35	2012
Leg 6	Jakarta–Port Kelang	0	726	0	726	0	726
Leg 7	Port Kelang–Singapore	0	201	0	201	0	201
Leg 8	Singapore–Laem Chabang	0	807	0	807	0	807
Leg 9	Laem Chabang–Hong Kong	40	1404	40	1404	40	1404
Leg10	Hong Kong–Shanghai	287	504	127	681	73	754

Discrete points of sailing speed v_k are selected from 18 to 22 knots which are normally the real 4250 TEU liner shipping speed. Thus, the bunker consumption values under different discrete speed points are presented in Table 3. Along with the increase in shipping speed, bunker consumption has an increasing trend and forms a convex shape. This means the nonlinear relationship between the ship speed and its corresponding bunker consumption.

Table 3. Sailing speed choices and the corresponding fuel consumption.

Parameters	Values				
Ship speed choices (knots)	17	18	19	20	21
The corresponding fuel consumption (tons)	0.165	0.174	0.183	0.194	0.205

In addition, as a simplification, we assume that the contract prices are identified by some ratios of average spot prices during the whole loop. The rationale behind this assumption is that the contract price is highly correlated with the spot price and it offers competitive prices and sufficient numbers of bunkers. Therefore, Equation (17) provides the contract prices as follows:

$$C_i(x_{i,con}) = \left\{ \begin{array}{c} w_0 x_{i,con} \quad if\ x_{i,con} \le 1000, w_0 = \frac{11}{10n} \sum\limits_{i=1,n} P_i \\ 1000w_0 + w_1(x_{i,con} - 1000)\ \ if\ 1000 < x_{i,con} \le 2000, w_1 = \frac{1}{n} \sum\limits_{i=1,n} P_i \\ 1000w_0 + 1000w_1 + w_2(x_{i,con} - 2000)\ if\ x_{i,con} > 2000, w_2 = \frac{9}{10n} \sum\limits_{i=1,n} P_i \end{array} \right\} \quad (17)$$

4.2. In-Sample Results of Bunker Procurement with Hedging Strategy under a Downside Measurement

There are three strategies of bunker procurement analyzing the impacts of futures and contracts on bunker procurement cost.

Strategy 1: bunker procurement from spot markets only.

Strategy 2: bunker procurement from spot markets and contracts with bunker suppliers.

Strategy 3: bunker procurement from spot markets, contracts with bunker suppliers, and purchasing futures as a hedging strategy.

Figure 4 depicts the optimized portfolio rate of return for the three strategies. From the figure, we can see that Strategy 3 obtains the highest portfolio rate of return according to the three risk measures compared with the other two strategies. This means that the hedging strategy of bunker futures has more positive returns with three downside measures. It shows that Strategy 2 gains a higher portfolio rate of return than Strategy 1. Aside from this, the solution with the Maximum Loss constraint is always greater than that with 90% CVaR constraint, and greater than that with VaR constraint. This is due to the facts that Maximum Loss has the least constraint.

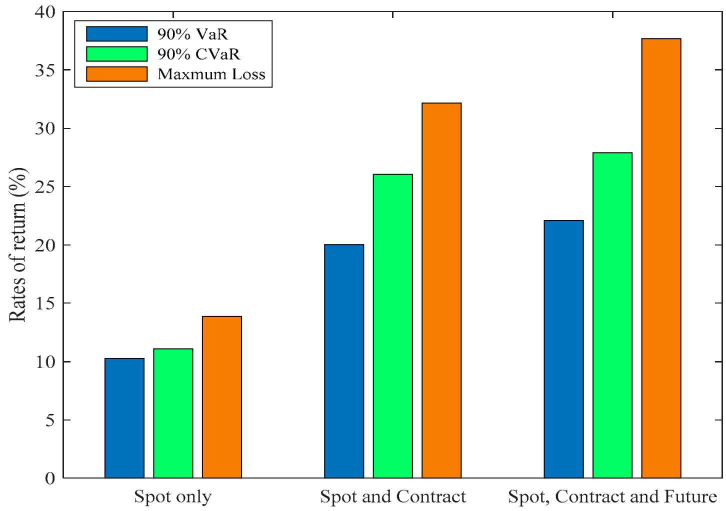

Figure 4. The optimized portfolio rate of return of all strategies.

