Cold Chain Shipping Mode Choice with Environmental and Financial Perspectives

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Abstract

Mode choice between reefer bulk and container in seaborne cold chains for time sensitive products is a practical problem, in which limited studies are available to guide decision makers. This study thoroughly investigates the cold chain mode choice problem by selecting shipping mode (containerized transport and bulk transport) for each shipment and determining shipment quantities and ship deployment in a multi-period planning environment with independent perishable product demands. Value-Based Management as a novel method in shipping is adopted to consider both economic and environmental objectives from operational and financial aspects. The value-based mode selection models also determine the sailing speed of the heterogeneous chartered reefer bulk fleet under different chartering terms. Furthermore, the paper evaluates greenhouse gas emissions from the cold chain shipping. Findings from a numerical example show that optimal ship speed decreases with a reducing rate when the bunker price increases and with a higher decline rate when goods are less perishable.

Keywords: seaborne cold chain, transport mode choice, speed optimization, ship deployment and routing, greenhouse gas emission, value-based management

1. Introduction

Tremendous expansion and change have taken place in seaborne shipments of perishable commodities over the last two decades (Kissinger, 2012). Nearly 60% of global food miles is transported through sea by ships (Poore and Nemecek, 2018). Perishable commodities can be transported by two means in the sea: full reefer vessels and container vessels stowing reefer containers which are typical sea-freight containers equipped with special devices to control inside temperatures. The reefer container fleet has grown immensely and has obtained increasing market shares against traditional specialized bulk vessels (Rodrigue and Notteboom, 2015). Seaborne cold chain as a profitable niche market will continue to grow and deserves more attention from both academia and industry. Moreover, shipping time sensitive refrigerated cargoes consumes more fuel which leads to environmental implications. Most studies in seaborne cold chain focus on the general economic trend (Rodrigue and Notteboom, 2015) and the competition between the refrigerated containers and bulk (Thanopoulou, 2012, Arduino et al., 2015). Zhang and Lam (2018) investigated the cold chain shipping mode choice problem, yet the study assumed that both container and bulk vessels sail at the design speed and the bulk vessel is only allowed to travel between an origin and a single destination. This study advances Zhang and Lam (2018)'s work by thoroughly examining the cold chain mode choice selection with five additional considerations, namely, optimal shipment scheduling, two different bulk ship deployment methods, reefer bulk ship speed optimization, time dependent cargo depreciation, and emissions.

Given the demand at each destination and production (supply) at a single origin in each period for a time sensitive (perishable) cold chain product, our problem optimizes the mode choice, shipment scheduling and quantities to be shipped with a value-based approach considering environmental and financial perspectives. For each shipment, the mode choice in this study is between containerized shipment of a fixed liner shipping service and reefer bulk ship chartering. In the case of containerized shipment, departure times from the origin and sailing times to destinations are given as input to the problem. In the case of reefer bulk ship deployment, we optimize bulk ship size selection, bulk ship speed and two ship scheduling variant problems, namely direct bulk shipment from the origin to a destination (modelled as a part of model I) and cold chain maritime inventory routing in which a reefer bulk ship can be routed between multiple destinations considering selected ship capacities (modelled as a part of model II).

Sailing speed optimization is a crucial problem in shipping for several reasons. As a key determinant of fuel consumption, it significantly affects the operating cost of ships and determines exhaust emissions per voyage. Moreover, it is a decisive factor of a shipping company's logistical operation and of the overall supply chain management. Sailing speed has a critical impact on fleet size, ship size, cargo inventory costs and the balance sheets of the shippers (Psaraftis and Kontovas, 2013, Venturini et al., 2017). Ships can burn fuel at a daily rate of tens of thousands of dollars, sailing at different speed may lead to a million-dollar difference on the annual balance sheet and may even make the difference between survival and bankruptcy especially in a flagging shipping market (Ronen, 1982). The volatile bunker price especially urges ship operators to balance the bunker savings and the corresponding revenue loss (Lam, 2015).

Sailing speed optimization is even more crucial and complicated in cold chain management. As a specific type of supply chain, a cold chain mainly deals with the handling of temperature sensitive products such as perishable food, confectionary and pharmaceuticals. The products handled in a cold chain are usually time sensitive (e.g. perishable products' value reduces over time). In this study, time dependent cargo depreciation is considered in each shipment. The revenue loss due to speed reduction is more serious in cold chains. Therefore, the speed optimization decisions are considered for bulk ship deployment case as containerized transport is offered by liner shipping companies with given service schedules and speeds. The Ship Routing and Scheduling Problem (SRSP) plays a central role in maritime logistics (Wen et al., 2017). In the case of reefer bulk ship deployment for a shipment, a ship can either serve the origin to a destination pair or a ship can serve more than one destination before sailing back to the origin which results in a cold chain maritime inventory routing problem including shipment scheduling (departure and arrival time at each point), ship speed and product quantities of shipments. A limited number of studies consider the ship routing and scheduling decisions with the sailing speed optimization (Rodrigues et al., 2019). To the best of our knowledge, there is no particular study that integrates mode choice, shipment scheduling and ship deployment considerations, and time sensitive cold chain products are not considered in a maritime inventory routing problem context. This study well addresses these existing literature gaps by investigating the cold chain mode choice, shipment scheduling and ship deployment problem from both environmental and financial perspectives.

Value-based approaches can overcome two key deficiencies of conventional models (Cai et al., 2009). Firstly, traditional financial models do not support conflicting performance metrics. The other drawback of conventional approaches is that they do not present clear inter-relationships among the metrics, especially how the operational and financial aspects jointly contribute to value creation (Cai et al., 2009). Value-based approaches provide a unique perspective for managers to integrate the operational and financial aspects rather than considering them as two separate components. Value driver trees and risk adjusted performance metrics are employed in value-based management and only the paramount performance metric which synchronizes value created by all investment, operation and financial decisions is adopted (O'Byrne and Young, 2001). In this study, Economic Value Added (EVA) is employed as the value-based performance indicator and a value driver tree adapted from Hahn and Kuhn (2012b)'s work is used to analyze the value drivers in a container-based seaborne cold chain. Two Mixed Integer Linear Programming (MILP) models are proposed based on the EVA value driver tree to enrich the cold chain shipping mode choice studies.

The rest of this paper is structured as follows. Section 2 reviews literature in seaborne cold chain, speed optimization, ship routing and scheduling, and value-based supply chain management. The decision models are introduced in Section 3 and a numerical example is presented in Section 4 to analyze the models and derive managerial implications from the results. Finally, Section 5 summarizes the contributions and proposes future research directions.

2. Literature Review

2.1 Seaborne cold chain and mode choice

Reefer shipping is a main transport mode for long-haul physical movement in cold chains. Most of the limited studies in this area focus on the technical aspects of cold chains of food (Kuo and Chen, 2010) and pharmaceutical (Bishara, 2006). While quantitative methods have been gradually adopted in the research of cold chain operation, few quantitative studies have been conducted in seaborne cold chain. Most literatures in seaborne cold chain are qualitative. Lam (2010) proposed a conceptual framework to synchronize various elements of a seaborne cold chain. Other studies focused on the erosion of the market share of traditional bulk reefer from reefer container, e.g. Thanopoulou (2012) from a product life cycle perspective and a SWOT review was conducted to reveal the grim future for bulk reefer operators. An opposing view was presented by Arduino et al. (2015), they stated that although the conventional reefer market is progressively replaced by reefer containership, bulk still holds a significant share of certain reefer commodities and such advantages will be sustained at least in the short-medium term. Rodrigue and Notteboom (2015) pointed out that the containerization of traditional commodities is reaching its end and the initially ignored niche market like refregerated trade should be the key component in the new phase of global containerization. Cheaitou and Cariou (2012) proposed an optimization model to smoothen liner shipping service which is one of the very limited quantitative studies in seaborne cold chain management. Zhang and Lam (2018) took the initiative to employ value-based approaches in cold chain management and proposed a decision model to address the mode choice problem between containerized shipment and reefer bulk ship. Considering shipment schedules in a containerized banana supply chain, Mees et al. (2018) optimized the temperature in the reefer containers in a dynamic way to prevent decay of time sensitive products and to minimize total energy consumption.

2.2 Sailing speed optimization and ship routing problems

Psaraftis and Kontovas (2013) have conducted a thorough survey of current speed models and proposed a framework to divide these models into two major categories: emissions speed models in which emissions are considered together with other considerations and non-emissions speed models in which emissions are neglected. Only selective models focusing on speed optimization are discussed in this section and the exhaustive list can be found in Psaraftis and Kontovas (2013)'s study.

All the initial speed models are non-emissions models. Ronen (1982) inspected the impact of bunker price on the optimal speed of a single vessel after the oil crisis in the 1970s. Three models for vessels under different commercial circumstances are presented by Ronen (1982), namely in the income generating leg, in the positioning leg and when the penalty/bonus for late/early arrival at the destination ports. A linear model for liner operators to optimize fleet deployment is proposed by Perakis and Jaramillo (1991), in which the speed problem is dealt as a component of the deployment problem. Fagerholt (2001) also optimized the sailing speed for the soft-time window case which imposes penalties for arrivals specified time windows. Notteboom and Vernimmen (2009) analyzed costs per Twenty-foot equivalent unit (TEU) for container lines at various commercial speeds, number of vessels and different vessel sizes. Arguing that most researches focus on the speed optimization for one vessel at a time, Ronen (2011) further investigated the relationship between bunker price and container line operation. Ronen (2011) proposed a procedure for liner operators to balance the sailing speed, cycle time and number of vessels to minimize the total operation costs. Wang and Meng (2012) proposed a mixed-integer nonlinear model to obtain the optimal speed of a container fleet considering transshipment and container routing (Zhen et al., 2017). Yu et al. (2017) proposed a bi-objective model to optimize the sailing speed of tramp ships and suggested a fast elitist non-dominated sorting genetic algorithm to solve the problem.

Emissions related speed models did not emerge until the most recent decade. Corbett et al. (2009) identified vessel speed reduction as a cost-effective measure to mitigate CO_2 emission and explored how to determine the optimal speed within a profit-maximizing function. Fagerholt et al. (2010) proposed an alternative solution methodology to investigate the speed driven emission reduction issue, in which the arrival times are discretized and the problem is formulated as a shortest path problem on an acyclic graph. Cariou (2011) studied the reduction of CO_2 emission attributed to slow steaming in various container trades. Venturini et al. (2017) proposed an Integer Linear Programming (ILP) model to solve the berth allocation problem with speed optimization and emission considerations for a fleet of ships.

Although the studied speed models have achieved significant improvements in recent decades and have covered different shipping markets, they do not focus on the value of the shipment. Time sensitive cargoes have not been considered in the literature either and no model has been proposed to optimize the sailing speed of reefer vessels. This study is the first attempt to address these limitations of the existing speed models and it investigates the optimal sailing speed in a seaborne cold chain.

Ship routing and scheduling have been extensively studied in the state-of-the-art. Wen et al. (2016) formulated the full-shipload tramp ship routing and scheduling problem as a three-index mixed integer linear model and proposed a branch and price algorithm and heuristic column generation to find the optimal route and the optimal sailing speed on each leg that would maximize the total profit. Wen et al. (2017) later investigated the tramp ship routing problem with multiple objectives, namely time, cost and emission. A branch and price algorithm and a constraint programming model are proposed to solve the problem. As stated by Wen et al. (2017), there are not many studies that consider the ship routing problem and the speed decision simultaneously and this new research area has much potential for further development. This study follows this gap by investigating the combined routing and speed decision. Similar to Xu et al. (2017)'s work, this study forms a compact model to couple the route choice and the speed decision. One version of the problem addressed in this paper routes the ships in a multi-period planning horizon. This version has similarities to Multi-period Vehicle Routing Problem (MVRP). Wen et al. (2010) modeled a Dynamic Multi-period Vehicle Routing Problem (DMVRP) as a mixed integer linear model and solved it by a three-phase heuristic method. The model addresses three objectives simultaneously by employing a scalar technique approach. In Archetti et al. (2015)'s work, exceeding due dates is allowed in DMVRP with a penalty cost and a branch-and-cut algorithm is proposed to minimize the overall cost. Dayarian et al. (2016) suggested adaptive large neighbourhood search for the DMVRP. In this study, we also consider the optimization of quantities to be shipped and ship deployment and routing (if bulk ship is selected for a shipment). Maritime inventory routing studies address a similar problem in which shipment departure times and shipment quantities are decided along with ship routing to meet the demand at destination ports and manage the inventory (Song and Furman, 2013). Eide et al. (2020) enhanced the maritime inventory routing problem by considering load-dependent ship sailing speed optimization.

2.3 Value-based supply chain management

The value-based management approach is derived from managerial accounting practices and aims to measure and manage business to create lasting value for shareholders by developing an integrated framework (Koller et al., 2010, Black and Wright, 2001). Therefore, maximizing value-based performance is the explicit objective of value-based management. Economic Value Added (EVA), among a variety of value-based performance indicators, is more superior in terms of measuring business performance and expressing a value judgement on the company (Melis et al., 2014).

Walters (1999) proposed an EVA-based framework including strategic and operational value drivers in supply chain management and identifies the strategic and operational value drivers. Strategic value drivers include product and market portfolio, supply chain assets, and financial structuring; while operational value drivers consist of customer retention, sales growth, and integration of supply chain partners. Christopher and Ryals (1999) summarized four value drivers that linked supply chain strategy and value-based management, namely revenue growth, operating cost reductions, fixed capital efficiency and working capital efficiency. Hahn and Kuhn (2012a) argued that although value driver trees facilitate identifying key value drivers in supply chain management, they fail to provide direct decision support for value-based optimization. Hahn and Kuhn (2012b) proposed a framework of value driver tree in supply chain management, based on which a decision model is developed to optimize physical and financial supply chain planning at a mid-term level. Later, the model is enhanced by integrating risk management (Hahn and Kuhn, 2012c). Zhang and Lam (2018) approached the cold chain mode choice problem from the value-based perspective and proved its superiority over the traditional optimization approach. As stated by Giovannini and Psaraftis (2018), most available models on containership speed optimization, fleet deployment, fleet size and mix, network design are at the tactical planning level. These models assume a fixed revenue for the ship operator and aim to minimize costs, therefore they miss the fundamental characteristic of shipping market behavior. A value-based optimization model would avoid this problem.

In a nutshell, several research gaps have been identified in the maritime cold chain domain. Castelein et al. (2020) presented a literature review and suggested a wide range of future research directions emphasizing the importance of mode choice and shipment management. The integrated shipping mode choice, shipment scheduling and ship deployment is hardly studied in the state-of-the-art. This study deals with such an integrated problem for time sensitive products with deterioration as a pioneering work. Although the speed optimization problem is well studied in liner and tramp shipping markets (Psaraftis and Kontovas, 2013), a limited number of studies can be found in the context of maritime cold chain. Our paper bridges several gaps by being the first in the literature to study integrated seaborne cold chain mode choice, shipment scheduling and ship deployment with speed optimization from the value-based perspective. Moreover, it is a pioneer work to study environmental consideration from a value-based perspective in shipping.

