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A HOLISTIC OPTIMIZATION MODEL FOR INTEGRATED TACTICAL LEVEL PLANNING IN LINER SHIPPING

By

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To my family.

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ABSTRACT

Supply chain management plays an important role in ensuring an efficient merchandise trade. Freight transportation is an integral part of supply chain management. A significant part of freight transportation is covered by maritime transportation, as the largest portion of the global merchandise trade, in terms of volume, is carried out by maritime transportation. Liner shipping, which runs on fixed routes and schedules, plays a colossal role for the global seaborne trade. Liner shipping companies deal with three decision levels, namely strategic level, tactical level, and operational level. The strategic-level decisions are taken for more than six months to several years. The tactical-level decisions are effective for three months to six months. Moreover, the operational level decisions are taken for a couple of weeks to less than three months.

This dissertation involves the tactical-level decisions in liner shipping, which include: (1) service frequency determination; (2) fleet deployment; (3) sailing speed optimization; and (4) vessel scheduling. The service frequency determination problem deals with determining the time headway between consecutive vessels along a liner shipping route. The fleet deployment problem assigns vessels from the liner shipping company's fleet (and sometimes, from other liner shipping companies' fleets) to liner shipping routes. The sailing speed optimization problem deals with selecting sailing speeds along different voyage legs of a given port rotation. The vessel scheduling problem lists the schedules (e.g., arrival time, handling time, departure time) at different ports.

A comprehensive review of the liner shipping literature revealed that the existing literature on the tactical-level decisions focused on these problems individually. Solutions from different solution methodologies for the separate problems may have compatibility problems. Moreover, they are not attractive to the liner shipping companies, who look for integrated solutions. Hence, this research aimed to develop a combined mathematical model that comprises the four tactical-level decisions in liner shipping (i.e., service frequency determination, fleet deployment, sailing speed optimization, and vessel scheduling). This mathematical model is named the Holistic Optimization Model for Tactical-Level Planning in Liner Shipping (HOMTLP).

The objective of the HOMTLP mathematical model is to maximize of the total profit from transport of cargo. The major route service cost components, found from the literature, are covered by the model, which include: (I) total late arrival cost; (II) total port handling cost; (III) total fuel consumption cost; (IV) total vessel operational cost; (V) total vessel chartering cost; (VI) total container inventory cost in sea; (VII) total container inventory cost at ports of call; (VIII) total emission cost in sea; and (IX) total emission cost at ports of call. Along with the integration of all four tactical-level decisions, the mathematical model has a number of key advantages. First, the model provides flexibility to both the liner shipping company and the marine container terminal operators, as it offers multiple time windows and handling rates at each port of call. Second, the payload carried by the vessels is considered while estimating fuel consumption. Third, the preference of customers is reflected by modification of the container demand at different sailing speeds. Fourth, container inventory is accounted for at ports of call and in sea. Fifth, emissions of different harmful substances are captured in order to preserve the environment.

This dissertation carried out a set of numerical experiments to test the performance of the HOMTLP model, where BARON was used as the solution approach. It was revealed that when there was an increase in the unit fuel cost, the unit emission cost, vessel availability, the unit late arrival cost, and the unit freight rate, the sailing speed was reduced. On the other hand, when there was an increase in the unit inventory cost, the unit operational cost, as well as the unit chartering cost, the sailing speed was increased. Moreover, the total required number of vessels was increased, when there as an increase in the unit fuel cost, the unit emission cost, vessel availability, the unit late arrival cost, and the unit freight rate. On the contrary, the total required number of vessels was decreased, when there was an increase in the unit inventory cost, the unit operational cost as well as the unit chartering cost. It was also revealed that the total profit was increased, when more choices were available for port arrival time windows and/or container handling rates. The numerical experiments highlighted several other findings. Most importantly, it was found that the HOMTLP model can provide effective tactical-level decisions. Hence, the mathematical model can assist liner shipping companies to take tactical-level decisions, which are effective and profitable.

CHAPTER 1

INTRODUCTION

A supply chain is defined as the network, which comprises all individuals, organizations, activities, resources, and technology that are involved in development as well as sale of different products. Supply chain activities range from delivery of materials from suppliers to manufacturers through to delivery of the final products to the end customers. Supply chain management can be construed as a systemic and strategic management of the activities regarding supply chains, which aims to obtain a sustainable competitive advantage. It can be divided into three major areas: purchasing, manufacturing, and transport. It includes decisions that are related to input materials, production quantities, inventory levels, distribution network configuration, and, finally, transportation of both input materials and products or freight transportation. Freight transportation is an integral part of supply chain management. In order to ensure efficiency of the supply chain operations, it is very important to build an economical transportation network. The magnitude of freight transport is rising day by day. According to the Bureau of Transportation Statistics (2017), freight transport in the U.S. increased from 4,172,989 million ton-miles in 1980 to 5,293,131 million ton-miles in 2014 (Figure 1).

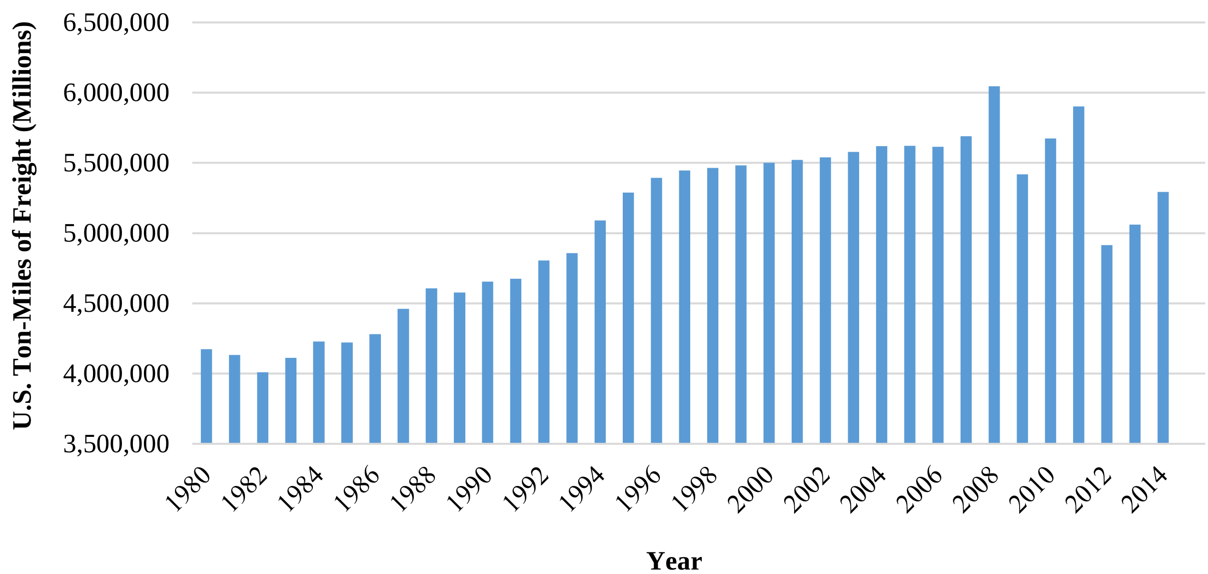


Figure 1 Changes in U.S. ton-miles of freight.

Freight transportation is not only increasing in magnitude, it plays an important role for the national economy. The U.S. gross domestic product (GDP) increased from $12,065.9 billion in 1999 to $16,397.2 billion in 2015 (Figure 2). Transportation generated about $1 out of every $10 generated in the U.S. GDP (Bureau of Transportation Statistics, 2017). Moreover, freight transportation generates a lot of jobs. In 2016, 4.987 million workers were employed in the U.S. freight transportation industry (Bureau of Labor Statistics, 2017).

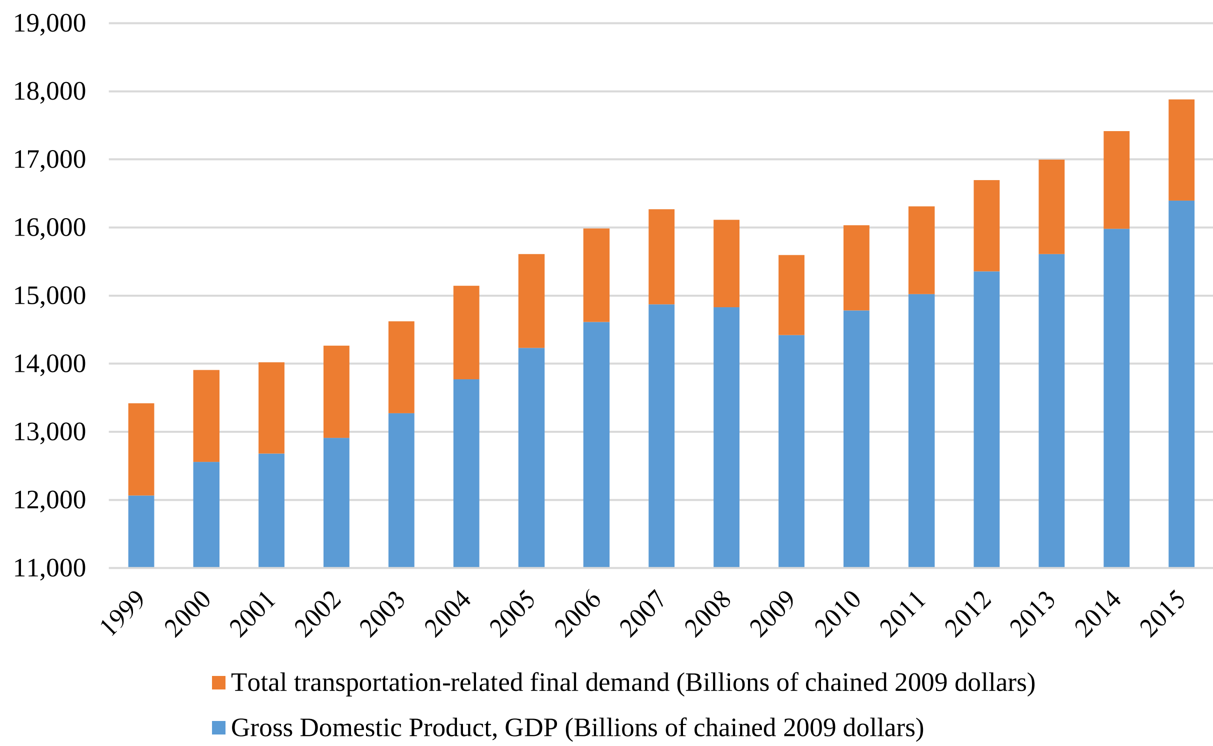


Figure 2 Contribution of transportation to the U.S. GDP.

1.1. Maritime Transportation

Freight transportation encompasses various modes, namely road, rail, air, maritime, pipeline, etc. For continental transportation, companies mostly rely on maritime transportation. That is because maritime transportation is the cheapest way to transport freight. Although maritime transportation is slower compared to the other modes, it is considered as a preferable transportation mode for a wide range of cargo types (primarily, bulk cargo). Maritime transportation comprises about 75% of the total volume as well as about 60% of the total value of the global merchandise trade (Lee and Song, 2017). A massive increase has been observed in the international seaborne trade over the last decades. From 1970 to 2016, the global seaborne trade increased by about 295% (Figure 3). The United Nations Conference on Trade and Development (UNCTAD) estimated that between 2017 and 2022, the international seaborne trade will increase annually by 3.2% (UNCTAD, 2017). Such increase can be explained by rising standards of living, rapid industrialization, growth of population, competitive markets, etc. (Umang et al., 2011). Liner shipping plays a colossal role for the global seaborne trade. It is preferred because of its high capacity. As the international trade is primarily dependent on maritime transportation and liner shipping, this dissertation primarily focuses on these areas.

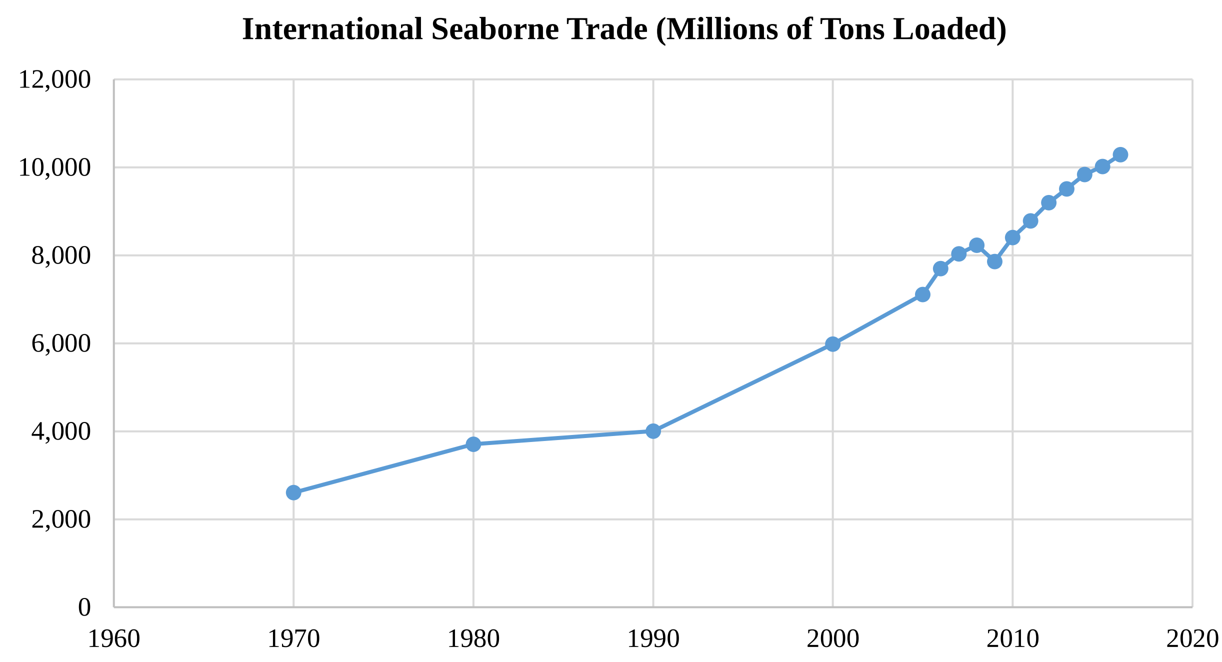


Figure 3 Growth in the international seaborne trade.

1.2. Challenges in Supply Chain Management

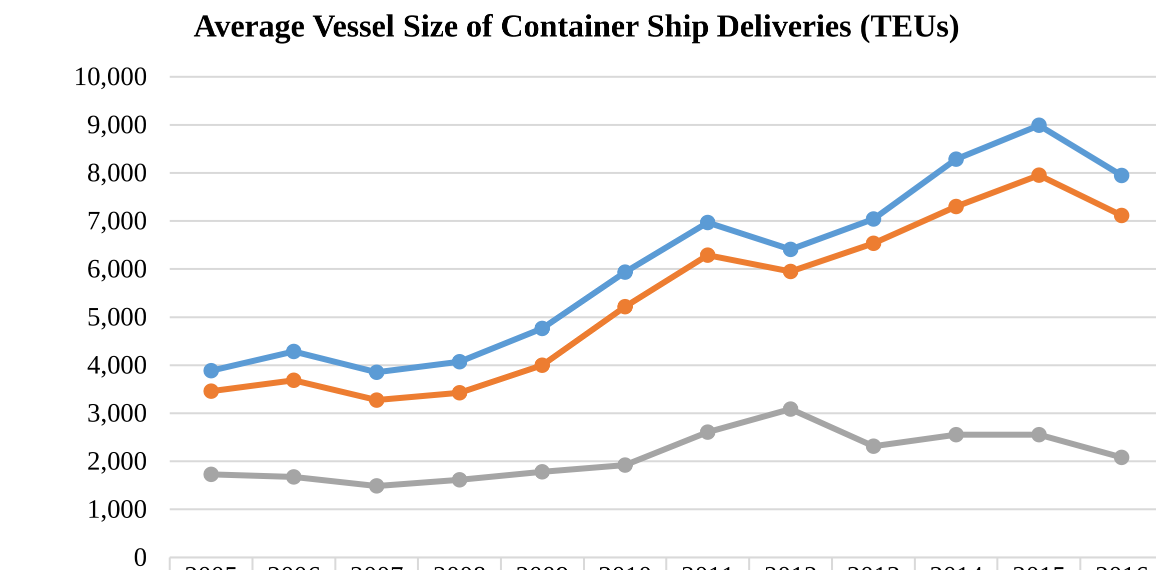
Supply chain management is associated with numerous challenges, such as market growth, resource availability, customer preferences, congestion, compliance, cost issues, etc. The cost of production is getting higher day by day. To offset it, companies are trying to expand their products to the emerging markets. Hence, the demand is getting higher with this expansion. From 2015 to 2016, demand growth in container shipping increased from 2% to 3%, whereas the growth in supply dipped from 8% to 1% (UNCTAD, 2017). During the previous years, the demand growth was even larger. Freight transporters have to exploit their existing resources to meet this demand. To move ahead in the competition, companies are providing a lot of flexibility to their customers. A new trend in today's market is express delivery or just-in-time delivery. A big problem for express delivery is congestion – not only on roadways but also at terminals. For these deliveries, a lot of changes in the design of the transportation network are needed. Next comes the issue of compliance, which supply chain managers must have a good understanding of. Shipping restrictions of cargo and handling requirements are some of the related challenges. However, environmental concerns are the biggest issues regarding compliance. Liner shipping emits a lot of carbon dioxide, carbon monoxide, hydrocarbons, nitrogen oxide, sulfur dioxide, particulate matter, etc. In order to preserve nature for future generations, these emissions must be minimized. Finally, all these issues must be handled with a limited budget. Supply chain managers have to deal with the task of cost minimization, aiming to improve economic sustainability of the supply chain operations.

Table 1 Major alliances in liner shipping.

Name of Alliance	**Participating Carriers**	**Control of Global Shipping Market (%)**
2M Alliance	Maersk (with Hamburg Süd) and Mediterranean Shipping Company	37
Ocean Alliance	CMA CGM, Evergreen, China Ocean Shipping (Group) Company, and Orient Overseas Container Line	33
"The Alliance"	Hapag-Lloyd (with United Arab Shipping Company), Ocean Network Express (K-Line, Nippon Yusen Kabushiki Kaisha, Mitsui Osaka Soshen Kaisha Lines), and Yang Ming	21

1.3. Alternatives for Meeting the Growing Demand

To face the growing number of challenges and meet the existing demand, freight transporters, especially liner shipping companies, have come up with some strategies. To gain competitive advantages in a crisis-strained market, liner shipping companies are promoting cooperation with competitors through strategic alliances. They are sharing their capacities and dedicated services to have steadier market positions. By 2016, the top 10 carriers are represented by 3 global alliances, namely 2M Alliance, Ocean Alliance, and "The Alliance" (Table 1). These 3 global alliances altogether control 91% of the global shipping market (Journal of Commerce, 2016). These alliances are contributing to the reduction of operational costs through the sharing of vessels and capacity.



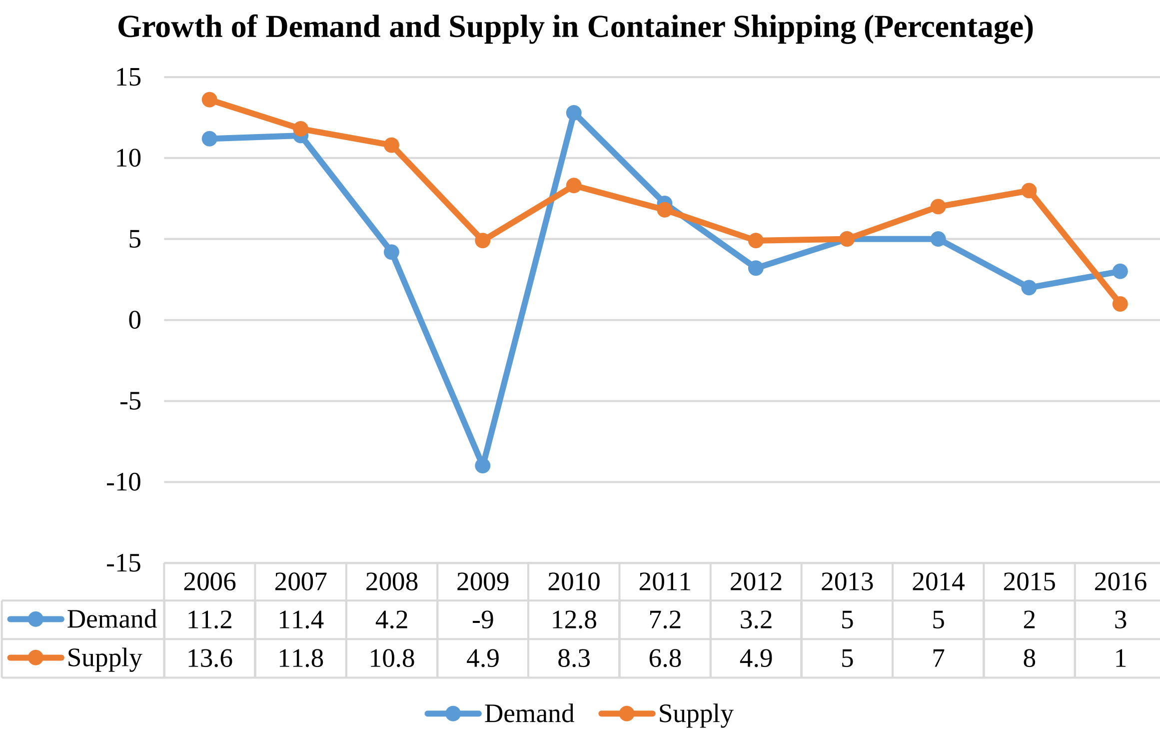
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Gearless	3885	4282	3853	4074	4766	5937	6969	6406	7040	8284	8989	7947
All	3457	3686	3275	3427	4001	5214	6291	5952	6534	7301	7952	7115
Geared	1725	1673	1486	1616	1781	1919	2609	3087	2311	2553	2554	2082

Gearless All Geared

Figure 4 Changes in vessel size.

Another important operational strategy, which has been adopted by liner shipping companies, is increasing size of vessels. Once every few weeks, shipping lines proclaim orders for even larger vessels. Since 2005, the TEU (Twenty-Foot Equivalent Unit) capacities of new gearless vessels have almost doubled (Figure 4). In 2005, the average vessel size of container ship deliveries was 3,457 TEUs. In 2015, it was increased to 7,952 TEUs. This trend was mostly observed for geared vessels. From 2005 to 2016, the average vessel size of geared container ship deliveries increased from 3,885 TEUs to 7,947 TEUs. However, the capacities of geared vessels have remained in the same region. In 2005, their average capacity was 1,725 TEUs, which increased by 357 TEUs toward 2016. In 2013, the largest vessel, in terms of capacity, was

Triple-E by Maersk (18,000 TEUs). It surpassed the record held by Emma Maersk (15,500 TEUs) by 16% (Maersk, 2017). At present, vessels that have capacities in excess of 18,000 TEUs are called 'megaships' (iContainers, 2016). Major maritime consultants predict that by 2020, the term "megaships" will be applied to those vessels, which have capacities greater than 24,000 TEUs. One of the major advantages from megaship deployment is economies of scale. A megaship with 18,000 TEU+ capacity consumes 35% less bunker per container as compared to a typical 13,100 TEU vessel (MarineLink, 2013). Certain practitioners indicate that megaships have peaked economies of scale. However, the capacities of megaships are expected to be raised in the upcoming years.



	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Demand	11.2	11.4	4.2	-9	12.8	7.2	3.2	5	5	2	3
Supply	13.6	11.8	10.8	4.9	8.3	6.8	4.9	5	7	8	1

Figure 5 Changes in container traffic.

Containerization has paved the way for large vessels. Since the mass exploitation of containers, the sizes of vessels are getting gigantic. The reference size of a container is 20" x 8'6" x 8", or 1 Twenty-foot Equivalent Unit (TEU), as discussed before. 40 feet long containers, called Forty-foot Equivalent Units (FEUs), have been also frequently used over the last years. However, TEU remains a standard management unit for marine transportation. Due to flexibility, low cost, safety, and other benefits, containers are adding extra speed on the process of handling, loading and unloading. Because of all the benefits, there has been a consistent rise in the global container traffic (Figure 5). According to UNCTAD (2017), the demand and supply in container shipping has been growing from 2005 to 2016. Only in the year of 2009, there was no growth in the demand of container shipping because of recession. The pace of growth in demand and supply of containers has reduced in the recent years. The rate of demand growth increased from 2% in 2015 to 3% in 2016. On the other hand, the rate of supply growth decreased rapidly. While the growth in 2015 was 8%, it was reduced to 1% in 2016. This reduction was due to a significant slowdown in fleet growth and an uprising trend in demand growth of container shipping.

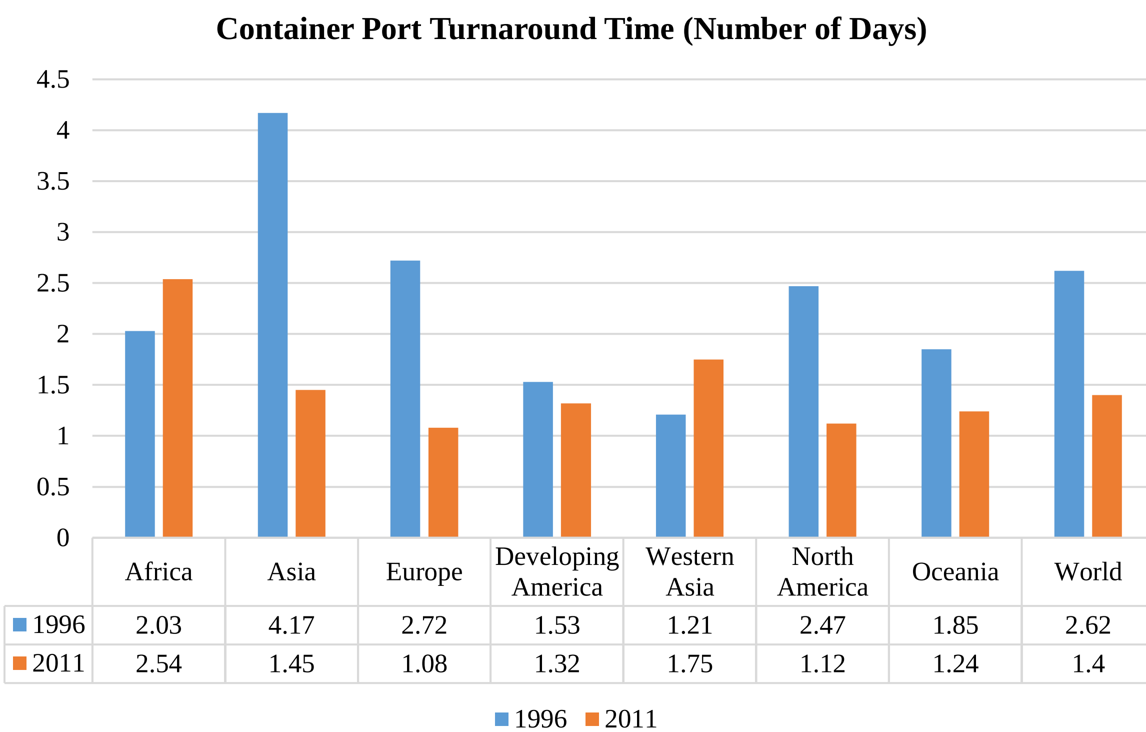
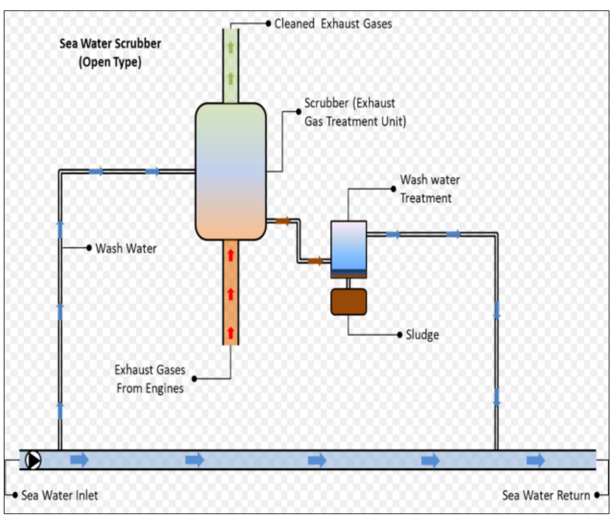


Figure 6 Changes in the vessel turnaround time.

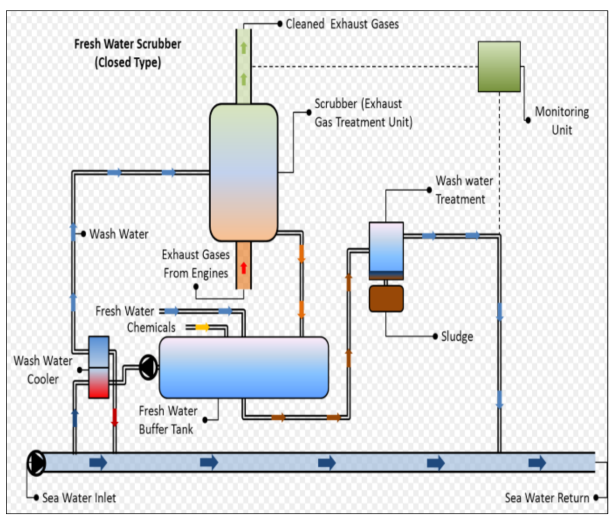
In order to facilitate service of incoming vessels, port authorities have been trying to build better infrastructures. This phenomenon has occurred mostly in the developing countries. Ports are being restructured to handle large vessels. In 2014, global port throughput was 674,980,729 TEUs. In 2015, it was increased to 686,689,563 TEUs (1.7% annual increase), and by 2016, it was increased to 699,703,546 TEUs (1.9% annual increase). Due to this phenomenon, the loading and unloading times have been reduced significantly. As illustrated in Figure 6, from 1996 to 2011, the average turnaround time of vessels at ports have dropped from 2.62 days to 1.4 days (Ducruet et al., 2014).

1.4. New Technologies for Sustainable Supply Chain Management

Advanced technologies are being deployed for various purposes. The use of scrubbers, a new kind of pollution control devices, has been a revelation. Scrubbers remove harmful compounds from exhaust gases and neutralize them. Scrubbers were found to be efficient in reducing sulfur dioxide (SO_2) emissions. There are two general types of scrubbers: open type and closed type. Open-type scrubbers exploit seawater to purify exhaust gas, whereas closed-type scrubbers use fresh water in a circuit along with an alkaline chemical, such as caustic soda (Figure 7). Scrubbers have added a new dimension to pollution control in maritime industry.



Open-Type Scrubber



Closed-Type Scrubber

Figure 7 Scrubber.
Source: shippipedia.com

There have been some remarkable advances in the field of cargo tracking. Radio-frequency identification (RFID) is one of the primary advancements. RFID employs electro-magnetic fields in order to identify and track tags attached to containers (Figure 8). Companies have a good knowledge about what is in their inventory. However, when their products are moved inside containers, they do not have much information about the status of their products. It is especially true for perishable goods, as these might spoil or lose quality before reaching the destinations. Also, containers could be opened in an unprotected environment, and it could lessen the quality of the products. RFID addresses these issues in an extraordinary manner. When an RFID tag is attached to a container, it can be read. These tags identify what is in a container and whether they match the content that is supposed to be in a container. This reading can be done by a handheld interrogator or through the setup of a portal. RFID informs about the quality of products too.