4.3. Out-of-Sample Results

We examine the consistency of out-of-sample and in-sample results with the same constraint of 90% CVaR values. Figure 5 shows the optimal portfolio profits of the out-of-sample and in-sample results. From the figure, we can see that the difference in the optimal portfolio profits between the two samples is 7.9%, which is less than 10%. The results show that our model has a relatively robust performance.

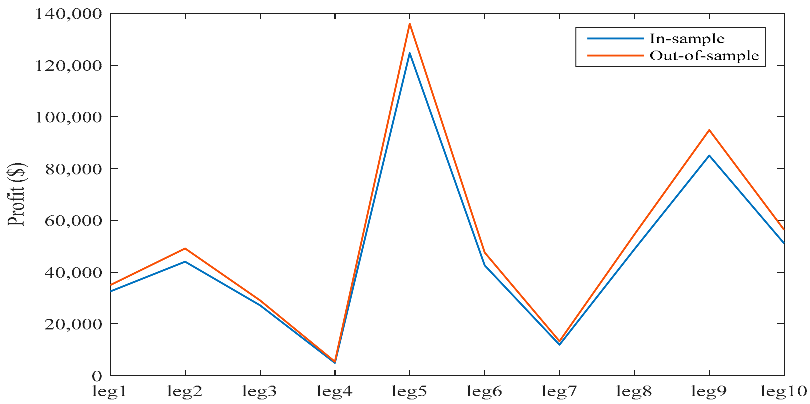

Figure 5. In-sample and out-of-sample optimal portfolio profits with 90% CVaR constraint.

4.4. Numerical Results

The numerical results of the optimal bunker consumption and hedging strategies of the three options are presented in Table 4. It can be seen that different priorities can lead to different optimal bunker consumption amounts and the corresponding total costs. Moreover, neither Option 1 of the shortest route nor Option 3 of the least usage of MGO is the optimal decision in the present situation. Option 2 of the joint hedging and operation strategies can obtain the optimal decision due to the fact that the hedging decision has reduced the average bunker procurement price. Thus, the bunker consumption amounts are also changed based on different options and speed choices.

Table 4. Numerical results of optimal bunker consumption and hedging strategies of three options.

	Option 1	**Option 2**	**Option 3**
Amount of spot bunker			
Consumption of spot MGO (ton)	67.84	51.69	37.39
Consumption of spot VLSFO (ton)	272.75	303.81	333.56
Amount of contracts bunker			
Consumption of contracts MGO (ton)	285.62	216.17	157.39
Consumption of contracts VLSFO (ton)	1079.59	1201.33	1321.72
Amount of Futures contracts and average hedging ratios			
Amount of MGO hedged (ton)	0	0	0
Average hedging ratios of MGO	0	0	0
Amount of VLSFO hedged (ton)	266.5	299.41	318.94
Average hedging ratios of VLSFO	0.977	0.986	0.955
Overview			
Expected total revenues (USD)	521,437	525,608	514,414
Difference (%)	0	0.8%	−1.3%
Expected total costs (USD) with 90% CVaR constraint	545,220	539,637	555,981
Difference (%)	0	−1.0%	2.0%
Cost standard deviation (USD)	7582	7078	4902
Difference (%)	0	−6.6%	−35.3%
Expected total costs (USD) with 75% CVaR constraint	545,254	539,801	556,283
Expected total costs (USD) with 90% VaR constraint	545,225	539,668	555,993
Expected total costs (USD) with 80% MaxL constraint	545,231	539,695	556,081