3. Problem definition and mathematical models

EVA indicates a firm's increased net present value, which is the difference between the net return and the cost of capital from the net return (Melis et al., 2014). In Equation (1), EVA equals net operating profit after tax (NOPAT) minus the net operating assets (NOA) factored by the weighted average cost of capital (WACC, denoted i^{WACC}).

$$EVA = NOPAT - NOA \cdot i^{WACC} \tag{1}$$

Figure 1 is a value driver tree of EVA in seaborne cold chain. The value driver tree facilitates to deconstruct top-level indicators, which cannot influence EVA directly, to various decision factors at operational level. According to Walters (1999), the major operational drivers are the Operating profit margin which derived from Sales and Costs of Goods Sold (COGS), asset utilization which includes Expenses and the cost of Fixed Assets, operational cash flow which comprises the cost of Current Assets and the WACC.

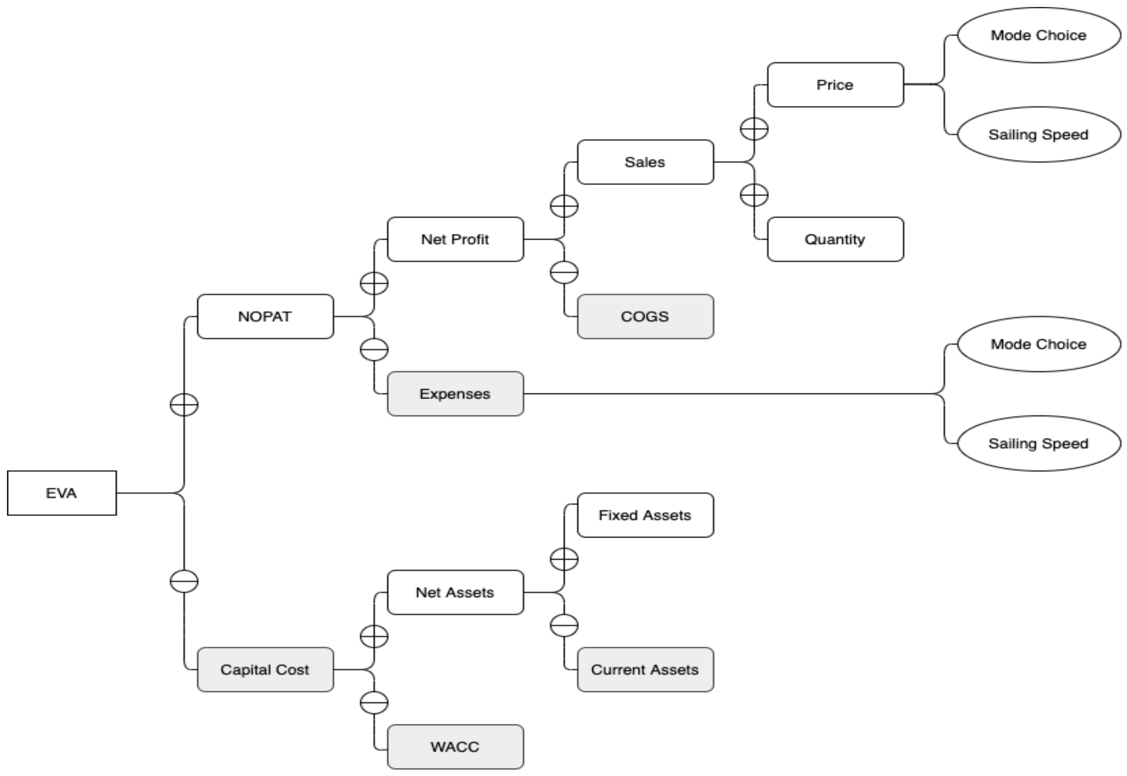

Figure 1 A Value Driver Tree of EVA in Seaborne Cold Chain

Source: Modified from Hahn and Kuhn (2012b) by authors

The problem consists of determining quantity to be sent per period to meet the demand of a cold chain product which is shipped from a single origin port. There are multiple destination ports (customer ports) to deliver the product and each customer port has an independent demand for the product in each period (week). The problem also aims to determine the shipping mode composition in each week to meet the demand on time. The problem considers the distance between origin port and destination ports. There are two possible shipping modes, namely containerized transport and bulk reefer ship. It is well-known that containerized liner service has a fixed schedule and fixed sailing time between ports. Meanwhile in the case of reefer bulk ship deployment, we decide the reefer ship size, the sailing speed for reefer bulk ship and make a shipment schedule. The detailed assumptions of the problem are listed in section 3.1 and 3.2, respectively.

Based on the value driver tree, two MILP models are developed to decide the shipping mode composition in each week, determine quantity to be sent, schedule the shipments, and determine the sailing speed of reefer bulks from the shipper's perspective. The objective function maximizes EVA which is the value-based performance of a trading company (the shipper). The two models only differ in way of handling reefer bulk ships, otherwise they are the same. The first model (Model I) assumes that each reefer ship can sail between origin port and one destination port in each shipment (based on a voyage chartering method). The reefer container vessels charge per container while the bulk vessels are on voyage chartering. The second model (Model II) relaxes this assumption and allows reefer bulk ship to serve multiple destination ports in each shipment by routing each reefer ship (based on a time chartering method) like a maritime inventory routing problem. Meanwhile the containerized liner service still follows a fixed schedule. Both models calculate quantity of products transported by each mode subject to ship capacity. The problem assumes that there are different kinds of reefer bulk ships to charter with different capacities and sailing speed limits.

The problem also considers time dependent cargo depreciation and speed dependent emissions. The value of the cargoes will drop exponentially as time elapses as shown in Eq. (2) (You, 2005). The intensity of price discount β reflects the depreciation rate of the value for a cargo over time. Due to this special character of reefer cargo, speed optimization plays a more important role in determining the value created. On the other side, high speed will lead to more GHG emissions on the top of the high emission base of reefer fleet. To investigate the optimal speed which balances the economic return and the environmental impact, a penalty parameter φ is introduced to reflect the environmental cost of every unit of fuel consumed.

Financial planning horizon is measured by means of months. The EVA is influenced by the balance between income and expenditures in each month. The time value of money is omitted, and only current assets and liabilities are considered as auxiliary variables in the financial aspect. For each month, constraints for balancing income and expenditures basis are crucial for the VBM. Sailing at a higher speed will increase the income as the value of the cargoes will be preserved to some extent, however, it will increase both the operational and environmental costs. The same dilemma exists for the client early payment and early payment to supplier. The client early payment refers to the amount of revenue received from the clients before the cargoes are delivered; the clients pay in advance to get an early payment discount. A high client early payment will mitigate the cash flow risk, but at the cost of sabotage of the profit. The early payment to supplier works exactly the other way around. The company could choose to pay to the supplier in advance to get an early payment discount. A high early payment to supplier will increase the profit while risk the cashflow.

3.1 Model I

Model I determines the shipping mode composition to meet the weekly demand of a product in several destination ports. The objective is to maximize EVA which integrates financial aspects with operational costs. Model I has decision variables about the amount of cargo shipped in different modes every week, scheduling of reefer bulk ships with speed optimization, and financial accounting balance and EVA calculation. Different methods have been applied to deal with the non-linearity of the fuel consumption and speed relationship. Most of the papers that consider speed optimization assume that daily fuel consumption is a cubic function of ship speed. The fuel consumption-speed relation is linearized adopting the Second-Order Cone Programming (SOCP) transformation, which is an equivalent transformation, in Hu et al. (2014). Linear regression (Lang and Veenstra, 2010), discretization of times (Iris et al. 2015) and speeds (Venturini et. al., 2017) have also been used to reflect the speed and fuel consumption relationship. In this study, the sailing speeds have been discretized to achieve the linearization.

To limit our research scope, following assumptions are made.

1. Liner reefer container service is available once a week from the port of origin to each port of destination and the cost is per TEU.
2. Reefer bulk vessels are available for chartering every other day and the chartering is charged based on voyage. For each bulk type, at most one bulk ship can be deployed in a day.
3. The financial status is reviewed monthly, and the monthly cash flow and short-term debt should meet the criteria set by the financial institute (e.g. banks).
4. The sailing speed of the liner service is fixed by the liner service provider. As such, traveling time between ports is fixed for liner service.
5. A discount θ^{AP} is offered by the supplier if the shipper pays for the procurement one month in advance, known as the early payment discount. In the same manner, a discount θ^{AR} is available for the clients who pay the shipper for their order one month in advance (Hahn & Kuhn, 2010).
6. The demands in the destination ports will be catered on weekly basis and backlog is not allowed. Besides, it is assumed that the cargo is unloaded in the same day.

7. The value of the products deteriorates with the time elapsed (You, 2005). Such a loss is directly reflected in the depreciated cargo price (and revenue consequently), as shown in Eq. (2), i.e., $qc_{op} = q_p \cdot \exp\left(-\beta \cdot \gamma c_{op}\right)$.

The notation used in this model is presented as follows.

Parameters and sets

P	Set of all destination ports, $P \in \{1, 2, \ \dots \ , \ N\}$, where N is the number of destination ports
L	Set of all the legs including the origin port and destination ports, where $L \in \{(1,1), (1,2), \ \dots \ , \ (1,N)\}$
T	Set of 1-day periods, $T \in \{1,2, \dots, H\}$, where H is the end of planning horizon
T^D	Set of dates when the bulk chartering is available, where $T^D \in \left\{2, 4, \ \dots \ , \ 2\lfloor\frac{H}{2}\rfloor\right\} \in T$
T^W	Set of dates when the reefer container is available, where $T^W \in \left\{7, 14, \ \dots \ , \ 7\lfloor\frac{H}{7}\rfloor\right\} \in T$
W	Set of one week periods, where W$\in \left\{1, 2, \ \dots, \lfloor\frac{H}{7}\rfloor\right\}$
M	Set of one month periods, where $M \in \left\{1, 2, \ \dots, \lfloor\frac{H}{28}\rfloor\right\}$
B	Set of reefer bulk vessel types, $B \in \{1,2, \dots, R\}$, where R is the number of available reefer bulk vessel types
V^b	Set of speeds for bulk vessel type $b \in B$
Z	Tax rate
i^{wacc}	Weighted average cost of capital
β	Intensity of daily price discount due to depreciation
α	Average balance of net operating fixed assets
ε_m	Fixed costs in month $m \in M$
l_{op}	Sailing distance of leg $(o,p) \in L$
γc_{op}	Sailing time (in days) for leg $(o,p) \in L$ by container reefer vessel
$\gamma_{op}^{b\tau}$	Sailing time (in days) for leg $(o,p) \in L$ by bulk vessel type b at speed $\tau \in V^b$
$capY^b$	Capacity of bulk reefer vessel $b \in B$
q_o	Initial price of the cargo at port $o \in O$
q_p	Price of the cargo without depreciation at port $p \in P$

qc_{op}	Depreciated cargo price transported by container reefer vessel via leg $(o,p) \in L$; $qc_{op} = q_p \cdot \exp(-\beta \cdot \gamma c_{op}),\ \forall (o,p) \in L, \forall p \in P$ (2)
$qm_{op}^{b\tau\beta}$	Depreciated cargo price while shipped by bulk refer vessel $b \in B$ at speed $\tau \in V^b$ via leg $(o,p) \in L$ when the intensity of daily price discount is β; $qm_{op}^{b\tau\beta} = \exp\left(-\beta \cdot \gamma_{op}^{b\tau}\right),\ \forall (o,p) \in L, \forall \tau \in V^b, \forall b \in B$ (3)
δ_{op}^{b}	Chartering cost per trip for bulk reefer vessel $b \in B$ on leg $(o,p) \in L$
δc	Shipping freight rate per TEU for container reefer vessel
$f^{b\tau}$	Fuel consumption for a unit distance when bulk vessel $b \in B$ sails at speed $\tau \in V^b$
φ	Penalty parameter for a unit fuel consumption
θ^{AP}	Early payment discount offered by the supplier
θ^{AR}	Early payment discount offered to the client
d_{pw}	Demand of the cargo at port $p \in P$ in week $w \in W$
i^{FI}	Interest rate for short-term financial investment
i^{DS}	Interest rate for short-term debts
DS^{max}	Bank line of credit
C^{min}	Minimum cash position required by the bank
fi^{0}	Initial position in short-term financial investments
c^{0}	Initial position in cash
ds^{0}	Initial position in short-term debts
ap^{0}	Initial position in client early payment
ar^{0}	Initial position in early payment to supplier
ca^{0}	Initial current assets; $ca^0 = fi^0 + ar^0 + c^0 - ap^0$ (4)
ec_m	Exogenous cash flow in month $m \in M$

Decision variables

$X_{om} \in \mathbb{Z}^+$	Quantity of cargo purchased at origin port o in month $m \in M$
$Y_{opta}^{b} \in \mathbb{Z}^+$	Quantity of cargo shipped by bulk reefer vessel $b \in B$ via leg $(o,p) \in L$, the ship departs on day $t \in T \cup \{0\}$ and arrives on day $a \in T$, 0 is the dummy period
$YC_{opt} \in \mathbb{Z}^+$	Quantity of cargo shipped by container reefer vessel via leg $(o,p) \in$

	L in period $t \in T \cup \{0\}$, 0 is the dummy period
$v_{opt}^{b\tau} \in \mathbb{B}$	1 if bulk vessel $b \in B$ on leg $(o,p) \in L$ sails at the speed $\tau \in V^b$ in period $t \in T \cup \{0\}$, 0 is the dummy period; 0 otherwise
$A_{opt}^{b} \in \mathbb{Z}^+$	The arrival time of bulk refer vessel $b \in B$ departs on day $t \in T$ via leg $(o,p) \in L$
$\Gamma_{opta}^{b} \in \mathbb{B}$	1 if bulk reefer vessel $b \in$ departs on day $t \in T \cup \{0\}$ and arrives on day $a \in T$ via leg $(o,p) \in L$; 0 otherwise
$Z_{opta}^{b\tau} \in \mathbb{Z}^+$	Quantity of cargo transported by bulk refer vessel $b \in B$ which departs on day $t \in T$ and arrives on day $a \in T$ via leg $(o,p) \in L$ at the speed $\tau \in V^b$. An intermediate variable to present the product of Y_{opta}^{y} and $v_{op}^{b\tau}$
$FI_m \in \mathbb{R}^+$	Position in short-term financial investments at the end of month $m \in M$
$C_m \in \mathbb{R}^+$	Cash balance at the end of month $m \in M \cup \{0\}$
$DS_m \in \mathbb{R}^+$	Short-term debt at the end of month $m \in M \cup \{0\}$
$AP_m \in \mathbb{R}^+$	Early payment to supplier at the end of month $m \in M \cup \{0\}$
$AR_m \in \mathbb{R}^+$	Client early payment at the end month $m \in M \cup \{0\}$
$AP_m{}' \in \mathbb{R}^+$	Early payment to the supplier for the procurement in the next month
$AR_m{}' \in \mathbb{R}^+$	Early payment from the client for the delivery in the next month

Auxiliary variables

Q_{opta}^{b}, total post-depreciation value of the cargo transported by bulk reefer vessel $b \in B$ via leg $(o,p) \in L$ sailing from time period t to a:

$$Q_{opta}^{b} = q_p \cdot \sum_{\tau \in V^b} (Z_{opta}^{b\tau} \cdot qm_{op}^{b\tau\beta}), \ \forall (o,p) \in L, \forall p \in P, \forall b \in B, \forall t, a \in T \tag{5}$$

NS_m, net sales in month $m \in M$:

$$NS_m = \sum_{(o,\ p) \in L} \sum_{t \in T} \sum_{a=30m-29}^{a=30m} \sum_{b \in B} Q_{opta}^{b} + \sum_{t=30m-29}^{t=30m} \sum_{(o,\ p) \in L} YC_{op(\max\{t-\gamma c_{op},0\})} \cdot qc_{op}, \forall m \in M \tag{6}$$