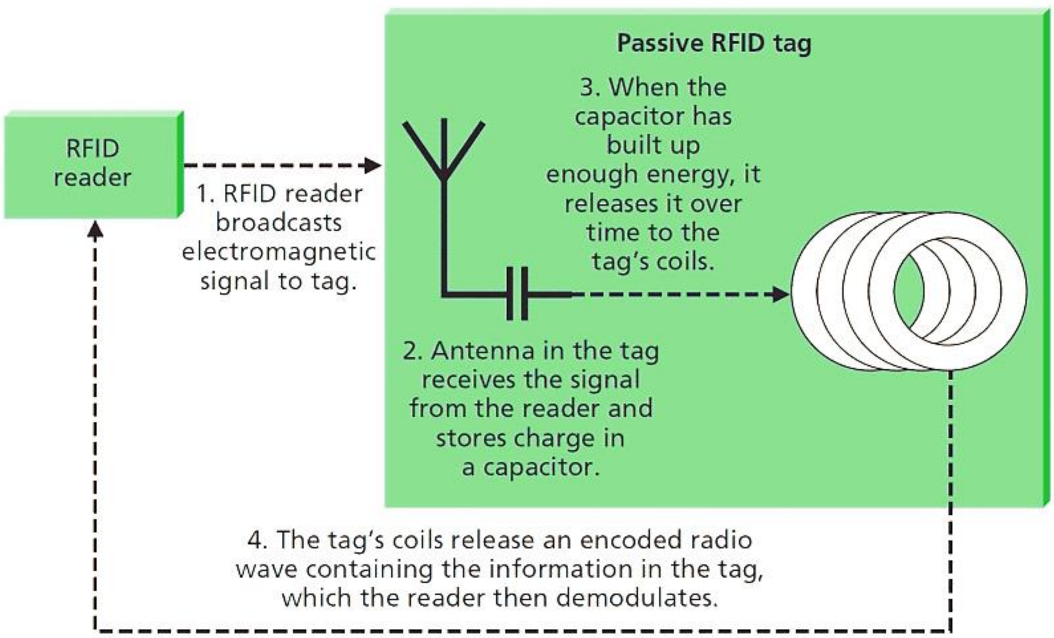


Figure 8 Mechanisms of RFID.
Source: Weinstein (2005)

Another advancement in the field of tracking has been the introduction of GPS tracking (see Figure 9). Prior to GPS tracking, there was a lack of appropriate container location information. Thus, the utilization of containers was not enough, and unnecessary inventory space was required. With the involvement of GPS tracking, these problems have been overcome mostly. Yard and fleet operations have become more efficient, and labor costs have been reduced. If containers are moved to any unplanned directions, respective authorities notice it instantly. Thus, the recovery of stolen containers has become faster, and the associated costs have been reduced. Last but not least, customer service has been improved with the application of GPS tracking. Other strategies, such as alternative handling equipment (see Figure 10), efficient engines, network trims, movement from ad hoc to contracts, etc., are also being deployed.

Figure 9 A typical GPS container tracker.
Source: globalsources.com

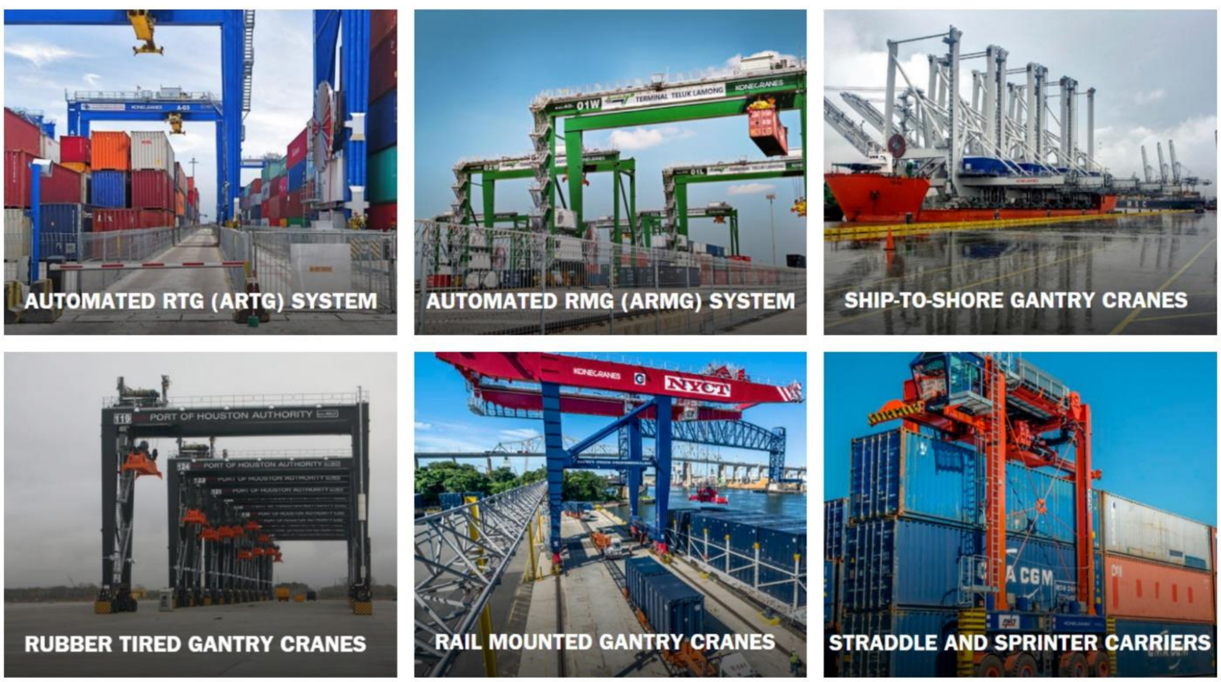


Figure 10 Some alternative handling equipment.
Source: 10onecranes.com

CHAPTER 2

DECISION PROBLEMS IN LINER SHIPPING

Liner shipping companies face three levels of decision problems, namely strategic level, tactical level, and operational level (Figure 11) (Meng et al., 2014; Dulebenets et al., 2019a; Pasha et al., 2020). Liner container shipping companies take long-term decisions at the strategic level, which are: (1) fleet size and mix; (2) alliance strategies; and (3) network design. The fleet size and mix problem deals with the number and type of vessels, which a liner container shipping company should have in its vessel fleet. Generally, liner shipping companies select their alliance partners at the strategic level. The network design problem determines the ports to be visited by the vessels, as well as the visiting order.

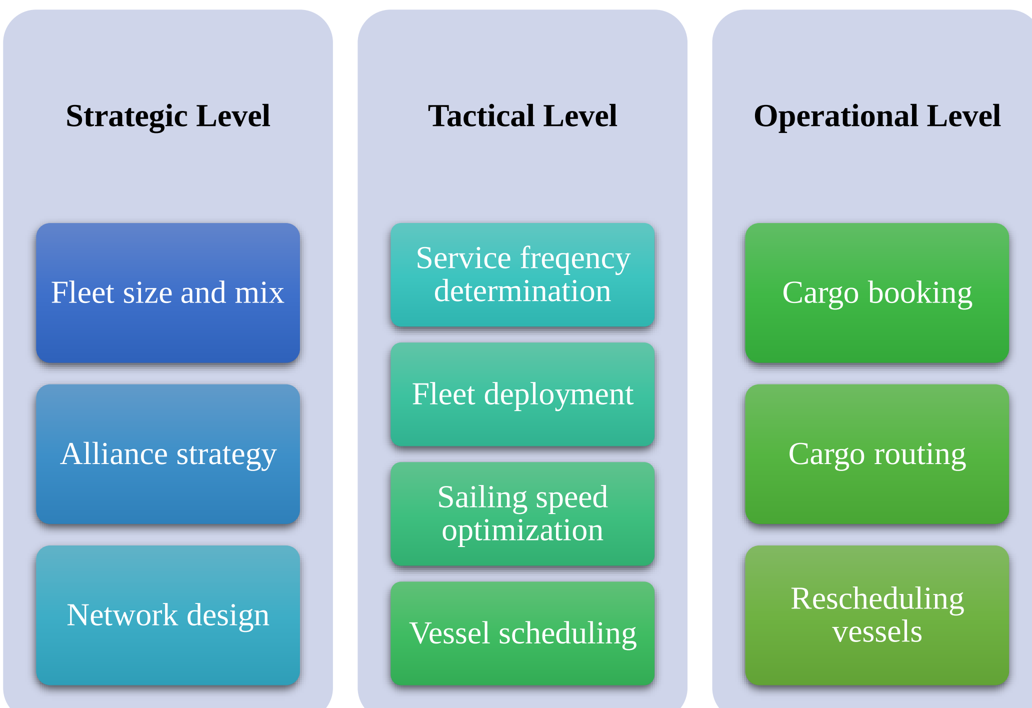


Figure 11 Liner shipping decision problems.

The tactical-level decisions are effective for three months to six months, based on (changes in) container demand. A liner container shipping company has to fix the frequency of its services, deploy vessels on the served itineraries, optimize vessel sailing speeds, and design vessel schedules. Service frequency is defined as the time headway between two consecutive vessels along a liner shipping route. If a high frequency is selected, the waiting time of containers at the origin ports becomes short; however, this results in the requirement of a large number of vessels to be deployed. Moreover, the liner shipping company cannot exploit economies of scale, which could come from the use of large vessels. Fleet deployment assigns vessels to liner shipping routes to minimize costs or to maximize profits. The vessel sailing speed substantially influences the fuel consumption cost (and also the route service cost), as increasing just a couple of knots makes a substantial increase in fuel consumption (Notteboom and Vernimmen, 2009). Fuel cost is a major component of the total liner shipping route service cost and could cover around 75% of the total operating cost (Ronen, 2011). The vessel schedules consist of the planned arrival times, handling times, and departure times at each of the ports of call. The vessel sailing speeds are adjusted after the vessel schedules are set.

Vessel schedule updates must be readily accessible, especially to exporters. Several factors are associated with this matter. If exporters utilize outdated vessel schedules, they would create inaccurate bookings. In case of vessel schedule changes, truckers should also be notified. If truckers do not take the cargoes to the ports within the newly specified time, a delayed departure would occur, which would result in demurrage. If the vessel schedules are shifted ahead of the pre-scheduled times, and exporters are not notified, it could lead to exporters missing critical cut-off times, which would also result in delay of cargo. Moreover, frequent changes in vessel schedules reduce schedule reliability for the respective liner shipping routes. In such cases, it becomes harder to minimize downstream costs and/or risk for the routes with unreliable schedules.

Changes in vessel schedules should also be notified to importers. Based on vessel schedules, importers develop production plans and sales plans. Hence, in order to avoid untimely programs and production cycles, importers need to know about all changes in arrival times. Moreover, importers generally appoint truckers for delivery and pickup. In case of changes in vessel schedules, trucker appointments must be changed accordingly. If importers do not have access to updated vessel schedules, they would not update trucker appointments. Thus, they would have to pay truckers for empty runs. In such cases, importers might also have to deal with missed delivery issues with their customers (e.g., they might have to refund the customers or apply discounts if the delivery time period exceeds the original planned one). Furthermore, without access to updated vessel schedules, importers could make late deliveries, miss sale dates, or even face the risk of factory shutdowns.

At the operational level, liner container shipping companies decide whether to accept cargoes or not, how to route the accepted cargoes, and how to reroute or reschedule vessels to deal with unexpected incidents (e.g., adverse weather/sea conditions, port congestion). Container cargo booking has not evolved much as that of airlines, which has many classes. Generally, it is assumed that the containers of the same origin-destination are homogeneous from the perspective of the liner shipping company. The liner shipping company just determines the number of containers to transport between each origin-destination, considering the shipping capacity of the company, in order to maximize profit. Disruptions in container liner shipping can occur due to many issues, such as bad weather, port contingencies, malfunctioning of engines, others. A schedule recovery strategy is either to increase the sailing speed (which would increase the fuel consumption cost) or to delay the delivery of cargoes in case if vessel sailing speed adjustment is considered for schedule recovery.

Supply chain management and freight transportation play a major role in the global economy, and most of freight transportation is conducted through liner shipping. Liner shipping is growing day by day but at the same time, it is faced with numerous challenges. Consolidation has helped a lot of companies but some companies, which are not in the shipping alliances, have seen a downfall in their profit. Some of the biggest liner shipping companies have gone bankrupt, such as Hanjin. Political crises have also stained this industry. Moreover, pricing/freight rates have always been an issue. Numerous studies have been carried out to date, which aimed to improve the liner shipping operations. Many of these studies have certain limitations and/or rely on the assumptions, which are rather unrealistic. This dissertation will primarily focus on the tactical-level decision problems in liner shipping, address limitations of the existing studies, and propose an integrated optimization model, which can be used for improving liner shipping operations.

CHAPTER 3

LITERATURE REVIEW

A comprehensive literature search was conducted through the major scientific publishers, including Elsevier, Springer, ASCE, Wiley, etc. Several keywords were used to identify the papers related to the theme of this dissertation, such as service frequency, frequency determination, fleet deployment, vessel fleet, speed optimization, sailing speed, vessel speed, ship speed, vessel scheduling, collaborative vessel scheduling, green vessel scheduling, liner shipping, liner shipping companies, etc. From the identified studies, 104 peer-reviewed journal papers were selected for a detailed review.

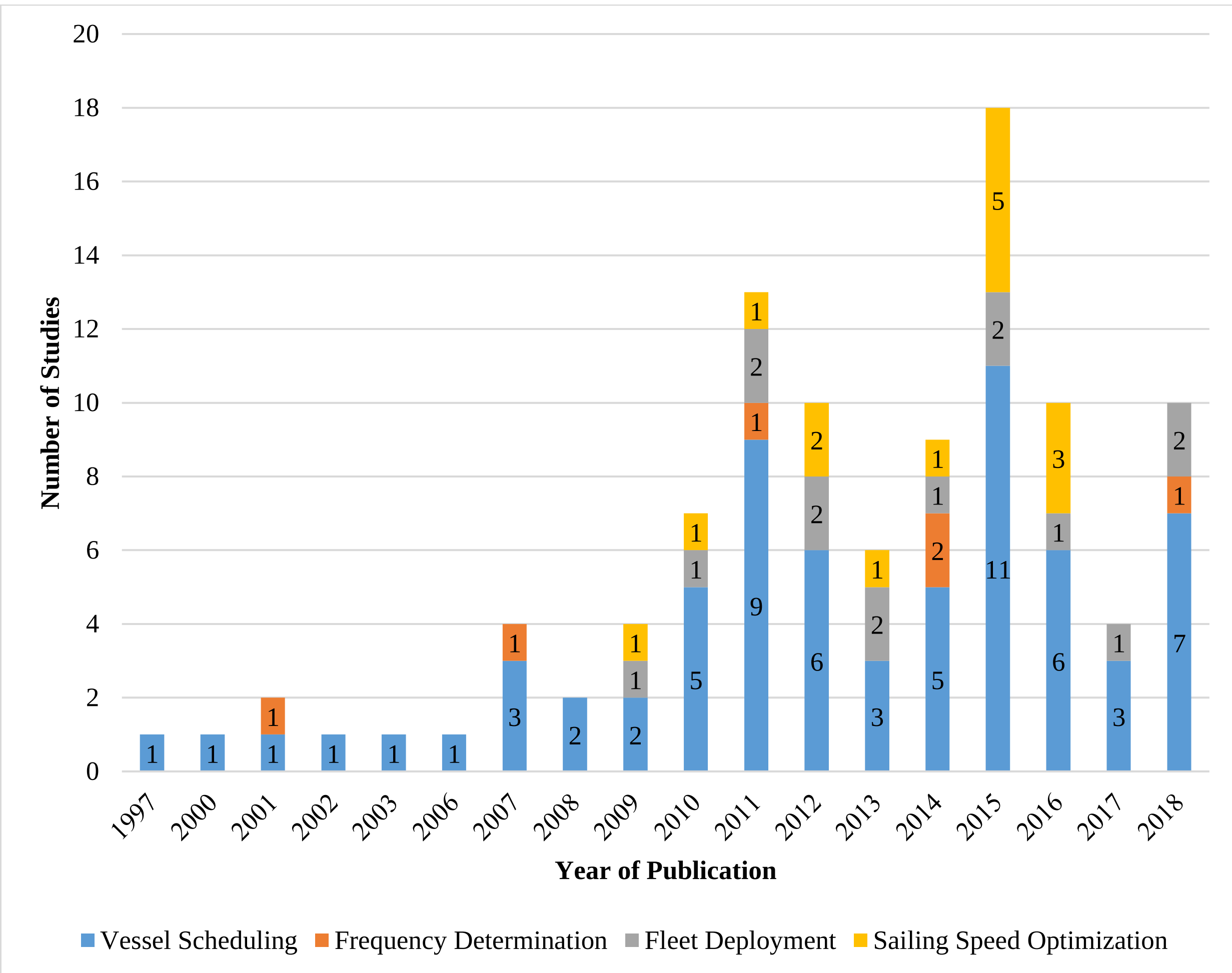


Figure 12 Distribution of studies by year of publication.

Figure 12 illustrates the distribution of the studies, which were reviewed in detail, by the year of publication, where the number of selected papers on vessel scheduling, frequency determination, fleet deployment, and speed optimization were 68, 6, 15, and 15, respectively. It can be noticed that the number of publications on vessel scheduling was not significant before 2007. However, vessel scheduling has started receiving much more attention since 2007. Based on the collected studies, it can be observed that the number of studies on vessel scheduling is rapidly growing. As for the problems of fleet deployment and sailing speed optimization, the number of publications has increased since 2009. This increment in the number of publications on these liner shipping decision problems can be explained by the existing tendencies in the international seaborne trade, as discussed in the introduction section of this dissertation.

The following sections of the dissertation will present the reviewed studies on the four major decision problems. Each section will have a description of the reviewed studies, followed by a summary of findings and future research directions.

3.1. Service Frequency Determination

3.1.1. Description of Studies

Several studies have integrated the service frequency determination problem with other decision problems in liner shipping. Bendall and Stent (2001) studied frequency determination along with fleet size design and fleet deployment. The study argued that high-speed vessels could incur profits, even though these vessels needed greater investment per unit of cargo. A mixed-integer programming model was designed to determine the optimal variable contribution of a high-speed feeder service that hauled on a short sailing distance. Based on a hub-and-spoke network, the model optimized the number of vessels to obtain the highest profit over the planning horizon. The model had two stages, where the first stage involved with the number of voyages during the planning extent, could be solved with a branch-and-bound algorithm. The second stage of the model scheduled the voyages that were selected during the previous stage, and heuristic algorithms were required to obtain the solutions. Numerical results revealed that serving ports with only one vessel was the most profitable. It was also found that more ports could be served if an extra vessel was added. However, such additions could reduce the operating surplus.

Hsu and Hsieh (2007) integrated frequency determination with routing and vessel size determination for a hub-and-spoke container network. A multi-objective model was formulated to minimize shipping and inventory costs. Applying tradeoffs between shipping and inventory cost, Pareto optimal solutions were generated using the Mathematica 4.0 software. Results demonstrated that port charges and efficiency had a significant impact on the optimal routes, vessel size, and sailing frequency. Meng and Wang (2011) determined the optimal service frequency for a long-haul liner shipping route. A mixed-integer nonlinear programming model, aimed to minimize the daily operating cost, was formulated at first. The model was later linearized and solved with a branch-and-bound-based algorithm. The developed algorithm provided the optimal solutions by minimizing the number of vessels and fuel consumption. It was suggested that an additional vessel might be deployed to control fuel consumption in case of high fuel price and normal operations. The study also argued that express service could reduce service frequency, but it would require more low-capacity vessels.

Lin and Tsai (2014) studied daily frequency where liner shipping companies would pick and deliver cargoes to customers at the major ports on a daily basis. It was argued that daily frequency enabled improved service quality and reliability along with reducing unoccupied resources. An integer programming model, minimizing the total cost, was developed to investigate the vessel routing and freight assignment of daily frequency operations. The optimization model was solved with a Lagrangian relaxation technique and a local search heuristic. Empirical studies revealed that daily frequency operations were dependent on the idle cost of vessels, delay costs and the service time commitment. Zhang and Lam (2014) assessed the effect of schedule reliability and service frequency upon liner shipping and port industry. The study examined Daily Maersk, a service offered by Maersk since late 2011 that is operated daily, i.e., has daily departures. It was indicated that the whole liner shipping industry had been going through a reform because of new trends, such as daily sailings. Maersk’s rival companies restructured their alliances to maintain their market shares in the wake of Daily Maersk. Because of this competition, hub ports would experience capacity and productivity problems, whereas ports and terminals were likely to face the challenge of better supply chain integration. In order to deal with the uprising issues, ports and liner shipping companies were advised to have an effective collaboration with their supply chain partners.

Unlike most studies that assumed weekly or bi-weekly service frequency, Giovannini and Psaraftis (2018) considered variable service frequency from a greater set for the profit maximization problem. The study also incorporated the effect of fluctuations in freight rates, bunker prices, and inventory costs. A nonlinear mathematical model was formulated to maximize the average daily profit. The study indicated that after applying piecewise linear approximation, the model could be solved with exact optimization algorithms, such as CPLEX. Numerical analysis revealed that enforcing a fixed frequency might give rise to an additional cost. For example, if a vessel was compelled to sail faster to maintain the fixed frequency, additional fuel cost might be incurred. On the other hand, if a vessel sailed slower at a service frequency lower than the optimal frequency, then revenues would be lost.

3.1.2. Summary of Findings

The summary of the findings from the literature reviewed on the service frequency determination problem is shown in Table 2.

Table 2 Summary of findings on service frequency determination.

Author(s)	Year of Publication	Sailing Speed	Port Time	Model Objective	Objective Components (Costs)	Solution Approach	Notes/Major Considerations
Bendall and Stent	2001	F	F	Maximize the total profit	REV; TOC; TFC; TPC	Branch-and-bound algorithm; Heuristic	short-haul
Hsu and Hsieh	2007	F	F	Minimize the total cost	TOC; TFC; TPC; TIC; MSC	Mathematica 4.0	tradeoff between shipping and inventory cost
Meng and Wang	2011	V	V	Minimize the total cost	TOC; TFC; TPC;	Heuristic	long-haul
Lin and Tsai	2014	F	F	Minimize the total cost	TOC; TPC; TVC; MSC	Lagrangian relaxation; Heuristic	daily service frequency
Zhang and Lam	2014	N/A	N/A	N/A	N/A	N/A	daily service frequency
Giovannini and Psaraftis	2018	V	F	Maximize the total profit	REV; TOC; TFC; TPC; TIC; MSC	Analytical method	variable service frequency; influence of freight rates, fuel prices and cargo inventory costs

Legend:

Sailing Speed/Port Time: V - variable; F - fixed.

Objective Components: TOC - total vessel operational cost; TFC - total fuel cost; TPC - total port handling cost; TVC - total cost for the violation of arrival TWs; TIC - total inventory cost; MSC - miscellaneous cost; REV - revenue.

3.1.3. Future Research Directions

In addition to the extensions indicated in the vessel scheduling section, the following directions were provided for future research.

- The liner shipping industry has gone through some major changes in the recent years. Several carriers have added ultra-large vessels and high-speed vessels to their fleet. Modeling these changes in the vessel fleets needs to be employed in future research.
- Due to the increasing competition in the market, several competition strategies have been adopted by the liner shipping companies, such as the formation of strategic alliances. Several authors have advocated for the necessity to include these strategies in the future models.
- Some of the proposed mathematical models were designed for a single route. These models could be evaluated for all the routes of a liner shipping network.

3.2. Fleet Deployment

3.2.1. Description of Studies

Gelareh and Meng (2010) assessed the short-term fleet deployment problem, where a mixed-integer nonlinear programming model was developed to minimize the total cost. This model interpreted optimal sailing speed as an equivalent to optimal sailing time. The nonlinear model was then transformed into a linear one applying some linearization techniques and solved with CPLEX. It was stated that the linearized mixed-integer model was flexible in developing the service frequency and the constraints regarding the service time windows (TWs). Wang et al. (2011) stated that an equation used by previous studies to calculate the maximum number of voyages to be completed during the planning extent was incorrect and reformulated it. The study also argued that the two mathematical models formulated by Gelareh and Meng (2010) were not equivalent at the optimal condition due to a constraint. After fixing that constraint, the study revised Gelareh and Meng's (2010) fleet deployment model to oust its combinatorial nature.

Wang and Meng (2012c) presented a mixed-integer optimization model for the fleet deployment problem, which allowed transshipment operations at any port. The variables regarding transshipment were not required to be defined explicitly. The objective of the model was to minimize the total cost. Numerical experiments, conducted for randomly generated large-scale liner shipping networks, revealed that the model could be solved efficiently with CPLEX. Wang and Meng (2012d) considered week-dependent container shipment demand for the fleet deployment problem. A space-time network approach was applied to generate container routes. Two relaxation models were proposed to provide lower bounds for the fleet deployment model. A global optimization heuristic was developed as a solution approach. Computational experiments, applied for the Asia-Europe-Oceania shipping network, exhibited the efficacy of the model and the solution algorithm.

Wang et al. (2013b) accounted for container demand uncertainty in fleet deployment. A joint chance-constrained programming model was formulated to minimize the total cost. A solution algorithm, inspired by sample average approximation, was applied on the mathematical model. Results showed that the differences between the lower and upper bounds of the solution were small. Finally, it was underscored that the proposed approach could be applied to other similar problems with demand uncertainty. Ng (2014) stated that determining probability distributions of shipment demand was complex in practice. So, the study proposed a fleet deployment model that required specifications of mean, standard deviation and an upper bound of container demand. The mixed-integer programming model, aimed to minimize the total cost, was solved with OSICPLEX. Results demonstrated the efficiency of the proposed approach. In conclusion, the study highlighted the need of tailored exact solution algorithms and metaheuristics capable to deal with large-scale instances of the tackled problem.

Ng (2015) developed a fleet deployment model to tackle uncertainty in demand. The model required fewer inputs as compared to the previous fleet deployment studies that considered demand uncertainty. In case of shipment demand, it only required mean and variance of the maximum demand. The proposed model also accounted for stochastic dependencies between demands on various routes. The stochastic dependences did not need to be defined explicitly. After solving with OSICPLEX, it was shown that the proposed model produced remarkable cost savings in comparison with prevalent models. A case study revealed that the recognition of stochastic dependencies in shipping demand had a tendency to increase the cost of fleet deployment. Zhao et al. (2016) evaluated route risk for the fleet deployment problem. The study argued that if all the environmental factors affecting navigational safety (and thereby, route risk) were considered, they would lessen the impact of the main factors and make the problem more complex. Hence, only the major environmental factors were taken into account, which were wind, ocean current, storm surge, ocean tide and visibility. Dempster-Shafer (D-S) evidence theory was employed to develop the route risk evaluation model. A novel fleet deployment model was then formulated to minimize the total cost. The model was further solved with the firefly algorithm.

Ng (2017) underlined an implicit and redundant assumption in the existing fleet deployment models. The assumption was that a vessel could not return to any of its visited ports before completing a round trip journey. The study argued that this assumption led to deployment of more vessels than it was required. Hence, a mixed-integer programming model, which aimed to minimize the total cost, was formulated by relaxing this assumption. After obtaining solutions with OSICPLEX, a numerical case study revealed that the model could decrease fleet deployment cost by up to 15 percent, and the savings in cost increased with increments in vessel size. Ng and Lin (2018) tackled the fleet deployment problem where only conditional shipment demand information was available. In such a case, the study developed a model that returned a set of upper and lower bounds on the optimal cost instead of the optimal solution. It was stated that the optimal solution could be determined by converging the bounds when a sufficiently refined partition would be available.

A number of studies have combined the fleet deployment problem with additional decision problems (Álvarez, 2009; Gelareh and Pisinger, 2011; Gelareh et al., 2013; Huang et al., 2015; Wang et al., 2018). Wang et al. (2018) studied the chartering of vessels which involved the decisions on the number of vessels to be chartered and the duration of chartering. The study considered this problem as a typical vessel composition problem and incorporated it with the fleet deployment and sailing speed optimization problem. A two-stage stochastic programming model was presented, which aimed to minimize the chartering cost. The mathematical model considered market uncertainties, and it was solved with CPLEX. Computational experiments, conducted on the data collected for a leading chemical shipping company in Norway (Odfjell), revealed that more accurate results could be attained by increasing the level of detail in fleet deployment (e.g., speed optimization, loop construction, etc.).

3.2.2. Summary of Findings

Table 3 represents the summary of findings from a detailed literature review of the literature on fleet deployment.

Table 3 Summary of findings on fleet deployment.

Author(s)	Year of Publication	Sailing Speed	Port Time	Model Objective	Objective Components (Costs)	Solution Approach	Notes/Major Considerations
Álvarez	2009	F	F	Minimize the total cost	REV; TOC; TFC; MSC	Heuristic	transshipment hub; regional trade imbalances
Gelareh and Meng	2010	V	F	Minimize the total cost	TOC; MSC	CPLEX	short-term fleet deployment
Gelareh and Pisinger	2011	F	F	Maximize the total profit	REV; TOC; MSC	Heuristic	demand uncertainty; transshipment
Wang et al.	2011	V	F	Minimize the total cost	TOC; MSC	CPLEX	maximum number of voyages
Wang and Meng	2012c	F	F	Minimize the total cost	TOC; TFC; TPC; MSC	CPLEX	transshipment
Wang and Meng	2012d	F	F	Minimize the total cost	TOC; TFC; TPC; MSC	Heuristic	demand uncertainty
Gelareh et al.	2013	F	F	Minimize the total cost; Minimize total time	TOC	Heuristic	several port rotations
Wang et al.	2013b	F	F	Minimize the total cost	TOC; MSC	Heuristic; CPLEX	demand uncertainty
Ng	2014	F	F	Minimize the total cost	REV; TOC; MSC	OSICPLEX	demand uncertainty
Huang et al.	2015	F	F	Minimize the total cost	TOC; TFC; TPC	CPLEX	transshipment; empty container repositioning
Ng	2015	F	F	Minimize the total cost	REV; TOC; MSC	OSICPLEX	demand uncertainty
Zhao et al.	2016	F	F	Minimize the total cost	TOC	Firefly algorithm	route risk
Ng	2017	F	F	Minimize the total cost	REV; TOC; MSC	OSICPLEX	demand uncertainty
Ng and Lin	2018	F	F	Minimize the total cost	REV; TOC; TVC; MSC	OSICPLEX	demand uncertainty
Wang et al.	2018	F	F	Minimize the total cost	REV; TOC; MSC	CPLEX	market uncertainties

Legend:

Sailing Speed/Port Time: V - variable; F - fixed.

Objective Components: TOC - total vessel operational cost; TFC - total fuel cost; TPC - total port handling cost; TVC - total cost for the violation of arrival TWs; MSC - miscellaneous cost; REV - revenue.

Different aspects of the findings from the reviewed studies on fleet deployment are discussed below.

3.2.2.1. Sailing Speed and Port Time

All the studies, which applied the fleet deployment problem, considered two types of sailing speeds: fixed and variable (Figure 13). A substantial portion of the selected studies assigned fixed sailing speeds (87%), whereas 13% of the studies allotted variable sailing speeds. Furthermore, each study on the fleet deployment problem considered the port times to be fixed.

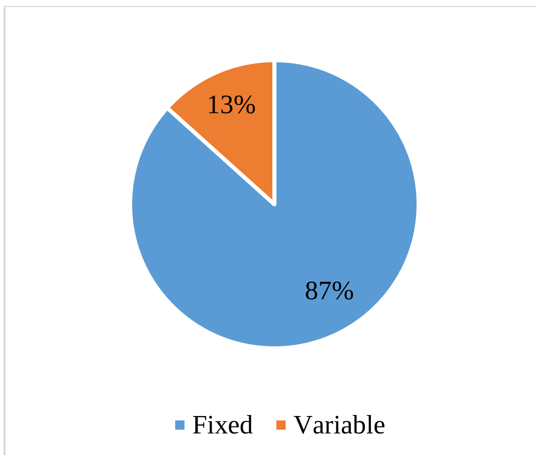


Figure 13 Distribution of fleet deployment studies based on sailing speed.