In more detail, although the Option 1 strategy provides the shortest service route and thus leads to the smallest amount of bunker consumption, the expected total costs are higher and the expected total revenues are lower than those of Option 2. Even worse, the cost standard deviation of Option 1 is the highest at 7582 USD, thus the shipping company faces great risk exposure. This may be due to the fact that it consumes the largest amount of MGO in Option 1, which is about 1.32 times the amount in Option 2 and 1.81 times the amount in Option 3. Even so, the amount of MGO hedged in futures contracts are all zeros in three options since the amount of MGO consumption is relatively low compared with that of VLSFO. Moreover, the values of VaR, CVaR, and Maximum Loss confirm that Option 1 has higher expected total costs compared with those of Option 2.

We also observe from the results of Option 3 that the strategy avoids the usage of MGO due to its high prices, which leads to longer service routes and more consumption amounts of VLSFO. As a result, it reaches the highest expected total costs and the lowest expected total revenues. Although Option 3 is the least attractive strategy due to the uneconomical consumption of fuel and time, it is worth noting that Option 3 has the smallest cost standard deviation of only 4902 USD, which is only about two thirds of that of Options 1 and 2. This means the hedging strategy of VLSFO and contracts control the risk of VLSFO volatility significantly.

In contrast, Option 2 integrates service routes as well as bunker consumption, which yields the lowest expected total costs and a lower risk. Thus, we can find that the optimal bunker decisions are affected by the two bunker price differences along with the corresponding changing service routes under the constraints of sailing time limitation in ports. Determining both the consumption amounts of VLSFO and MGO and the sailing speed can optimize the total bunker costs.

Overall, from the view of the consumption amounts, we can find that contracts are still the main procurement pattern since the contract prices are often lower than the spot prices in reality. Hedging amounts of VLSFO are almost the same as with the spot procurement amounts of VLSFO due to the hedging ratios being close to 1. However, there is no hedging amount of MGO in any of the three options due to the limited consumption of spot MGO. In addition, expected total costs with 90% CVaR constraint, 75% CVaR constraint, 90% VaR constraint, and 80% Maximum Loss constraint confirm that the joint strategy of Option 2 provides the liner with a more well-rounded view with all available options.

4.5. Sensitivity Analysis

From the above numerical results, we can find that a combination of VLSFO and MGO would have impacts on the total relevant costs, allowing the carrier to change the routes in ECA and non-ECA. Thus, we investigate the sensitivity of solutions with the change routes in ECA and non-ECA ratios from 0.3625 of Option 1 to 0.1569 of Option 3. Aside from the original ECA/non-ECA ratio at 0.2428 of Option 2, we add another four options at 0.30754 of Option 2a, 0.2726 of Option 2b, 0.2149 of Option 2c, and 0.1866 of Option 2d. Figure 6 illustrates the total cost, bunker consumption, and loop changes of the proposed 7 options. It illustrates the trade-off between the total cost, changes in VLSFO consumption, MGO consumption, and Loop distance. The decrease in shipping in the ECA area implies the decreased consumption of MGO; at the same time, the increase in consumption of VLSFO can lead to a long loop distance. Nevertheless, the U-type total cost indicates a decrease at first and then an increase in the total cost, which is due to the composition of price and consumption of VLSFO and MGO. Notably, the total cost reaches the lowest value when the ECA/non-ECA ratio equals 0.2428 because the sum of all the products of shipping distance and the corresponding bunker prices is the lowest.