VC_m, variable cost in month $m \in M$:

$$VC_m = \sum_{(o,\ p)\in L}\sum_{t\in T}\sum_{a=30m-29}^{a=30m}\sum_{b\in B} Y^b_{opta} + \sum_{t=30m-29}^{t=30m}\sum_{(o,p)\in L} YC_{op(\max\{t-\gamma c_{op},0\})}\cdot q_0 +$$
$$\sum_{(o,\ p)\in L}\sum_{t\in T}\sum_{a=30m-29}^{a=30m}\sum_{b\in B}\Gamma^b_{opta}\cdot\delta^b_{op} + \sum_{t=30m-29}^{t=30m}\sum_{(o,p)\in L} YC_{op(\max\{t-\gamma c_{op},0\})}\cdot\delta c\ \cdot\gamma c_{op} + ,\ \forall m\in M \tag{7}$$
$$\varphi\cdot\sum_{b\in B}\sum_{\tau\in V^b}\sum_{(o,p)\in L} f^{b\tau}\cdot l_{op}\cdot v^{b\tau}_{op} - AP^{'}_m\cdot\theta^{AP} + AR^{'}_m\cdot\theta^{AR}$$

TCM_m, total contribution margin in month $m \in M$:

$$TCM_m = NS_m - VC_m,\ \forall m\in M \tag{8}$$

OCF_m, cash flow from operations in month $m \in M$:

$$OCF_m = X_{om}\cdot q_o + \sum_{(o,\ p)\in L}\sum_{t\in T}\sum_{a=30m-29}^{a=30m}\sum_{b\in B}\Gamma^b_{opta}\cdot\delta^b_{op} + \sum_{t=30m-29}^{t=30m}\sum_{(o,\ p)\in L} YC_{opt}\cdot\delta c\cdot\gamma c_{op},\ \forall m\in M \tag{9}$$

OM_m, open items management in month $m \in M$:

$$OM_m = AR_{m-1} + AR_m^{'}\left(1-\theta^{AR}\right) - AP_{m-1} - AP_m^{'}\left(1-\theta^{AP}\right),\forall m\in M \tag{10}$$

FM_m , short-term financial management (return and cost) in month $m \in M$:

$$FM_m = FI_{m-1}\cdot\left(1+i^{FI}\right) - FI_m - DS_{m-1}\cdot\left(1+i^{DS}\right) + DS_m,\ \forall m\in M \tag{11}$$

CA_m, operating current net assets at the end of month $m \in M$:

$$CA_m = FI_m + AR_m + C_m - AP_m,\ \forall m\in M \tag{12}$$

Objective function

$$\max EVA = \sum_{m\in M}\left(TCM_m - \varepsilon_m\right)\cdot(1-z) - \sum_{m\in M}(\alpha + CA_{m-1})\cdot i^{WACC} \tag{13}$$

subject to:

$$\sum_{\tau\in V^b} v^{b\tau}_{opt} \le 1, \forall t\in T, (o,p)\in L, \forall b\in B \tag{14}$$

$$A^b_{opt} = t\cdot\sum_{\tau\in V^b} v^{b\tau}_{opt} + \sum_{\tau\in V^b} v^{b\tau}_{opt}\cdot\gamma^{b\tau}_{op},\ \ \forall t\in T, \forall(o,p)\in L, \forall b\in B \tag{15}$$

$$\Gamma^b_{opta} = 0,\ \forall t\in T, (o,p)\in L, \forall b\in B, \forall a\in[0,t]\bigcup[t+\max(\gamma^{b\tau}_{op}),\infty] \tag{16}$$

$$Y_{opta}^{b}=0,\ \forall t\in T,(o,p)\in L,\forall b\in B,\forall a\in[0,t]\bigcup[t+\max(\gamma_{op}^{b\tau}),\infty] \tag{17}$$

$$A_{opta}^{b}=\sum_{a=t}^{a=\max(\gamma_{op}^{b\tau})} a\cdot\Gamma_{opta}^{b},\ \forall t\in T,(o,p)\in L,\forall b\in B \tag{18}$$

$$Y_{opta}^{b}\le capY^{b}\Gamma_{opta}^{b},\ \forall a\in T,\forall t\in T,\forall(o,p)\in L,\forall b\in B \tag{19}$$

$$\sum_{\tau\in V^{b}} v_{opt}^{b\tau}=\sum_{a=t}^{a=t+\max(\gamma_{op}^{b\tau})}\Gamma_{opta}^{b},\ \forall t\in T,(o,p)\in L,\forall b\in B \tag{20}$$

$$\sum_{(o,\ p)\in L} YC_{opt}=0,\ \forall t\in T\setminus T^{W} \tag{21}$$

$$\sum_{(o,\ p)\in L}\sum_{b\in B}\sum_{\tau\in V^{b}} v_{opt}^{b\tau}=0,\ \forall t\in T\setminus T^{D} \tag{22}$$

$$\sum_{(o,\ p)\in L}\sum_{t\in T}\sum_{a=30m-29}^{a=30m}\sum_{b\in B} Y_{opta}^{b}+\sum_{t=30m-29}^{t=30m}\sum_{(o,\ p)\in L} YC_{opt}=X_{om},\ \forall m\in M \tag{23}$$

$$\sum_{(o,\ p)\in L}\sum_{b\in B}\sum_{t\in T}\sum_{a=7w-6}^{a=7w} Y_{opta}^{b}+\sum_{(o,\ p)\in L}\sum_{t=7w-6}^{t=7w} YC_{op\left(\max\left\{t-\gamma c_{op},0\right\}\right)}=d_{pw},\ \forall w\in W,p\in P \tag{24}$$

$$YC_{op0}=0,\ \forall(o,p)\in L,\forall b\in B \tag{25}$$

$$Y_{op0a}^{b}=0,\ \forall(o,p)\in L,\forall b\in B \tag{26}$$

$$\sum_{a\in T} Z_{opta}^{b\tau}\le v_{opt}^{b\tau}\cdot capY^{b},\ \forall t\in T,\forall(o,p)\in L,\forall b\in B,\forall\tau\in V^{b} \tag{27}$$

$$\sum_{\tau\in V^{b}} Z_{opta}^{b\tau}\le Y_{opta}^{b},\ \forall t\in T,\forall a\in T,\forall(o,p)\in L,\forall b\in B \tag{28}$$

$$Z_{opta}^{b\tau}\ge Y_{opta}^{b}-capY^{b}\cdot(1-v_{opt}^{b\tau})\ \forall t\in T,\forall a\in T,\forall(o,p)\in L,\forall b\in B,\forall\tau\in V^{b} \tag{29}$$

$$\sum_{(o,\ p)\in L}\sum_{(o,\ p)\in L}\sum_{t\in T}\sum_{a=30m-29}^{a=30m}\sum_{b\in B} Q_{opta}^{b}+\sum_{t=30m-29}^{t=30m}\sum_{(o,\ p)\in L} YC_{op\left(\max\left\{t-\sum_{\tau\in V^{b}} l_{op}/v_{op}^{b\tau},0\right\}\right)}\cdot qc_{op}=AR_{m}+AR_{m-1}^{'},\forall m\in M \tag{30}$$

$$\begin{aligned}&X_{om}\cdot q_{o}+\sum_{(o,\ p)\in L}\sum_{t\in T}\sum_{a=30m-29}^{a=30m}\sum_{b\in B}\Gamma_{opta}^{b}\cdot\delta_{op}^{b}+\sum_{t=30m-29}^{t=30m}\sum_{(o,p)\in L} YC_{op(\max\left\{t-\gamma c_{op},0\right\})}\cdot\delta c\ \ \cdot\gamma c_{op}\\&+\varphi\cdot\sum_{b\in B}\sum_{\tau\in V^{b}}\sum_{(o,p)\in L} f^{b\tau}\cdot l_{op}\cdot v_{op}^{b\tau}=AP_{m}+AP_{m-1}^{'},\forall m\in M\end{aligned} \tag{31}$$

$$C_m = C_{m-1} - OCF_m + OM_m + FM_m, \forall m \in M \tag{32}$$

$$DS_m \le DS^{max}, \ \forall m \in M \tag{33}$$

$$C_m \ge C^{min}, \ \forall m \in M \tag{34}$$

$$FI_0 = fi^0 \tag{35}$$

$$C_0 = c^0 \tag{36}$$

$$DS_0 = ds^0 \tag{37}$$

$$AP_0 = ap^0 \tag{38}$$

$$AR_0 = ar^0 \tag{39}$$

$$CA_0 = ca^0 \tag{40}$$

$$AP_0^{'} = 0 \tag{41}$$

$$AR_0^{'} = 0 \tag{42}$$

$$v_{opt}^{b\tau}, \Gamma_{opta}^{b} \in \{0,1\}, \forall a \in T, \forall t \in T, \forall b \in B, \forall (o,p) \in L, \forall \tau \in V^b \tag{43}$$

$$X_{om}, Y_{opta}^{b}, Y_{opt}^{y}, A_{opt}^{b}, Z_{opta}^{b\tau} \ge 0, \ \forall a \in T, \forall t \in T, \forall m \in M, \forall (o,p) \in L, \forall o \in O, \forall b \in B, \forall \tau \in V^b \tag{44}$$

$$FI_m, C_m, DS_m, AP_m, AR_m, AP_m^{'}, AR_m^{'} \ge 0, \ \forall m \in M \tag{45}$$

The objective of this model is to maximize the *EVA* which is defined in Eq. (1) and formulated in Eq. (13). The *EVA* equals to the net operating profit after tax *NOPAT* minus the capital cost. The components of *NOPAT* are presented in Eq. (6) – (8), in which the total contribution margin *TCM* is the difference between the net sales *NS* and the variable cost *VC*. The capital cost is generated by the average balance of net operating fixed assets α and the operating current net assets *CA*. *CA* consists of the short-term financial investment *FI*, the client early payment *AR* and the cash flow *C* excluding the early payment to supplier *AP* as shown in Eq. (12). Cash flow from operations *OCF* represents all early payment to supplier as presented in Eq. (9). As shown in Eq. (10), open items management *OM* equals to the balance of the early payment to supplier and client early payment after the discount. Eq. (11) introduces short-term financial management *FM*, which is the earning from the *FI* minus the cost of the short-term debt DS.

The model I subjects to two sets of constraints, namely, operational constraints and financial constraints. The constraints from the operational requirements are presented in Constraints (14) – (29), while Constraints (30) – (45) reflect the financial aspects. Constraint (14) ensures that each bulk sails with one speed per leg. Constraint (15) links the arrival time of each reefer bulk ship with the binary speed variables for each leg. In (15), each ship b that departs at time t is ensured to arrive at A^{b}_{opt} with the selected speed τ. In Constraints (16) – (18), the arrival time and the binary assignment variable Γ, which points out the departure and arrival time of a bulk vessel *b*, are linked. Constraints (16)-(17) eliminate variables with infeasible departure and arrival time pairs. Constraint (18) links the arrival time variable to the binary variable which points out departure and arrival time. For each port pair (*o, p*), bulk ship and realized departure time *t*, the arrival time to p is unique and it is between $t+1$ and $t+max(\gamma^{b\tau}_{op})$ where $max(\gamma^{b\tau}_{op})$ is the maximum travel time on the pair (*o, p*). The amount of cargo transported by reefer bulk vessel is set in Constraints (19) – (21). They limit the amount shipped per vessel and ensure that the vessels can be deployed every other day. Constraint (19) imposes the reefer bulk ship capacity limit on each shipment, while constraint (20) guarantees that bulk ship speed on a pair is selected only if the bulk ship is scheduled on that pair within the given departure and arrival time. Constraint (21) establishes the weekly schedule for container vessels. The monthly procurement amount and the weekly demand in each destination port are obtained in Constraints (23) and (24). In (24), it is ensured that weekly demand at each port of destination is exactly met without backlog. The amount shipped by container and bulk vessels are set to zero in dummy period in Constraints (25) and (26). Constraints (27) – (29) obtain intermediate variable ($Z^{b\tau}_{opta}$) which is the product of an integer variable (Y^{y}_{opta}) and a binary variable ($v^{b\tau}_{op}$) by introducing three linear constraints. In the financial aspect, Constraint (30) ensures that all sales are collected by either the regular amount received or early amount received; and constraint (31) makes sure that the amount payed sums up to the total cost. Monthly cash flow is defined by constraint (32) as the sum of the cash flow in the previous month, open items management *OM* and short-term financial management *FM* deducted by the cash flow from operations *OCF*. The monthly cash flow should be larger than C^{min} and short-term borrowings are lesser than the bank line of credit

DS^{max} required by the bank (33-34). Constraints (35) – (42) set the initial values of all the financial variables. The domains of all the variables are imposed in (43) - (45).

3.2 Model II

The model II is a MILP model and solves exactly the same problem as model I except bulk vessels are allowed to deliver cargo to different destination ports and arrive at origin port in one route. The remainder assumptions of model I hold for model II. To formulate model II, the weekly demand at each destination port is set as cargoes (represented with a cargo set) with a time window of one week. Time discretization is used to linearize the speed dependent variables. For the consumption cost calculation, the travelling distance for each cargo point is estimated as the distance between the port of origin and port of destination rather than the actual distance of the leg in the routing route.