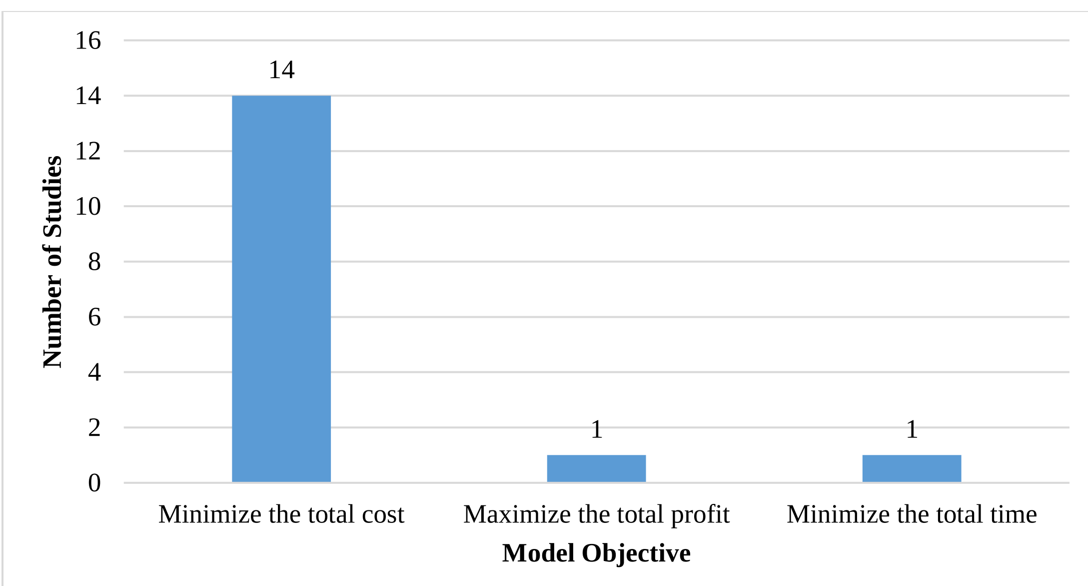


Figure 14 Distribution of fleet deployment studies by model objective.

3.2.2.2. Model Objective(s)

The model objective, which was considered by the majority of the reviewed studies (14 studies), was to minimize the total cost (Figure 14). One of the proposed models was a multi-objective model that incorporated the minimization of the total time along with the minimization of the total cost. In addition, only one study aimed to maximize the total profit.

3.2.2.3. Objective Components

A detailed review of the existing literature on fleet deployment found that all of the selected papers included total operating cost in the representative mathematical models (Figure 15). Total fuel cost was incorporated in 4 studies, while 3 studies considered total port handling cost. Several other cost components were included, such as chartering cost, total cost for the violation of arrival TWs, etc. Moreover, revenue was incorporated in 7 mathematical models.

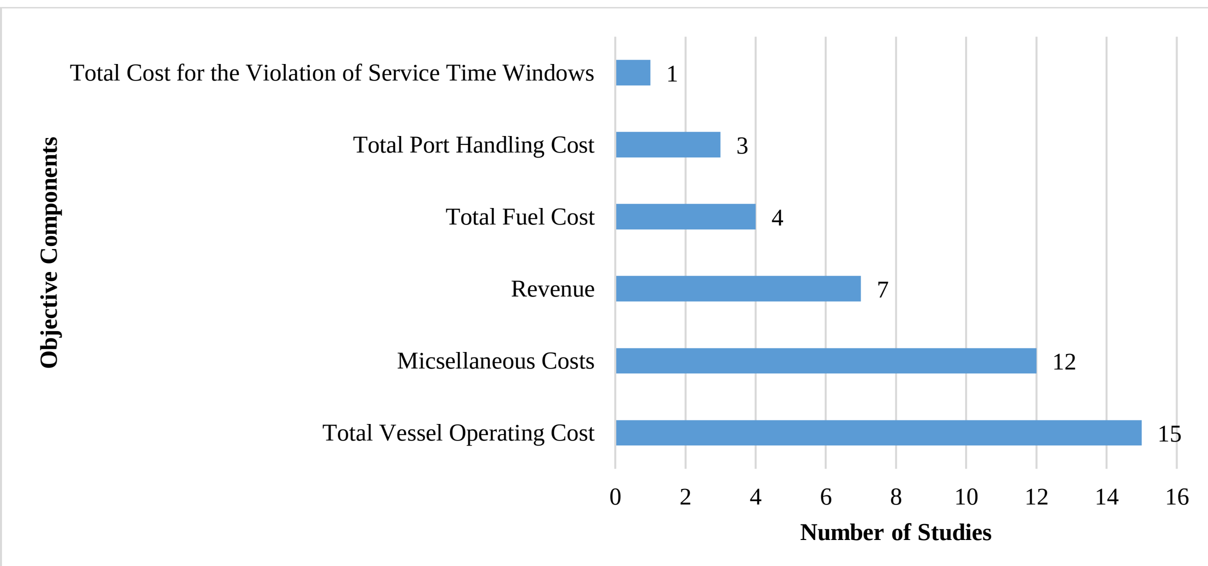


Figure 15 Distribution of fleet deployment studies by objective components.

3.2.2.4. Solution Approach

5 heuristics, 1 metaheuristic, and 2 different exact solution algorithms were used to tackle the mathematical models formulated (Figure 16). The exact solution algorithms were CPLEX (6 studies) and OSICPLEX (4 studies). One study employed the firefly algorithm to solve the presented optimization model.

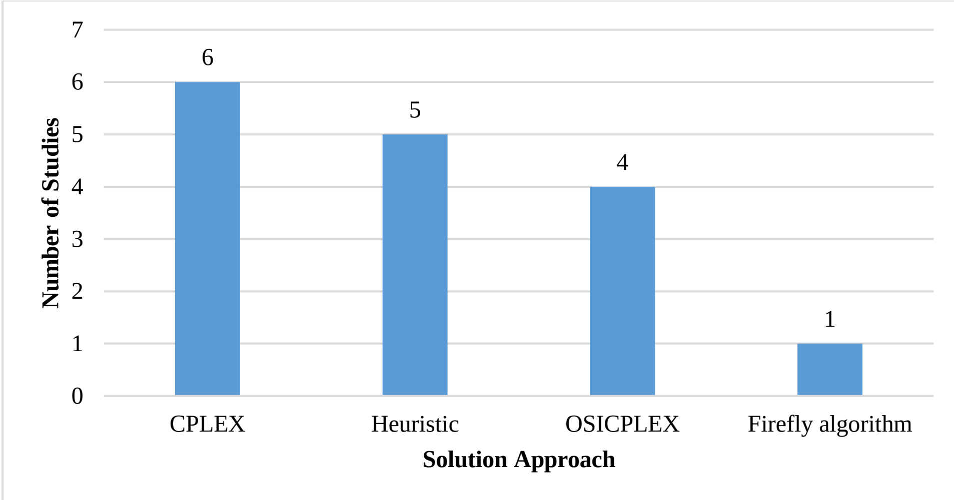


Figure 16 Distribution of fleet deployment studies by solution approach.

3.2.3. Future Research Directions

The following future research directions were presented by the reviewed papers on fleet deployment.

- Several time periods are typically considered as constants in the fleet deployment models, such as container loading and unloading time, inland intermodal transportation time of containers, etc. In real life, these times can fluctuate significantly. So, modeling of these times could be conducted by future studies.
- Several uncertainties, such as uncertainties in transit times, demand uncertainty, etc., should be accurately modeled.
- Most studies do not consider transshipment of containers in the mathematical models. Consideration of transshipment will make the fleet deployment models more applicable in practice.
- A number of studies pointed out the necessity of efficient network design, including hub port location and feeder port allocation.
- Some studies suggested that future research could design fleet deployment models for the entire global liner shipping network.
- A significant portion of the reviewed studies highlighted the need of alternative modeling and solution approaches for their respective problems.

3.3. Sailing Speed Optimization

3.3.1. Description of Studies

Fuel consumption is a crucial factor affecting vessel sailing speed, since optimal speeds are adjusted based on fuel price and consumption. Notteboom and Vernimmen (2009) studied the impacts of increasing fuel prices on the design of sailing speed, vessel size, and the required number of vessels to be deployed at each port rotation. Survey results revealed that liner shipping companies had reduced the number of port-calls on the Europe-Far East trade route to deal with this phenomenon. In contrast, the size and number of vessels were increased. New strategies were being adopted, such as slow streaming and adding new vessels to service routes. It was highlighted that introducing additional vessels could alleviate the delays due to port congestion. Fagerholt et al. (2010) stated that fuel consumption and emissions were cubic functions of vessel sailing speed in general. The study presented a mixed-integer nonlinear programming model to minimize fuel consumption along the given port rotation. The problem was solved with a shortest path algorithm. IPOPT, a free nonlinear programming solver, was also employed for comparison with the developed heuristic. Results showed that the shortest path algorithm consumed significantly lower CPU time than IPOPT.

Ronen (2011) examined the relationship between fuel price, sailing speed, service frequency, and fleet size. Analytical results revealed that decreasing sailing speed by 20% lowered fuel consumption by 50%. However, it increased the required number of vessels to be operated on the given port rotation. Therefore, a cost model, based on tradeoffs between sailing speed and fleet deployment, was proposed that could determine the optimal speed for any liner shipping service operated on a fixed service frequency. Wang and Meng (2012e) accounted for transshipment and container routing while optimizing the sailing speed for each leg of each route in a liner shipping service network. A mixed-integer nonlinear programming model, focused on minimizing the total operating cost, was proposed and solved with an outer-approximation algorithm. The study suggested that the developed heuristic could be considered as an exact optimization algorithm, since it provided an epsilon-optimal solution. It was also highlighted that fuel consumption was dependent on the voyage legs.

Yao et al. (2012) devised a fuel management strategy consisting of three components: selection of bunkering port, determination of bunkering quantity, and tuning of sailing speed. An empirical model, aimed to minimize the total bunkering related costs, was presented to optimize these three components altogether. After solving the mathematical model with CPLEX, it was suggested that bunkering price evolution along the port rotation affected bunkering port decisions significantly. Hvattum et al. (2013) discussed that increments in fuel price and environmental considerations compelled liner shipping companies to optimize the sailing speeds of their vessels. The study formulated a nonlinear optimization model to minimize the cost. Finally, an exact solution algorithm was presented as a solution approach that could determine optimal sailing speeds in quadratic time. Sheng et al. (2014) determined bunkering ports and sailing speed under the uncertainty of fuel consumption. The determination was conducted dynamically for single vessels in a liner shipping route. A large-scale mixed-integer programming model was formulated that acknowledged a stochastic character of fuel price. A heuristic, inspired by the scenario tree generation scheme as well as a non-standard rolling horizon approach, was used as the solution approach for the large dynamic problem. Numerical results revealed that the proposed approach outperformed a static model in terms of total cost and level of service.

Andersson et al. (2015) combined the sailing speed optimization problem and the fleet deployment problem for RoRo shipping, which is a part of liner shipping. A mathematical model was presented that employed piecewise linear approximation to measure fuel consumption. A rolling horizon heuristic was developed as a solution approach for the integrated problem. A case study from RoRo shipping demonstrated that the proposed approach attained satisfactory solutions with a slight overestimation of fuel consumption.

Guericke and Tierney (2015) designed a cargo allocation model incorporating service levels for transit time requirements that optimized the sailing speed along each voyage leg. The objective of the proposed model was to maximize the total profit, and it was solved with Gurobi, a commercial mixed-integer programming solver. Computational experiments showed that optimal results for a number of liner shipping networks could be returned in less than 30 minutes. Finally, the study highlighted the need to consider transit times for the design for shipping networks. Sheng et al. (2015) studied vessel refueling and speed optimization with uncertainties in fuel price and consumption. The (s, S) replenishment policy was adopted for refueling, where ‘s’ was the reorder point for refueling, and ‘S’ was the maximum amount of fuel. As for speed optimization, a mathematical model was proposed to minimize the expected total cost, and it was solved with a progressive hedging algorithm and sample average approximation. Numerical experiments revealed that the (s, S) refueling policy resulted in significant cost savings.

Wang and Xu (2015) discussed the consequences of carbon tax on sailing speed. Three schemes were considered for the speed optimization problem, including no carbon emission tax, imposing taxes after emissions exceed a threshold, and imposing taxes based on carbon emissions. Three profit maximization models were formulated to evaluate the three schemes. After extracting solutions with random simulation, it was observed that the taxation scheme that imposed taxes after exceeding a certain threshold was better than taxing based on carbon emission, since it resulted in more profit and less emissions. Wong et al. (2015) studied slow steaming as a means to reduce fuel cost and carbon emissions. The study developed two continuous utility-based models for risk-averse and risk-neutral decision makers to assess the impact of slow steaming or speed reduction. On-time delivery of cargo was also considered for the models. It was highlighted that slow steaming might veer the vessels from on-time delivery and lead to the poor dispatch as well as deviation from usual port rotations.

Reinhardt et al. (2016) optimized vessel sailing speeds by adjusting berth times at ports of call. The study aimed to minimize the total fuel cost along with retaining customer transit times. Changes in berth times were allowed if the associated cost savings exceeded a certain threshold value. The proposed optimization model was tackled with CPLEX, where some portions of the liner shipping network were rescheduled. If rescheduling was required for the whole network and limits were imposed on all the transit times, global optimality could not be obtained. High sailing speeds increase shipping capacity (low operating cost) but also increase fuel consumption (high fuel cost). So, liner shipping companies need to focus on optimizing the sailing speeds in order to minimize the total cost. To address this issue, Wang (2016) developed a mathematical model to minimize the sum of operating cost, fuel cost, and inventory cost.

Numerical results demonstrated that the optimal speed increased with inventory cost rate and operating cost, while decreasing with fuel price and fuel consumption coefficients. Wang and Wang (2016) examined speed optimization, where a liner shipping company had to distribute its limited number of vessels over different shipping routes (resource sharing). The level of service was included in the problem by modeling from the point of view of supply chain management and a liner shipping company. A polynomial-time algorithm, inspired by bi-section search, was designed to solve the two speed optimization models. The solution algorithm could be applied to other models linked with resource sharing constraints.

Table 4 Summary of findings on sailing speed optimization.

Author(s)	Year of Publication	Sailing Speed	Port Time	Model Objective	Objective Components (Costs)	Solution Approach	Notes/Major Considerations
Notteboom and Vernimmen	2009	N/A	N/A	N/A	N/A	N/A	increasing fuel price
Fagerholt et al.	2010	V	F	Minimize total fuel consumption	N/A	Heuristic	emissions
Ronen	2011	V	F	Minimize the total cost	TOC; TFC	Analytical method	tradeoff between speed reduction and adding vessels
Wang and Meng	2012e	V	F	Minimize the total cost	TOC; TFC; TPC	Heuristic	transshipment
Yao et al.	2012	V	F	Minimize the total cost	TFC; MSC	CPLEX	fuel management
Hvattum et al.	2013	V	F	Minimize the total cost	TFC	Heuristic	exact solution algorithm
Sheng et al.	2014	V	F	Minimize the total cost	TFC; TIC; MSC	Heuristic	uncertainty in fuel consumption
Andersson et al.	2015	V	F	Minimize the total cost	TOC; TPC; TVC; MSC	Heuristic	RoRo shipping
Guericke and Tierney	2015	V	V	Maximize the total profit	REV; TOC; TFC; TPC; MSC	Gurobi	service levels for transit time requirements
Sheng et al.	2015	V	F	Minimize the total cost	TFC; TIC; TVC; MSC	Sample average approximation; Heuristic	uncertainties in fuel price and fuel consumption
Wang and Xu	2015	V	F	Maximize the total profit	REV; TFC; TPC; TVC; TEC; MSC	Random simulation	emissions tax
Wong et al.	2015	V	F	Minimize fuel cost, carbon emissions, and delay	TFC; MSC	Analytical method	on-time delivery of cargo; slow steaming
Reinhardt et al.	2016	V	F	Minimize the total cost	TOC; TFC; TVC	CPLEX	customer transit time
Wang	2016	V	F	Minimize the total cost	TOC; TFC; TIC	Heuristic	continuous number of vessels
Wang and Wang	2016	V	F	Minimize the total cost	TFC; TIC; MSC	Heuristic	multiple routes; level of service

Legend:

Sailing Speed/Port Time: V - variable; F - fixed.

Objective Components: TOC - total vessel operational cost; TFC - total fuel cost; TPC - total port handling cost; TVC - total cost for the violation of arrival TWs; TIC - total inventory cost; TEC - total emission cost; MSC - miscellaneous cost; REV - revenue.

3.3.2. Summary of Findings

The findings from the literature review on the sailing speed optimization problem is summarized in Table 4. Variations in different aspects of the reviewed studies on sailing speed optimization are presented below.

3.3.2.1. Sailing Speed and Port Time

One of the studies on speed optimization adopted the survey method and did not offer any mathematical model. All the other studies provided mathematical models, and sailing speed was a variable in those models. As for port time, only one study considered it as a variable. The rest of the studies assigned fixed port times.

3.3.2.2. Model Objective(s)

Figure 17 shows the distribution of the reviewed studies by model objective. The majority of the studies were focused on minimizing the total cost (10 studies), while two studies aimed to maximize the total profit. The mathematical model of one of the papers had the model objective of minimizing total fuel consumption. Furthermore, there was one model objective to minimize the weighted sum of fuel cost, carbon emissions, and delay.

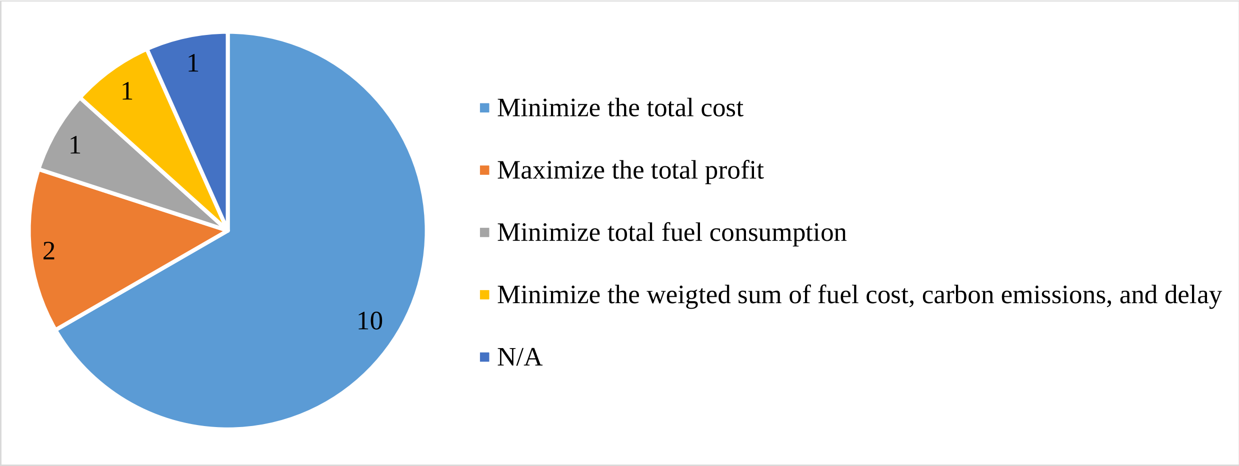


Figure 17 Distribution of sailing speed optimization studies by model objective.

3.3.2.3. Objective Components

A number of cost components were incorporated in the representative mathematical models. As demonstrated in Figure 18, most of the studies on sailing speed optimization included total fuel cost in the mathematical models (12 studies). The latter consideration can be explained by the fact that fuel cost is one of the major determinants of sailing speed. Vessels tend to sail slower when fuel cost is high, and vice versa. The other common cost components were: total operating cost (6 studies), total port handling cost (4 studies), total cost for the violation of service TWs (4 studies), and total inventory cost (4 studies). The rest of the cost components included chartering cost, inventory cost, etc. Moreover, two of the studies aimed to maximize the total profit and incorporated revenue in the mathematical model.

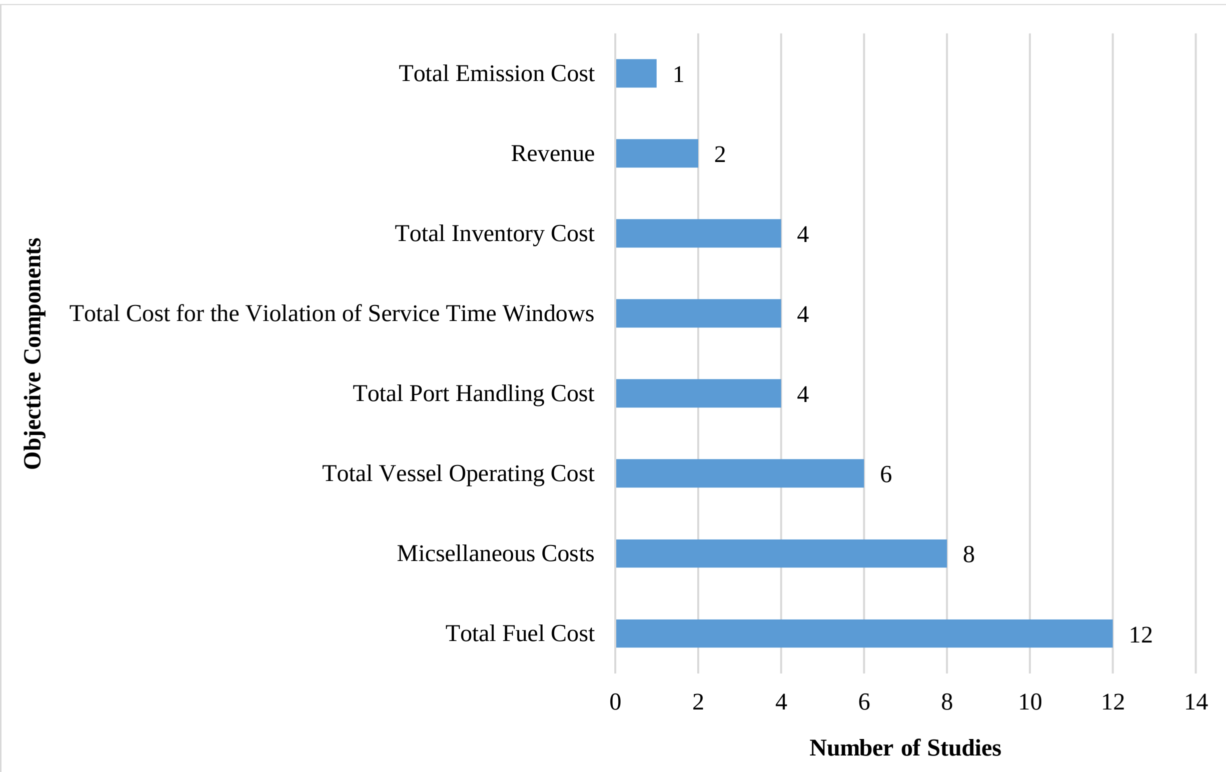


Figure 18 Distribution of sailing speed optimization studies by objective components.

3.3.2.4. Solution Approach

Several heuristic, metaheuristic, and exact solution algorithms were used to solve the mathematical models formulated. A significant portion of the reviewed studies (8 studies) developed heuristics for the specific models (Figure 19). CPLEX was used by 2 studies, while 2 other studies employed analytical methods. The other solution approaches were Gurobi, sample average approximation, and random simulation.

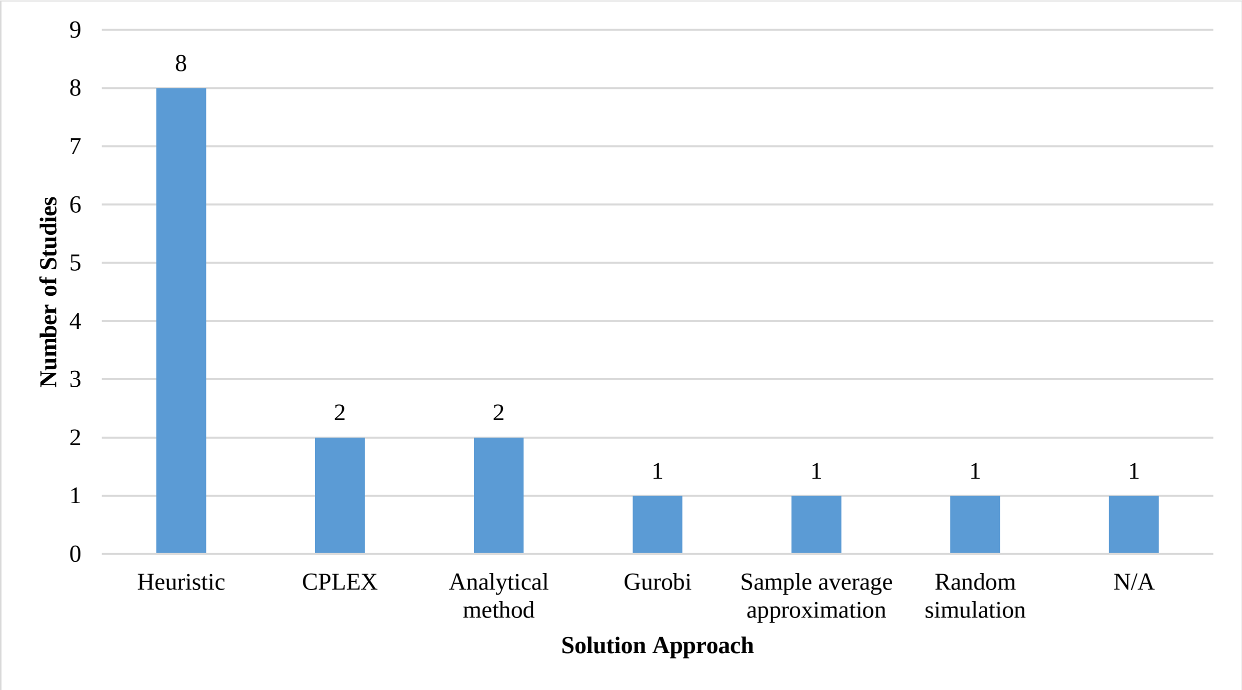


Figure 19 Distribution of sailing speed optimization studies based on solution approach.

3.3.3. Future Research Directions

A number of future research directions were provided by the studies reviewed, including the following:

- The aspects regarding fuel play a vital role in the determination of sailing speed. Hence, fuel price forecasting models, uncertainties in fuel consumption, role of fuel costs at different roundtrip distances, efficient refueling policies, etc. should be incorporated in future research.
- Other uncertainties, such as uncertainties in weather conditions, berthing availability, mechanical issues, vessel handling time at ports of call, etc., need to be considered.
- Several studies highlighted the lack of sufficient data required for emission modeling, necessitating a need of a universal database for vessel emissions.
- A number of the proposed models were applied for small-size problem instances. These models should be tested for large-scale problems. Furthermore, more advanced solution algorithms along with efficient modeling techniques should be developed.

3.4. Vessel Scheduling

3.4.1. Categories

The studies reviewed for the vessel scheduling problem were classified into the following 8 categories.

I. ***General Vessel Scheduling***: The general vessel scheduling studies propose mathematical models and solution approaches for the design of vessel schedules, including the determination of sailing speeds at each leg, arrival and departure times at each port of call, handling rates (HRs) at the ports, and the number of vessels to be employed to maintain the agreed service frequency.

II. ***Uncertainty in Liner Shipping Operations***: These studies deal with uncertainties in port times, sailing times, demand, and other factors that may significantly influence the design of vessel schedules.

III. ***Collaborative Agreements***: These studies propose collaborative agreements between liner shipping companies and marine container terminal (MCT) operators to create flexible HRs, service TWs, etc.

IV. ***Vessel Schedule Recovery***: These studies focus on the recovery of vessel schedules due to disruptions.

V. ***Green Vessel Scheduling***: The green vessel scheduling studies propose mathematical models and solutions approaches for the vessel scheduling problem, considering production of various types of emissions (i.e., non-greenhouse gas emissions or/and greenhouse gas emissions), specific environmental regulations, and other important environmental aspects, which may significantly affect the design of vessel schedules.

VI. ***Environmental Aspects in Vessel Scheduling***: These studies consider the environmental impacts of sailing vessels and the changes in vessel schedules due to environmental regulations but do not develop optimization models or solution algorithms.

VII. ***Routing and Scheduling***: The studies develop mathematical models and solution approaches to simultaneously provide the sequence of ports to be visited (routing) and the arrival and departure times at each port of call (scheduling).

VIII. ***Vessel Scheduling for Tramp Shipping***: The studies deal with the scheduling of tramp ships (ships that do not have any permanent schedule and fixed itinerary or ports of call to be visited).

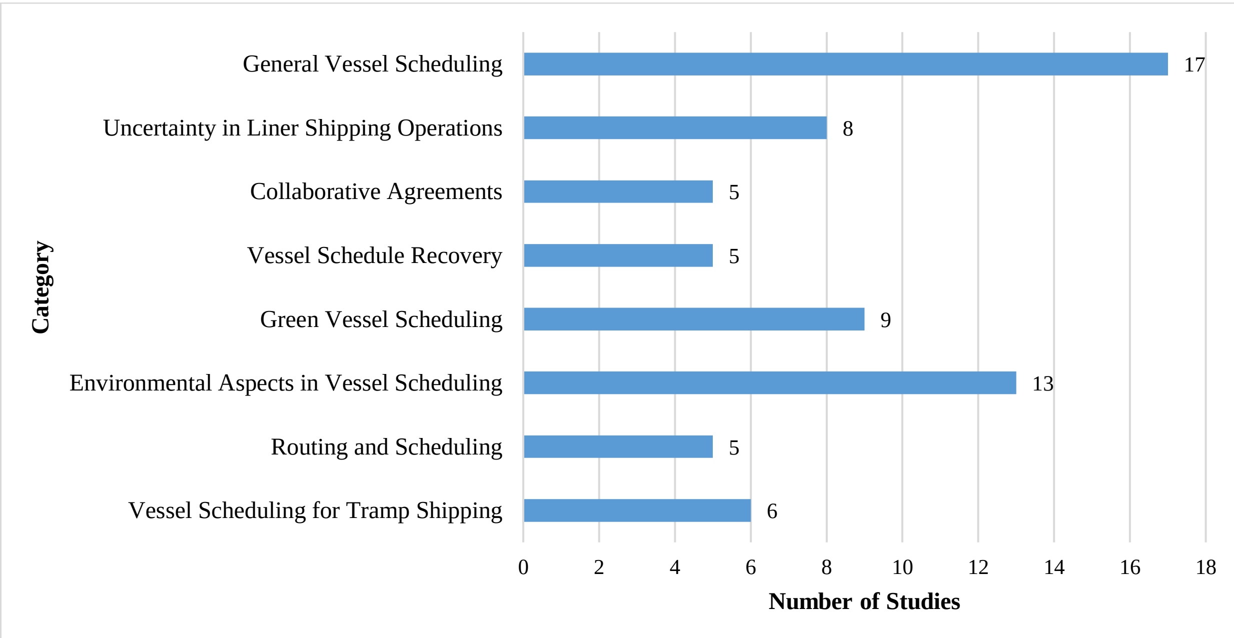


Figure 20 Number of studies on each category of vessel scheduling.

Among the 68 vessel scheduling papers that were selected for a detailed review, 17 papers studied general vessel scheduling, and 13 papers were focused on the environmental aspects in vessel scheduling (Figure 20). Every category consisted of at least 5 papers, a detailed review of which is presented in the following sections.

3.4.1.1. General Vessel Scheduling

Appropriate scheduling of vessels has the prospect of raising profits in bulk trade. Kim and Lee (1997) developed an optimization-based decision support system that aimed to maximize profit. The proposed model was inspired by set-packing model for vessel scheduling. It exhibited simplicity without the loss of validity. A heuristic algorithm that generated binary decision variables was used to solve the problem. Numerical experiments, conducted for different problem instances, demonstrated the applicability of the proposed optimization model.