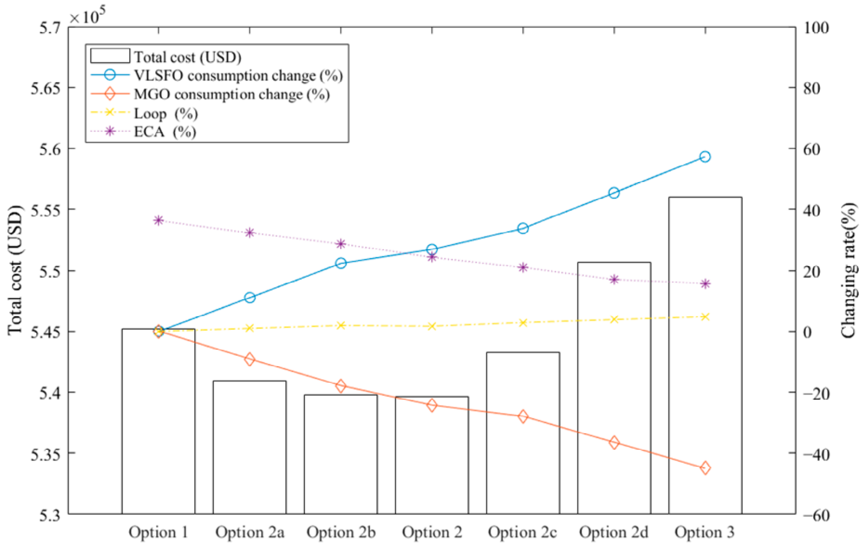

Figure 6. Sensitivity analysis of the total costs with diverse options.

5. Conclusions

Considering the fluctuating bunker prices and the emission regulations of international shipping transportation, liner carriers have to adopt efficient technologies to improve their profitability and sustainability [34]. This paper develops a novel joint optimization model that solves the bunker procurement and operational allocation for liner shipping using downside measures. The proposed strategy includes spot, contract, and futures hedging, which stabilizes the bunker price efficiently and obtains the optimized portfolio rate of return by CVaR technology. Numerical experiments are performed for the south and east of Asia line, served by the COSCO shipping company, to measure the risk and efficiency of the presented solution.

The results of the real case study elucidate that the joint decision of bunker hedging and routing optimization on average reduces the expected bunker cost by 35.3% from the economic aspect. Furthermore, the proposed hedging strategy in bunker futures markets stabilizes the bunker procurement prices significantly and brings positive returns successfully. This financial technology is advisable in maritime bunker management. In addition, the optimized integrated service routes as well as the bunker consumption of MGO and VLSFO can serve as an effective operational strategy for shipping firms. Specifically, the sensitivity analysis of solutions with the change routes in ECA and non-ECA helps in understanding the impacts of maritime environmental regulations. The expected U-type total costs reveal that both the consumption amounts of VLSFO and MGO and the sailing speed can optimize the total bunker costs. These findings provide insights for shipping companies, practitioners, and researchers into the effective decision mechanism from the joint perspective under the emission regulations.

This paper provides a first contribution to the formalization of bunker hedging with shipping routing operations to shipping participants in the process of business. It offers a useful guide for shipping participants and policy makers in understanding the risk of bunker markets more in-depth and managing operational planning problems in an integrated way. As for shipping operation decision makers, they can identify the bunker risk in advance and reduce this risk by purchasing futures in derivative markets. Specifically, they can optimize the operational bunker consumption amounts considering the new bunker cost after the hedging strategy. For policy makers, they can better prepare the policy measures taking the bunker markets into account due to the significant impacts on shipping companies, thus novel and more environmentally friendly regulations with regard to cost may benefit the shipping companies and environmental protection synchronously.

Nevertheless, our study still has limitations. For instance, the hedging process in the futures market is based on the shipping legs amongst all the ports according to shipping operations, despite the fact that the futures trading process might be adjusted through multiple time–stage frameworks, such as weeks. Additionally, the authors are currently investigating the possible impacts of price differences between MGO and VLSFO on optimal solutions.

Future studies may concentrate on the following aspects. First, the implementation of the joint approach could be applied to various shipping service routes. Second, the authors could consider more comprehensive environmental impacts such as carbon emission limitations. Third, the uncertainty of bunker prices might also be modeled to involve identifying the cost and risk of joint solutions accurately.

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