Parameters and sets

N	Set of all cargoes required to be delivered, $N \in \{1, 2, \dots, Q\}$, where Q is the number of cargoes and Cargo q to be delivered to port $\begin{cases} mod\left(\frac{q}{3}\right), & mod\left(\frac{q}{3}\right) \neq 0 \\ 3, & mod\left(\frac{q}{3}\right) = 0 \end{cases}$ in respective week
S	Set of all bulk vessels, $S \in \{1, 2, \dots, N\}$, where N is the total number of ships, each reefer bulk ship has a bulk type *b* in the set $B \in \{1,2, \dots, R\}$, where R is the number of available reefer bulk vessel types
L	Set of all the legs between different cargoes, where $L \in \{(1, 2), (1,3), \dots, (Q-1, Q)\}$, L^{en}, set of legs where ending node is delivery point of cargo *n*, L^{sn}, set of legs where starting node is delivery point of cargo *n*,
T	Set of 1-day periods, $T \in \{0,1,2, \dots, H\}$, where H is the end of planning horizon and 0 is the dummy period
T^D	Set of dates when the bulk chartering is available, where $T^D \in \left\{2, 4, \dots, 2\lfloor\frac{H}{2}\rfloor\right\} \in T$
T^W	Set of dates when the reefer container is available, where $T^W \in \left\{7, 14, \dots, 7\lfloor\frac{H}{7}\rfloor\right\} \in T$
W	Set of one week periods, where W $\in \left\{1, 2, \dots, \lfloor\frac{H}{7}\rfloor\right\}$
M	Set of one month periods, where $M \in \left\{1, 2, \dots, \lfloor\frac{H}{28}\rfloor\right\}$
V^b	Set of speeds for bulk vessel $b \in S$, and V is set of all speeds
tws^n	The starting day of time window for cargo $n \in N$

twe^n	The ending day of time window for cargo $n \in N$
twm^n	$twm^n = \frac{twe^n}{28} + 1$ for cargo $n \in N$
N^m	Set of cargoes within delivery time windows in month $m \in M$, where $tws^n, tws^n \in (28m-27, 28m)$ $\forall m \in M, \forall n \in N^m$
s_l^τ	The sailing time (in days) on leg $l \in L$ at speed $\tau \in V$
D	Set of sailing time (in days), where $D \in \{\min(d_l^\tau), \ldots, \max(d_l^\tau)\}$
$f^{s\tau}$	Fuel consumption for a unit distance when bulk vessel $s \in S$ sails at speed $\tau \in V$
k^l	Sailing distance for leg $l \in L$
Z	Tax rate
i^{wacc}	Weighted average cost of capital
β	Intensity of daily price discount
α	Average balance of net operating fixed assets
ε_m	Fixed costs in month $m \in M$
γc_{1n}	Sailing time (in days) for cargo $n \in N$ by container reefer vessel
$capY^b$	Capacity of bulk reefer vessel $b \in B$
q^0	Initial price of the cargo
q^n	Price of the cargo without depreciation when delivered as cargo $n \in N$
qc_{1n}	Depreciated cargo price transported by container reefer vessel for leg $(1, n) \in L$; $qc_{1n} = q_n \cdot \exp(-\beta \cdot \gamma c_{1n}),\ \forall n \in N$ (46)
qs^d	Depreciation parameter for sailing time $d \in D$; $qs^d = \exp(-\beta \cdot d), \forall d \in D$ (47)
δ^s	Daily chartering cost for bulk reefer vessel $s \in S$
δc	Freight per TEU per day by container reefer vessel
φ	Penalty parameter for a unit fuel consumption
θ^{AP}	Early payment discount offered by the supplier
θ^{AR}	Early payment discount offered to the client
d^n	Demand for cargo $n \in N$
i^{FI}	Interest rate for short-term financial investment
i^{DS}	Interest rate for short-term debts
DS^{max}	Bank line of credit
C^{min}	Minimum cash position required by the bank

fi^0	Initial position in short-term financial investments
c^0	Initial position in cash
ds^0	Initial position in short-term debts
ap^0	Initial position in early payment
ar^0	Initial position in client early payment
ca^0	Initial current assets; $$ca^0 = fi^0 + ar^0 + c^0 - ap^0 \quad (48)$$
ec_m	Exogenous cash flow in month $m \in M$

Decision variables

$X_l^{s\tau} \in \mathbb{B}$	1 if bulk vessel $s \in S$ sails on leg $l \in L$ at speed $\tau \in V$; 0 otherwise
$Y^{ns} \in \mathbb{Z}^+$	Quantity of cargo $n \in N$ shipped by bulk vessel $s \in S$
$W^{ns} \in \mathbb{Z}^+$	The day when bulk vessel $s \in S$ unloads cargo $n \in N$
$C^{nt} \in \mathbb{Z}^+$	Quantity of cargo $n \in N$ shipped by container vessel which arrives in day $t \in T$
$YB^{nm} \in \mathbb{Z}^+$	Quantity of cargo $n \in N$ shipped by bulk vessel in month $m \in M$
$YBB^{nbm\tau} \in \mathbb{B}$	1 if the bulk vessel $b \in S$ sails at speed $\tau \in V^b$ serves cargo $n \in N$, departs in month $m \in M$; 0 otherwise
$\Gamma^{sm} \in \mathbb{Z}^+$	The sailing time (in days) of bulk vessel $s \in S$ in month $m \in M$
$B^{nd} \in \mathbb{B}$	1 if the total sailing time for cargo $n \in N$ is $d \in D$ days; 0 otherwise
$U^n \in \mathbb{Z}^+$	Intermediate variable to ensure a uniform speed on one leg
$Z^{nd} \in \mathbb{Z}^+$	Quantity of cargo $n \in N$ shipped by bulk vessel with sailing time $d \in D$
$FI_m \in \mathbb{R}^+$	Position in short-term financial investments at the end of month $m \in M$
$C_m \in \mathbb{R}^+$	Cash balance at the end of month $m \in M \cup \{0\}$
$DS_m \in \mathbb{R}^+$	Short-term debt at the end of month $m \in M \cup \{0\}$
$AP_m \in \mathbb{R}^+$	Early payment to supplier at the end of month $m \in M \cup \{0\}$
$AR_m \in \mathbb{R}^+$	Client early payment at the end month $m \in M \cup \{0\}$
$AP_m{}' \in \mathbb{R}^+$	Early payment to the supplier for the procurement in the next month
$AR_m{}' \in \mathbb{R}^+$	Early payment from the client for the delivery in the next month

Auxiliary variables

Q^n, total post-depreciation value of cargo $n \in N$ transported by bulk reefer vessel:

$$Q^n = q^n \cdot \sum_{d \in D} (Z^{nd} \cdot qs^d), \ \forall n \in N \tag{49}$$

NS_m, net sales in month $m \in M$:

$$NS_m = \sum_{n \in N^m} Q^n + \sum_{n \in N} \sum_{t=28m-27}^{t=28m-27} C^{nt} \cdot qc_{1n}, \ \forall m \in M \tag{50}$$

VC_m, variable cost in month $m \in M$:

$$\begin{aligned} VC_m = & \sum_{n \in N} YB^{nm} \cdot q^n + \sum_{s \in S} \Gamma^{sm} \cdot \delta^s + \sum_{n \in N} \sum_{t=(28m-27)+\gamma c_{1n}}^{t=(28m-27)+\gamma c_{1n}} C^{nt} \cdot q^0 + \sum_{n \in N} \sum_{t=(28m-27)+qc_{1n}}^{t=(28m-27)+qc_{1n}} C^{nt} \cdot \delta c \ \cdot \gamma c_{1n} \\ & + \varphi \cdot \sum_{n \in N} \sum_{s \in S} \sum_{\tau \in V^b} f^{s\tau} \cdot k^l \cdot YBB^{ns\tau} - AP_m^{'} \cdot \theta^{AP} + AR_m^{'} \cdot \theta^{AR} \end{aligned}, \forall m \in M \tag{51}$$

TCM_m, total contribution margin in month $m \in M$:

$$TCM_m = NS_m - VC_m, \ \forall m \in M \tag{52}$$

OCF_m, cash flow from operations in month $m \in M$:

$$\begin{aligned} OCF_m = & \sum_{n \in N} YB^{nm} \cdot q^n + \sum_{s \in S} \Gamma^{sm} \cdot \delta^s + \sum_{n \in N} \sum_{t=(28m-27)+\gamma c_{1n}}^{t=(28m-27)+\gamma c_{1n}} C^{nt} \cdot q^0 + \sum_{n \in N} \sum_{t=(28m-27)+\gamma c_{1n}}^{t=(28m-27)+\gamma c_{1n}} C^{nt} \cdot \delta c \ \cdot \gamma c_{1n} \\ & + \varphi \cdot \sum_{n \in N} \sum_{s \in S} \sum_{\tau \in V^b} f^{s\tau} \cdot k^l \cdot YBB^{ns\tau} \end{aligned}, \forall m \in M \tag{53}$$

OM_m, open items management in month $m \in M$:

$$OM_m = AR_{m-1} + AR_m^{'} \left(1-\theta^{AR}\right) - AP_{m-1} - AP_m^{'} \left(1-\theta^{AP}\right), \forall m \in M \tag{54}$$

FM_m, short-term financial management in month $m \in M$:

$$FM_m = FI_{m-1} \cdot \left(1+i^{FI}\right) - FI_m - DS_{m-1} \cdot \left(1+i^{DS}\right) + DS_m, \ \forall m \in M \tag{55}$$

CA_m, operating current net assets at the end of month $m \in M$:

$$CA_m = FI_m + AR_m + C_m - AP_m, \ \forall m \in M \tag{56}$$

Objective function

$$\max EVA = \sum_{m\in M}\left(TCM_m - \varepsilon_m\right)\cdot\left(1-z\right) - \sum_{m\in M}(\alpha + CA_{m-1})\cdot i^{WACC} \quad (57)$$

subject to:

$$\sum_{l\in L^{en}}\sum_{s\in S}\sum_{\tau\in V} X_l^{s\tau} \le 1 \,, \forall n\in N \quad (58)$$

$$\sum_{l\in L^{sn}}\sum_{\tau\in V} X_l^{s\tau} - \sum_{l\in L^{en}}\sum_{\tau\in V} X_l^{s\tau} = 0 \,, \forall n\in N, \forall s\in S \quad (59)$$

$$\sum_{l\in L^{s1}}\sum_{\tau\in V} X_l^{s\tau} = 1, \forall s\in S \quad (60)$$

$$\sum_{l\in L^{e1}}\sum_{\tau\in V} X_l^{s\tau} = 1, \forall s\in S \quad (61)$$

$$\sum_{s\in S}\sum_{\tau\in V} X_l^{s\tau} = 0 \,, \forall l\in L^{sn\setminus 1}\bigcap L^{en\setminus 1}, \forall n\in N \quad (62)$$

$$U^k \ge U^n + 1 - (1 - \sum_{\tau\in V} X_l^{s\tau})\cdot M \,, \forall (k,n)\in l\in L^{sn\ge 2}\bigcap L^{en\ge w} \quad (63)$$

$$\sum_{n\in N} C^{nt} = 0 \,, \forall t\in T\setminus T^W \quad (64)$$

$$C^{1t} = 0, \forall t\in T \quad (65)$$

$$C^{n0} = 0, \forall n\in N \quad (66)$$

$$\sum_{m<twm^n} 28\cdot m\cdot YBB^{nsm\tau} \ge W^{1s} - (1 - \sum_{l\in L^{sn}} X_l^{s\tau})\cdot M \,, \forall n\in N, \forall s\in S, \forall \tau\in V \quad (67)$$

$$\sum_{m\in M}\sum_{s\in S}\sum_{\tau\in V^s} YBB^{nsm\tau} \le 1, \forall n\in N \quad (68)$$

$$\sum_{m<twm^n} YB^{nm} + \sum_{t\in[tws^n, twe^m]} C^{nt} = d^n \,, \forall n\in N \quad (69)$$

$$YB^{nm} \le \sum_{s\in S}\sum_{\tau\in V} YBB^{nsm\tau} \cdot M \text{ , } \forall n \in N, \forall m \in [0, twm^n] \in M \tag{70}$$

$$\sum_{l\in L^{sn}} X_l^{s\tau} = \sum_{m<twm^n} YBB^{nsm\tau} \text{ , } \forall n \in N, \forall s \in S, \forall \tau \in V \tag{71}$$

$$W^{ns} \le \sum_{l\in L^{en}}\sum_{\tau\in V} X_l^{s\tau} \cdot M \text{ , } \forall n \in N, \forall s \in S \tag{72}$$

$$Y^{ns} \le \sum_{l\in L^{sn}}\sum_{\tau\in V} X_l^{s\tau} \cdot M \text{ , } \forall n \in N, \forall s \in S \tag{73}$$

$$W^{l(e)s} \ge W^{l(s)s} + \sum_{\tau\in V} X_l^{s\tau} \cdot s_l^{\tau} - (1 - \sum_{\tau\in V} X_l^{s\tau}) \cdot M \text{ , } \forall l \in L, \forall s \in S \tag{74}$$

$$\textstyle\sum_{m\in M} \Gamma^{sm} \ge W^{ns} - W^{1s}, \forall n \in N, \forall s \in S \tag{75}$$

$$tws^n \le \sum_{s\in S} W^{ns} + (1 - \sum_{l\in L^{en}}\sum_{s\in S}\sum_{\tau\in V} X_l^{s\tau}) \cdot M \text{ , } \forall n \in N \tag{76}$$

$$twe^n \ge \sum_{s\in S} W^{ns} \text{ , } \forall n \in N \tag{77}$$

$$C^{nt} = 0 \text{ , } \forall n \in N, \forall t \in [0, tws^n] \bigcap [twe^n, H] \in T \tag{78}$$

$$\sum_{n\in N} Y^{ns} \le (1 - \sum_{\tau\in V} X_{(1,1)}^{s\tau}) \cdot M \text{ , } \forall s \in S \tag{79}$$

$$Y^{l(s)s} \ge Y^{l(e)s} - \textstyle\sum_{t\in[tws^{l(s)}, twe^{l(s)}]} C^{l(s)t} + d^{l(s)} \cdot \sum_{\tau\in V} X_l^{s\tau} - (1 - \sum_{\tau\in V} X_l^{s\tau}) \cdot M, \forall l \in L, l(s) \ne 1, \forall s \in S \tag{80}$$

$$Y^{ns} \le capY \;\; \forall n \in N, \forall s \in S \tag{81}$$

$$d^n \le \sum_{s\in S} Y^{ns} + \sum_{t\in[tws^n, twe^n]} C^{nt} \text{ , } \forall n \in N \tag{82}$$

$$\sum_{s \in S} Y^{ns} \geq \sum_{m < twm^n} YB^{nm} \text{ , } \forall n \in N \tag{83}$$

$$\sum_{t \in T} B^{nt} \cdot t \geq W^{ns} - W^{1s} \text{ , } \forall n \in N, \forall s \in S \tag{84}$$

$$\sum_{t \in T} B^{nt} \leq 1, \forall n \in N \tag{85}$$

$$Z^{nt} \leq B^{nt} \cdot d^n \text{ , } \forall n \in N, \forall t \in T \tag{86}$$

$$\sum_{t \in T} Z^{nt} \leq \sum_{m < twm^n} YB^{nm} \text{ , } \forall n \in N \tag{87}$$

$$Z^{nt} \geq \sum_{m < twm^n} YB^{nm} - (1 - B^{nt}) \cdot d^n \text{ , } \forall n \in N, \forall t \in T \tag{88}$$

$$\sum_{n \in N^m} Q^n + \sum_{n \in N} \sum_{t=28m-27}^{t=28m-27} C^{nt} \cdot qc_{1n} = AR_m + AR'_m, \ \forall m \in M \tag{89}$$

$$\sum_{n \in N} YB^{ns} \cdot q^n + \sum_{s \in S} \Gamma^{sm} \cdot \delta^s + \sum_{n \in N} \sum_{t=(28m-27)+\gamma_{1n}^y}^{t=(28m-27)+\gamma_{1n}^y} C^{nt} \cdot q^0 + \sum_{n \in N} \sum_{t=(28m-27)+q_{1n}^y}^{t=(28m-27)+q_{1n}^y} C^{nt} \cdot \delta c \ \cdot \gamma c_{1n} = AP_m + AP'_m, \forall m \in M \tag{90}$$

$$C_m = C_{m-1} - OCF_m + OM_m + FM_m, \forall m \in M \tag{91}$$

$$DS_m \leq DS^{max}, \ \forall m \in M \tag{92}$$

$$C_m \geq C^{min}, \ \forall m \in M \tag{93}$$

$$FI_0 = fi^0 \tag{94}$$

$$C_0 = c^0 \tag{95}$$

$$DS_0 = ds^0 \tag{96}$$

$$AP_0 = ap^0 \tag{97}$$

$$AR_0 = ar^0 \tag{98}$$

$$CA_0 = ca^0 \tag{99}$$

$$AP_0^{'} = 0 \tag{100}$$

$$AR_0^{'} = 0 \tag{101}$$

$$X_l^{s\tau}, YB^{nm}, YBB^{nsm\tau}, B^{nd} \in \{0,1\}, \forall l \in L, \forall n \in N \forall s \in S, \forall m \in M, \forall \tau \in V, \forall d \in D \tag{102}$$

$$Y^{ns}, W^{ns}, C^{nt}, \Gamma^{sm}, U^n, Z^{nd} \in \mathbb{Z}^+, \forall n \in N \forall s \in S, \forall t \in T, \forall d \in D \tag{103}$$

$$FI_m, C_m, DS_m, AP_m, AR_m, AP_m^{'}, AR_m^{'} \geq 0, \ \forall m \in M \tag{104}$$

The objective of this model is to maximize the *EVA* which is defined in Eq. (1) and expanded as shown in Eq. (57). Similarly, the first part of the *EVA* is presented in Eq. (49) – (52) where the total contribution margin *TCM* equals to the difference between the net sales *NS* and the variable cost *VS.* The capital cost and other financial terms as shown in Eq. (53) – (56) are the same as the ones in the first model.