Fagerholt and Christiansen (2000) studied a vessel scheduling problem that was a combination of a multi-ship pickup and delivery problem with TWs and multi-allocation problem. It was mentioned that the separation of the vessels' flexible cargo holds and the allocation of cargoes to the holds turned the problem into a multi-allocation problem. Hence, it was called a combined Ship Scheduling and Allocation Problem. A mathematical model was formulated to minimize the sum of fleet operating costs and spot shipment costs. A set partitioning approach was used to solve the problem. Numerical experiments revealed that the proposed approach could obtain optimal solutions for the cases tested. It was also shown that the computational time could be lowered by reducing the number of candidate schedules.

Fagerholt (2001) considered a vessel scheduling problem as a multi-ship pickup and delivery problem with soft TWs (m-PDPSTW). The latter consideration was inspired by the idea that controlled TW violations for some customers could result in better schedules and momentous cutbacks in transportation costs. The inconvenience costs were levied for violated TWs. A heuristic, inspired by set partitioning of the m-PDPSTW, was used to solve the problem, where columns symbolized candidate schedules. Another algorithm was developed for the schedule optimization that included soft TWs. Computational results illustrated the applicability of the proposed approach. However, the developed approach could not provide the optimal solutions for large-size problems.

Christiansen and Fagerholt (2002) focused on vessel scheduling for the pickup and delivery of bulk cargoes with multiple TWs. It was stated that ports might be closed at night and during weekends. For loading/unloading operations, vessels might stay inactive for a notable period, while port time depended on the arrival time of vessels. It was also highlighted that vessel schedules could be sensitive to bad weather and uncertain port times. The study proposed a set partitioning approach that aimed to generate robust vessel schedules, which could tackle all the aforementioned issues. Numerical experiments revealed that the robustness of the schedules could be raised by increasing transportation costs.

Ting and Tzeng (2003) assessed a vessel scheduling problem with terminal berth TW constraints. The objective of the proposed model was to minimize the variation in berth TWs.

The considered decision problem was solved by means of a dynamic programming algorithm. Computational results revealed that the complexity of the scheduling problem increased with increasing berth TW constraints. Moreover, the solution algorithm reduced the bunker costs as well as port handling times. Chen et al. (2007) developed a vessel scheduling model that allowed bi-directional flows. A three-step heuristic was developed to solve the mathematical model, which had NP-hard complexity, and it was pointed out that two special cases of the problem could be solved as linear problems.

Boros et al. (2008) optimized cycle time required by a liner shipping company to remove empty containers keeping in view the conflicting objectives of vessel and MCT operations scheduling. The objectives of the vessel scheduling problem aimed to maximize the total profit and minimize the cycle time. An iterative heuristic was employed to solve the model. Numerical experiments indicated that the developed heuristic optimized the cycle time and the total profit. Brønmo et al. (2010) presented a Dantzig–Wolfe approach for vessel scheduling with flexible cargo sizes. This problem was similar to the widely-known pickup and delivery problem. However, unlike the pickup and delivery problem, cargo sizes were defined by intervals in this problem. A mathematical model, aiming to maximize the total profit, was formulated. The proposed Dantzig–Wolfe approach did not guarantee the global optimality for all solutions. Still, a bound on the difference between the true optimal objective and the objective at the generated solution was provided. The proposed approach was then compared with a priori column generation approach. Results exhibited that the proposed approach was faster and could deal with larger or more loosely constrained problem instances.

Álvarez (2012) interpreted container inventory cost as a service level indicator. The study formulated a two-tier mathematical model, in which the top tier determined fleet deployment, vessel speed, and vessel routing, whereas the bottom tier determined merchandise flows along with transshipment quantities. A binary expression was developed, which estimated the sailing time as a function of liner shipping route, vessel deployment, vessel sailing speed, merchandise flow patterns, as well as service synchronization. Wang et al. (2013a) studied the optimal containership scheduling problem, where the container shipment demand was transit-time-sensitive. The demand was assumed to be a continuous function of transit time. The study proposed a non-convex optimization model to maximize the total profit of a route. A branch-and-bound based holistic solution approach was used to solve the problem. A real trans-Pacific liner shipping route was analyzed through the numerical experiments that illustrated the effectiveness of the proposed solution approach. It was noted that when the demand declined rapidly with transit time, the sailing speed of ships was higher.

Dulebenets (2015) discussed that slow steaming, a common strategy undertaken by liner shipping companies, reduced bunker consumption costs by decreasing sailing speeds. On the contrary, it might require more vessels to be deployed to maintain the agreed service frequency at ports of call. The study described various bunker consumption optimization methods to analyze the relationship between these contradicting measures. A new metaheuristic for the vessel scheduling problem was then developed that had the advantage of variable sailing speeds. Computational experiments were conducted for the French Asia Line 1 route, served by CMA CGM liner shipping company, and demonstrated that the developed metaheuristic was efficient and required a reasonable computational time.

Wang et al. (2015a) estimated the perceived value of transit time of containers that are transported by liner shipping lines. The notion behind that estimation was that the designed schedule that shipping lines show in their website was the optimal schedule that minimized the sum of fuel cost as well as the time associated costs of the containers. The adopted value of transit time was derived with mathematical models, and it was a good substitute of the perceived value of transit time. After applying the proposed approach, the adopted values of transit time for nine trans-Pacific services, served by Orient Overseas Container Line (OOCL), and five trans-Pacific services, served by Maersk Line, were estimated within the range of \$5/TEU/day and \$30/TEU/day.

Port operators inform shipping companies about the commencement of operation time at ports based on the handling capacity at each period. Zhen et al. (2016) determined the starting operation time of vessels at ports, more specifically, at transshipment hubs. A mixed-integer programming model was developed that aimed to minimize the holding cost of the transshipped containers and the total bunker costs. A local branching-based solution approach was proposed for some large-scale problem instances. Computational results showed that the optimality gap of the solutions provided by the developed approach for large-scale problems was less than 3%.

Dulebenets and Ozguven (2017) focused on modeling transportation of assets that could decay due to certain operational and environmental factors. A mixed-integer nonlinear model was developed to minimize the total route service cost. Along with other cost components, it included the total asset decay cost. The model was linearized by linear secant approximations. Once the model was linearized, the problem was solved using CPLEX. Finally, extensive computational experiments performed using the data collected for the French Asia Line 1 route, served by CMA CGM liner shipping company, demonstrated that this model could assist liner shipping companies to reduce the decay of perishable assets effectively.

Some of the vessel scheduling decisions that are undertaken by liner shipping companies are fundamentally conflicting. For instance, liner shipping companies sometimes reduce sailing speeds to lower the fuel cost. In that case, more vessels are required to be deployed to maintain service frequency, resulting in an increase of total operational cost. Still, the majority of models on vessel scheduling unified all the conflicting decision components under a single objective function, focused to minimize the route service cost. Such an approach imposes limitations upon the tradeoff analysis among the objectives, which are conflicting. To address the latter issue, Dulebenets (2018a) presented a multi-objective mathematical model that divided the major route service cost components into two contrasting groups. The study linearized the original model, and a heuristic was proposed to attain Pareto Fronts for vessel schedules. Numerical experiments revealed that negotiation of arrival TWs and HRs between MCT operators and liner shipping companies could remarkably lower the components of the total route service cost.

Dulebenets (2018b) studied the heterogeneous fleet vessel scheduling problem. A nonlinear mathematical model was developed to minimize the total vessel turnaround cost. In the model, the total vessel turnaround time comprised of five parts, namely vessel operating cost, port handling cost, fuel consumption cost, late arrival cost, and container inventory cost. Due to high nonlinearity, BARON, a commercial nonlinear optimization solver, was employed. Numerical experiments illustrated the efficiency of the proposed approach. It was also observed that vessel schedules were more susceptible to the addition of large-size vessels in the fleet than increasing bunker cost. Mallidis et al. (2018) assessed the impact of sailing speed reduction on the total landed logistics costs and the total route service cost. An activity-based model was proposed in order to identify vessel's voyage costs per container. The study also employed an inventory-planning model, based on a continuous review, in order to calculate a liner shipping company's total landed logistics costs at the intermediate port of a network. Numerical experiments highlighted that a reduction in the sailing speed of vessels did not affect the total route cost. However, there was an increase in the liner shipping company's logistics costs caused by a reduction in the sailing speed of vessels.

3.4.1.2. Uncertainty in Liner Shipping Operations

Notteboom (2006) inspected the tradeoffs linked to managing the time factor in liner shipping service design. This survey deliberated the measures that are taken by liner shipping companies in order to maximize schedule reliability, including port swapping and skipping, sailing speed adjustment, and deployment of more vessels. It was underscored that congestion at ports due to increasing port volumes along with capacity constraints were the main reason behind schedule unreliability. Vernimmen et al. (2007) also focused on schedule unreliability in liner shipping operations. The study discussed that the difference between the demand for container services and the supply of container handling capacity at ports around the world might cause a surge in terminal utilization levels, leading to severe congestion during peak periods.

Chuang et al. (2010) analyzed the vessel routing and scheduling problem. A fuzzy genetic algorithm was presented, so that long-term profits could be attained. Previous studies assumed that market demand was crisp, which could be impractical. Hence, the study employed the fuzzy sets theory which addressed demand uncertainty. This algorithm considered market demand, shipping and berthing time of container ships simultaneously and provided routes that resulted in increasing long-term profits. Qi and Song (2012) designed vessel schedules with the aim of minimizing fuel consumption and emissions. Uncertainties in port times and frequency requirements on vessel schedules were considered. Simulation-based stochastic approximation methods were further adopted to solve the vessel scheduling problem. It was shown that the optimal schedule could be attained through non-linear optimization. The shortest leg was found to be the most difficult one for designing the optimal schedule focused on obtaining 100% service level. Also, the distribution of the optimal planned leg-transit time was not proportional to the distance.

Wang and Meng (2012a) focused on the vessel scheduling problem and captured the effects of uncertainties in port operations, encompassing uncertainties in wait times due to port congestion as well as uncertain handling times of containers. A mixed-integer nonlinear stochastic programming model was formulated that minimized the expected weekly total costs. A solution algorithm was proposed, which was based on sample average approximation, a decomposition technique, and linearization techniques. Numerical experiments, performed based on the information collected for an Asia–America–Europe ship route, indicated that the proposed algorithm achieved near-optimal solutions that had the optimality gaps of less than 1.5% within 1 hour of computational time. Wang and Meng (2012b) studied the vessel scheduling problem with uncertainties in sea and at ports. A mixed-integer nonlinear stochastic programming model was proposed that minimized the vessel cost and bunker cost. An exact cutting-plane based solution algorithm was presented to solve the problem. A set of computational experiments, conducted for an Asia-Europe-Oceania shipping network, illustrated that violation of transit times allowed a portion of liner shipping routes significantly reducing the total cost for strict TWs. Also, it was suggested that the sailing speed of vessels should be reduced in case of a high bunker price.

Song et al. (2015) assessed a joint tactical liner shipping planning problem, aiming to determine the planned maximum sailing speed, the number of ships, and the liner service schedule considering uncertainties in port times. It was intended to concurrently optimize the three key performance indicators (KPIs) that are expected cost, service reliability, and emissions. A stochastic multi-objective optimization problem was devised. Both conflicting and compatible interconnections among the KPIs, with respect to the decision variables, were demonstrated. A multi-objective Genetic Algorithm was applied that could generate Pareto-optimal solutions. Shipping lines could elect different solutions based on their needs by weighing the three KPIs.

The capacity of all the ships in a string may not be the same. Thus, the sequence of ships in a string affects the delay of containers at ports because of demand uncertainty. Wang (2015) addressed the latter issue by determining the optimal sequence of vessels in a string that minimized the delay of containers. The probability distribution function for future demand was not entailed. Three rules to estimate optimal or near-optimal sequence of vessels were presented, and their efficacy was proved through numerical experiments. Finally, it was roughly estimated that the optimal sequence would result in yearly monetary savings of more than $6 million for all liner shipping companies in the world.

3.4.1.3. Collaborative Agreements

Wang et al. (2014) examined the vessel scheduling problem with multiple TW availability at ports of call. Multiple TW availability at ports of call is also common in practice (especially, at low-volume and medium-volume ports). A mixed-integer nonlinear nonconvex optimization model was formulated to minimize the total cost that included operational cost, bunker cost, as well as inventory cost. A holistic solution approach was applied, where the port TW constraints were initially relaxed, to attain a mixed-integer nonlinear programming model. It was later converted to a mixed-integer linear programming model, and it was repeatedly solved with the addition of the relaxed port TW constraints. As a result, a feasible solution was obtained which was proved to be the global optimal. The solution approach proposed was applied to the trans-Atlantic shipping route. It was found that the port TWs, bunker price, port handling efficiency, and unit inventory cost influenced the total cost, the optimal number of vessels to deploy, and the optimal schedule.

Alharbi et al. (2015) studied the vessel schedule design problem for liner shipping networks and considered port TWs. The study proposed a mixed-integer nonlinear programming model that aimed to minimize the sum of operational cost and fuel cost. The model was later linearized to formulate a mixed-integer linear programming model. An iterative solution approach was proposed to solve the problem, and the model was applied for two case studies. It was found that TW availability at ports, shorter port time, as well as lower bunker price could reduce the total cost along with the required amount of ships to be deployed. It was suggested that liner shipping companies should charter more ships if the bunker price was expected to increase. Wang et al. (2015b) investigated collaborative agreements among MCT operators and liner shipping companies. It was presumed that the liner shipping company had to pay different utility costs to the MCT operator based on the port arrival time. Numerical experiments revealed that increments in the fuel and inventory cost reduced the utility. On the other hand, the MCT operator must provide compensation to the carrier for starting service at days with negative utility values. It was underlined that the utilities, estimated by liner shipping companies, are more precise compared to the utilities, estimated by port operators.

Conventionally, the container HRs at ports are fixed independently by port authorities. Liu et al. (2016) indicated that port operators might handle containers at a higher rate, and it might cause some additional costs. However, the additional costs might be lower than the amount of money saved by shipping lines because of faster handling. Hence, the study proposed a mixed-integer nonlinear programming model that minimized the sum of bunker cost and compensation costs for port operators. A solution approach to determine the optimal planning decisions under collaboration between port operators and shipping lines was presented. Finally, numerical experiments for a trans-Pacific shipping route of OOCL revealed that this proposed approach could obtain substantial cost reductions for the shipping lines with no loss caused to the port operators.

Dulebenets (2019a) presented a new collaborative agreement among shipping lines and terminal operators. According to the agreement, terminal operators might offer multiple vessel arrival TWs and vessel HRs during the available TWs to the liner shipping companies. The original mixed-integer nonlinear formulation was further linearized. The linearized model was solved with the CPLEX solver. Numerical experiments were based on the Pacific Atlantic 1 ship route of the NYK shipping company and showed that the proposed agreement outperformed the other collaborative agreements, presented in the literature, in terms of the total service cost, endured by the shipping line. From the sensitivity analysis, it was observed that lowering the duration of vessel arrival TWs, increasing unit fuel cost as well as weekly vessel operational cost would even increase monetary benefits from implementing the developed mechanism.

3.4.1.4. Vessel Schedule Recovery

Paul and Maloni (2010) offered a decision support tool for weather or terrorism-related delays at ports. A mixed-integer nonlinear programming model was presented, aiming to minimize the total operational (transportation, capital and port) costs. An algorithm was proposed in order to route the inbound ships to ports and achieve the optimal usage of the network capacity based on the total operational costs. Regression-based parametric meta-models, gleaned from a simulation model, updated the port capacity changes due to port congestion situations. The proposed methodology was applied for the North American port network. Numerical results highlighted that the cost increased due to port shutdowns that resulted from disruptions.

Brouer et al. (2013) discussed how vessel schedules could be recovered after disruptions in liner shipping. A mixed-integer model was further developed to minimize the vessel operating cost at a given speed. The proposed model considered the effects of delayed or misconnecting cargo. CPLEX was used to solve the proposed mathematical formulation. Four real life cases from Maersk Line were used to depict the efficiency of the model. The proposed solutions approach was able to obtain the solutions within a satisfactory CPU time for the generated instances. Results showed that omitting a port call or swapping port calls could reduce delays, associated with the cargo delivery to ports of call as a result of disruptions. Li et al. (2015) studied uncertainties that might disrupt the original schedule of a vessel in liner shipping. The study analyzed some operational-level solutions to these delays, namely speeding up, port swapping, and port skipping. A nonlinear model was developed for cases, where only speeding up was feasible. Structural results showed that speeding could tackle the delays that are not substantial. For significant delays, other options, such as port skipping and port swapping, were suggested. A number of different dynamic programming-based algorithms were proposed to tackle the problem. Results indicated that the dynamic programming algorithms provided solutions of high accuracy. This study also suggested that vessels should not always speed up to their maximum potentials to lessen the impacts of delay.

Li et al. (2016) studied recovery policies for liner shipping under several regular uncertainties. The study differentiated between two types of uncertainties in liner shipping and proposed different schemes to tackle them. A multi-stage stochastic control model was presented, aiming to minimize the total expected fuel cost and delay penalty. Through probabilistic models, an optimal control policy was attained. Numerical studies demonstrated the efficiency of the proposed real-time control approach in improving reliability of liner shipping operations. Cheraghchi et al. (2018) focused on the problem of vessel schedule recovery and used the strategy of speeding up. A model with multiple objectives was formulated, in which the first objective minimized the total financial loss. On the other hand, the second objective function minimized the total delay. Six multi-objective Evolutionary Algorithms were applied to obtain the optimal Pareto Front for route-based speed profiles. The problem was assessed under three cases: vessel steaming policies, scalability analysis, and voyage distance analysis. Among the examined Evolutionary Algorithms, Non-dominated Sorting Genetic Algorithm II (NSGA-II) was found to be the most effective one.

3.4.1.5. Green Vessel Scheduling

Chang and Wang (2014) considered speed reduction as a means to minimize shipping costs and CO_2 emissions. The cost of speed reduction was compared against the benefits. The optimum speed was found when the charter rates were low and bunker costs were high. A framework was developed for the optimal speed reduction. First, the optimal balance between bunker cost and cost of delay was found. Then, the engine speeds were to be tuned so that the engines could run under reduced output levels for a long time. Finally, shipping lines needed to make sure that the adjusted speeds were enough to meet the demand without employing additional vessels. It was also suggested that strategic alliances should be formed to offset the demand loss. Kontovas (2014) studied the green ship routing and scheduling problem that minimizes the total transportation cost. It was argued that the consideration of speed and payload was more realistic compared to the other formulas. Several ways to model emissions were discussed, including emission cost as a component of the objective function, emission cost as the entire objective function, emission cost used in the constraints, and emission cost as one of multiple objective functions.

Fagerholt and Psaraftis (2015) studied the vessel scheduling and routing problem within Emission Control Areas (ECAs). The study analyzed the use of high cost-low sulfur fuel inside ECAs, as the use of costlier fuel tends to reduce vessel sailing speeds inside the ECAs. Two optimization models were proposed to maximize daily profit. The first model determined optimal sailing speeds for both in and out of the ECAs. The second model analyzed the optimal crossover through the emission control zone's boundaries, along with finding the optimal speeds. Numerical experiments revealed that it was optimal for vessels to travel short distances within ECAs and long distances outside ECAs in cases where the fuel price ratios were high. As strict limits with respect to the sulfur content of fuel were previously imposed within the ECAs, shipping lines are required to use high cost-low sulfur fuel while passing though the ECAs. As a result of such regulations, an increase in the unit cost of fuel further influenced the vessel sailing speed and the design of vessel schedules. To alleviate the impact of this increase in fuel price, Fagerholt et al. (2015) developed an optimization model that minimized the total cost of fuel while determining sailing paths and speeds. The regulations for the ECAs were considered. Results exhibited that ships often sailed on a higher extent to avoid the ECAs. Also, they cruised at comparatively lower speeds within ECAs to avoid substantial use of the costly fuel.

Zis et al. (2015) modeled the emissions of sulfur dioxide, carbon dioxide, nitrogen oxides, as well as black carbon from the operation of marine engines. A linear programming model was developed, aiming to minimize the fuel cost. The ultimate goal of the study was to enhance the environmental performance of shipping via the fuel consumption minimization. The authors evaluated the impacts of slow steaming, fuel regulations, near-port speed reduction schemes, as well as cold ironing in order to save the environment. Through the numerical analysis, it was found that port and country characteristics, vessel specifications, fuel prices, as well as journey details had significant effects on the amount of produced emissions.

The International Maritime Organization (IMO) introduced several regulations to mitigate the negative environmental externalities that are associated with maritime transportation. However, they did not enforce any restriction on the amount of emissions, which would be produced within ECAs. Hence, Dulebenets (2016) examined the impacts of the restrictions enforced by the IMO and an alternative policy that imposed restrictions on emissions within ECAs along with the IMO restrictions. Two mixed-integer nonlinear programming models were formulated to evaluate the impacts of these policies. Linearization techniques were applied on these models, and the dynamic secant approximation-based methodology was used to solve them. The computational results revealed that the enforcement of emission restrictions within ECAs would reduce the pollution but would increase the total cost of route service.

Dulebenets et al. (2017) developed a mixed-integer model for the problem of green vessel scheduling, forcing constraints on emissions from vessels on each sailing leg of the route. The objective of this model was to minimize the total cost of route service. The original model was then linearized, and CPLEX was employed to solve the linearized model. The Europe Pakistan India Consortium route of CMA CGM liner shipping company was used for the numerical experiments. The results showed that emission constraints lowered the sailing speeds at voyage legs, reducing the total fuel cost. On the other hand, the total operating cost, handling cost at ports, late arrival penalty, and inventory cost increased. Dulebenets (2018c) studied the problem of green vessel scheduling with transit time requirements. A mixed-integer nonlinear optimization model was formulated with constraints on emissions exhausted by vessels within ECAs. Several linearization methods were employed on the nonlinear model. The dynamic secant approximation-based methodology was then applied to solve the problem. A set of numerical experiments, conducted for the French Asia Line 2 route, operated by CMA CGM liner shipping company, demonstrated the efficiency of the proposed approach. It was also found that violation of transit time requirements incurred an extra penalty cost for certain cargo types.

Dulebenets (2018d) aimed to model the emissions of CO_2 in sea as well as at ports of call. The study presented a mixed-integer nonlinear model, minimizing the total cost of route service. The model incorporated CO_2 emission costs in sea as well as CO_2 emission costs at ports of call. The nonlinear model was later linearized and solved with CPLEX. Numerical experiments were then conducted on the Asia-North America AZX route, operated by Nippon Yusen Kaisha (NYK) liner shipping company. Computational results revealed that increasing CO_2 tax might drastically change schedules of vessels, cause additional costs of route service, and sustain the environment.

3.4.1.6. Environmental Aspects in Vessel Scheduling

The studies reviewed under this section considered the environmental impacts of vessel emissions and regulations but do not develop optimization models or solution algorithms to model the effects of vessel emissions and regulations on schedules of vessels. Several papers have studied the environmental aspects in vessel scheduling (Psaraftis and Kontovos, 2009;

Eyring et al., 2010; Kontovas and Psaraftis, 2011; Miola and Ciuffo, 2011; Psaraftis, 2012; Zis et al., 2014).

For example, Corbett et al. (2009) examined the impacts of fuel tax as well as speed reduction on CO_2 emissions. The study revealed that an average speed-related CO_2 decrease of 20–30% could be generated by a fuel tax of about $150 per ton of fuel. Psaraftis and Kontovos (2010) assessed the implications of several restrictions regarding vessel emissions on world commercial fleet. The study indicated that cargo vessels generated the highest CO_2 emissions (839.95 million tons per year), followed by passenger vessels (93.67 million tons per year). Moreover, measures, including speed reduction, changing the number of vessels in the fleet, as well as conventional logistics attributes, e.g., in-transit inventory holdings, could reduce emissions produced by vessels.

Cariou (2011) discussed that slow steaming had reduced the CO_2 emissions by about 11% since 2008, as opposed to a target of 15% by 2018. It was argued that whenever freight rates increased, slow steaming would remain a sustainable option of reducing CO_2 emissions if bunker prices increased. However, several technical issues were not considered. For example, when the sailing speed was very low, design and safety issues could become significant. Heitmann and Khalilian (2011) explored the economic and regulatory issues and implications associated with different options proposed by the Subsidiary Body for Scientific and Technological Advice of the United Nations Framework Convention on Climate Change (UNFCCC). An evaluation of the options based on possibility of legal implementation, environmental effectiveness, and fairness of burden sharing was conducted. It was found that none of the options were satisfactory in terms of all the three factors considered.

Lindstad et al. (2011) scrutinized the effect of speed decrease on CO_2 emissions as well as maritime transportation costs. The study revealed that a CO_2 emissions decrease by 18% could be obtained with negative abatement cost. Moreover, a reduction of 28% CO_2 emissions could be obtained with zero abatement cost. However, the latter results were obtained at lower vessel sailing speeds. New technology could avail target levels of speed reduction without no other significant change. Finally, it was suggested that more vessels needed to be built to sustain the total transport capacity. In order to reduce the CO_2 emissions, an international bunker-levy was under consideration by the IMO. As the IMO could not reach an accord for a short period, the European Commission considered another speed limit for vessels accessing the European ports. Cariou and Cheaitou (2012) examined the implications of the emission reduction measure, suggested by Lindstad et al. (2011), and alleged that it might be unavailing. It was argued that speed limits might not decrease the amount of CO_2 produced globally by commercial vessels. Moreover, shipping lines might not be willing to pay the high cost that would be incurred.

Cullinane and Bergqvist (2014) discussed that several policies regarding emission restriction had the potency to decrease emissions. A transferable methodology was applied to investigate some of these policies based on ship-call data. CO_2, SO_2, NO_x, and black carbon emissions were considered. It was highlighted that emissions were dependent on visiting fleet, durations of berthing, baseline operating pattern of calling vessels, sulfur reduction policies, and the emissions' intensity of electricity supply. It was also argued that the potency of emission restriction policies varied from port to port, due to the uniqueness of each port and vessel.

3.4.1.7. Routing and Scheduling

Fagerholt and Lindstad (2007) presented TurboRouter, a decision support system to assist liner shipping companies for vessel routing and scheduling. TurboRouter was used by several companies at that time. It was written in Visual C++ version 8.0 and could be run in all the existing Windows operating systems. This decision support system offered flexibility to the planners by providing multiple high-quality solutions instead of only one optimal solution. Moreover, it saved computational time notably. Agarwal and Ergun (2008) formulated a mixed-integer linear programming model for the vessel routing and scheduling problem that enforced several constraints, including the weekly frequency constraint on the service routes, and emerging trends (e.g., the transshipment of cargo between two or more shipping routes). The proposed model could provide superior routes for a fleet up to 100 vessels.

RoRo ships are those that carry vehicles and other rolling equipment. Øvstebø et al. (2011) studied the routing and scheduling of RoRo ships with a number of variations in consideration regarding optional cargoes, flexible cargo quantities, and ship stability restrictions.

The problem was distinct in the sense that decisions were required not only for routing and scheduling but also for the stowage of cargo. A mixed-integer programming model was prepared for the maximization of revenues, and it was solved with Xpress (which is considered as a standard MIP solver). A heuristic, inspired by Tabu Search and Squeaky Wheel Optimization, was also proposed as a solution approach. Extensive numerical experiments revealed that the proposed heuristic was superior to Xpress in case of real-life problem instances.

De et al. (2016) tackled the problem of vessel routing and scheduling. The study considered operational measures, such as slow steaming and optimization of sailing speed, to reduce carbon emissions. A mixed-integer nonlinear programming model, which aimed to minimize various costs, was developed. It addressed the issues related to multiple time periods, sustainability aspects as well as fluctuating demand and supply at various ports. The problem was NP-hard in terms of computational complexity, and so a metaheuristic, called Particle Swarm Optimization-Composite Particle (PSO-CP), was applied. The computational experiments showed that the proposed algorithm outperformed Particle Swarm Optimization and Genetic Algorithm in terms of total cost. The results indicated that several aspects associated with sustainability could be incorporated in the model.

Christiansen et al. (2017) studied the problem of routing and scheduling of fuel supply vessels that served customer vessels outside the major ports. An arc-flow model and a path-flow model, aiming to minimize the total transportation costs, were proposed and compared. The numerical experiments showed that the path-flow model was better than the arc-flow model. It could be used for real-life planning where new orders came and divergence from plans arose.

3.4.1.8. Vessel Scheduling for Tramp Shipping

Andersson et al. (2011) introduced a certain part of tramp shipping, named project shipping. In case of project shipping, cargoes are distinctive and shipped on a one-time basis. For such specific problem, a mathematical model was formulated that intended to maximize the total profit. Three alternative solution approaches were proposed, based on path flow formulations and a-priori-generation of ship routes. Numerical experiments, conducted for 27 test instances, demonstrated that the proposed method could find the optimal solutions.

Based on the majority of the vessel routing and scheduling studies, one single cargo is not allowed to be shipped by more than one vessel. Korsvik et al. (2011) eliminated the latter constraint. In the study, every cargo could be shipped by multiple vessels (i.e., split loads were introduced). A mathematical model was formulated, maximizing the total profit. A large neighborhood search heuristic was proposed to solve the problem, and its efficiency was demonstrated through 25 test cases. Results revealed that liner shipping companies could make better use of their fleet capacity and ship additional spot cargoes by the initiation of split loads. Norstad et al. (2011) also adopted the concept of spot cargoes. In addition, the study considered speed to be variable and dependent on fuel consumption. Speed on each sailing leg was regarded as a decision variable. A multi-objective mathematical model was presented to maximize profit and minimize fuel cost. Two solution algorithms were developed. One of the algorithms was faster but it could only be applied to the cases where fuel consumption functions were not dependent on the shipload. The numerical experiments exhibited that variable speed could result in better profit.

Vilhelmsen et al. (2013) integrated bunker planning with the routing and scheduling of tramp vessels. A mixed-integer programming mathematical model was formulated to maximize the total profit, while considering load dependent costs, speed and bunker consumption. A dynamic programming algorithm, inspired by the column generation scheme, was developed. Computational results from 150 generated instances demonstrated that there was a little integrality gap for the fractional solutions. It was stated that the choice of cargoes and the respective ships was influenced by bunker integration and bunker price. Armas et al. (2015) studied the determination of the set of contracts that should be fulfilled by tramp vessels and the TWs that tramp vessels should use for each contract. It was argued that the employment of discretized TWs made the consideration of various features and constraints simpler. A mathematical model was formulated with the objective of minimizing the total cost. A hybridization of Greedy Randomized Adaptive Search Procedure (GRASP) and a Variable Neighborhood Search (VNS) was proposed to solve the problem. Such hybrid GRASP-VNS was found to be efficient in terms computational time. In fact, this hybrid algorithm returned solutions for the instances, where even CPLEX could not provide feasible solutions in two hours.

Wen et al. (2016) studied the problem of routing and scheduling for tramp vessels with full load. The objective of the study was to find the optimal route and optimal schedule to maximize the total profit. A mixed-integer programming model, along with a set-packing model, was presented. A Branch-and-Price Algorithm, which employed efficient data pre-processing and heuristic column generation, was employed to tackle the problem. The computational experiments revealed that the optimized speed could increase the total profit by about 16%. It was also stated that fuel price had a substantial impact on sailing speed and total profit.

3.4.2. Summary of Findings

The summary of the findings from the literature review conducted for the vessel scheduling problem is exhibited in Table 5.

Table 5 Summary of findings on vessel scheduling.

Author(s)	**Year of Publication**	**Problem Category**	**Sailing Speed**	**Port Time**	**Model Objective**	**Objective Components (Costs)**	**Solution Approach**	**Notes/Major Considerations**
Kim and Lee	1997	Vessel Scheduling for Bulk Cargoes	V	F	Maximize the total profit	REV; TOC	Heuristic	set-packing model
Fagerholt and Christiansen	2000	General Vessel Scheduling	F	V	Minimize the total cost	TOC; TPC; MSC	Set partitioning	multiple arrival TWs
Fagerholt	2001	General Vessel Scheduling	V	F	Minimize the total cost	TOC; TFC; TPC; TVC	Heuristic	soft arrival TWs
Christiansen and Fagerholt	2002	Vessel Scheduling for Bulk Cargoes	F	V	Minimize the total cost	TOC; TVC; TPC; MSC	Set partitioning	disruptions
Ting and Tzeng	2003	General Vessel Scheduling	V	V	Minimize the total variation in port arrival time	N/A	Dynamic programming	quay crane dispatching decisions
Notteboom	2006	Uncertainty in Liner Shipping Operations	N/A	N/A	N/A	N/A	Survey	schedule reliability

Table 5 - Continued.

Author(s)	Year of Publication	Problem Category	Sailing Speed	Port Time	Model Objective	Objective Components (Costs)	Solution Approach	Notes/Major Considerations
Chen et al.	2007	General Vessel Scheduling	F	F	Minimize the total cost	TOC; TIC	Heuristic	bi-directional flows
Fagerholt and Lindstad	2007	Routing and Scheduling	F	F	Maximize the total profit	REV; TOC; MSC	Heuristic	commercial decision support system
Vernimmen et al.	2007	Uncertainty in Liner Shipping Operations	N/A	N/A	N/A	N/A	Case study	schedule reliability
Agarwal and Ergun	2008	Routing and Scheduling	F	F	Maximize the total profit	REV; TOC; MSC	Heuristic	heterogeneous fleet; transshipment
Boros et al.	2008	General Vessel Scheduling	F	V	Maximize the total profit	REV; TVC; MSC	Heuristic	container-yard capacity optimization
Corbett et al.	2009	Environmental Aspects in Vessel Scheduling	N/A	N/A	N/A	N/A	N/A	speed reduction
Psaraftis and Kontovas	2009	Environmental Aspects in Vessel Scheduling	N/A	N/A	N/A	N/A	N/A	estimation of carbon dioxide emissions
Brønmo et al.	2010	General Vessel Scheduling	F	V	Maximize the total profit	REV; TOC	Column generation	flexible cargo size
Chuang et al.	2010	Uncertainty in Liner Shipping Operations	U	U	Maximize the total profit	REV; TOC; TFC; TPC	Heuristic	uncertainty in port times, sailing times, and demand
Eyring et al.	2010	Environmental Aspects in Vessel Scheduling	N/A	N/A	N/A	N/A	N/A	impact of emissions
Paul and Maloni	2010	Vessel Schedule Recovery	F	V	Minimize the total cost	TPC; TOC; TFC; MSC	Heuristic	Disruptions at ports of call

Table 5 - Continued.

Author(s)	Year of Publication	Problem Category	Sailing Speed	Port Time	Model Objective	Objective Components (Costs)	Solution Approach	Notes/Major Considerations
Psaraftis and Kontovas	2010	Environmental Aspects in Vessel Scheduling	N/A	N/A	N/A	N/A	N/A	impact of emission regulations
Andersson et al.	2011	Vessel Scheduling for Tramp Shipping	F	F	Maximize the total profit	REV; TOC	Heuristic	tramp shipping
Cariou	2011	Environmental Aspects in Vessel Scheduling	N/A	N/A	N/A	N/A	N/A	speed reduction
Heitmann and Khalilian	2011	Environmental Aspects in Vessel Scheduling	N/A	N/A	N/A	N/A	N/A	allocating carbon dioxide emissions from international shipping to individual countries
Kontovas and Psaraftis	2011	Environmental Aspects in Vessel Scheduling	N/A	N/A	N/A	N/A	N/A	speed reduction
Korsvik et al.	2011	Vessel Scheduling for Tramp Shipping	F	V	Maximize the total profit	REV; TOC; TPC	Heuristic	tramp shipping
Lindstad et al.	2011	Environmental Aspects in Vessel Scheduling	N/A	N/A	N/A	N/A	N/A	speed reduction
Miola and Ciuffo	2011	Environmental Aspects in Vessel Scheduling	N/A	N/A	N/A	N/A	N/A	estimation of emissions

Table 5 - Continued.

Author(s)	Year of Publication	Problem Category	Sailing Speed	Port Time	Model Objective	Objective Components (Costs)	Solution Approach	Notes/Major Considerations
Norstad et al.	2011	Vessel Scheduling for Tramp Shipping	V	V	Maximize the total profit; Minimize the total fuel consumption	REV; TOC; TFC; MSC	Heuristic	tramp shipping
Øvstebø et al.	2011	Routing and Scheduling	F	V	Maximize the total profit	REV; TOC; MSC	Xpress; Heuristic	RoRo ships
Álvarez	2012	General Vessel Scheduling	F	V	Minimize the total cost	TIC	Analytical method	connection time at transshipment ports
Cariou and Cheaitou	2012	Environmental Aspects in Vessel Scheduling	N/A	N/A	N/A	N/A	N/A	speed reduction
Psaraftis	2012	Environmental Aspects in Vessel Scheduling	N/A	N/A	N/A	N/A	N/A	impact of market-based measures
Qi and Song	2012	Uncertainty in Liner Shipping Operations	V	U	Minimize the total cost	TFC; TVC	Sample average approximation	uncertainty in port times
Wang and Meng	2012a	Uncertainty in Liner Shipping Operations	V	U	Minimize the total cost	TOC; TFC	Sample average approximation	uncertainty in port waiting and handling times
Wang and Meng	2012b	Uncertainty in Liner Shipping Operations	U	U	Minimize the total cost	TOC; TFC; TVC	Cutting-plane algorithm	uncertainty in port and sailing times
Brouer et al.	2013	Vessel Schedule Recovery	V	V	Minimize the total cost	TOC; TFC; TPC; TVC; MSC	CPLEX	disruptions
Vilhelmsen et al.	2013	Vessel Scheduling for Tramp Shipping	F	V	Maximize the total profit	REV; TOC; TFC	Dynamic programming; Column generation	tramp shipping

Table 5 - Continued.

Author(s)	**Year of Publication**	**Problem Category**	**Sailing Speed**	**Port Time**	**Model Objective**	**Objective Components (Costs)**	**Solution Approach**	**Notes/Major Considerations**
Wang et al.	2013a	General Vessel Scheduling	V	V	Maximize the total profit	REV; TOC; TFC	Branch-and-bound algorithm	transit-time-sensitive demand
Chang and Wang	2014	Green Vessel Scheduling	V	F	Maximize the total profit	REV; TOC; TFC; TPC	Analytical method	speed reduction
Cullinane and Bergqvist	2014	Environmental Aspects in Vessel Scheduling	N/A	N/A	N/A	N/A	N/A	ECA regulations
Kontovas	2014	Green Vessel Scheduling	V	F	Minimize the total cost	TOC; TFC; TEC	N/A	discussion of emission modeling alternatives
Wang et al.	2014	Collaborative Agreements	V	F	Minimize the total cost	TOC; TFC; TIC	Iterative optimization algorithm	multiple service TWs
Zis et al.	2014	Environmental Aspects in Vessel Scheduling	N/A	N/A	N/A	N/A	N/A	speed reduction; alternative marine power
Alharbi et al.	2015	Collaborative Agreements	V	F	Minimize the total cost	TOC; TFC; TVC	Iterative optimization algorithm	multiple service TWs
Armas et al.	2015	Vessel Scheduling for Tramp Shipping	F	V	Minimize the total cost	TOC	GRASP; Variable neighborhood search	tramp shipping
Dulebenets	2015	General Vessel Scheduling	V	V	Minimize the total cost	TOC; TFC; TPC; TVC	Heuristic	memetic algorithm to solve the problem
Fagerholt and Psaraftis	2015	Green Vessel Scheduling	V	F	Maximize the total profit	REV; TFC	Analytical method	use of low sulfur fuel within ECAs
Fagerholt et al.	2015	Green Vessel Scheduling	V	F	Minimize the total cost	TFC	Xpress-MP	use of low sulfur fuel within ECAs

Table 5 - Continued.

Author(s)	Year of Publication	Problem Category	Sailing Speed	Port Time	Model Objective	Objective Components (Costs)	Solution Approach	Notes/Major Considerations
Li et al.	2015	Vessel Schedule Recovery	V	V	Minimize the total cost	TFC; TVC	Dynamic programming	disruptions
Song et al.	2015	Uncertainty in Liner Shipping Operations	V	U	Minimize the total cost; Minimize the schedule unreliability; Minimize the total carbon dioxide emissions	TFC; TVC; TEC; MSC	Heuristic	uncertainty in port times
Wang	2015	Uncertainty in Liner Shipping Operations	F	U	Minimize the total delay	N/A	Heuristic	uncertainty in demand
Wang et al.	2015a	General Vessel Scheduling	V	F	Minimize the total cost	TFC; TIC	Iterative optimization algorithm	perceived value of container transit times
Wang et al.	2015b	Collaborative Agreements	V	F	Maximize the utility minus the transportation cost	TOC; TPC; TIC; MSC	Case study	utility of liner shipping companies
Zis et al.	2015	Green Vessel Scheduling	V	F	Minimize the total cost	TFC	Analytical method	Estimation of carbon dioxide, sulfur dioxide, nitrogen oxides, and black carbon emissions
De et al.	2016	Routing and Scheduling	V	V	Minimize the total cost	TOC; TPC; TVC; TFC	Particle swarm optimization - composite particle	multiple service TWs
Dulebenets	2016	Green Vessel Scheduling	V	V	Minimize the total cost	TOC; TFC; TVC; TIC; TPC	Iterative optimization algorithm	Use of low sulfur fuel within ECAs

Table 5 - Continued.

Author(s)	**Year of Publication**	**Problem Category**	**Sailing Speed**	**Port Time**	**Model Objective**	**Objective Components (Costs)**	**Solution Approach**	**Notes/Major Considerations**
Li et al.	2016	Vessel Schedule Recovery	V	U	Minimize the total cost	TFC; TPC; TVC; MSC	Dynamic programming	disruptions
Liu et al.	2016	Collaborative Agreements	U	U	Minimize the total cost	TIC; TFC; TPC	Dynamic programming	multiple HRs
Wen et al.	2016	Vessel Scheduling for Tramp Shipping	V	V	Maximize the total profit	REV; TOC; TFC	Heuristic	tramp shipping
Zhen et al.	2016	General Vessel Scheduling	V	V	Minimize the total cost	TIC; TFC	Local branching	transshipment
Christiansen et al.	2017	Routing and Scheduling	F	F	Minimize the total cost	REV; TOC	Path generation algorithm	fuel supply vessels
Dulebenets and Ozguven	2017	General Vessel Scheduling	V	V	Minimize the total cost	TFC; TOC; TVC; TIC; TPC; MSC	CPLEX	perishable assets
Dulebenets et al.	2017	Green Vessel Scheduling	V	V	Minimize the total cost	TOC; TFC; TVC; TIC; TPC	CPLEX	Constraints on CO_2, SO_2, and NO_x
Cheraghchi et al.	2018	Vessel Schedule Recovery	V	F	Minimize the total cost; Minimize the total delay	TFC; TVC	Heuristic	speed-based vessel schedule recovery
Dulebenets	2018a	General Vessel Scheduling	V	V	Minimize the total cost	TFC; TEC; TOC; TVC; TIC; TPC	Heuristic	conflicts among route service cost components
Dulebenets	2018b	General Vessel Scheduling	V	V	Minimize the total cost	TFC; TOC; TVC; TIC; TPC	BARON	heterogeneous fleet
Dulebenets	2018c	Green Vessel Scheduling	V	V	Minimize the total cost	TOC; TFC; TVC; TIC; TPC; MSC	Iterative optimization algorithm	Use of low sulfur fuel within ECAs; Transit time requirements

Table 5 - Continued.

Author(s)	Year of Publication	Problem Category	Sailing Speed	Port Time	Model Objective	Objective Components (Costs)	Solution Approach	Notes/Major Considerations
Dulebenets	2018d	Green Vessel Scheduling	V	V	Minimize the total cost	TOC; TFC; TPC; TVC; TIC; TEC	CPLEX	CO_2 costs in sea and at ports
Mallidis et al.	2018	General Vessel Scheduling	V	F	Minimize the total cost	TOC; TFC; TIC; TPC; TVC; MSC	Analytical method	speed reduction
Dulebenets	2019a	Collaborative Agreements	V	V	Minimize the total cost	TOC; TFC; TPC; TIC; TVC	CPLEX	multiple service TWs; multiple HRs

Legend:

Sailing Speed/Port Time: V - variable; F - fixed; U - uncertain.

Objective Components: TOC - total vessel operational cost; TFC - total fuel cost; TPC - total port handling cost; TVC - total cost for the violation of arrival TWs; TIC - total inventory cost; TEC - total emission cost; MSC - miscellaneous cost; REV - revenue.

The reviewed studies had significant differences in several aspects. These aspects are discussed in the following sections.

3.4.2.1. Sailing Speed

All of the collected studies considered sailing speeds, except the ones on the environmental aspects in vessel scheduling. The distribution of studies based on sailing speed is shown in Figure 21. Half of the reviewed studies (34 studies) assigned variable sailing speeds. 16 studies considered fixed sailing speeds for the vessels. Some of the studies on the uncertainties in liner shipping operations and vessel schedule recovery considered the sailing speeds of the vesseles to be uncertain (3 studies).

3.4.2.2. Port Time

Figure 22 presents the distribution of studies based on port time. A significant portion of the reviewed studies considered variable port times (27 studies). 18 of the studies used fixed port times, while 8 of the collected studies considered port times to be uncertain. The rest of the studies did not consider port times.

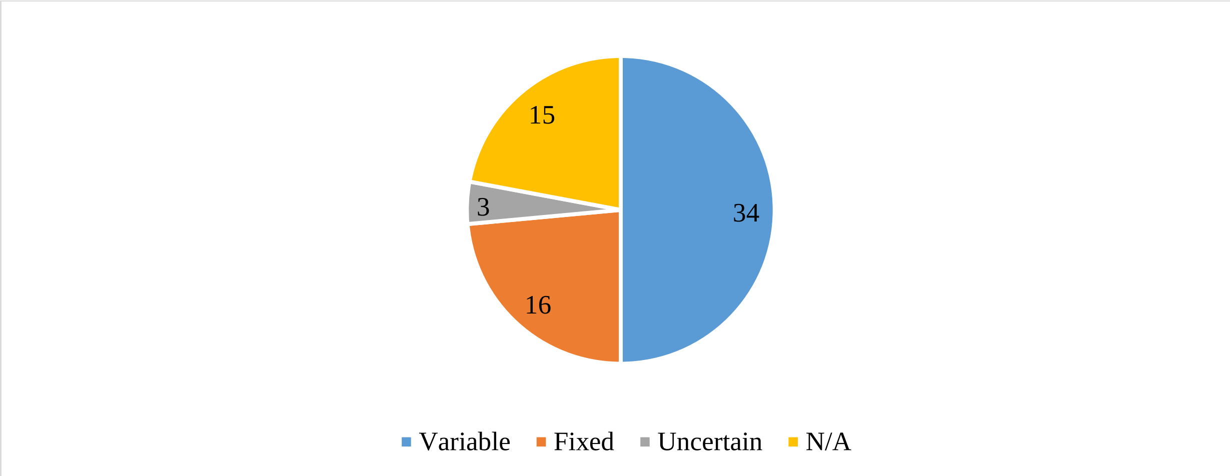


Figure 21 Distribution of vessel scheduling studies based on sailing speed.

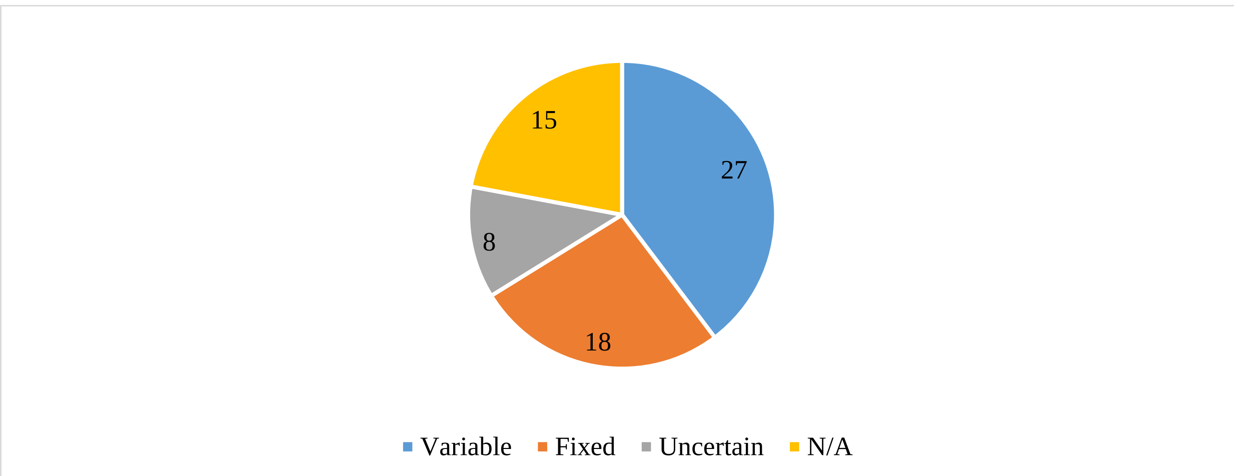


Figure 22 Distribution of vessel scheduling studies based on port time.

3.4.2.3. Model Objective(s)

The reviewed studies of all problem categories, except the ones on the environmental aspects in vessel scheduling, proposed mathematical models. Each model had one or multiple objective functions. Half of the studies had the objective of minimizing the total cost (Figure 23). 15 of the studies focused on maximizing the total profit by maximizing the total revenue, while 2 of the studies had the objective of minimizing the total delay. The other model objectives were to maximize the utility minus the transportation cost, to minimize the schedule unreliability, to minimize the total carbon dioxide emissions, to minimize the total expected variation in time, and to minimize the total fuel consumption. However, each of these objective functions was used only once.

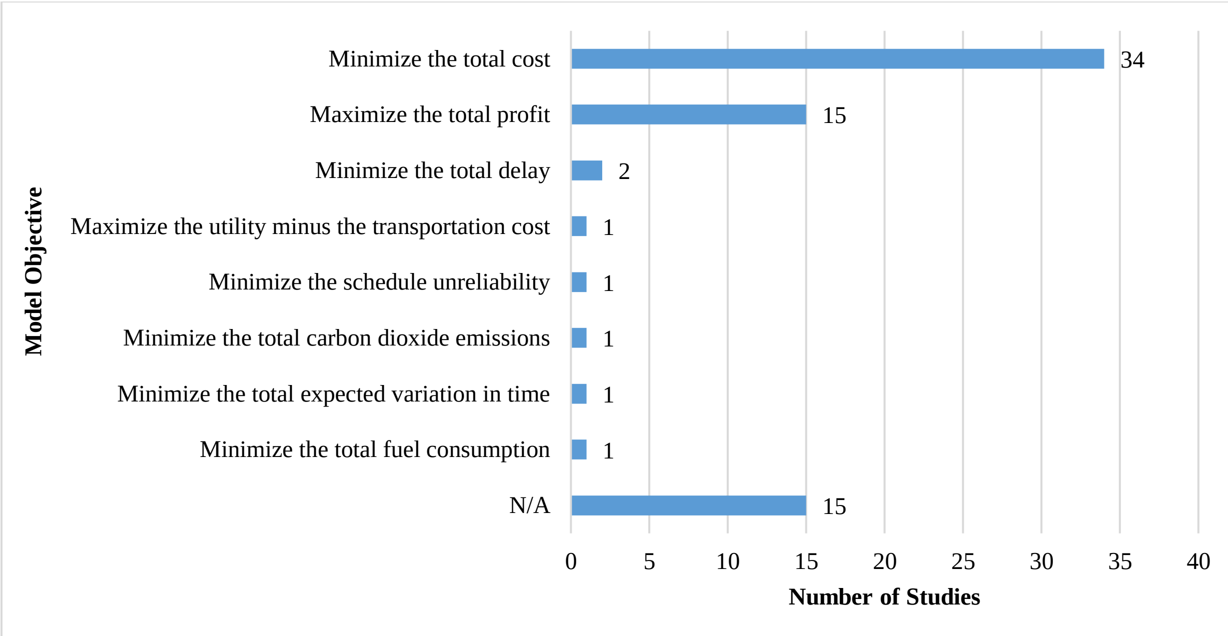


Figure 23 Distribution of vessel scheduling studies by model objective.

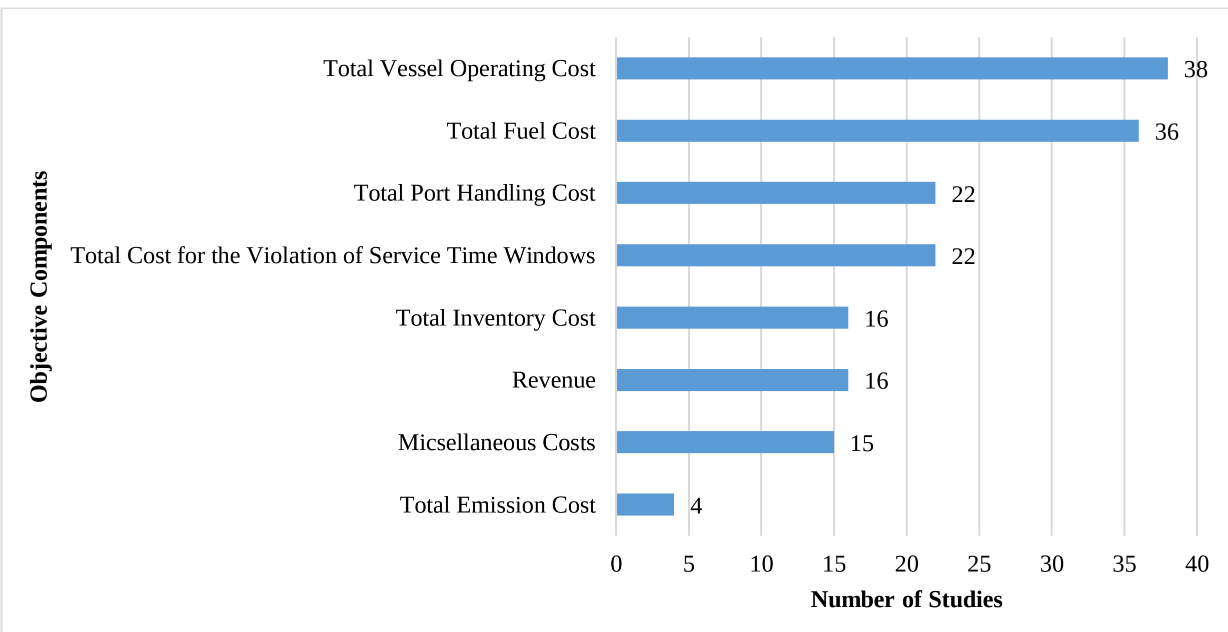


Figure 24 Distribution of vessel scheduling studies by objective components.

3.4.2.4. Objective Components

The models, developed by the collected studies, had several objective components related to costs. The cost components considered by these studies were total fuel cost, total vessel operational cost, total port handling cost, total cost for the violation of service TWs, total emission cost, total inventory cost, etc. The distribution of studies by objective components (costs) is illustrated in Figure 24. Most of the studies considered total vessel operational cost (38 studies) and total fuel cost (36 studies). The handling cost at ports was considered by 22 studies, and 22 studies included the penalty cost associated with the violation of the service TWs. Some of the other costs incorporated in the mathematical models were total inventory cost (16 studies) and total emission cost (4 studies). Moreover, 16 publications aimed to maximize the total profit, and, therefore, included the total revenue in the model objective.

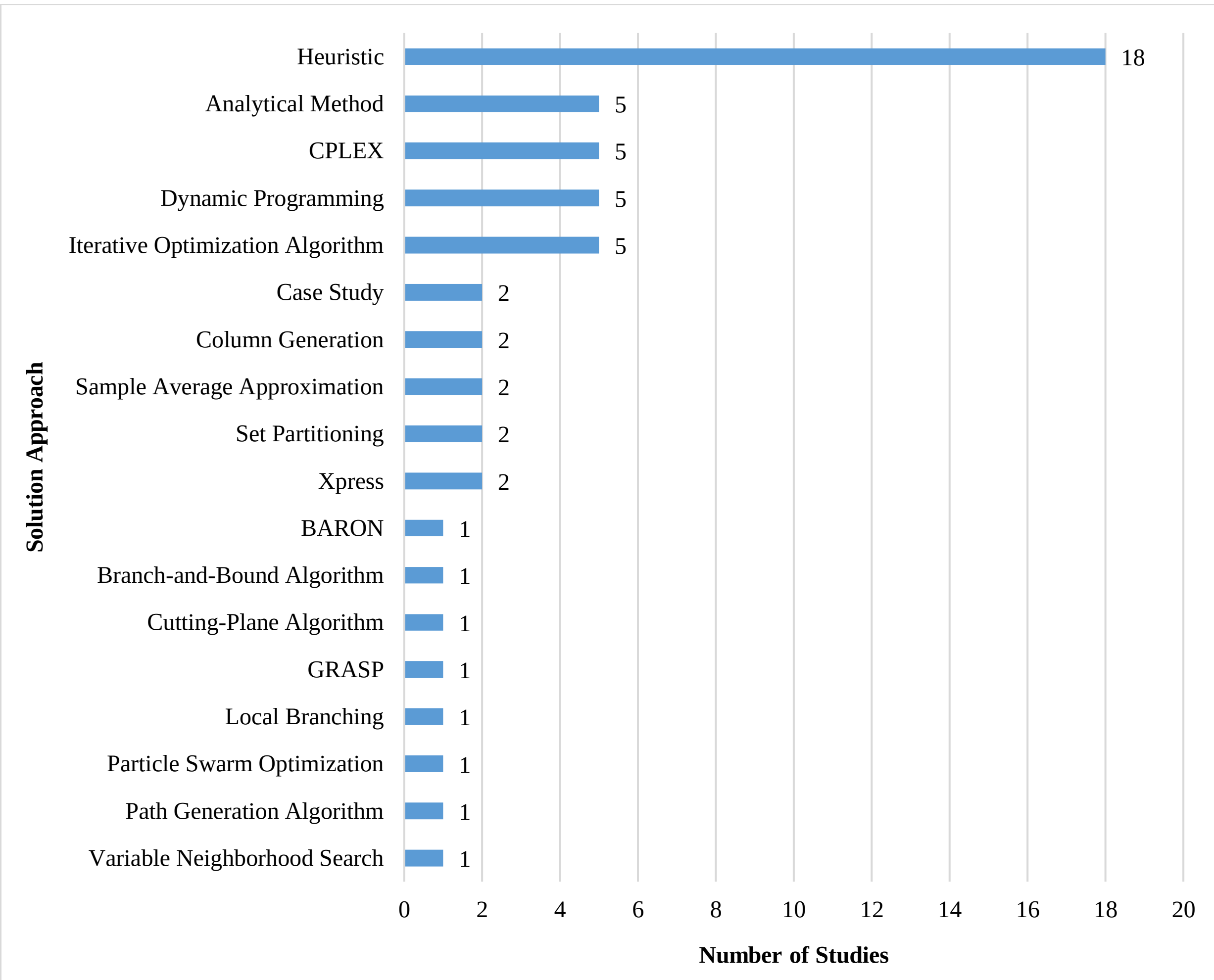


Figure 25 Distribution of vessel scheduling studies by solution approach.

3.4.2.5. Solution Approach

Several solution approaches were employed to solve the mathematical models formulated in the reviewed studies. The mostly commonly used solution approaches were heuristics.

Heuristics were developed by 18 studies (Figure 25). 5 of the studies employed CPLEX (the commercial optimization software which guarantees the global optimality of the obtained solutions), iterative optimization algorithm, dynamic programming, and analytical methods (each approach was employed by 5 different studies). Some of the publications used column generation, sample average approximation, set partitioning, case studies, and Xpress. Each of these approaches was used by two papers. The rest of the employed solution approaches were BARON, branch-and-bound algorithm, cutting-plane algorithm, empirical methods, evolutionary algorithm, GRASP, local branching, particle swarm optimization, path generation algorithm, and variable neighborhood search. These approaches were used only once.

3.4.3. Future Research Directions

Existing research needs on the vessel scheduling problem, as suggested by the studies reviewed, are presented below.

- The vessel schedules developed by the reviewed literature are applicable only for certain liner shipping routes. Several authors have advocated for the need of a common vessel schedule design methodology that can be applied for different routes.
- Most of the concurrent literature considered the vessels of the entire fleet to be homogeneous, which is not the case for many liner shipping routes. Consideration of a heterogeneous fleet would allow for contemplation of different rates of fuel consumption, sailing times, emissions, etc.
- Waiting times at ports and handling times of vessels at ports can change due to many reasons, such as disruptions. Considerations of these uncertainties will make the vessel schedules more robust.
- A lot of decision problems in liner shipping are conflicting in nature. Inclusion of the conflicting problems in a holistic model can facilitate decision making for liner shipping companies and assist with the analysis of important tradeoffs.
- Various gases released from vessel engines are harmful for the environment. Restrictions are now being posed by authorities for these emissions, necessitating a consideration of emissions in the design of vessel schedules.

- Fuel price changes from time to time. Also, different types of fuels are required by different types of vessels. These uncertainties need to be considered.
- MCT operators can sometimes offer multiple TWs and elevated vessel HRs at a higher cost. The waiting times at ports can also be avoided or at least minimized by providing a charge, according to collaborative agreements. Hence, these agreements need to be considered for the design of vessel schedules.
- Several ECAs are now being established where vessels need to use low-sulfur fuel. Therefore, ECAs need to be considered for the vessel scheduling problem.

3.5. Literature Review Conclusion and Dissertaion Contribution

Supply chain management is the management of supply chain activities to attain a sustainable competitive advantage. Freight transportation is an integral part of supply chain management. A substantial portion of freight transportation is covered by maritime transportation. A rapidly increasing trend has been observed in the international seaborne trade, where liner shipping has played a vital role. However, liner shipping companies as well as the major supply chain stakeholders face a number of challenges, such as market growth, resource availability, customer preferences, congestion, compliance, cost issues, etc. In order to cope up with the existing and upcoming challenges, liner shipping companies have devised some strategies, including the formation of strategic alliances, increasing vessel size, containerization, development of new technologies (e.g., scrubbers, RFID, GPS tracking, alternative handling equipment, etc.), and others.

Liner shipping companies tackle three levels of decision-making problems, which are strategic, tactical, and operational levels. This dissertation aims to undertake the tactical-level decision problems in liner shipping, which are made for three to six months. The tactical-level decision problems include service frequency determination, fleet deployment, sailing speed optimization, and vessel scheduling. As part of the dissertation, the contemporary studies on the tactical-level decision problems in liner shipping were identified, and the most relevant studies were selected for a critical review. Moreover, the studies on the vessel scheduling problem were classified into eight categories, namely, general vessel scheduling, uncertainty in liner shipping operations, collaborative agreements, vessel schedule recovery, green vessel scheduling, environmental aspects in vessel scheduling, routing and scheduling, and vessel scheduling in tramp shipping.

The major problem attributes, considered in this dissertation, included the vessel sailing speed assumptions, port handling time assumptions, objective function(s), objective function components, solution approaches, and others. A detailed review of the selected literature found that most of the reviewed papers modeled variable port handling times and variable sailing speeds. Different model objectives for the tactical-level decision problems were found in the existing literature that include total route service cost minimization, total profit maximization, total delay minimization, minimization of the total variation in port arrival times, unreliability minimization, minimization of the total carbon dioxide emissions, total fuel cost minimization, and maximization of the total utility. Different solution approaches, including heuristics, metaheuristics, and exact solution algorithms, were employed to tackle the developed mathematical models. Finally, limitations in the state-of-the-art were underscored, some of which will be further addressed as a part of this dissertation.