The constraints in this model are also categorized into operational constraints (58) – (88) and financial constraints (89) – (101). The financial constraints are similar to the ones in the first model, while the operational constraints are different. Constraint (58) ensures that each cargo is delivered by at most one bulk ship with a single speed on the delivery leg. Constraint (59) guarantees that each bulk ship delivering a cargo should leave the same cargo node. Constraints (60) and (61) ensure each bulk ship (consequently the route) starts and ends at the port of origin. Constraints (62)-(63) eliminate potential subtours of each bulk ship. Constraints (64)-(66) ensure that the container vessel service sticks with the weekly schedule. Particularly, cargo allocation is not possible for the days where reefer service is not available. The arrival time (W^{ns}) of bulk ship $s \in S$ to deliver cargo $n \in N$ is determined by constraint (67). Constraint (68) ensures that each cargo is delivered by at most one bulk ship in the proper time window with a single speed. The weekly demand for each port (cargo demand) is met through constraint (69) by summing containerized transport and reefer bulk cargo delivery in the respective time window. Constraint (70) links integer variable YB^{nm} and binary $YBB^{nsm\tau}$ variable, while Constraint (71) links $YBB^{nsm\tau}$ and $X_l^{s\tau}$. Constraint (74) sets the arrival time of each bulk ship correctly. By sailing on leg *l*, the arrival time to node *l(e)* is the sum of the departure time at *l(s)* and the sailing time in this leg. The sailing time Γ^{sm} for each bulk vessel $s \in S$ is set by constraints (74) and (75). Constraints (76) - (78) ensure that every cargo is delivered within the correct time window when it is delivered by reefer bulk ship. Constraint (79) guarantees that ships that are not used to meet the cargo demand stay at the origin port while constraint (80) ensures that each vessel carry enough cargo to meet the demand and the amount shipped by bulk is capacitated by (81). Constraint (82) ensures that the total cargo on boarding sailing towards a node is at least the demand of that node *n* in the respective week as the bulk ship might be also carrying cargo for the next node, say *n+1*. Constraint (83) matches two integer variables for delivery, and bulk reefer ship is assigned correctly. Constraints (84) and (85) initialize the binary variable B^{nd}, which presents the sailing time for each cargo. Constraints (86) – (88) employ the same method introduced in the first model to link Y^{ns}, Y^{ns} and B^{nd} in a linear way. The financial constraints (89)-(101) and the domains are similar to the ones in the model I.

4. Results and Implications

4.1 Numerical Example

In this section, a numerical example is used to demonstrate the results from the models. This example considers the shipment between one port of origin and three ports of destination over seven months. The shipping mode choice is between reefer bulk vessels (three sizes of vessels sailing every other day) and reefer container liner vessels (sailing once a week at the end of a week). Table 1 shows the parameters in this example.

Table 1 Parameters in the numerical example

O	$\{1\}$
P	$\{1, 2, 3\}$,
L	$\{(1, 1), (1, 2), (1,3)\}$
T	$\{1,2, \dots ,210\}$
T^D	$T^D \in \{2, 4, \dots , 210\} \in T$
T^W	$T^W \in \{7, 14, \dots , 210\} \in T$
W	$\{1, 2, \dots , 30\}$
M	$\{1, 2, \dots , 7\}$
B	$\{1, 2, 3\}$
V^b	$V^1 \in \{11, 12, \dots ,17\}$ knots $V^2 \in \{11, 12, \dots ,17\}$ knots $V^3 \in \{11, 12, \dots ,17\}$ knots
z	24%
i^{wacc}	6%
β	0.1%
α	5,000,000 USD

ε_m	100,000 USD
l_{op}	[5760, 6720, 7680] NM for leg $(o,p) \in L$
$\gamma_{11}^{1\tau}$	[17, 16, 15, 15, 13, 13, 11] days at speed $\tau \in V^1$
$\gamma_{12}^{1\tau}$	[21, 20, 20, 19, 18, 16, 15] days at speed $\tau \in V^2$
$\gamma_{13}^{3\tau}$	[24, 20, 20, 22, 19, 17, 16] days at speed $\tau \in V^3$
$\gamma_{11}^{2\tau}$	[17, 16, 15, 15, 13, 13, 11] days at speed $\tau \in V^1$
$\gamma_{12}^{2\tau}$	[21, 20, 20, 19, 18, 16, 15] days at speed $\tau \in V^2$
$\gamma_{13}^{2\tau}$	[27, 25, 23, 22, 20, 19, 18] days at speed $\tau \in V^3$
$\gamma_{11}^{3\tau}$	[20, 19, 18, 16, 15, 15, 14] days at speed $\tau \in V^1$
$\gamma_{12}^{3\tau}$	[24, 22, 20, 19, 18, 17, 16] days at speed $\tau \in V^2$
$\gamma_{13}^{3\tau}$	[27, 25, 23, 22, 20, 19, 18] days at speed $\tau \in V^3$
γ_{op}^{y}	[14, 16, 19] days for leg $(o,p) \in L$
δ_{op}^{1}	[1,000,000, 1,200,000, 1,400,000] USD/Voyage on leg $(o,p) \in L$
δ_{op}^{2}	[2,200,000, 2,400,000, 2,800,000] USD/Voyage on leg $(o,p) \in L$
δ_{op}^{3}	[3,400,000, 4,000,000, 1,700,000] USD/Voyage on leg $(o,p) \in L$
δ_{op}^{y}	[2,450, 2,800, 3,325] USD/TEU on leg $(o,p) \in L$
$capY^b$	[500, 1000, 1500] TEU-equivalent for bulk type $b \in B$
q_o	[6000] USD/TEU at port $o \in O$
q_p	[13000, 14000, 15000] USD/TEU at port $p \in P$
$f^{1\tau}$	[0.244, 0.422, 0.670, 1.000, 1.424, 1.953, 2.600] at speed $\tau \in V^1$
$f^{2\tau}$	[0.422, 0.579, 0.770, 1.000, 1.271, 1.588, 1.953] at speed $\tau \in V^2$
$f^{3\tau}$	[0.512, 0.651, 0.813, 1.000, 1.214, 1.456, 1.728] at speed $\tau \in V^3$
φ	300 USD/tonnes
θ^{AP}	4%
θ^{AR}	2%
d_{pm}	Appendix I
i^{FI}	5%
i^{DS}	7%
DS^{max}	11,000,000 USD
C^{min}	2,000,000 USD
fi^0	0 USD
c^0	25,000,000 USD
ds^0	20,000,000 USD
ap^0	10,000,000 USD
ar^0	10,000,000 USD
ec_m	20,000 USD $\forall m \in M$

Source: Authors, with reference to Contchart (2016)

To highlight some of the key parameters, the tax rate *z* is set as 24% which is the global average corporate tax rate in 2016. Fixed cost is approximately $100,000 per month. Weighted average cost per capital (after tax) is 6%. Three types of reefer bulk vessels, with equivalent capacity of 1500, 1000 and 500 TEUs, are available for choice and the sailing speed of the reefer bulk vessel is negatively correlated to its capacity. The intensity of price discount when freshness is decreased by one unit is set as 0.3%. The weekly demand data can be found in Appendix I.

4.2 Results Analysis of Model I

Model I consists of 5,000,505 constraints, 470,952 binary variables and 3,663,811 integer variables. The model is solved with ILOG CPLEX Optimization Studio v12.6 CPLEX version 12.5 by using a computer with Intel Core™ 2 Quad processor (3.00 GHz) and 8 GB RAM memory. The average computational time is around 63 seconds, and the instance is solved to optimality. With the parameter provided in Table 1, the optimized EVA for the planning horizon is $0.331 billion with 44,375 TEU equivalent of cargoes shipped by reefer bulk vessels and 48,700 TEU of cargoes shipped by liner reefer container vessels during 7 months of planning horizon. The results indicate that the utilization of reefer bulk vessel and liner container is balanced when the price discount rate $\beta = 0.1\%$ and the penalty parameter $\varphi = 300$. Therefore, this scenario is used as a benchmark for the sensitivity analysis in the next section. Figure 2 presents the optimal fleet deployment plan on a daily level to meet the cargo demand at each destination port in each week. Figure 2 has the amount of cargo shipped on y-axis while the day to be sent is on x-axis. The mode choice of each shipment is also illustrated, particularly square symbols refer to containerized shipment and circular symbols refer to bulk ship deployment. The breakdown of the deployment on different legs is shown in Figure 3. According to Figure 3, cargoes on leg <1, 3> (origin to destination port 3), the leg with the longest distance, are mainly shipped by the big bulk vessels due to its economy of scale; and the container vessels are heavily used for shorter legs. The medium size bulk vessels are dedicated to the leg with medium distance. The average sailing speeds of both type 1 and type 3 vessels are 11 knots and the medium size bulk vessels sail at an average speed of 11.8 knots. The ship deployment strategy changes under different circumstances are analyzed in detail in the following section.

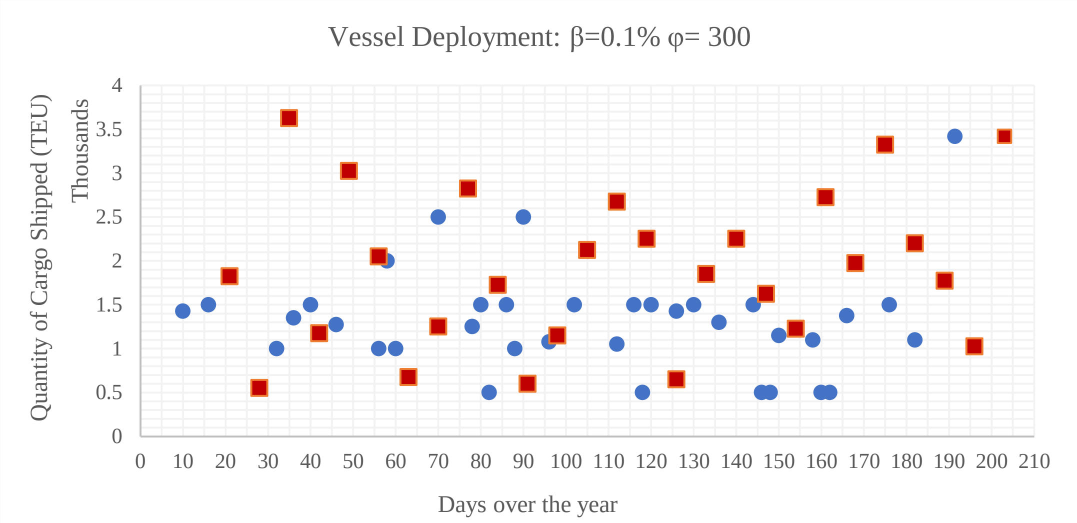

Figure 2 Vessel deployment when β = 0.1% and φ = 300

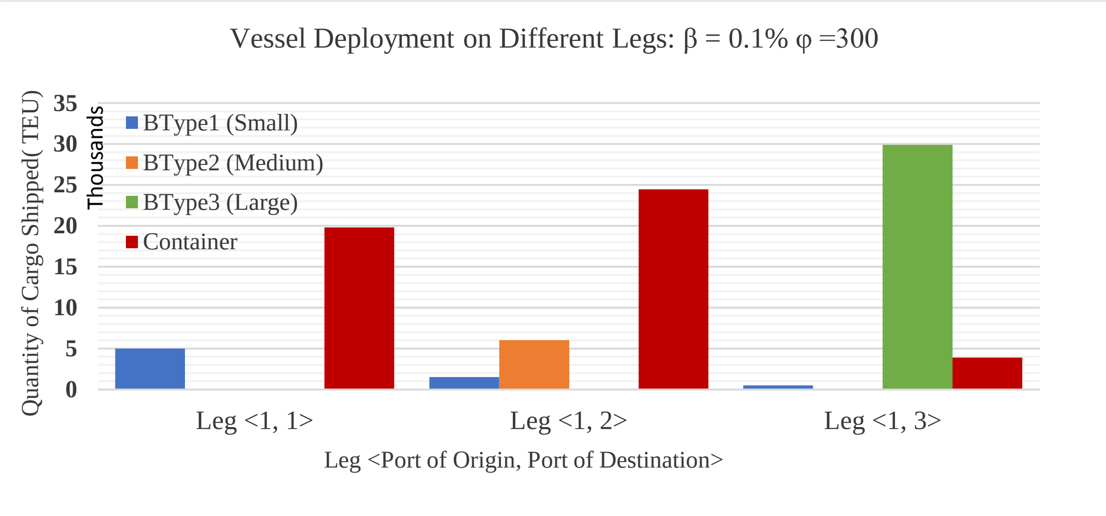

Figure 3 Vessel deployment on different legs when β =0.1% and φ = 300

4.2.1 Sensitivity Analysis

In Model I, both the price discount rate β and the emission penalty φ play important roles in deciding the optimal fleet deployment strategy and the most economic sailing speed. This section investigates how the objective function and decision variables change under different conditions.

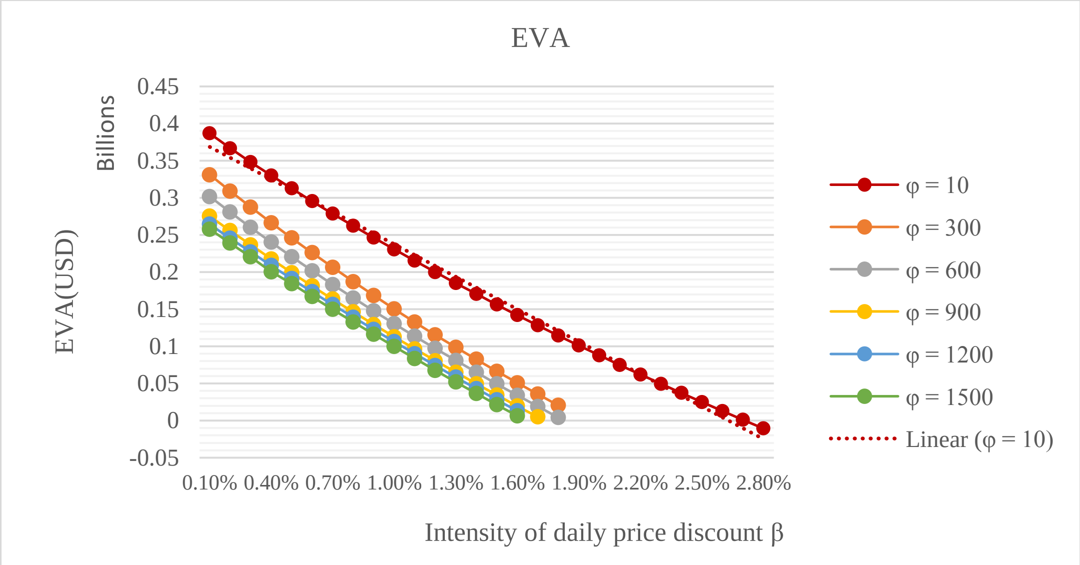

Figure 4 The change of EVA over different β and fuel emission penalty (φ)

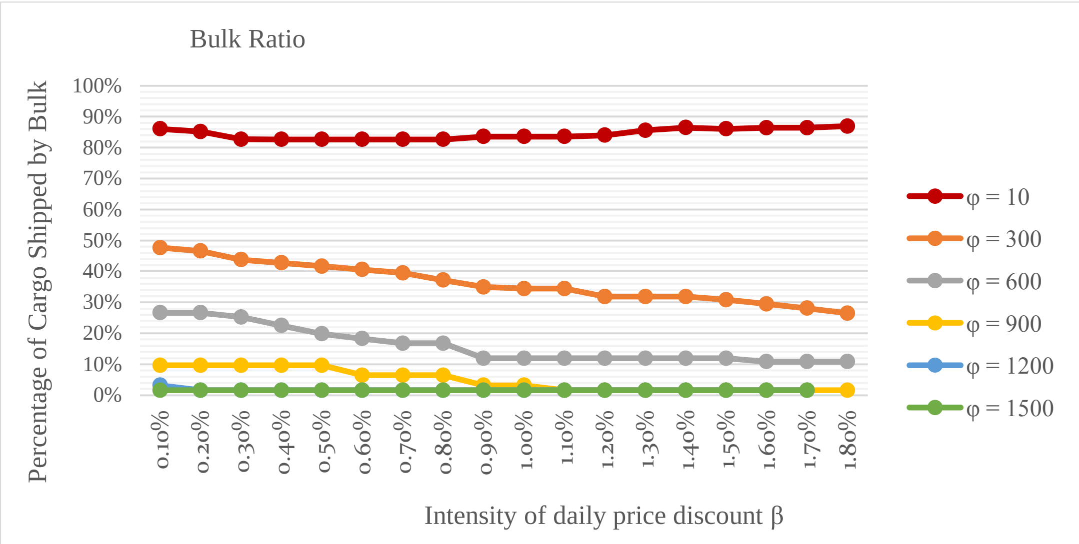

Figure 5 The change of bulk ratio over different β and fuel emission penalty (φ)

* The data are not presented for β>1.8%, φ = 300-1200 and for β>1.7%, φ = 1500 because the EVA becomes negative.