A substantial number of researches have been published on each one of the tactical-level decision problems in liner shipping. However, most of the studies were focused on separate problems. A few of the contemporary studies combined multiple decision problems, but only a few of those studies included the vessel scheduling problem for joint planning. Note that the design of vessel schedules is the most complicated decision problem at the tactical level. Therefore, a joint planning model that does not address the vessel scheduling problem is not sufficient for effective tactical-level decision making in liner shipping. Moreover, none of the reviewed studies combined all the tactical-level decision problems.

In contrast with the existing literature, this dissertation will formulate a novel holistic optimization model, which will address all the tactical-level decision problems in liner shipping. In brief, the holistic model will determine the optimal port service frequency, assign vessels to port rotations, optimize the vessel sailing speeds, and design vessel schedules (which comprise of arrival time, departure time, waiting time, arrival TWs, potential vessel arrival delays, and HRs at each port of call). The objective of the model will be to maximize the total profit, computed as the difference between the total revenue and the total cost of serving the liner shipping routes. The major cost components, reported in literature, will be incorporated into this model, including the following: (I) total vessel operating cost; (II) total vessel chartering cost; (III) total fuel consumption cost; (IV) total late arrival cost; (V) total port handling cost; (VI) total container inventory costs in sea and at ports of call; and (VII) total emission costs in sea and at ports of call.

Some of the recent studies on liner shipping have addressed the environmental impacts due to liner shipping operations. More specifically, the green vessel scheduling studies designed vessel schedules that accounted for emissions, produced in sea as well as at ports of call, modeled ECAs, emission taxes, etc. This dissertation will also take into account the environmental considerations and will explicitly model emissions, produced by vessels in sea, and emissions at ports of call, produced by the vessel handling equipment, in order to improve the environmental sustainability. It is expected that a mixed-integer nonlinear programming model for the holistic tactical-level planning in liner shipping would have a high computational complexity. As an attempt to reduce complexity, a set of linearization techniques will be applied to the model. After complete formulation of the holistic optimization model, it will be attempted to solve the model with exact optimization approaches. Finally, comprehensive numerical experiments will be carried out to demonstrate the efficiency of the proposed holistic optimization model.

Liner shipping companies have to take a significant number of decisions in order to effectively manage their operations. Even just for the tactical level, there are a considerable number of decisions to be taken. Currently, the liner shipping companies have to apply different models regarding separate tactical-level decision problems, leading to inefficiency and increased complexity. The proposed holistic optimization model and the developed solution approach will ease the decision-making process for liner shipping companies by offering only one solution to all the tactical-level decision problems at the same time. The aforementioned contributions of this dissertation to the state-of-the-art and the state-of-the-practice can be concisely summarized as follows:

- a novel holistic optimization model, which addresses all tactical-level decision problems in liner shipping (i.e., service frequency determination, fleet deployment, sailing speed optimization, and vessel scheduling);
- the objective of the model, which aims to maximize the total profit, considering the major cost components reported in the literature (total vessel operating cost, total vessel chartering cost, total fuel consumption cost, total late arrival cost, total port handling cost, total container inventory costs in sea and at ports of call, and total emission costs in sea and at ports of call);
- consideration of emissions, produced by vessels in sea, and emissions at ports of call, produced by the vessel handling equipment, to ensure environmental sustainability of tactical-level decisions in liner shipping;
- a set of linearization techniques to reduce the degree of nonlinearity of the proposed holistic optimization model for tactical-level planning in liner shipping;
- comprehensive numerical experiments to demonstrate effectiveness of the proposed holistic optimization model for tactical-level planning in liner shipping.

CHAPTER 4

PROBLEM DESCRIPTION

A comprehensive description of the problem tackled by the dissertation is presented in this section, which covers the following areas: (1) liner shipping port rotations; (2) vessel fleet; (3) service at ports of call; (4) fuel consumption; (5) sensitivity of container demand; (6) service frequency; (7) container inventory; (8) emissions from liner shipping; (9) selection of vessel sailing speeds; and (10) objective of a liner shipping company. It should be noted that this study captures each of the major tactical-level decisions, which a liner shipping company has to address.

4.1. Liner Shipping Port Rotations

Liner shipping companies or alliances, consisting of liner shipping companies, serve liner shipping routes. Several ports of call are included in these liner shipping routes. A liner shipping route likely covers more/less ports than another liner shipping route. Moreover, the order of ports to be visited (i.e., port rotations) also varies from one route to another. Here, $R = \{1, \dots, n^1\}$ represents the set of port rotations, and the group of ports included in port rotation r is denoted by $P_r = \{1, \dots, n_r^2\}, r \in R$. A voyage leg ($p$) connects two consecutive ports (p and $p + 1$). Details about the port rotations are generally published on the website of a liner shipping company. These details include: (1) name of the port of call; (2) country of port; (3) distance to the next port; etc. Under a given port rotation, each port has fixed vessel schedules.

Figure 26 depicts a hypothetical liner shipping network that includes four port rotations. The voyage legs of each port rotation altogether create a loop, which means a given port rotation starts and stops at the same port. For example, in port rotation “1” of the hypothetical network, each vessel starts its voyage at Tokyo, then goes to Nagoya, then to Yokkaichi, then to Kobe, and finally returns to Tokyo. This port rotation has 4 ports of call. It should be noted that multiple port rotations may include a given port. For instance, port rotations “2” and “3” in the provided example cover Hong Kong. Moreover, vessels may visit a given port more than once within a port rotation (e.g., Penang is visited two times within port rotation "4"). The port calling sequence, however, distinguishes these visits (i.e., calls) as separate ones.

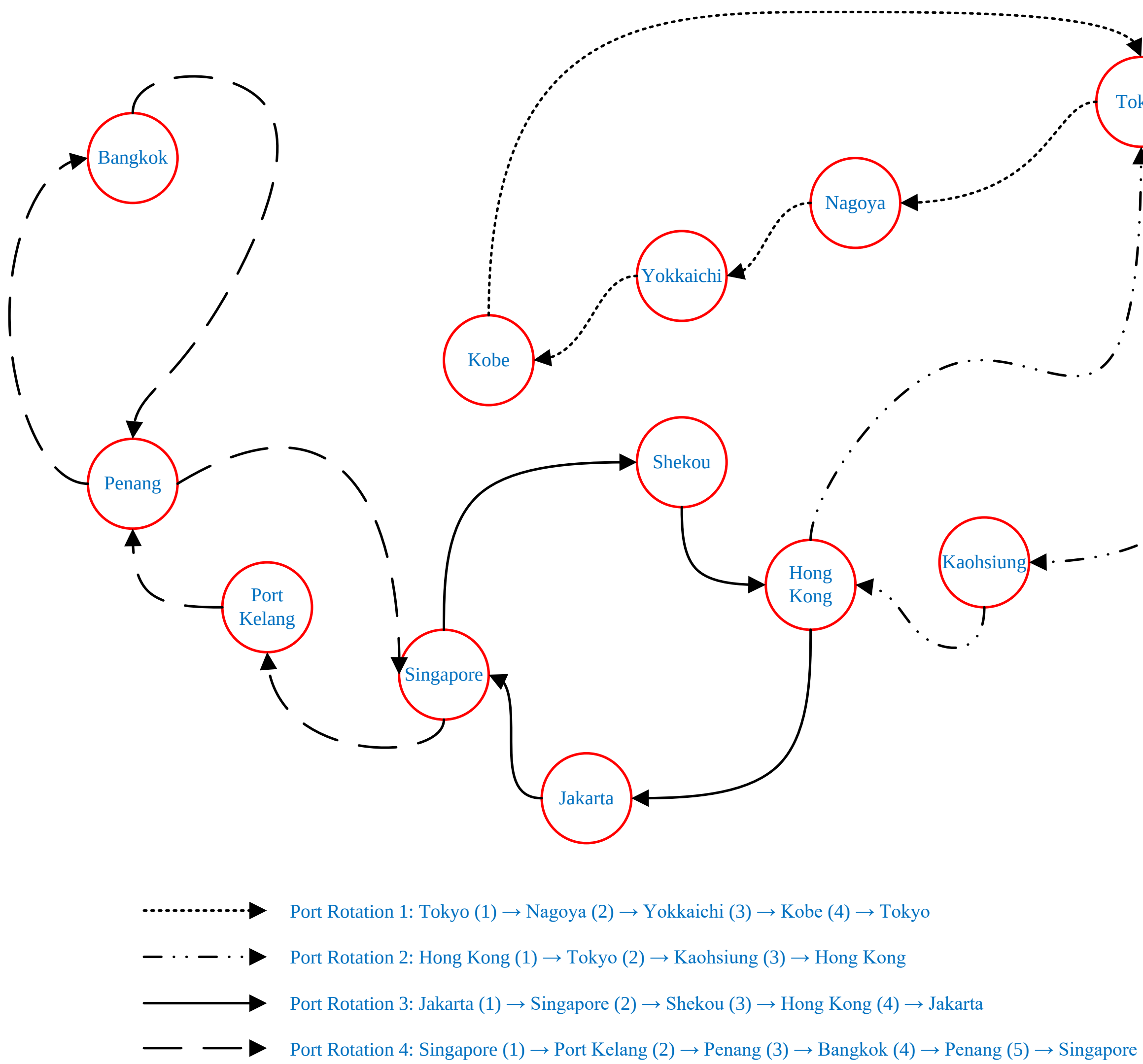


Figure 26 A hypothetical liner shipping network.

4.2. Vessel Fleet

The available vessel types ($V = \{1, \dots, n^3\}$) are assigned to the existing port rotations during the task of fleet deployment. Let $\boldsymbol{d}_{vr} = 1$ if port rotation r is served by vessel type v. In general, a given port rotation is served by one type of vessel (Wang and Meng, 2017). This assumption can be imposed by the following equation:

$$\sum_{v \in V} \boldsymbol{d}_{rv} = 1 \ \forall r \in R \quad (1)$$

When vessels are homogeneous, their technical properties are also the same, such as the same maximum sailing speed, the same fuel consumption rate, the same amount of emissions coming from the vessel engines (i.e., main and auxiliary), and so on. However, this assumption is not necessarily true in many cases, as the properties of the same type of vessel are likely to vary because of dissimilarities in vessel structure, age, past repair/maintenance, capacity, and other reasons. Still, at the tactical level of liner shipping (both academic and practice), it is commonly assumed that all the vessels of the same type have the same properties (Wang and Meng, 2017). If the total number of available vessels of a given type in the company's own fleet ($q_v^{own-m}, v \in V$ – vessels) is less than the number of vessels required, which are to be sent to serve a given route or port rotation, then vessels from other liner shipping companies' fleets might be chartered. In case of chartering, the liner shipping company has to pay extra chartering costs ($c_v^{char}, v \in V$ – USD/vessel).

4.3. Service at Ports of Call

This dissertation supports collaborative agreements between MCT operators and liner shipping companies. At every port of call, the MCT operator offers several arrival TWs to the liner shipping companies. In some cases (e.g., busy ports), the MCT operator can offer just one arrival TW to the vessels. It is expected that vessels arrive within the agreed TW (at each port of call). $T_{rp} = \{1, \dots, n_{rp}^4\}, r \in R, p \in P_r$ denotes the set of arrival TWs offered at port p of port rotation r. Each arrival TW has the following attributes: (1) $\tau_{rpt}^{st}, r \in R, p \in P_r, t \in T_{rp}$ – start of arrival TW t at port rotation r's port p (hours); and (2) $\tau_{rpt}^{end}, r \in R, p \in P_r, t \in T_{rp}$ – end of arrival TW t at port rotation r's port p (hours). This research allows soft TWs, which means vessels can arrive outside the arrival TWs. If a vessel arrives before the start of a TW, it should wait for service. If it arrives after the end of a TW, the liner shipping company will have to pay a late arrival cost. This late arrival cost is proportional to the number of hours the vessels are late ($\boldsymbol{\tau}_{rp}^{late}, r \in R, p \in P_r$ – hours) as well as the unit late arrival cost ($c_{rp}^{late}, r \in R, p \in P_r$ – USD/hour). Vessels are not encouraged to arrive late, as delays in arrivals of vessels jeopardize port operations, and so, late arrival costs are imposed. The total late arrival cost ($\boldsymbol{LAC}$ – USD) will be determined from the following equation:

$$\boldsymbol{LAC} = \sum_{r\in R}\sum_{p\in P_r} c_{rp}^{late}\boldsymbol{\tau}_{rp}^{late} \tag{2}$$

Each arrival TW at a given port of call has an associated HR. If a port has multiple arrival TWs (which is common), it is likely to have multiple HRs. $H_{rpt} = \{1, \dots, n_{rpt}^5\}, r \in R, p \in P_r, t \in T_{rp}$ denotes the set of HRs offered at port of call p under port rotation r during TW t. Note that a handling productivity comes with a given HR. The handling productivity ($ph_{rpthv}, r \in R, p \in P_r, t \in T_{rp}, h \in H_{rpt}, v \in V$) is the amount of twenty-foot equivalent units (TEUs) handled for each vessel per unit time (hour in this case). The handling productivity could differ from port to port according to the available equipment. In busy ports, the MCT operator may offer only one handling productivity, as they have to assign the other equipment to the other vessels (from another liner shipping company). If the amount of containers handled at port p of port rotation r is denoted by $\boldsymbol{QC}_{rp}^{PORT}, r \in R, p \in P_r$ (TEUs), then the vessel handling time for type v vessels at port rotation r's port p under HR h during TW t should be $\boldsymbol{\tau}_{rpthv}^{hand} = \frac{\boldsymbol{QC}_{rp}^{PORT}}{ph_{rpthv}}\ \forall r \in R, p \in P_r, t \in T_{rp}, h \in H_{rpt}, v \in V$ (hours). Similar to arrival TWs, the handling cost ($c_{rpthv}^{hand}, r \in R, p \in P_r, t \in T_{rp}, h \in H_{rpt}, v \in V$ – USD/TEU), associated with a handling productivity, is negotiated between the MCT operator and the liner shipping company at each port. Let $\boldsymbol{x}_{rpthv}$ = 1 when HR h is chosen to serve vessels of type v vessels at port rotation r's port p under HR h during TW t. Then, the total port handling cost ($\boldsymbol{PHC}$ – USD) will be determined from the following equation:

$$\boldsymbol{PHC} = \sum_{r\in R}\sum_{p\in P_r}\sum_{t\in T_{rp}}\sum_{h\in H_{rpt}}\sum_{v\in V} c_{rpthv}^{hand}\boldsymbol{QC}_{rp}^{PORT}\boldsymbol{x}_{rpthv} \tag{3}$$

4.4. Fuel Consumption

As discussed earlier, in most cases, the liner shipping company assigns a homogenous fleet of vessels to each port rotation. For homogeneous vessels, the main engines' fuel consumption rate is assumed to be equal (Wang and Meng, 2017). Several factors affect the fuel consumption rate, like sailing speed, weather conditions, payload, and geometric characteristics of vessels (Wang and Meng, 2012a; Kontovas, 2014; Bialystocki and Konovessis, 2016). Researchers found that the vessel sailing speed is the major factor, which affects fuel consumption (Wang and Meng, 2012a). For each nautical mile (nmi), the design fuel consumption ($\boldsymbol{f}_{rpv}^{design}, r \in R, p \in P_r, v \in V$ – tons/nmi) will be determined from the following equation:

$$\boldsymbol{f}_{rpv}^{design} = \frac{\gamma_v(\boldsymbol{\vartheta}_{rp})^{(\alpha_v-1)}}{24} \; \forall r \in R, p \in P_r, v \in V \tag{4}$$

where:

$\alpha_v, \gamma_v, v \in V$ – are the fuel consumption function coefficients for vessel type v;

$\boldsymbol{\vartheta}_{rp}, r \in R, p \in P_r$ – is the sailing speed at voyage leg p along port rotation r (knots).

Recently, it was pointed out that the payload carried by vessels is a major predictor of a vessel engine's fuel consumption (Kontovas, 2014; Zhao et al, 2019). This research assumes that the design fuel consumption of vessel engines is calculated considering the maximum payload capacity. Thus, the final fuel consumption of vessels ($\boldsymbol{f}_{rpv}, r \in R, p \in P_r, v \in V$ – tons/nmi) will be determined from the following equation (MAN Diesel & Turbo, 2012; Adland and Jia, 2016):

$$\boldsymbol{f}_{rpv} = \boldsymbol{f}_{rpv}^{design} \cdot \left(\frac{\boldsymbol{QC}_{rp}^{SEA} \cdot AWC + LWT_v}{TWC_v + LWT_v}\right)^{\frac{2}{3}} = \frac{\gamma_v(\boldsymbol{\vartheta}_{rp})^{(\alpha_v-1)}}{24} \cdot \left(\frac{\boldsymbol{QC}_{rp}^{SEA} \cdot AWC + LWT_v}{TWC_v + LWT_v}\right)^{\frac{2}{3}} \tag{5}$$

$\forall r \in R, p \in P_r, v \in V$

where:

$\boldsymbol{QC}_{rp}^{SEA}, r \in R, p \in P_r$ – is the number of containers transported at voyage leg p of port rotation r (TEUs);

AWC – is the average cargo weight inside of a standard 20-ft container (tons);

$LWT_v, v \in V$ – is the empty weight of a type v vessel (tons);

$TWC_v, v \in V$ – is the total weight of containers (or cargo), which a vessel of type v can carry (tons).

The total fuel consumption cost ($\boldsymbol{FCC}$ – USD) depends on the voyage leg length ($l_{rp}, r \in R, p \in P_r$ – nmi), the unit fuel cost (c^{fuel} – USD/ton), and, of course, the total fuel consumption. The total fuel consumption cost will be determined from the following equation:

$$\boldsymbol{FCC} = c^{fuel} \sum_{r\in R} \sum_{p\in P_r} \sum_{v\in V} l_{rp} \boldsymbol{f}_{rpv} \boldsymbol{d}_{rv} \tag{6}$$

This research does not capture any factor that can change the fuel consumption rate, such as bad weather, problems in engines, crew errors, and others. The auxiliary vessel engines are used for providing power on board, and their fuel consumption generally does not fluctuate significantly along a voyage leg. So, the fuel consumption cost of auxiliary engines is included in the total operational cost. The sailing time of a vessel at voyage leg p along port rotation r ($\boldsymbol{\tau}_{rp}^{sail}, r \in R, p \in P_r$ – hours) is determined based on the vessel sailing speed and the voyage leg length, as follows:

$$\boldsymbol{\tau}_{rp}^{sail} = \frac{l_{rp}}{\boldsymbol{\vartheta}_{rp}} \ \forall r \in R, p \in P_r \tag{7}$$

4.5. Sensitivity of Container Demand

This dissertation considers elastic container demand at ports ($\boldsymbol{QC}_{rp}^{PORT}, r \in R, p \in P_r$ – TEUs) that is dependent on sailing speeds. The main idea here is that customers like to transport more cargo when the sailing speed is comparatively higher. Thus, the container demand at ports is estimated from the following equation (Cheaitou and Cariou, 2019):

$$\boldsymbol{QC}_{rp}^{PORT} = \alpha_{rp}^{dem} - \frac{\beta_{rp}^{dem}}{\boldsymbol{\vartheta}_{rp}} \ \forall r \in R, p \in P_r \tag{8}$$

where:

$\alpha_{rp}^{dem}, \beta_{rp}^{dem}, r \in R, p \in P_r$ – are the container demand sensitivity coefficients.

When a vessel arrives at a port, the import containers for that port are offloaded, and after that, the export containers from the port are loaded on the vessel. Hence, the number of containers transported at the voyage legs ($\boldsymbol{QC}_{rp}^{SEA}, r \in R, p \in P_r$ – TEUs) are estimated as follows:

$$\boldsymbol{QC}_{r(p+1)}^{SEA} = \boldsymbol{QC}_{rp}^{SEA} - \boldsymbol{QC}_{r(p+1)}^{PORT} \cdot Import_{r(p+1)} + \boldsymbol{QC}_{r(p+1)}^{PORT} \cdot \left(1 - Import_{r(p+1)}\right) \forall r \in R, p \in P_r, p < n_r^2 \quad (9)$$

$$\boldsymbol{QC}_{r(1)}^{SEA} = QC_r^{SEA-0} - \boldsymbol{QC}_{r(1)}^{PORT} \cdot Import_{r(1)} + \boldsymbol{QC}_{r(1)}^{PORT} \cdot \left(1 - Import_{r(1)}\right) \forall r \in R \quad (10)$$

where:

$Import_{rp}, r \in R, p \in P_r$ – is the portion of import containers at port rotation r's port p;

$QC_r^{SEA-0}, r \in R$ – is the total number of containers on the vessel before it moors at the first port to be visited (i.e., port "1"), which is under port rotation r (TEUs).

It should be noted that the total cargo carrying capacity of a given vessel type should not be less that the number of containers to be transported. Thus, the following inequality must be respected:

$$\boldsymbol{QC}_{rp}^{sea} \cdot AWC \leq TWC_v + M(1 - \boldsymbol{d}_{rv}) \; \forall r \in R, p \in P_r, v \in V \quad (11)$$

where:

M – is a large positive real number.

4.6. Service Frequency

The port service frequency is generally estimated according to the container demand. The following relationship must be maintained to ensure the agreed service frequency (Wang et al., 2014; Alharbi et al., 2015; Dulebenets and Ozguven, 2017):

$$24\boldsymbol{\phi}_r\boldsymbol{q}_r = \sum_{p \in P_r} \boldsymbol{\tau}_{rp}^{sail} + \sum_{p \in P_r} \sum_{t \in T_{rp}} \sum_{h \in H_{rpt}} \sum_{v \in V} \boldsymbol{\tau}_{rpthv}^{hand} \boldsymbol{x}_{rpthv} + \sum_{p \in P_r} \boldsymbol{\tau}_{rp}^{wait} \; \forall r \in R \quad (12)$$

where:

$\boldsymbol{q}_r, r \in R$ – is the total number of vessels required for deployment at port rotation r (vessels);

$\boldsymbol{\phi}_r, r \in R$ – is the service frequency at port rotation r (days);

$\boldsymbol{\tau}_{rp}^{wait}, r \in R, p \in P_r$ – is the waiting time of vessels at port rotation r's port p (hours).

Equation (12) suggests that the product of the total number of vessels required and service frequency at a port rotation, as well as the number "24", should be equal to the total turnaround time of vessels at that port rotation. Note that the total turnaround time is the total time required by a vessel to start its voyage from the first port of call, visit all ports, and return to the port, where it started its voyage. The turnaround time has the following components: (I) total sailing time along the respective port rotation; (II) total handling time at all the ports of that port rotation; and (III) total waiting time at all the ports of that port rotation. Equation (12) is used to determine the required number of vessels. As discussed earlier, the vessels, which are used for a port rotation, could be from the company's own fleet and/or chartered from outside (other companies). This dissertation assumes that the vessels of a given type are homogeneous. Thus, their unit vessel operational costs ($c_v^{oper}, v \in V$ – USD/day) are the same. The total number of required vessels for port rotation r ($\boldsymbol{q}_r, r \in R$ – vessels) and the total operational cost ($\boldsymbol{VOC}$ – USD) will be determined from the following equations:

$$\boldsymbol{q}_r = \sum_{v \in V} (\boldsymbol{q}_{rv}^{own} + \boldsymbol{q}_{rv}^{char}) \ \forall r \in R \tag{13}$$

$$\boldsymbol{VOC} = \sum_{r \in R} \sum_{v \in V} c_v^{oper} \boldsymbol{q}_{rv}^{own} \boldsymbol{\phi}_r \tag{14}$$

where:

$\boldsymbol{q}_{rv}^{own}, r \in R, v \in V$ – is the number of type v vessels deployed along port rotation r from the company's own fleet (vessels);

$\boldsymbol{q}_{rv}^{char}, r \in R, v \in V$ – is the number of chartered vessels of type v deployed along port rotation r (vessels).

The total chartering cost ($\boldsymbol{VCC}$ – USD) depends on the unit chartering cost ($c_v^{char}, v \in V$ – USD/day) and is determined from the following equation:

$$\boldsymbol{VCC} = \sum_{r \in R} \sum_{v \in V} c_v^{char} \boldsymbol{q}_{rv}^{char} \boldsymbol{\phi}_r \tag{15}$$

4.7. Container Inventory

This dissertation captures the container inventory cost in sea and at ports of call. The sailing time along the voyage legs dictate the inventory costs in sea. On the other hand, the waiting time at ports and the handling time at ports affect the inventory cost at ports. Practically, the vessel sailing times are greater than the sum of waiting times and handling times at ports of call. Eventually, the inventory cost in sea becomes higher than that at ports. The total container inventory cost in sea ($\boldsymbol{CIC}^{SEA}$ – USD) and the total container inventory cost at ports of call ($\boldsymbol{CIC}^{PORT}$ – USD) are determined as follows (Wang et al., 2014; Dulebenets, 2018b):

$$\boldsymbol{CIC}^{SEA} = \sum_{r\in R}\sum_{p\in P_r} c^{inv}\boldsymbol{QC}_{rp}^{SEA}\,\boldsymbol{\tau}_{rp}^{sail} \tag{16}$$

$$\begin{aligned}\boldsymbol{CIC}^{PORT} &= \sum_{r\in R}\sum_{p\in P_r} c^{inv}\boldsymbol{QC}_{rp}^{SEA}\,\boldsymbol{\tau}_{rp}^{wait} \\ &+ \sum_{r\in R}\sum_{p\in P_r}\sum_{t\in T_{rp}}\sum_{h\in H_{rpt}}\sum_{v\in V} c^{inv}(\boldsymbol{QC}_{rp}^{SEA}-\boldsymbol{QC}_{rp}^{PORT})\,\boldsymbol{\tau}_{rpthv}^{hand}\,\boldsymbol{x}_{rpthv}\end{aligned} \tag{17}$$

where:

c^{inv} – is the unit inventory cost (USD/TEU/hour).

4.8. Emissions from Liner Shipping

This dissertation accounts for the emissions, produced by vessels in sea and at ports of call throughout container handling (e.g., CO_2, NO_x, SO_x, etc.). The emission factor in sea (EF^{SEA} – tons of emissions/ton of fuel) and the fuel consumption of the vessel engines affect the quantity of emissions produced in sea ($\boldsymbol{EP}_{rp}^{SEA}, r \in R, p \in P_r$ – tons) as follows (Psaraftis and Kontovas, 2013; Kontovas, 2014; Psaraftis and Kontovas, 2014):

$$\boldsymbol{EP}_{rp}^{SEA} = \sum_{v\in V} EF^{SEA} l_{rp}\boldsymbol{f}_{rpv}\,\boldsymbol{d}_{rv}\ \forall r\in R, p\in P_r \tag{18}$$

The type of handling equipment used at the ports affect the quantity of emissions produced at ports. It is also affected by the handling productivity. For example, a high handling productivity will require more handling equipment, and the quantity of emissions produced at ports will be increased. The quantity of emissions produced at ports ($\boldsymbol{EP}_{rp}^{PORT}, r \in R, p \in P_r$ – tons) can be calculated based on the number of containers handled at a port, the emission factor at ports of call ($EF_{rphv}^{PORT}, r \in R, p \in P_r, h \in H_{rpt}, v \in V$ – tons of emissions/TEU), and the chosen HR, as follows (Tran et al., 2017; Dulebenets, 2018d):

$$\boldsymbol{EP}_{rp}^{PORT} = \boldsymbol{QC}_{rp}^{PORT} \sum_{t \in T_{rp}} \sum_{h \in H_{rpt}} \sum_{v \in V} (EF_{rphv}^{PORT} \boldsymbol{x}_{rpthv}) \; \forall r \in R, p \in P_r \tag{19}$$

The total emission cost produced by the vessels in sea ($\boldsymbol{EC}^{SEA}$ – USD) and by handling of containers at ports of call ($\boldsymbol{EC}^{PORT}$ – USD) will be determined from the following equations:

$$\boldsymbol{EC}^{SEA} = c^{emis} \sum_{r \in R} \sum_{p \in P_r} \boldsymbol{EP}_{rp}^{SEA} \tag{20}$$

$$\boldsymbol{EC}^{PORT} = c^{emis} \sum_{r \in R} \sum_{p \in P_r} \boldsymbol{EP}_{rp}^{PORT} \tag{21}$$

where:

c^{emis} – is the unit emission cost (USD/ton).

It should be noted that equations (18) to (21) could be used to model the major pollutants. For instance, the CO_2 emission factor at sea is 3.082 tons of CO_2 per ton of fuel (Psaraftis and Kontovas, 2013; Kontovas, 2014; Psaraftis and Kontovas, 2014), while the CO_2 emission factor at ports comprises 0.01729 tons of CO_2 per TEU handled for the base handling productivity of 180 TEUs/hour (Tran et al., 2017), which can be used for calculating the CO_2 emissions, produced by vessels in sea and by the container handling equipment at ports. Based on the available literature, the unit CO_2 emission cost is 32 USD per ton of CO_2 (Schroten et al., 2011; Tran et al., 2017; Dulebenets, 2018d), which can be further used for estimating the total cost of CO_2 emissions in sea and at ports of call.

4.9. Selection of Vessel Sailing Speeds

A number of factors are considered while selecting sailing speeds at each port rotation. The main vessel engines' capacity determines the highest possible speed, whereas engine wear influences the lowest possible speed (Psaraftis and Kontovas, 2013; Wang et al., 2013). Sailing speeds are also affected by a number of other factors (e.g., transit time, unit fuel cost, unit emission cost, unit inventory cost, unit vessel operational cost). For example, Ronen (2011) highlighted that decreasing the sailing speed by 20% could reduce fuel consumption by up to 50%. Moreover, reduction of the vessel sailing speed will further lead to a reduction in the amount of emissions produced by vessels in sea at the considered port rotations. However, lowering the sailing speed will increase the total transit time as well as the corresponding inventory costs. Hence, the total turnaround time will increase, which will require the liner shipping company to use more vessels in order to guarantee a certain port service frequency at ports of call for the considered port rotations. If the number of deployed vessels becomes high, the total operating/chartering cost will also be high. Application of handling rates with higher handling productivities at ports will reduce the total vessel turnaround time. In this case, however, the port handling cost and the amount of emissions produced at ports will increase. Hence, the aforementioned tradeoffs should be considered while determining vessel sailing speeds.

4.10. Objective of a Liner Shipping Company

Every liner shipping company aims to maximize the total profit. The total profit can be estimated from the total route service costs and the total revenue. The route service costs include the following: (I) total late arrival cost ($\boldsymbol{LAC}$); (II) total port handling cost ($\boldsymbol{PHC}$); (III) total fuel consumption cost ($\boldsymbol{FCC}$); (IV) total vessel operational cost ($\boldsymbol{VOC}$); (V) total vessel chartering cost ($\boldsymbol{VCC}$); (VI) total container inventory cost in sea ($\boldsymbol{CIC}^{SEA}$); (VII) total container inventory cost at ports of call ($\boldsymbol{CIC}^{PORT}$); (VIII) total emission cost in sea ($\boldsymbol{EC}^{SEA}$); and (IX) total emission cost at ports of call ($\boldsymbol{EC}^{PORT}$). The total revenue ($\boldsymbol{REV}$ – USD) is determined as the product of the total container demand the unit freight rate ($c_{rp}^{rev}, r \in R, p \in P_r$ – USD/TEU) (Giovannini and Psaraftis, 2018):

$$\boldsymbol{REV} = \sum_{r \in R} \sum_{p \in P_r} c_{rp}^{rev} \boldsymbol{QC}_{rp}^{PORT} \tag{22}$$

The liner shipping company has to make a number of major decisions to maximize the total profit. These decisions include: (a) the sailing speed along each of the voyage legs at each of the port rotations; (b) port service frequency at each of the port rotations; (c) the TW at each of the ports of call; (d) the HR at each of the ports of call; (e) the number of own vessels, of each type, that are to be deployed along each of the port rotations; (f) the number of chartered vessels, of each type, that are to be deployed along each of the port rotations.