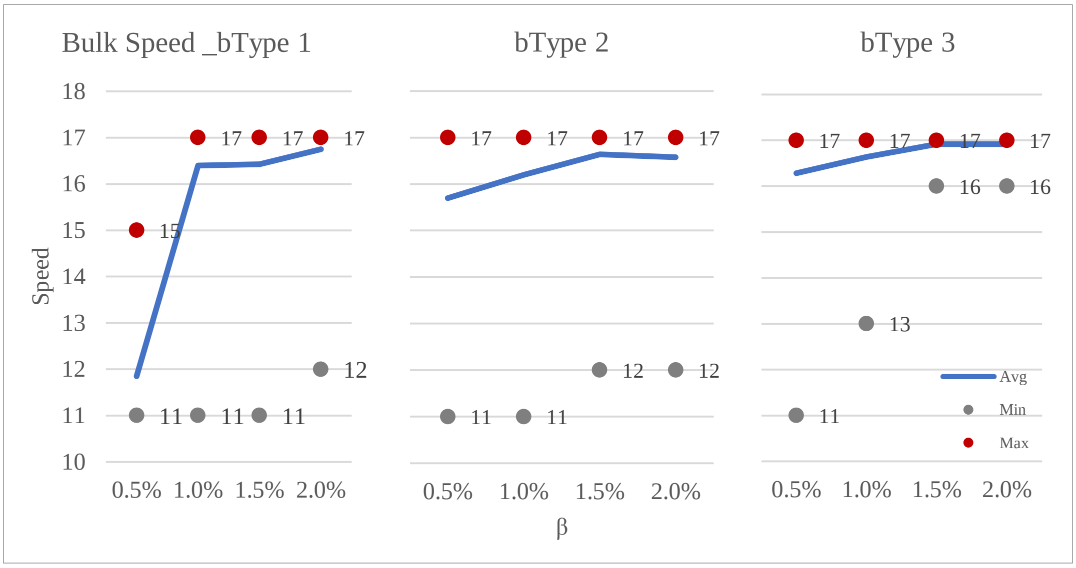

Figure 6 Bulk speed when φ = 10, red and grey dots represent maximum and minimum speed, respectively

The EVA and the bulk ratio (the percentage of cargoes shipped by bulk) are affected by the price discount rate and the emission penalty. Results are shown in Figure 4 and Figure 5, respectively. It is obvious that the optimal EVA drops while either β or φ increases. However, the EVA does not decrease at a constant rate when β or φ increases linearly. Taking the cases when φ = 10 as an example, it can be observed from Figure 4 that the reduction of EVA decreases when the β is less than 1.8% and then becomes constant when β exceeds 1.8%. The decreasing reduction rate of EVA when β < 1.8% is contributed by the mode choice adjustment. When β < 1.8%, the mode choice keeps changing (as shown in Figure 5), such change slows down decrease in the EVA. As shown in Figure 5, most cargoes are shipped by bulk when the price discount rate is extremely low, then the quantity shipped by container climbs up when β increases. Before β reaches 0.8%, the bulks sail more slowly than the containers, therefore more cargoes are shipped by containers to mitigate the value loss due to price depreciation. This phase ends when β exceeds 0.8%, after which the value loss is higher than the emission penalty caused by the acceleration of bulks. When β is in (0.8%, 1.8%), more cargoes are shipped by bulks which sail at a higher speed as shown in Figure 6. Results in Figure 6 show that, in the case of reefer bulk ship deployment with high product depreciation rates, sailing speed is usually higher than industry average of other shipping market segments. Results also suggest that a higher sailing speed is selected for the trip from origin to the destination (i.e. laden trip), which aligns with intuition since loaded vessels should sail faster to minimize the value depreciation of the cargoes. Eventually, when β reaches 1.8%, the amount shipped by bulk and container become stabilized since all the bulks are sailing at the maximum speed and no improvement could be achieved. This is also the underlying reason for the decreasing rate of EVA.

It can also be observed that the reduction in EVA slows down when the emission penalty increases. The reason is also revealed by Figure 5. When the emission penalty increases, fewer cargoes are shipped by bulk especially when β is high. Therefore, although more costs are generated by the increased φ for each bulk, the reduction in the total number of bulks deployed limits the increase of total cost. As a result, the EVA decreases in a slower manner.

4.2.2 Scenario Analysis

The sensitivity analysis provides a view of how the cargo properties and the emission policy would affect the fleet deployment (mode choice), speed and therefore the EVA. To understand the operation details, an analysis of scenarios with various combinations of β and φ is required. This section investigates the mode choice selection details on each leg and the corresponding sailing speed of each reefer bulk type under four scenarios, namely, β = 0.1% and φ = 10, β = 0.1% and φ = 300, β = 0.5% and φ = 300, along with β = 1.5% and φ = 300.

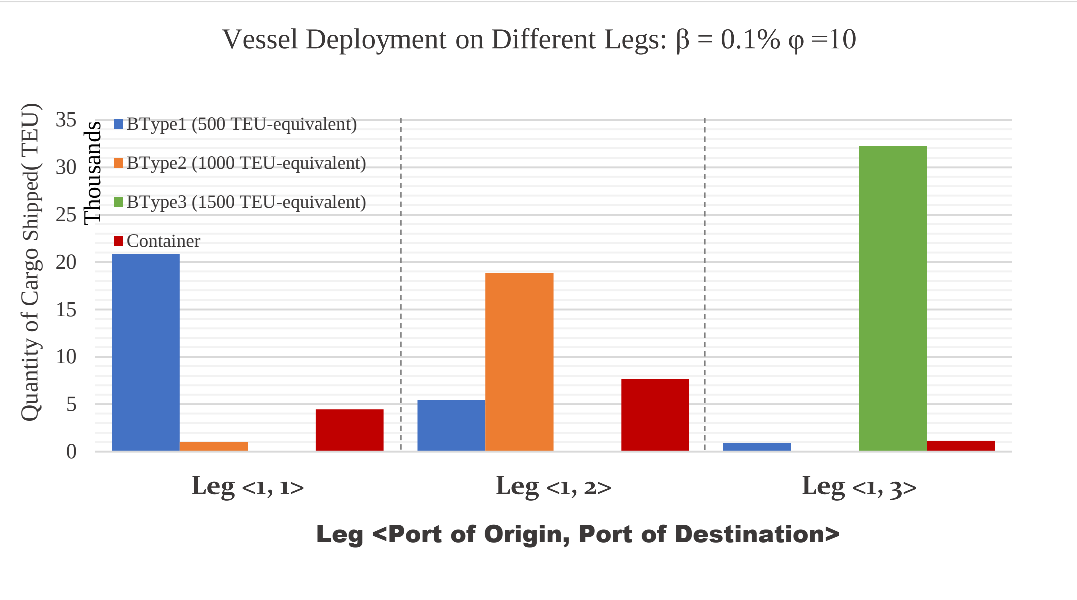

Figure 7 Vessel deployment on different legs: β = 0.1% φ = 10

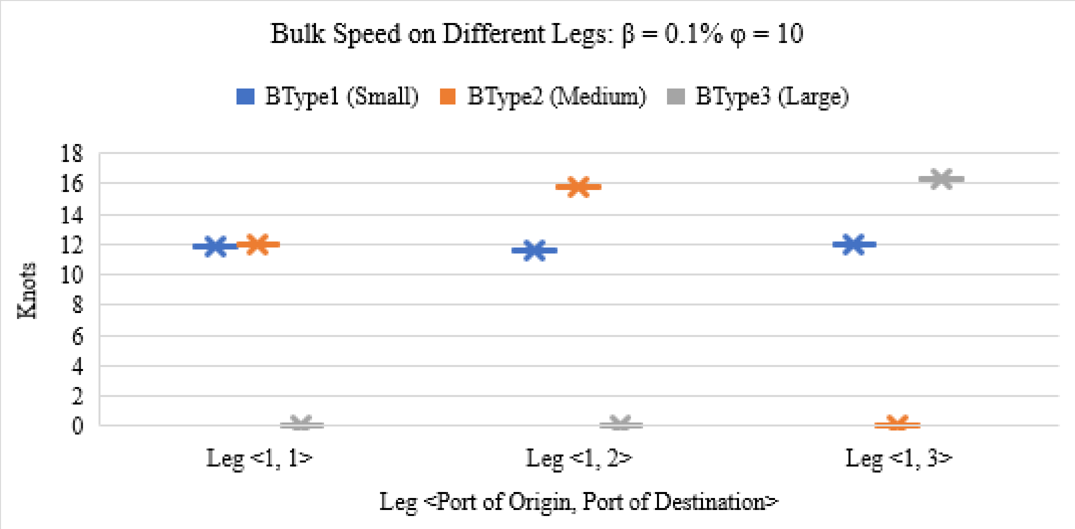

Figure 8 Bulk speed on different legs: β = 0.1% φ = 10

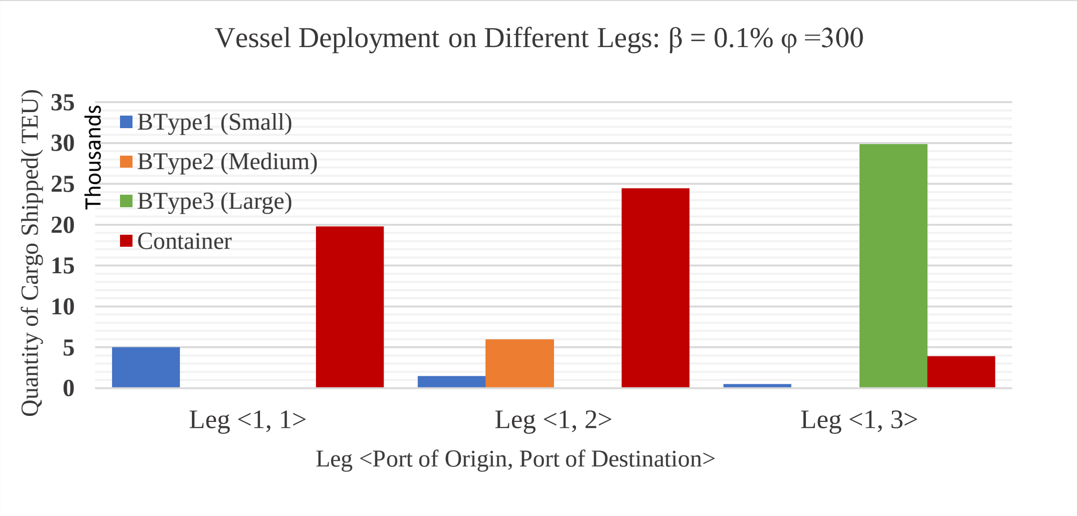

Figure 9 Vessel deployment on different legs: β = 0.1% φ = 300

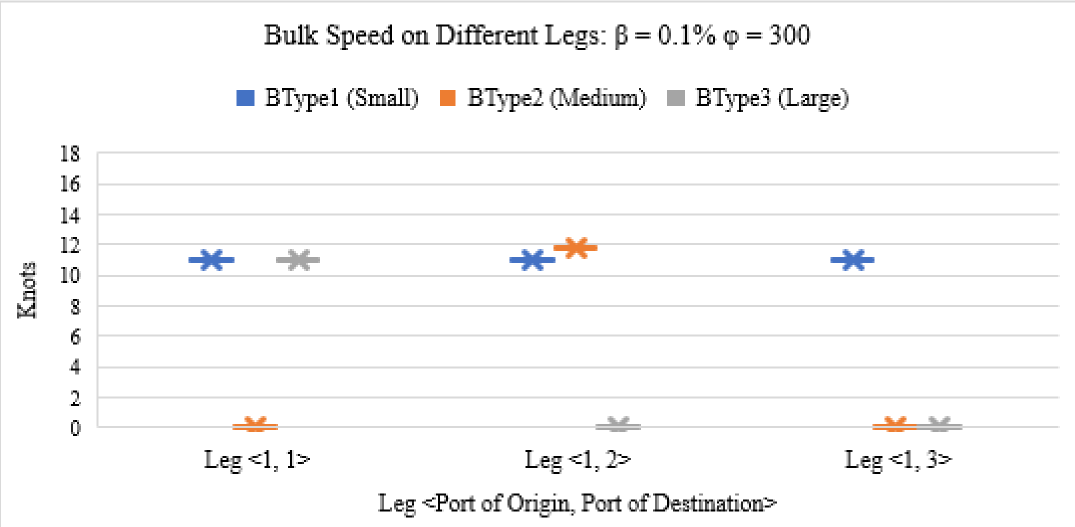

Figure 10 Bulk speed on different legs: β = 0.1% φ = 300

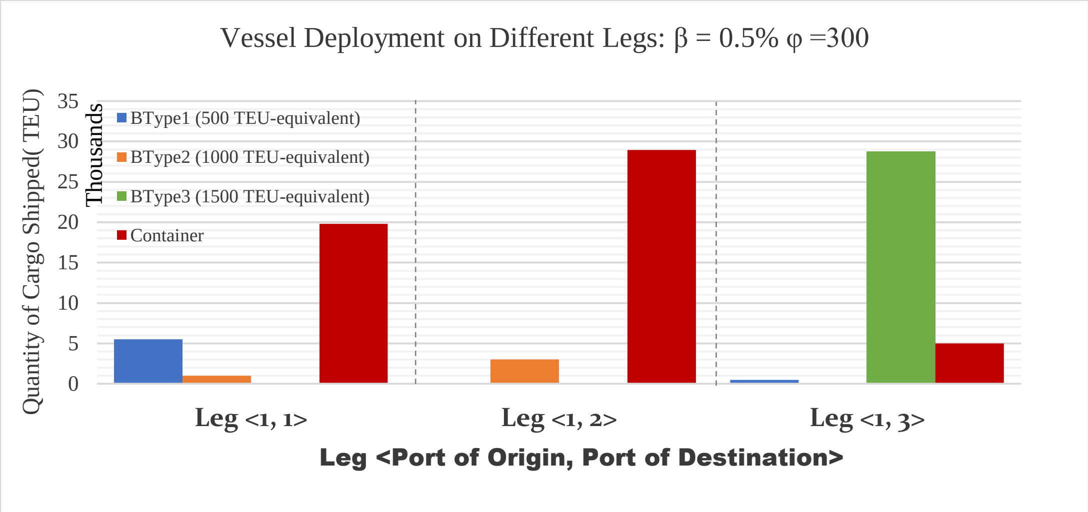

Figure 11 Vessel deployment on different legs: β = 0.5% φ = 300

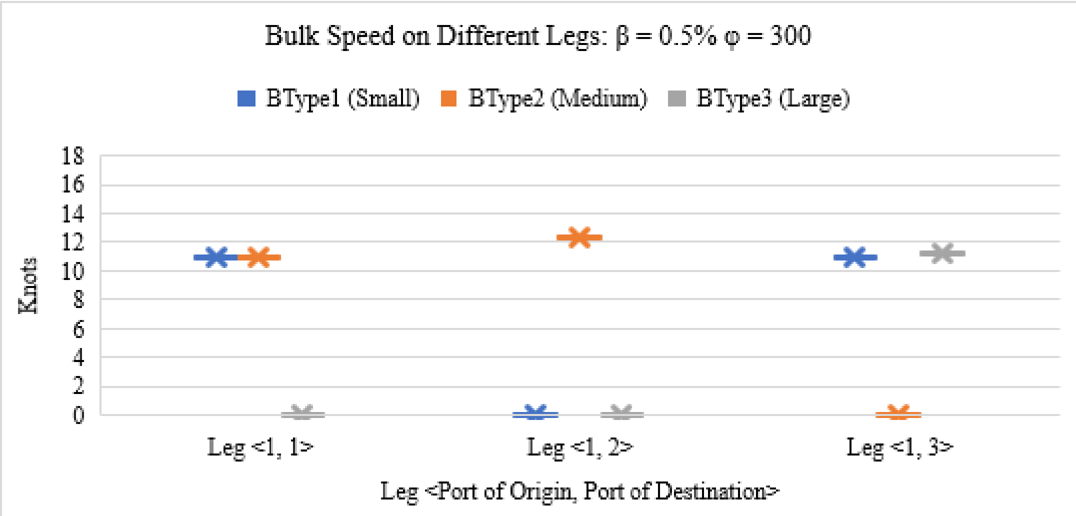

Figure 12 Bulk speed on different legs: β = 0.5% φ = 300

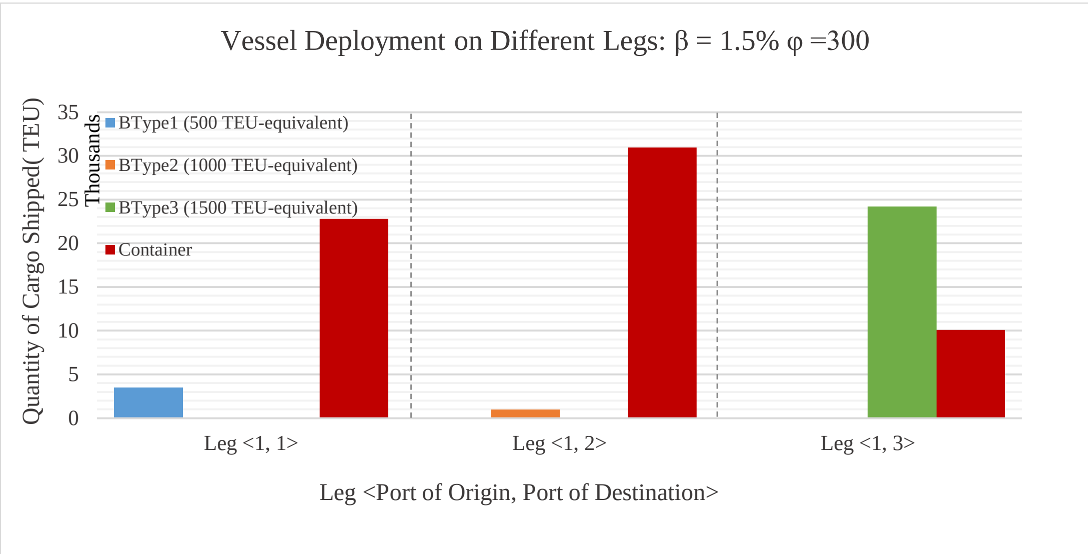

Figure 13 Vessel deployment on different legs: β = 1.5% φ = 300

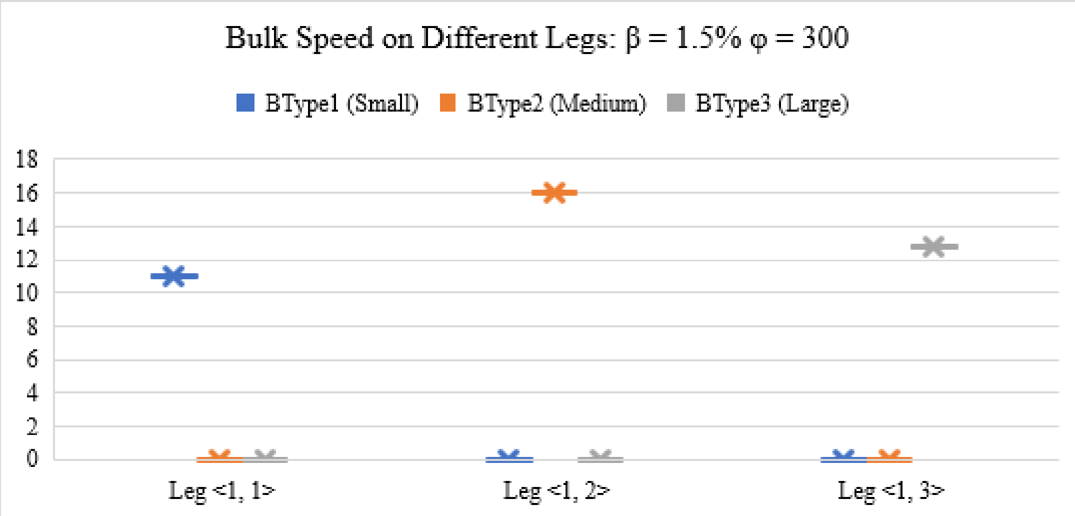

Figure 14 Bulk speed on different legs: β = 1.5% φ = 300

Figure 7 and Figure 8 present the vessel deployment (mode choice) on different legs and the average sailing speed of each type bulk type with β = 0.1% and φ = 10. As shown in Figure 7, most cargoes are shipped by bulk when both price discount rate and emission penalty are low. Since the depreciation rate of the cargo value is low, bulk is a more economic choice. With respect to bulk type, small bulks are mainly sailing slowly on the legs with shorter distances while the medium-size bulks are dedicated to leg<1, 2>, the distance of which is medium. The larger bulk ships solely serve the longest leg and sail at a high speed since the emission penalty is low. Figure 9 and Figure 10 provide a scenario with the same price discount rate but a higher emission penalty. Figure 9 indicates that with a higher emission penalty, the share of containerized transport increases. Although the bulk ships are less deployed, a similar strategy is observed, namely small vessels serve nearer ports. Comparing Figure 10 with Figure 8, it is obvious that the speed of the bulks has dropped significantly as the emission penalty increases. It shows that when the emission penalty is higher than the expected loss due to value depreciation, the owner would prefer slow steaming. Figure 11 - Figure 14 present scenarios with different price discount rate under the same stringent environmental policy. As shown in Figure 11 and Figure 13, the share of bulk ships keeps decreasing when the price discount rate increases despite bulk ships' lower voyage fee and flexibility. The reason is reflected in Figure 12 and Figure 14. Although β increases from 0.5% to 1.5%, the bulk ships almost sail at the same speed. Since the bulk ships' speeds are capped due to high emission penalty, bulk ships are used lesser when the cargoes depreciate faster.

The sensitivity analysis and the scenario analysis reveal that the flexibility to choose between different vessel types could reduce the economic loss while shipping more perishable cargoes or when the environmental policy becomes more stringent. However, the effect of mode adjustment has its limitation and will stop abating the EVA loss once the price discount rate or the emission penalty passes a threshold. Such threshold depends on commodity market and the fleet setting. The results also show that although chartered reefer bulk vessels are generally more economically sound, once the punishment for emission is high, the speed of the bulk will be locked up and make it a bad choice for perishable or time-sensitive goods. It is worth noting that the high bunker price would have the same effect. Lastly, the scenario analysis depicts a clear pattern of vessel deployment regardless of the cargo depreciation rate or the emission penalty. The consistently preferred deployment strategy is to send small bulk to the nearer ports with a low speed and make larger bulk to serve longer legs with a higher speed. Liner service which requires booking on container ships is also used.

4.3 Results Analysis of Model II

Model II which allows bulk ships to be routed between ports before sailing back to origin port is solved with ILOG CPLEX Optimization Studio v12.6 CPLEX version 12.5 by using a computer with Intel Core^{TM} 2 Quad processor (3.00 GHz) and 8 GB RAM memory. The running time limit is set to be 36000 seconds for all scenarios. Given the running time, the optimality gap varies between scenarios as shown in Table 2. The average optimality gap for model II is 56.3%. Table 2 also compares the results generated by two models. As shown in Table 2, the time chartering-based method (model II) increases the EVA by 53% and reduces the GHG by 80% in average compared to model I. Results for model II show that 3,600 TEU equivalent of cargoes are shipped by reefer bulk vessels and 89,475 TEU of cargoes shipped by liner reefer container vessels. The breakdown of vessel deployment on each leg is shown in Figure 15. As shown in both Table 2 and Figure 15, the bulk ratio is relatively low in most tested scenarios for the model II and it is difficult to observe the deployment pattern of different bulk types. Bulk ratio reaches its peak when $\beta = 0.1\%$ and $\varphi = 10$. Figure 16 presents the deployment pattern of this scenario. It can be observed from Figure 16 that the larger bulk ship is highly preferred over the other two types. This is expected since bulk less-than-load (LTL) ship routing is allowed in this model and a larger bulk vessel is more likely to be deployed in the case of long sailing distances.

Table 2 Results comparison: models

	Model II (with bulk routing)				Model I (without bulk routing)					
	EVA	**Bulk Ratio**	**Optimality Gap**	**Emission**	**EVA**	**Bulk Ratio**	**Optimality Gap**	**Emission**	**Δ EVA**	**Δ Emission**
β = 0.1, φ = 10	4.47×10^8	25%	35%	2031418	3.67×10^8	85%	0%	6433782	22%	-68%
β = 0.1, φ = 300	3.88×10^8	4%	45%	6859296	3.31×10^8	48%	0%	40548638	17%	-83%
β = 0.5, φ = 10	3.2×10^8	2%	71 %	168488	3.13×10^8	83%	0%	9659381	3%	-98%
β = 0.5, φ = 300	3.29×10^8	4%	53%	10334176	2.46×10^8	42%	0%	37543792	34%	-72%
β = 0.5, φ = 600	3.22×10^8	4%	42%	10580472	2.21×10^8	20%	0%	33279653	46%	-68%
β = 0.1, φ = 900	3.16×10^8	0%	31%	0	1.99×10^8	10%	0%	40798720	59%	-100%
β = 0.1, φ = 1200	3.51×10^8	6%	7%	20293776	1.91×10^8	2%	0%	30805333	84%	-34%
β = 1.0, φ = 10	2.63×10^8	6%	82%	366774	2.31×10^8	84%	0%	12247181	14%	-97%
β = 1.0, φ = 300	2.69×10^8	4%	63%	6712644	1.5×10^8	34%	0%	32505201	79%	-79%
β = 1.5, φ = 10	2.04×10^8	11%	106%	656361	1.56×10^8	86%	0%	13399225	30%	-95%
β = 1.5, φ = 300	1.99×10^8	4%	89%	4739737	6.63×10^7	31%	0%	37482032	200%	-87%