CHAPTER 5

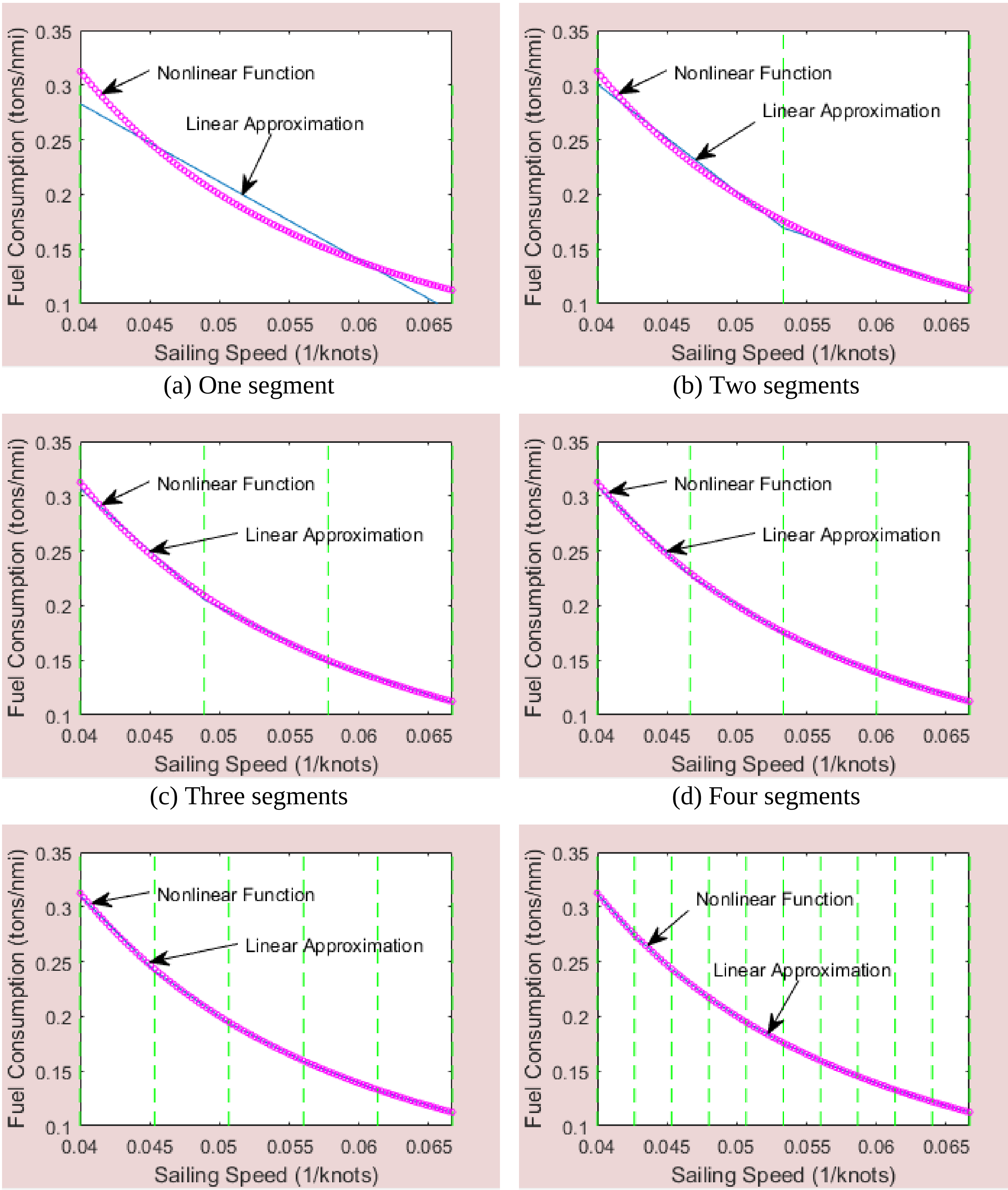
MATHEMATICAL MODEL

The Holistic Optimization Model for Tactical-Level Planning in Liner Shipping (**HOMTLP**) is described in detail in this section of the dissertation.

5.1. Preliminary Linearization Techniques

The liner shipping literature has commonly used constraints (4), (7), and (8) to estimate the design fuel consumption, the sailing times, and the quantity of containers to be handled at the ports of call, respectively (Wang et al., 2013b; Wang et al., 2014; Cheaitou and Cariou, 2019). Note that they are nonlinear constraints. Hence, a set of linearization techniques will be used to decrease the mathematical complexity of the model studied herein. In order to linearize constraints (7) and (8), the vessel sailing speed reciprocal $\boldsymbol{y}_{rp} = \frac{1}{\boldsymbol{\vartheta}_{rp}}\ \forall r \in R, p \in P_r$ (knots^{-1}) will replace the vessel sailing speed ($\boldsymbol{\vartheta}_{rp}, r \in R, p \in P_r$ – knots). Moreover, piecewise linear approximations will be applied to the design fuel consumption function $\boldsymbol{f}_{rpv}, r \in R, p \in P_r, v \in V$ to linearize it. $S_v = \{1, \dots, n_v^6\}, v \in V$ denotes the set of piecewise linear segments for the design fuel consumption function. These segments will be used to estimate the design fuel consumption (at each segment). In this way, constraint (4) will be linearized. The aforementioned techniques will decrease the extent of nonlinearity of the mathematical model, and, thereby, will reduce its computational complexity.

An example of linearizing the nonlinear design fuel consumption function $\left(\boldsymbol{f}^{design} = \frac{\gamma(\boldsymbol{\vartheta})^{(\alpha-1)}}{24}\right)$ with piecewise secant approximations is presented in Figure 27. Here, $\alpha = 3$, and $\gamma = 0.012$ (Wang and Meng, 2012a; Psaraftis and Kontovas, 2013). The range of the vessel sailing speed was 15 knots to 25 knots. Thus, the sailing speed reciprocal values were within 0.040 knots^{-1} to 0.067 knots^{-1} (Wang and Meng, 2012a; Wang and Meng, 2012b).



(a) One segment

(b) Two segments

(c) Three segments

(d) Four segments

(e) Five segments

(f) Ten segments

Figure 27 Fuel consumption linear approximations.

In Figure 27(a), only one linear segment was used. So, a significant difference between the nonlinear design fuel consumption function and its linear approximation can be observed.

Two linear segments were introduced in Figure 27(b). Hence, the difference between the nonlinear design fuel consumption function and its linear approximation was somewhat decreased. Similarly, the number of linear segments in Figure 27(c), Figure 27(d), Figure 27(e), and Figure 27(f) are three, four, five, and ten, respectively. When more and more linear segments were introduced, the difference between the nonlinear design fuel consumption function and its linear approximation was decreased more and more. Among these figures, Figure 27(f) has the highest number of linear segments, and the nonlinear design fuel consumption function and its linear approximation are very close. Hence, it can be said that the piecewise secant approximation technique has been effective in approximating the design fuel consumption function with a satisfactory level of accuracy.

5.2. Nomenclature

5.2.1. Sets

$R = \{1, \ldots, n^1\}$	set of port rotations (port rotations)
$P_r = \{1, \ldots, n_r^2\}, r \in R$	set of ports within port rotation r (ports)
$V = \{1, \ldots, n^3\}$	set of vessel types available (vessel types)
$T_{rp} = \left\{1, \ldots, n_{rp}^4\right\}, r \in R, p \in P_r$	set of TWs available at port p under port rotation r (TWs)
$H_{rpt} = \left\{1, \ldots, n_{rpt}^5\right\}, r \in R, p \in P_r,$ $t \in T_{rp}$	set of port HRs available at port p under port rotation r during TW t (HRs)
$S_v = \{1, \ldots, n_v^6\}, v \in V$	set of linear segments for the piecewise function of the fuel consumption for vessel type v (segments)

5.2.2. Decision Variables

$\boldsymbol{y}_{rp} \in \mathbb{R}^+ \ \forall r \in R, p \in P_r$	sailing speed reciprocal at voyage leg p under port rotation r (knots^{-1})
$\boldsymbol{\phi}_r \in \mathbb{N} \ \forall r \in R$	port service frequency for port rotation r (days)
$\boldsymbol{q}_{rv}^{own} \in \mathbb{N} \ \forall r \in R, v \in V$	number of type v vessels in company's own fleet to deploy at port rotation r (vessels)
$\boldsymbol{q}_{rv}^{char} \in \mathbb{N} \ \forall r \in R, v \in V$	number of chartered vessels of type v to deploy at port

	rotation r (vessels)
$\boldsymbol{d}_{rv} \in \mathbb{B}\ \forall r \in R, v \in V$	=1 if vessel type v is assigned to serve port rotation r (=0 otherwise)
$\boldsymbol{z}_{rpt} \in \mathbb{B}\ \forall r \in R, p \in P_r, t \in T_{rp}$	=1 if TW t is selected at port p under port rotation r (=0 otherwise)
$\boldsymbol{x}_{rpthv} \in \mathbb{B}\ \forall r \in R, p \in P_r, t \in T_{rp}$, $h \in H_{rpt}, v \in V$	=1 if HR h is selected for vessels of type v at port p under port rotation r during TW t (=0 otherwise)
$\boldsymbol{g}_{rpvs} \in \mathbb{B}\ \forall r \in R, p \in P_r, v \in V$, $s \in S_v$	=1 if segment s is selected for estimating the fuel consumption of type v vessels at voyage leg p of port rotation r (=0 otherwise)

5.2.3. Auxiliary Variables

$\boldsymbol{q}_r \in \mathbb{N}\ \forall r \in R$	number of vessels to deploy at port rotation r (vessels)
$\boldsymbol{RF}_{rpvs} \in \mathbb{R}^+\ \forall r \in R, p \in P_r, v \in V$, $s \in S_v$	fuel consumption within segment s for vessel type v at voyage leg p under port rotation r (tons/nmi)
$\boldsymbol{QC}_{rp}^{SEA} \in \mathbb{N}\ \forall r \in R, p \in P_r$	number of containers to be transported at voyage leg p under port rotation r (TEUs)
$\boldsymbol{QC}_{rp}^{PORT} \in \mathbb{N}\ \forall r \in R, p \in P_r$	number of containers to be handled at port p under port rotation r (TEUs)
$\boldsymbol{\tau}_{rp}^{sail} \in \mathbb{R}^+\ \forall r \in R, p \in P_r$	sailing time at leg p under port rotation r (hours)
$\boldsymbol{\tau}_{rp}^{arr} \in \mathbb{R}^+\ \forall r \in R, p \in P_r$	arrival time at port p under port rotation r (hours)
$\boldsymbol{\tau}_{rp}^{wait} \in \mathbb{R}^+\ \forall r \in R, p \in P_r$	waiting time of vessels at port p under port rotation r (hours)
$\boldsymbol{\tau}_{rp}^{late} \in \mathbb{R}^+\ \forall r \in R, p \in P_r$	late arrival hours at port p of port rotation r (hours)
$\boldsymbol{\tau}_{rpthv}^{hand} \in \mathbb{R}^+\ \forall r \in R, p \in P_r, t \in T_{rp}$, $h \in H_{rpt}, v \in V$	handling time for vessels of type v at port p of port rotation r during TW t under HR h (hours)
$\boldsymbol{\tau}_{rp}^{dep} \in \mathbb{R}^+\ \forall r \in R, p \in P_r$	departure time of a vessel from port p under port rotation r (hours)
$\boldsymbol{EP}_{rp}^{SEA} \in \mathbb{R}^+\ \forall r \in R, p \in P_r$	quantity of emissions produced at leg p under port rotation r (tons)

$\boldsymbol{EP}_{rp}^{PORT} \in \mathbb{R}^+ \; \forall r \in R, p \in P_r$	quantity of emissions produced at port p under port rotation r (tons)
$\boldsymbol{REV} \in \mathbb{R}^+$	total revenue (USD)
$\boldsymbol{VOC} \in \mathbb{R}^+$	total operational cost of vessels (USD)
$\boldsymbol{VCC} \in \mathbb{R}^+$	total vessel chartering cost of vessels (USD)
$\boldsymbol{PHC} \in \mathbb{R}^+$	total port handling cost (USD)
$\boldsymbol{LAC} \in \mathbb{R}^+$	total late arrival cost (USD)
$\boldsymbol{FCC} \in \mathbb{R}^+$	total fuel consumption cost (USD)
$\boldsymbol{CIC}^{SEA} \in \mathbb{R}^+$	total inventory cost in sea (USD)
$\boldsymbol{CIC}^{PORT} \in \mathbb{R}^+$	total inventory cost at ports of call (USD)
$\boldsymbol{EC}^{SEA} \in \mathbb{R}^+$	total emission cost in sea (USD)
$\boldsymbol{EC}^{PORT} \in \mathbb{R}^+$	total emission cost at ports of call (USD)

5.2.4. Parameters

$n^1 \in \mathbb{N}$	number of port rotations (port rotations)
$n_r^2 \in \mathbb{N} \; \forall r \in R$	number of ports within port rotation r (ports)
$n^3 \in \mathbb{N}$	number of vessel types available (vessel types)
$n_{rp}^4 \in \mathbb{N} \; \forall r \in R, p \in P_r$	number of TWs available at port p under port rotation r (TWs)
$n_{rpt}^5 \in \mathbb{N} \; \forall r \in R, p \in P_r, t \in T_{rp}$	number of port HRs available at port p under port rotation r during TW t (HRs)
$n_v^6 \in \mathbb{N} \; \forall v \in V$	number of segments for the fuel consumption function for vessel type v (segments)
$l_{rp} \in \mathbb{R}^+ \; \forall r \in R, p \in P_r$	length of voyage leg p under port rotation r (nmi)
$\phi^{max} \in \mathbb{N}$	maximum service frequency (days)
$q_v^{own-m} \in \mathbb{N} \; \forall v \in V$	number of type v vessels available in company's own fleet for deployment (vessels)
$q_v^{char-m} \in \mathbb{N} \; \forall v \in V$	number of type v chartered vessels available for deployment (vessels)
$\vartheta^{max} \in \mathbb{R}^+$	maximum vessel sailing speed (knots)

$\vartheta^{min} \in \mathbb{R}^+$	minimum vessel sailing speed (knots)
$Sl_{vs} \in \mathbb{R}^+ \ \forall v \in V, s \in S_v$	slope of the fuel consumption function for linear segment s for type v vessels (ton/hour)
$In_{vs} \in \mathbb{R}^+ \ \forall v \in V, s \in S_v$	intercept of the fuel consumption function for linear segment s for type v vessels (tons/nmi)
$Bn_{vs} \in \mathbb{R}^+ \ \forall v \in V, s \in S_v$	speed reciprocal value at the start of linear segment s for type v vessels (knots^{-1})
$Ed_{vs} \in \mathbb{R}^+ \ \forall sv \in V, s \in S_v$	speed reciprocal value at the end of linear segment s for type v vessels (knots^{-1})
$\alpha_{rp}^{dem}, \beta_{rp}^{dem} \in \mathbb{R}^+ \ \forall r \in R, p \in P_r$	container demand sensitivity coefficients to sailing speed at port p under port rotation r
$Import_{rp} \in \mathbb{R}^+ \ \forall r \in R, p \in P_r$	portion of import containers at port p under port rotation r (%)
$QC_r^{SEA-0} \in \mathbb{N} \ \forall r \in R$	total quantity of containers on board a vessel before it moors at the beginning port of call under port rotation r (TEUs)
$ph_{rpthv} \in \mathbb{R}^+ \ \forall r \in R, p \in P_r, t \in T_{rp}, h \in H_{rpt}, v \in V$	handling productivity under HR h during TW t at port p of port rotation r for vessels of type v (TEUs/hour)
$AWC \in \mathbb{R}^+$	average cargo weight in a standard 20-ft container (tons)
$LWT_v \in \mathbb{R}^+ \forall v \in V$	empty weight of a type v vessel (tons)
$TWC_v \in \mathbb{R}^+ \ \forall v \in V$	total cargo carrying capacity of a type v vessel (tons)
$\tau_{rpt}^{st} \in \mathbb{R}^+ \ \forall r \in R, p \in P_r, t \in T_{rp}$	start of TW t at port p under port rotation r (hours)
$\tau_{rpt}^{end} \in \mathbb{R}^+ \ \forall r \in R, p \in P_r, t \in T_{rp}$	end of TW t at port p under port rotation r (hours)
$EF^{SEA} \in \mathbb{R}^+$	emission factor in sea (tons of emissions/ton of fuel)
$EF_{rphv}^{PORT} \in \mathbb{R}^+ \ \forall r \in R, p \in P_r, h \in H_{rpt}, v \in V$	emission factor at port p within port rotation r under HR h for type v vessels (tons of emissions/TEU)
$c_v^{oper} \in \mathbb{R}^+ \ \forall v \in V$	unit operational cost for a vessel of type v (USD/day)
$c_v^{char} \in \mathbb{R}^+ \ \forall v \in V$	unit chartering cost for a vessel of type v (USD/day)
$c_{rpthv}^{hand} \in \mathbb{R}^+ \ \forall r \in R, p \in P_r, t \in T_{rp}, h \in H_{rpt}, v \in V$	unit handling cost for type v vessels at port p under port rotation r during TW t under HR h (USD/TEU)

$c_{rp}^{late} \in \mathbb{R}^+ \ \forall r \in R, p \in P_r$	unit late arrival cost imposed at port p under port rotation r (USD/hour)
$c^{fuel} \in \mathbb{R}^+$	unit fuel cost (USD/ton)
$c^{inv} \in \mathbb{R}^+$	unit container inventory cost (USD/TEU/hour)
$c^{emis} \in \mathbb{R}^+$	unit emission cost (USD/ton)
$c_{rp}^{rev} \in \mathbb{R}^+ \ \forall r \in R, p \in P_r$	unit freight rate for cargo delivered to port p under port rotation r (USD/TEU)
$M_1, M_2 \in \mathbb{R}^+$	large positive numbers

5.3. Holistic Optimization Model for Tactical-Level Planning in Liner Shipping (HOMTLP):

$$max\ [\boldsymbol{REV} - (\boldsymbol{VOC} + \boldsymbol{VCC} + \boldsymbol{PHC} + \boldsymbol{LAC} + \boldsymbol{FCC} + \boldsymbol{CIC}^{SEA} + \boldsymbol{CIC}^{PORT} + \boldsymbol{EC}^{SEA} + \boldsymbol{EC}^{PORT})] \quad (23)$$

Subject to:

$$\sum_{v \in V} \boldsymbol{d}_{rv} = 1 \ \forall r \in R \quad (24)$$

$$\sum_{t \in T_{rp}} \boldsymbol{z}_{rpt} = 1 \ \forall r \in R, p \in P_r \quad (25)$$

$$\sum_{t \in T_{rp}} \sum_{h \in H_{rpt}} \sum_{v \in V} \boldsymbol{x}_{rpthv} = 1 \ \forall r \in R, p \in P_r \quad (26)$$

$$\boldsymbol{x}_{rpthv} \leq \boldsymbol{d}_{rv} \ \forall r \in R, p \in P_r, t \in T_{rp}, h \in H_{rpt}, v \in V \quad (27)$$

$$\boldsymbol{x}_{rpthv} \leq \boldsymbol{z}_{rpt} \ \forall r \in R, p \in P_r, t \in T_{rp}, h \in H_{rpt}, v \in V \quad (28)$$

$$\boldsymbol{QC}_{rp}^{PORT} = \alpha_{rp}^{dem} - \boldsymbol{y}_{rp} \cdot \beta_{rp}^{dem} \ \forall r \in R, p \in P_r \quad (29)$$

$$\boldsymbol{QC}_{r(p+1)}^{SEA} = \boldsymbol{QC}_{rp}^{SEA} - \boldsymbol{QC}_{r(p+1)}^{PORT} \cdot Import_{r(p+1)} + \boldsymbol{QC}_{r(p+1)}^{PORT} \cdot \left(1 - Import_{r(p+1)}\right) \ \forall r \in R, p \in P_r, p < n_r^2 \quad (30)$$

$$\boldsymbol{QC}_{r(1)}^{SEA} = QC_r^{SEA-0} - \boldsymbol{QC}_{r(1)}^{PORT} \cdot Import_{r(1)} + \boldsymbol{QC}_{r(1)}^{PORT} \cdot \left(1 - Import_{r(1)}\right) \ \forall r \in R \quad (31)$$

$$\boldsymbol{QC}_{rp}^{sea} \cdot AWC \leq TWC_v + M_1(1 - \boldsymbol{d}_{rv}) \ \forall r \in R, p \in P_r, v \in V \quad (32)$$

$$\boldsymbol{\tau}_{rpthv}^{hand} = \frac{\boldsymbol{QC}_{rp}^{PORT}}{ph_{rpthv}} \ \forall r \in R, p \in P_r, t \in T_{rp}, h \in H_{rpt}, v \in V \quad (33)$$

$$\sum_{v \in V} \sum_{s \in S_v} \boldsymbol{g}_{rpvs} = 1 \ \forall r \in R, p \in P_r \quad (34)$$

$$\boldsymbol{g}_{rpvs} \leq \boldsymbol{d}_{rv} \ \forall r \in R, p \in P_r, v \in V, s \in S_v \tag{35}$$

$$Bn_{vs}\boldsymbol{g}_{rpvs} \leq \boldsymbol{y}_{rp} \leq Ed_{vs} + M_2\left(1 - \boldsymbol{g}_{rpvs}\right) \ \forall r \in R, p \in P_r, v \in V, s \in S_v \tag{36}$$

$$\boldsymbol{RF}_{rpvs} \geq \left(Sl_{vs}\boldsymbol{y}_{rp} + In_{vs}\right) \cdot \left(\frac{\boldsymbol{QC}_{rp}^{sea} \cdot AWC + LWT_v}{TWC_v + LWT_v}\right)^{\frac{2}{3}} - M_2\left(1 - \boldsymbol{g}_{rpvs}\right) \tag{37}$$

$\forall \ r \in R, p \in P_r, v \in V, s \in S_v$

$$\frac{1}{\vartheta^{max}} \leq \boldsymbol{y}_{rp} \leq \frac{1}{\vartheta^{min}} \ \forall r \in R, p \in P_r \tag{38}$$

$$\boldsymbol{\tau}_{rp}^{sail} = l_{rp}\boldsymbol{y}_{rp} \ \forall r \in R, p \in P_r \tag{39}$$

$$\boldsymbol{\tau}_{r(p+1)}^{wait} \geq \sum_{t \in T_{rp}} \tau_{r(p+1)t}^{st}\boldsymbol{z}_{r(p+1)t} - \boldsymbol{\tau}_{rp}^{dep} - \boldsymbol{\tau}_{rp}^{sail} \ \forall r \in R, p \in P_r, p < n_r^2 \tag{40}$$

$$\boldsymbol{\tau}_{r(1)}^{wait} \geq \sum_{t \in T_{rp}} \tau_{r(1)t}^{st}\boldsymbol{z}_{r(1)t} - \boldsymbol{\tau}_{rp}^{dep} - \boldsymbol{\tau}_{rp}^{sail} + 24\boldsymbol{\phi}_r\boldsymbol{q}_r \ \forall r \in R, p \in P_r, p = n_r^2 \tag{41}$$

$$\boldsymbol{\tau}_{rp}^{late} \geq \boldsymbol{\tau}_{rp}^{arr} - \sum_{t \in T_{rp}} \tau_{rpt}^{end}\boldsymbol{z}_{rpt} \ \forall r \in R, p \in P_r \tag{42}$$

$$\boldsymbol{\tau}_{rp}^{dep} = \boldsymbol{\tau}_{rp}^{arr} + \boldsymbol{\tau}_{rp}^{wait} + \sum_{t \in T_{rp}} \sum_{h \in H_{rpt}} \sum_{v \in V} \boldsymbol{\tau}_{rpthv}^{hand}\boldsymbol{x}_{rpthv} \ \forall r \in R, p \in P_r \tag{43}$$

$$\boldsymbol{\tau}_{r(p+1)}^{arr} = \boldsymbol{\tau}_{rp}^{dep} + \boldsymbol{\tau}_{rp}^{sail} \ \forall r \in R, p \in P_r, p < n_r^2 \tag{44}$$

$$\boldsymbol{\tau}_{r(1)}^{arr} = \boldsymbol{\tau}_{rp}^{dep} + \boldsymbol{\tau}_{rp}^{sail} - 24\boldsymbol{\phi}_r\boldsymbol{q}_r \forall r \in R, p \in P_r \tag{45}$$

$$24\boldsymbol{\phi}_r\boldsymbol{q}_r = \sum_{p \in P_r} \boldsymbol{\tau}_{rp}^{sail} + \sum_{p \in P_r} \sum_{t \in T_{rp}} \sum_{h \in H_{rpt}} \sum_{v \in V} \boldsymbol{\tau}_{rpthv}^{hand}\boldsymbol{x}_{rpthv} + \sum_{p \in P_r} \boldsymbol{\tau}_{rp}^{wait} \ \forall r \in R \tag{46}$$

$$\boldsymbol{\phi}_r \leq \phi^{max} \ \forall r \in R \tag{47}$$

$$\boldsymbol{q}_r = \sum_{v \in V} (\boldsymbol{q}_{rv}^{own} + \boldsymbol{q}_{rv}^{char}) \ \forall r \in R \tag{48}$$

$$\boldsymbol{q}_{rv}^{own} \leq q_v^{own-m}\boldsymbol{d}_{rv} \ \forall r \in R, v \in V \tag{49}$$

$$\sum_{r \in R} \boldsymbol{q}_{rv}^{own} \leq q_v^{own-m} \ \forall v \in V \tag{50}$$

$$\boldsymbol{q}_{rv}^{char} \leq q_v^{char-m}\boldsymbol{d}_{rv} \ \forall r \in R, v \in V \tag{51}$$

$$\sum_{r \in R} \boldsymbol{q}_{rv}^{char} \leq q_v^{char-m} \ \forall v \in V \tag{52}$$

$$\boldsymbol{EP}_{rp}^{SEA} = \sum_{v \in V} \sum_{s \in S_v} EF^{SEA} l_{rp}\boldsymbol{RF}_{rpvs} \ \forall r \in R, p \in P_r \tag{53}$$

$$\boldsymbol{EP}_{rp}^{PORT} = \boldsymbol{QC}_{rp}^{PORT} \sum_{t \in T_{rp}} \sum_{h \in H_{rpt}} \sum_{v \in V} (EF_{rphv}^{PORT}\boldsymbol{x}_{rpthv}) \ \forall r \in R, p \in P_r \tag{54}$$

$$\boldsymbol{REV} = \sum_{r\in R}\sum_{p\in P_r} c_{rp}^{rev}\boldsymbol{QC}_{rp}^{PORT} \tag{55}$$

$$\boldsymbol{VOC} = \sum_{r\in R}\sum_{v\in V} c_v^{oper}\boldsymbol{q}_{rv}^{own}\,\boldsymbol{\phi}_r \tag{56}$$

$$\boldsymbol{VCC} = \sum_{r\in R}\sum_{v\in V} c_v^{char}\boldsymbol{q}_{rv}^{char}\,\boldsymbol{\phi}_r \tag{57}$$

$$\boldsymbol{PHC} = \sum_{r\in R}\sum_{p\in P_r}\sum_{t\in T_{rp}}\sum_{h\in H_{rpt}}\sum_{v\in V} c_{rpthv}^{hand}\boldsymbol{QC}_{rp}^{PORT}\boldsymbol{x}_{rpthv} \tag{58}$$

$$\boldsymbol{LAC} = \sum_{r\in R}\sum_{p\in P_r} c_{rp}^{late}\boldsymbol{\tau}_{rp}^{late} \tag{59}$$

$$\boldsymbol{FCC} = c^{fuel}\sum_{r\in R}\sum_{p\in P_r}\sum_{v\in V}\sum_{s\in S_v} l_{rp}\boldsymbol{RF}_{rpvs} \tag{60}$$

$$\boldsymbol{CIC}^{SEA} = \sum_{r\in R}\sum_{p\in P_r} c_v^{inv}\boldsymbol{QC}_{rp}^{SEA}\,\boldsymbol{\tau}_{rp}^{sail} \tag{61}$$

$$\begin{aligned}\boldsymbol{CIC}^{PORT} &= \sum_{r\in R}\sum_{p\in P_r} c_v^{inv}\boldsymbol{QC}_{rp}^{SEA}\,\boldsymbol{\tau}_{rp}^{wait}\\ &\quad + \sum_{r\in R}\sum_{p\in P_r}\sum_{t\in T_{rp}}\sum_{h\in H_{rpt}}\sum_{v\in V} c_v^{inv}(\boldsymbol{QC}_{rp}^{SEA} - \boldsymbol{QC}_{rp}^{PORT})\,\boldsymbol{\tau}_{rpthv}^{hand}\,\boldsymbol{x}_{rpthv}\end{aligned} \tag{62}$$

$$\boldsymbol{EC}^{SEA} = c^{emis}\sum_{r\in R}\sum_{p\in P_r}\boldsymbol{EP}_{rp}^{SEA} \tag{63}$$

$$\boldsymbol{EC}^{PORT} = c^{emis}\sum_{r\in R}\sum_{p\in P_r}\boldsymbol{EP}_{rp}^{PORT} \tag{64}$$

The **HOMTLP** objective function (23) suggests that the liner shipping company aims to maximize the total profit that depends on the total revenue and the overall route service cost, which consists of (I) total late arrival cost; (II) total port handling cost; (III) total fuel consumption cost; (IV) total vessel operational cost; (V) total vessel chartering cost; (VI) total container inventory cost in sea; (VII) total container inventory cost at ports of call; (VIII) total emission cost in sea; and (IX) total emission cost at ports of call.

Constraint (24) ensures that only one type of vessel will be deployed to serve each port rotation. Constraint (25) guarantees that the liner shipping company will choose only one TW at each port of call under a port rotation. Constraint (26) indicates that only one port handling rate will be chosen at each port of call under each port rotation. Constraint (27) ensures that at each port rotation, the MCT operator will provide the chosen HR for the chosen type of vessel. Constraint (28) guarantees that the MCT operator will provide the chosen handling rate during the agreed arrival TW at each port for each port rotation. Constraint (29) determines the number of containers that are going to be handled at each port. Constraints (30) and (31) estimate the number of containers that are going to be transported by the vessels at each voyage leg. Constraint (32) limits the maximum cargo load on board the vessels according to the cargo carrying capacity of the vessels. Constraint (33) calculates the port handling time for the chosen arrival TW at each port of call.

Constraint (34) ensures that only one linear fuel consumption function segment will be chosen for the selected vessel type at each voyage leg. Constraint (35) guarantees that the chosen segment will be used for approximation of the fuel consumption function for the chosen vessel type at each of the voyage legs for each port rotation. Constraint (36) calculates the reciprocal of vessel sailing speed based on the chosen segment at each voyage leg of each port rotation. Constraint (37) estimates the fuel consumption according to the selected segment at each voyage leg for each port rotation. Constraint (38) ensures that the reciprocal of vessel sailing speed will be within the predetermined range.

Constraint (39) computes the sailing time at each of the voyage legs. Constraints (40) and (41) estimate the vessel waiting time at each port of call (in case a vessel arrives at a given port before the arrival TW start). Constraint (42) computes the late arrival hours of vessels at each port of call. Constraint (43) estimates the time of vessel departure from each port of call. Constraints (44) and (45) calculate the arrival times at the next port of call. Constraint (46) ensures that the liner shipping company will maintain the agreed port service frequency in case of each port rotation. Constraint (47) imposes a requirement on the port service frequency for a given port rotation and ensures that that the port service frequency is less than or equal to the maximum port service frequency.