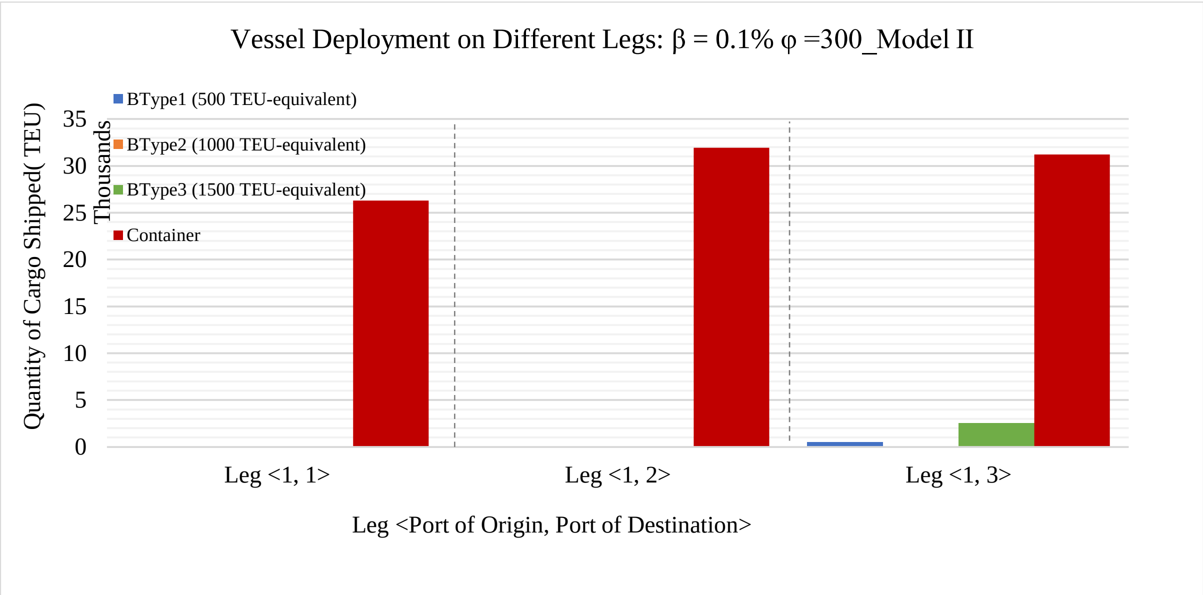

Figure 15 Vessel deployment on different legs: β = 0.1% φ = 300_model II

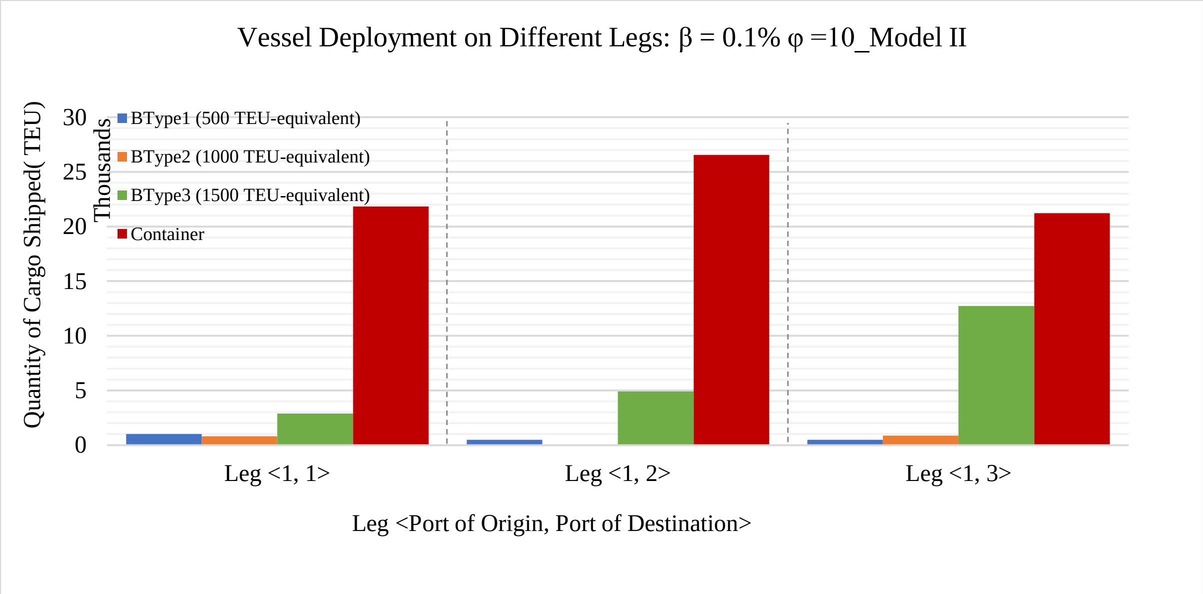

Figure 16 Vessel deployment on different legs: β = 0.1% φ = 10_ model II

To have a better understanding of the impact of reefer bulk ship routing on the mode choice, we have tested another batch of scenarios in which the bulk vessel capacity is tripled for each vessel. The results are summarized in Table 3. Larger bulk vessel capacities would generate more economic value with the cost of higher emissions. The mode choice pattern can be better observed in the scenarios with higher bulk capacity. Figure 17 – Figure 19 present the detailed vessel deployment patterns for different scenarios with various cargo depreciation rate. The largest bulk vessel is not preferable and the bulk vessel with a capacity equivalent to 1500 TEUs is still the most deployed bulk vessel type. It seems that while routing is considered and the demand range is fixed, there exists an optimal vessel capacity which is most suitable for LTL routing and this will maximize the value generated. Similar to the results of model I, deploying bulk vessels to the longer legs better contributes to value creation (i.e. resulting in higher EVA).

Table3 Results comparison: Effect of capacity

	Model II (with triple bulk capacity)				Model II					
	EVA	**Bulk Ratio**	**Optimality Gap**	**Emission**	**EVA**	**Bulk Ratio**	**Optimality Gap**	**Emission**	**Δ EVA**	**Δ Emission**
β = 0.1, φ = 10	4.98×10^8	44%	24%	3798616	4.47×10^8	25%	35%	2031418	11%	87%
β = 0.1, φ = 300	4.84×10^8	47%	21%	19320238	3.88×10^8	4%	45%	6859296	25%	182%
β = 0.5, φ = 10	4.17×10^8	38%	34%	3218496	3.2×10^8	2%	71%	168488	30%	1810%
β = 0.5, φ = 300	3.81×10^8	28%	40%	13316190	3.29×10^8	4%	53%	10334176	16%	29%
β = 0.5, φ = 600	3.46×10^8	11%	47%	14347125	3.22×10^8	4%	42%	10580472	7%	36%
β = 0.1, φ = 900	3.24×10^8	4%	49%	6703007	3.16×10^8	0%	31%	0	3%	-
β = 0.1, φ = 1200	3.16×10^8	2%	44%	2250000	3.51×10^8	6%	7%	20293776	-10%	-89%
β = 1.0, φ = 10	2.92×10^8	27%	69%	1948097	2.63×10^8	6%	82%	366774	11%	431%
β = 1.0, φ = 300	2.92×10^8	9%	60%	9195188	2.69×10^8	4%	63%	6712644	9%	37%
β = 1.5, φ = 10	2.46×10^8	20%	75%	1808114	2.04×10^8	11%	106%	656361	21%	175%
β = 1.5, φ = 300	1.91×10^8	4%	112%	2378250	1.99×10^8	4%	89%	4739737	-4%	-50%

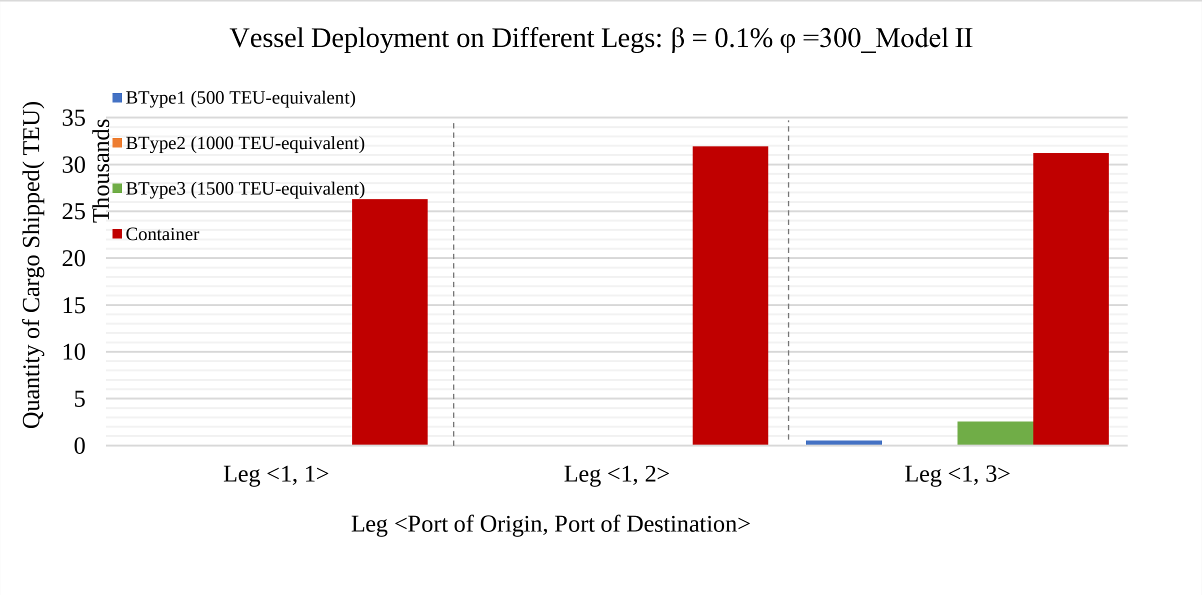

Figure 17 Vessel deployment on different legs: β = 0.1% φ = 300_ model II with triple bulk vessel capacity

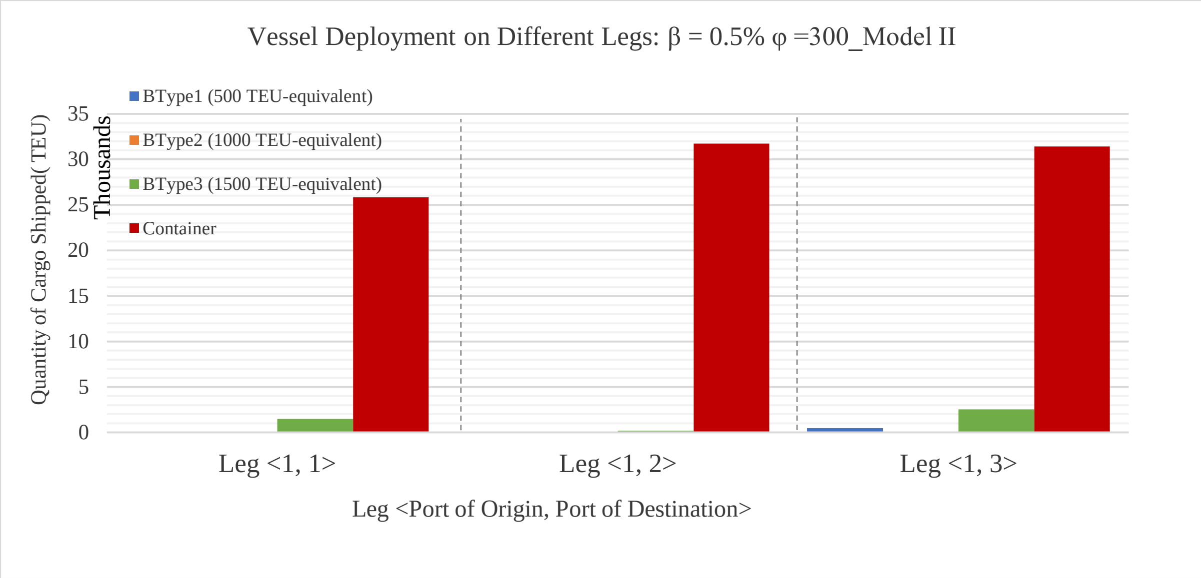

Figure 18 Vessel deployment on different legs: β = 0.5% φ = 300_ model II with triple bulk vessel capacity

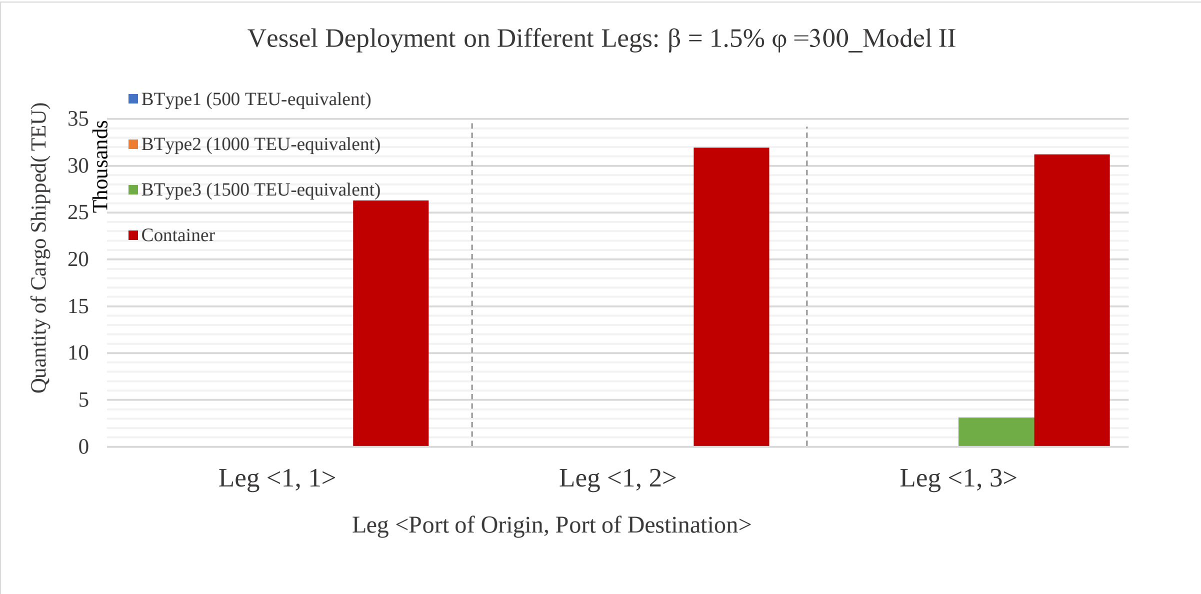

Figure 19 Vessel deployment on different legs: β = 1.5% φ = 300_ model II with triple bulk vessel capacity

Using available liner shipping service becomes a dominant case as emission penalty and product depreciation rates increase. Incorporating reefer bulk ship routing in bulk vessel deployment would increase the value for shippers and reduce the emissions in many cases. The results of the two models provide interesting insights which would stimulate reflection on the current maritime cold chain practice. Recently, roughly 80% of shipments use reefer containers in the industry (Castelein et al., 2020), our results support this trend for many cases, but there is also room for using reefer bulk in a smart way (with proper bulk type selection, routing planning and speed optimization) together with containerized transport.

This would effectively add value for shippers and reduce the environmental impact. Moreover, even with stringent environmental regulation (e.g. high emission penalty case) or higher bunker price, the cold chain average sailing speed is higher than other maritime modes.

5. Conclusion

This paper is the first to tackle the maritime cold chain mode choice, shipment scheduling and ship deployment problem with speed optimization for time sensitive (e.g. perishable) products. The contribution of this study is threefold. First, it has made an original contribution to the study area of cold chain mode choice between containerized transport and reefer bulk ship and shipment scheduling by considering different reefer bulk planning methods, sailing speed optimization, cargo value depreciation and GHG emission. Secondly, a novel method, value-based optimization, has been introduced to advise shippers on mid-term vessel deployment strategies. Containerization of refrigerated commodity is progressing steadily with the well-developed global freight distribution system. In this context, we thoroughly investigate the mid-term vessel deployment strategies from the shipper's perspective using value-based management tools which are indicated by EVA. Lastly, this paper proposes a decision framework and two decision models to select between chartered reefer fleet deployment methods and to decide the optimal operation of the reefer bulk fleet.

A numerical example of a refrigerated cargo is presented to illustrate the results and provide practical implications. The two decision models have been used in this example, and the sensitivity analysis and scenario analysis have been conducted to shed light on how the commodity characteristic and environmental consideration would affect the shipping decisions. The results indicate that the optimal speed decreases with a reducing rate when the bunker price increases and it decreases with a higher decline rate when the goods are less perishable. This observation implies that the cargo type may have a more significant impact on the speed selection than the environmental constraints. Managers need to be aware of this implication if they target to influence shippers' behavior. Moreover, the analysis also reveals the existence of a pervasive deployment strategy, which is to make small bulk and container ships serve short legs and deploy larger bulk to long distance legs.

Industry practitioners can use the proposed models as a reference for decision making. Specifically, the models help managers to properly choose between container and reefer bulk vessels given the characters of the perishable cargo and the market situation. Industry players can use the financial results to evaluate ship investment decisions for cold chain products.

Managers could increase environmental, operational and financial performances by optimizing the mode choice selection and bulk fleet deployment. Scholars could appreciate the utilization of VBM tools in sophisticated decision models and the combined routing and speed optimization problem.

The factors we would like to take into consideration in our future work include but not limited to: 1. Estimate financial period and integrate capital management and time period to fully realize value-based management tools' potential in financial management. 2. Investigate temperature fluctuation in a cold chain. The stowage limitations (Iris et al. 2018) on container ships can also be considered. 3. The current model only considers the GHG emissions. As environmental issues become increasingly prominent, the model can cover a wider range of emissions (e.g. the recently regulated Sulphur oxides emissions) to stay relevant.

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APPENDIX I WEEKLY DEMAND (NORMAL DISTRIBUTION)

Week	Demand in Port D1	Demand in Port D2	Demand in Port D3
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0	0
6	550	1825	1425
7	1400	1100	1950
8	900	1350	875
9	1375	1775	1350
10	775	825	825
11	1250	1275	1275
12	975	1250	675
13	1025	1125	1650
14	1200	1575	1725
15	1275	525	1250
16	1500	1725	1600
17	1425	800	1850
18	1525	700	1075
19	800	1075	1575
20	1350	1450	1050
21	925	1750	1550
22	450	925	1425
23	400	1350	1950
24	1300	1225	1300
25	1200	900	1525
26	1050	1525	1150
27	1925	1925	1100
28	700	1400	1375
29	550	1350	1650
30	1025	1225	1100