Constraint (48) determines the total number of vessels required to be deployed for service at each of the port rotations. Constraints (49) to (52) enforce the condition that the required number of the company's own vessels and chartered vessels (from other companies) will not exceed the available number of vessels in the liner shipping company's fleet and the available number of charted vessels, respectively. Constraints (53) and (54) determine the quantity of emissions produced in sea and the quantity of emissions produced at ports of call, respectively. Constraints (55) to (64) estimate different components of the objective function (23), which comprise the total revenue, total operational cost, total chartering cost, total handling cost, total late arrival cost, total fuel consumption cost, total container inventory cost in sea, total container inventory cost at ports of call, total emission cost in sea, as well as total emission cost at ports of call, respectively.

5.4. Solution Approach

The **HOMTLP** mathematical model, which is a mixed-integer nonlinear programming model, has the potential to be solved with exact optimization approaches to the global optimality. Several exact optimization approaches can be found in the state-of-the-art (e.g., SCIP, LINDO, COUENNE, BONMIN, BARON). This dissertation will employ BARON as the solution approach. It is used to solve nonconvex mathematical problems (to the global optimality). Several modeling languages have made BARON available (i.e., GAMS, AMPL, AIMMS). BARON amalgamates duality, interval analysis, and constraint propagation in reduce arsenal under branch-and-bound techniques (AIMMS, 2019). BARON has a modular nature, and so, it can be used for specific applications. However, it cannot tackle constraints with goniometric functions or with references to external functions. For BARON, all nonlinear variables and expressions in the tackled mathematical program must have upper and lower bounds. Furthermore, commercial exact optimization solvers, such as BARON, could require extensive computational time to solve large-scale problem instances (Dulebenets, 2015; Lee and Song, 2017; Dulebenets et al., 2018; Dulebenets et al., 2019b; Dulebenets et al., 2020; Kavoosi et al., 2019; Theophilus et al., 2019; Kavoosi et al., 2020a; Kavoosi et al., 2020b).

CHAPTER 6

NUMERICAL EXPERIMENTS

Several numerical experiments were performed in order to exhibit the potential of the **HOMTLP** model for tactical-level decision making. A Dell Alienware IntelI Core™ i7-7700K processor that had 32 GB of RAM and Windows 10 Operating System was used to conduct the numerical experiments. To produce the fuel consumption function's secant approximations, MATLAB 2016a was used (MathWorks, 2019). GAMS (General Algebraic Modeling System) was used to encode the **HOMTLP** model, while BARON was used to solve the model to the global optimality (GAMS, 2019).

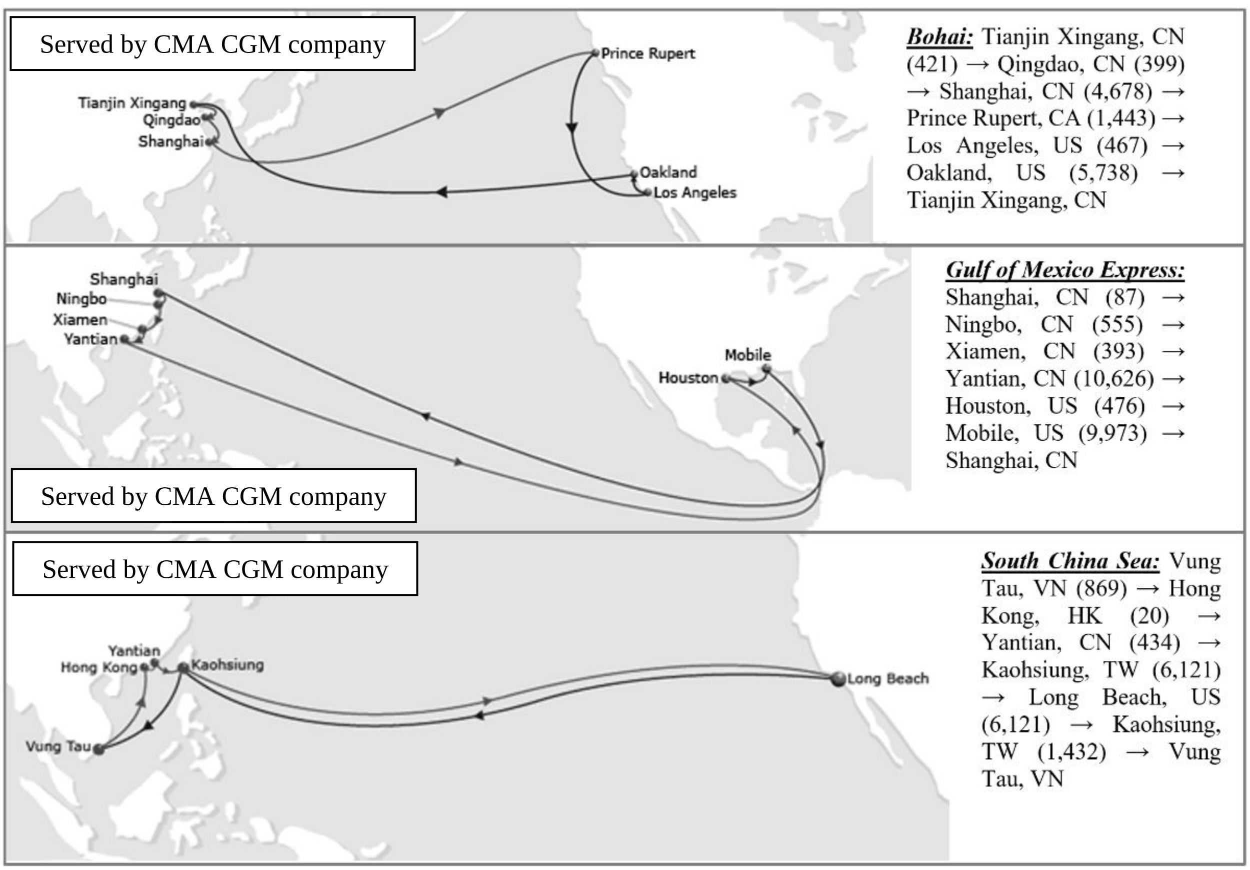


Figure 28 The three considered routes.

6.1. Input Data

Three liner shipping routes extending from Asia to North America, which are covered by the CMA CGM liner shipping company, were used to check the performance of the proposed approach. Figure 28 depicts these routes, where the lengths of the voyage legs ($l_{rp}, r \in R, p \in P_r$ – nmi) are highlighted in parentheses (CMA CGM, 2019a; Ports.com, 2019; SEA-DISTANCES.ORG, 2019). The adopted values of the parameters of the **HOMTLP** mathematical model, obtained from the liner shipping as well as operations research literature, are presented in Table 6 (Wang and Meng, 2012b; Wang and Meng, 2012e; Psaraftis and Kontovas, 2013; Wang et al., 2014; Dulebenets, 2018a; Dulebenets, 2018d; Abioye et al., 2019; CMA CGM, 2019a; CMA CGM, 2019b; Dulebenets, 2019a; Dulebenets, 2019b; Dulebenets, 2019c; Dulebenets, 2020; Pasha et al., 2020). Throughout the numerical experiments, this research considered two vessel types (i.e., $n^3 = 2$), while three TWs were considered for each port (i.e., $n^4_{rp} = 3$). Moreover, four container HRs were associated with each arrival TW (i.e., $n^5_{rpt} = 4$).

Table 6 The adopted values of the model parameters.

Parameter	**Value**
Number of port rotations (port rotations): n^1	3
Number of ports within port rotation r (ports): $n^2_r\ \forall r \in R$	6
Number of vessel types available (vessel types): n^3	2
Number of TWs available at port p under port rotation r (TWs): $n^4_{rp}\ \forall r \in R, p \in P_r$	3
Number of port HRs available at port p under port rotation r during TW t (HRs): $n^5_{rpt}\ \forall r \in R, p \in P_r, t \in T_{rp}$	4
Maximum service frequency (days): ϕ^{max}	14
Number of type v vessels available in company's own fleet for deployment (vessels): $q^{own-m}_v\ \forall v \in V$	$[3; 4]$
Number of type v chartered vessels available for deployment (vessels): $q^{char-m}_v\ \forall v \in V$	$[5; 6]$
Maximum vessel sailing speed (knots): ϑ^{max}	25

Table 6 – Continued.

Parameter	Value
Minimum vessel sailing speed (knots): ϑ^{min}	15
Coefficient of fuel consumption: α_v $\forall v \in V$	$[3; 3.2]$
Coefficient of fuel consumption: γ_v $\forall v \in V$	$[0.012; 0.014]$
Container demand sensitivity coefficient to sailing speed at port p under port rotation r: α_{rp}^{dem} $\forall r \in R, p \in P_r$	$U[400; 1{,}800]$
Container demand sensitivity coefficient to sailing speed at port p under port rotation r: β_{rp}^{dem} $\forall r \in R, p \in P_r$	$U[1{,}250; 3{,}000]$
Portion of import containers at port p under port rotation r (%): $Import_{rp}$ $\forall r \in R, p \in P_r$	$U[40; 60]$
Total quantity of containers on board a vessel before it moors at the beginning port of call under port rotation r (TEUs): QC_r^{SEA-0} $\forall r \in R$	$U[4{,}000; 7{,}000]$
Handling productivity under HR h during TW t at port p of port rotation r for vessels of type v (TEUs/hour): ph_{rpthv} $\forall r \in R, p \in P_r, t \in T_{rp}, h \in H_{rpt}, v \in V$	$U[50; 125]$
Average cargo weight in a standard 20-ft container (tons): AWC	11
Empty weight of a type v vessel (tons): $LWT_v \forall v \in V$	$[48{,}000; 50{,}000]$
Total cargo carrying capacity of a type v vessel (tons): TWC_v $\forall v \in V$	$[144{,}000; 150{,}000]$
Duration of arrival TWs (hours)	$U[24; 72]$
Emission factor in sea (tons of emissions/ton of fuel): EF^{SEA}	3.082
Emission factor at port p within port rotation r under HR h for type v vessels (tons of emissions/TEU): EF_{rphv}^{PORT} $\forall r \in R, p \in P_r, h \in H_{rpt}, v \in V$	0.01729 for $h = 180$
Unit operational cost for a vessel of type v (USD/day): c_v^{oper} $\forall v \in V$	$[39{,}000; 43{,}000]$
Unit chartering cost for a vessel of type v (USD/day): c_v^{char} $\forall v \in V$	$[59{,}000; 65{,}000]$
Unit handling cost for type v vessels at port p under port rotation r during TW t under HR h (USD/TEU): c_{rpthv}^{hand} $\forall r \in R, p \in P_r, t \in T_{rp}, h \in H_{rpt}, v \in V$	$U[150; 550]$

Table 6 – Continued.

Parameter	**Value**
Unit late arrival cost imposed at port p under port rotation r (USD/hour): $c_{rp}^{late}\ \forall r \in R, p \in P_r$	$U[5{,}000; 8{,}000]$
Unit fuel cost (USD/ton): c^{fuel}	200
Unit container inventory cost (USD/TEU/hour): c^{inv}	0.25
Unit emission cost (USD/ton): c^{emis}	32
Unit freight rate for cargo delivered to port p under port rotation r (USD/TEU): $c_{rp}^{rev}\ \forall r \in R, p \in P_r$	$U[1{,}000;\ 2{,}500]$
Large positive number: M_1	$100{,}000{,}000$
Large positive number: M_2	100

The maximum port service frequency was assumed to be 14 days. The number of vessels, of each type, available from the liner shipping company's fleet ($q_v^{own-m}, v \in V$) and available from other companies ($q_v^{char-m}, v \in V$) were set as 3-6 vessels. Similar to Wang and Meng (2012b) and Wang and Meng (2012e), the sailing speed was within 15-25 knots. The container demand coefficients (α_{rp}^{dem}, $\beta_{rp}^{dem}, r \in R, p \in P_r$) were taken as $U[400; 1{,}800]$ TEUs and $U[1{,}250; 3{,}000]$ TEUs, respectively. Here, U represents pseudorandom numbers that are uniformly distributed. The percentage of import containers at the ports ($Import_{rp}, r \in R, p \in P_r$) was taken as $U[40\%; 60\%]$. In addition, the payload at the last voyage leg was set as $QC_r^{SEA-0} = U[4{,}000; 7{,}000]\ \forall r \in R$ (TEUs). The handling productivity was taken as $U[50; 125]$ TEUs/hour.

COSCO GLORY is one of the vessels that are operated by the CMA CGM liner shipping company on the Bohai route (CMA CGM, 2019b). The nominal capacity of COSCO GLORY is 13,114 TEUs. The deadweight tonnage (capacity to carry containers, fuel, water, etc.) of the vessel is 140,637 tons (CMA CGM, 2019b). Based on the aforementioned features, the weight of cargo in a 20-ft container (AWC) is supposed to be around 10-11 tons. So, the value of AWC was taken as 11 tons. The empty vessel weight was taken as 48,000-50,000 tons, and the cargo carrying capacity of the vessels was set to 144,000-150,000 tons (CMA CGM, 2019b).

The start of TWs was generated as follows: $\tau^{st}_{r(p+1)t} = \tau^{st}_{rpt} + \frac{l_{rp}}{U[\vartheta^{min}; \vartheta^{max}]}\ \forall r \in R, p \in P_r, t \in T_{rp}$ (hours) (Dulebenets, 2018a; Abioye et al., 2019). Furthermore, the duration of TWs was assumed to vary uniformly between 24 hours to 72 hours (Dulebenets, 2018a; Dulebenets, 2018d; Dulebenets, 2018e). During the numerical experiments, carbon dioxide was assumed to be the major environmental pollutant. Hence, the emission factor in sea was taken as 3.082 tons of emissions/ton of fuel (Psaraftis and Kontovas, 2013; Psaraftis and Kontovas, 2014). Furthermore, the emission factor at ports was computed from the following equation: $EF^{PORT}_{rphv} = 0.01729 + U[1.0; 1.2] \cdot \frac{[(\sum_{t \in T_{rp}} ph_{rpthv}/n^4_{rp}) - 180]}{180} \cdot 0.01729\ \forall r \in R, p \in P_r, h \in H_{rpt}, v \in V$ (tons of emissions/TEU) (Dulebenets, 2018a). Note that for the baseline handling productivity, which was 180 TEUs/hour, the emission factor at ports was taken as 0.01729 tons of emissions/TEU (Tran et al., 2017).

The value of the unit operational cost of the considered vessels ($c^{oper}_v, v \in V$) was set to 39,000 to 43,000 USD/day, whereas the value of the unit chartering cost ($c^{char}_v, v \in V$) was set to 59,000 to 65,000 USD/day. The unit handling cost was computed from the following equation: $c^{hand}_{rpthv} = U[150;\ 550]\ \forall r \in R, p \in P_r, t \in T_{rp}, h \in H_{rpt}, v \in V$ (USD/TEU). The unit late arrival cost ($c^{late}_{rp}, r \in R, p \in P_r$) was assumed to be $U[5{,}000; 8{,}000]$ USD/hour (Dulebenets, 2018a; Abioye et al., 2019). The unit fuel cost (c^{fuel}) was taken as 200 USD/ton (Wang and Meng, 2012b; Wang and Meng, 2012e). The unit inventory cost (c^{inv}) was assumed to be 0.25 USD/TEU/hour, whereas the unit emission cost (c^{emis}) was set to be 32 USD/ton (Schroten et al., 2011; Tran et al., 2017). In addition, the unit freight rate was set to $U[1{,}000;\ 2{,}500]$ (USD/TEU).

6.2. Performance of the Solution Approach Adopted

6.2.1. Solution Quality and Computational Time Analysis

BARON was used to solve the **HOMTLP** model to the global optimality, as mentioned earlier. By changing the start and end of TWs, 20 problem instances were generated to test the performance of the proposed approach. The maximum runtime of the solution approach (BARON) was fixed as 15 minutes, and the maximum optimality gap was set to 3%, for each of the problem instances. The CPU times and optimality gaps for the tested instances are illustrated in Figure 29. For the 20 tested instances, the CPU times varied between 140.54 seconds (instance #1) and 608.54 seconds (instance #13). Furthermore, for 18 of the 20 developed instances, the CPU time did not exceed 400 seconds. The optimality gaps were also satisfactory, as they varied between 2.2% and 3% for the developed instances. Note that the **HOMTLP** model had 1,853 variables and 3,063 constraints for each of the tested instances, which further showcases the efficiency of the adopted solution approach for fairly large-size instances. From this point on, the TWs generated for instance #1 will be used for the remainder of the numerical experiments.

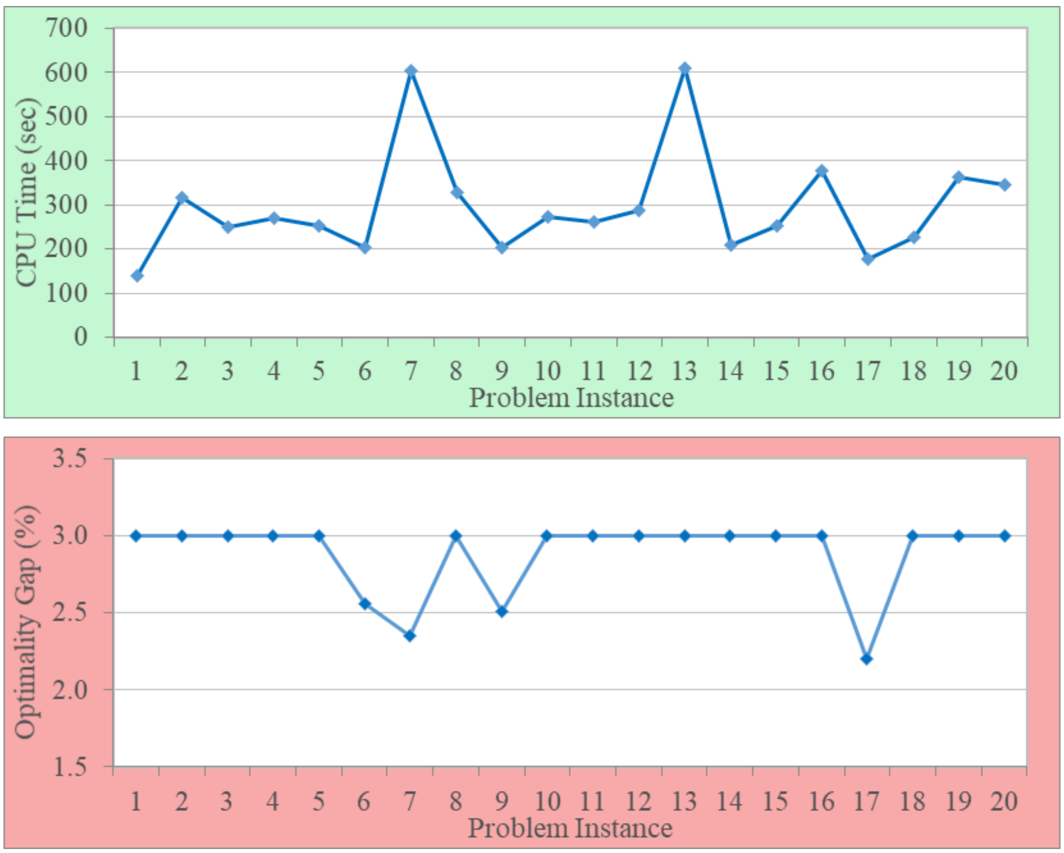


Figure 29 CPU times and optimality gaps for the problem instances considered.

6.2.2. Efficiency of the Adopted Linearization Techniques

A set of well-established and widely employed linearization techniques (e.g., application of the vessel sailing speed reciprocal instead of the actual vessel sailing speed, application of the static piecewise secant approximation for the fuel consumption function), found from the liner shipping literature, have been applied to the proposed **HOMTLP** model in order to reduce the degree of its nonlinearity. After application of such techniques, the CPU time of the proposed **HOMTLP** model was within reasonable limits (i.e., ~10 min for the target optimality gap of 3%). Moreover, the difference between the objective functions of the initial nonlinear model and the **HOMTLP** model, whose degree of nonlinearity was reduced, was not significant. To corroborate this in case of the optimization model with nonlinear fuel consumption function and the **HOMTLP** model, where the fuel consumption function was linearized with the static piecewise secant approximation technique, 20 scenarios were developed. With increments of 50 USD/ton, the unit fuel cost was increased from 50 USD/ton in scenario #1 to 1,000 USD/ton in scenario #20. The rest of the parameters were kept unchanged.

Table 7 Effect of static piecewise secant approximation for the fuel consumption function.

Scenario	Unit Fuel Cost (USD/ton)	Z (USD)	Z^* (USD)	Δ (%)	Scenario	Unit Fuel Cost (USD/ton)	Z (USD)	Z^* (USD)	Δ (%)
1	50	25,996,602	26,050,114	0.21%	11	550	20,540,033	20,961,329	2.01%
2	100	25,143,479	25,261,939	0.47%	12	600	20,047,032	20,504,846	2.23%
3	150	24,783,290	24,924,220	0.57%	13	650	19,549,612	20,053,380	2.51%
4	200	23,972,668	24,157,299	0.76%	14	700	19,047,799	19,061,966	0.07%
5	250	23,476,984	23,745,187	1.13%	15	750	18,652,898	19,200,690	2.85%
6	300	23,001,720	23,328,485	1.40%	16	800	18,131,498	18,150,578	0.11%
7	350	22,474,838	22,756,050	1.24%	17	850	17,651,259	17,659,668	0.05%
8	400	22,059,693	22,405,549	1.54%	18	900	17,302,996	17,919,970	3.44%
9	450	21,423,258	21,853,041	1.97%	19	950	17,080,235	17,086,770	0.04%
10	500	20,999,366	21,457,834	2.14%	20	1,000	16,658,997	16,658,803	0.00%

Table 7 demonstrates the effect of static piecewise secant approximation for the fuel consumption function upon the objective function. Note that $\boldsymbol{Z}$ represents the objective function of the **HOMTLP** model (with the linear fuel consumption function), while $\boldsymbol{Z}^*$ denotes the objective function of the optimization model with the nonlinear fuel consumption function. $\Delta = \left|\frac{\boldsymbol{Z}^* - \boldsymbol{Z}}{\boldsymbol{Z}^*}\right|$ represents the difference in the objective functions of the aforementioned models. It was observed that the difference between the objective functions of the two models ranged between 0.00% and 3.44% (on average not exceeding 1.24%), which could be viewed as satisfactory. Note that for this computational experiment, the fuel consumption function of the **HOMTLP** model was approximated with 10 linear segments. If the number of segments was increased, the differences between the objective functions would have been less; however, the CPU times would have increased.

6.3. Model Performance against the Exiting Literature

The most notable aspect of the **HOMTLP** mathematical model is that it addresses all the tactical-level decisions in liner shipping. Not addressing a tactical-level decision might lead to loss of profit. For a demonstration purpose, a simplified version of the **HOMTLP** model was formulated, where $\boldsymbol{d}_{rv}$ (which represents assignment of vessel types to port rotations) was not a decision variable. Instead, it was treated as a parameter (i.e., fleet deployment decisions were not made by the mathematical model). Such mathematical formulation replicates the model that was proposed by the recent liner shipping study, conducted by Giovannini and Psaraftis (2018), where the authors directly modeled the port service frequency determination decisions, the sailing speed optimization decisions, and some of the vessel schedule design decisions. However, the fleet deployment decision problem was not considered.

To compare different components of the simplified model and the original **HOMTLP** model, a total of 20 scenarios were developed. With increments of 50 USD/ton, the unit fuel cost was increased from 50 USD/ton in scenario #1 to 1,000 USD/ton in scenario #20. Moreover, the averages of different components for the 20 developed scenarios were then estimated for a better demonstration. Results from the simplified model along with those of the original **HOMTLP** model are presented in Table 8.

It can be observed that on average, the simplified model required less CPU time than the original **HOMTLP** model, since the simplified model had to take less decisions. The average vessel operational cost was higher for the original **HOMTLP** model, while the average vessel chartering cost was higher for the simplified model. Such finding can be supported by the fact that the original **HOMTLP** model attempted to employ more of the liner shipping company's own vessels (which were less expensive), while the simplified model had to charter more vessels (as fleet deployment decisions were not up to the simplified model). Moreover, the average fuel consumption cost, the average port handling cost, and the average emission cost in sea for the simplified model were significantly higher than those for the original **HOMTLP** model. On the other hand, the original **HOMTLP** model's average late arrival cost was significantly higher than that of the simplified model. The other cost components were close, on average, for the aforementioned models. However, the objective function, which is the total profit, was higher for the original **HOMTLP** model, as compared to the simplified model. Therefore, the original **HOMTLP** model is preferred to the models, which leave any major tactical-level decisions in liner shipping.

Table 8 Differences between different components of the HOMTLP model, which addresses all tactical-level decisions and the simplified model, which addresses all tactical-level decisions except fleet deployment.

Status of d_{rv}	**Parameter**	**Variable**	**Parameter**	**Variable**	**Parameter**	**Variable**	**Parameter**	**Variable**
Unit Fuel Cost (USD/ton)	**Profit (USD)**		**REV (USD)**		**VOC (USD)**		**VCC (USD)**	
50	24,987,973	25,996,602	38,773,048	38,749,966	2,799,000	3,500,000	1,652,000	910,000
100	24,189,709	25,143,479	38,791,269	38,721,539	2,842,000	3,117,000	1,652,000	1,560,000
150	23,330,370	24,783,290	38,725,743	38,687,198	2,842,000	3,578,000	1,770,000	910,000
200	22,628,938	23,972,668	38,777,507	38,665,094	2,842,000	3,320,000	1,652,000	1,430,000
250	21,930,500	23,476,984	38,760,913	38,703,132	2,604,000	3,242,000	2,124,000	1,430,000
300	21,174,602	23,001,720	38,739,263	38,671,980	2,647,000	3,242,000	2,124,000	1,430,000
350	20,556,368	22,474,838	38,635,165	38,562,605	2,569,000	3,523,000	2,714,000	1,300,000
400	19,987,396	22,059,693	38,639,444	38,644,054	2,725,000	3,578,000	2,655,000	910,000
450	19,363,596	21,423,258	38,636,017	38,683,334	2,452,000	3,234,000	2,832,000	1,300,000
500	18,761,883	20,999,366	38,604,307	38,660,921	2,647,000	3,320,000	2,832,000	1,430,000
550	18,283,661	20,540,033	38,609,170	38,559,109	2,725,000	3,695,000	2,655,000	910,000
600	17,673,953	20,047,032	38,569,128	38,537,802	2,725,000	3,523,000	2,655,000	1,300,000
650	17,104,386	19,549,612	38,523,388	38,536,119	2,725,000	3,523,000	2,714,000	1,300,000
700	14,630,639	19,047,799	38,665,808	38,693,067	1,638,000	2,408,000	3,894,000	3,120,000
750	15,986,419	18,652,898	38,484,459	38,522,580	2,725,000	3,351,000	2,714,000	1,950,000
800	13,224,584	18,131,498	38,664,008	38,601,325	1,638,000	2,408,000	3,894,000	3,250,000
850	12,518,805	17,651,259	38,661,927	38,479,903	1,638,000	2,021,000	3,894,000	4,160,000
900	14,387,601	17,302,996	38,371,228	38,454,303	2,940,000	3,523,000	2,714,000	1,950,000
950	11,115,162	17,080,235	38,660,551	38,604,420	1,638,000	2,236,000	3,894,000	3,640,000
1,000	10,417,684	16,658,997	38,664,008	38,593,099	1,638,000	2,236,000	3,894,000	3,640,000
Average	18,112,711	20,899,713	38,647,818	38,616,578	2,449,950	3,128,900	2,746,450	1,891,500

Table 8 – Continued.

Status of d_{rv}	Parameter	Variable	Parameter	Variable	Parameter	Variable	Parameter	Variable
Unit Fuel Cost (USD/ton)	**FCC (USD)**		**PHC (USD)**		**LAC (USD)**		**CIC^{SEA} (USD)**	
50	772,377	554,656	3,730,278	3,443,941	92,270	0	2,942,294	3,007,535
100	1,540,097	1,100,834	3,731,796	3,366,075	67,077	58,426	2,949,912	3,039,382
150	2,189,862	1,591,520	3,822,543	3,395,006	10,089	65,247	3,023,321	3,076,600
200	3,064,053	2,077,763	3,814,040	3,392,594	13,584	58,426	2,957,120	3,104,889
250	3,565,618	2,633,573	3,811,857	3,525,881	0	35,409	3,063,191	3,088,181
300	4,236,760	3,204,926	3,809,232	3,361,950	2,655	58,426	3,097,811	3,080,036
350	4,184,015	3,403,347	3,804,384	3,352,182	0	58,426	3,356,412	3,253,115
400	4,605,759	4,182,913	3,803,567	3,496,738	0	66,235	3,478,224	3,085,345
450	5,405,993	4,934,434	3,804,316	3,407,119	0	50,853	3,348,591	3,012,798
500	5,679,737	5,083,846	3,800,536	3,404,073	0	35,409	3,495,473	3,146,190
550	6,287,032	5,497,029	3,800,955	3,449,747	2,655	58,426	3,483,043	3,192,042
600	6,788,401	5,792,896	3,879,152	3,373,890	2,655	58,426	3,489,350	3,248,930
650	7,181,301	6,276,660	3,875,228	3,381,713	69,388	58,426	3,529,203	3,262,839
700	9,848,591	6,085,253	3,676,266	3,650,832	2,655	67,294	3,354,433	3,187,644
750	8,238,186	6,527,763	3,891,540	3,429,259	80,180	63,028	3,532,649	3,451,481
800	11,227,593	6,698,807	3,704,385	3,691,360	2,655	69,603	3,358,135	3,302,178
850	11,938,707	6,286,966	3,696,400	3,858,151	2,655	75,820	3,356,470	3,457,409
900	9,138,669	7,460,173	3,947,834	3,422,484	314,463	153,565	3,681,986	3,586,170
950	13,333,973	7,438,512	3,704,212	3,802,141	2,655	35,409	3,357,783	3,371,067
1,000	14,034,493	7,792,783	3,704,385	3,820,670	2,655	76,261	3,358,135	3,374,078
Average	6,663,061	4,731,233	3,790,645	3,501,290	33,415	60,156	3,310,677	3,216,395

Status of d_{rv}	Parameter	Variable	Parameter	Variable	Parameter	Variable	Parameter	Variable
Unit Fuel Cost (USD/ton)	**CIC^{PORT} (USD)**		**EC^{SEA} (USD)**		**EC^{PORT} (USD)**		**CPU Time (seconds)**	
50	268,427	238,310	1,523,499	1,094,047	4,930	4,875	147.65	92.56
100	294,840	245,775	1,518,905	1,085,686	4,933	4,882	164.09	386.78
150	292,836	236,200	1,439,820	1,046,414	4,902	4,920	110.59	141.03
200	289,912	279,275	1,510,946	1,024,586	4,914	4,894	250.78	308.5
250	250,213	227,208	1,406,622	1,038,934	4,910	4,963	266.2	216.92
300	249,475	234,439	1,392,821	1,053,609	4,908	4,875	386.12	236.5
350	267,186	233,831	1,178,984	959,005	4,817	4,861	369.87	282.87
400	244,087	228,749	1,135,596	1,031,339	4,816	5,044	719.89	272.54
450	239,902	234,516	1,184,802	1,081,453	4,817	4,904	468.53	623.23
500	262,550	234,361	1,120,317	1,002,778	4,812	4,898	533.5	611.18
550	239,643	226,202	1,127,368	985,707	4,812	4,923	422.14	565.9
600	234,977	236,568	1,115,832	952,198	4,808	4,862	529.96	1,001.03
650	230,467	226,638	1,089,613	952,353	4,801	4,878	741.29	1,359.73
700	228,739	263,934	1,387,582	857,360	4,904	4,951	109.46	1,500.40
750	228,350	233,800	1,083,310	858,392	4,824	4,959	1,600.78	1,784.70
800	225,548	219,130	1,384,138	825,829	4,970	4,921	139.53	1,800.04
850	226,733	235,000	1,385,227	729,466	4,929	4,833	160.57	1,800.03
900	240,431	233,464	1,001,436	817,502	4,807	4,948	1,800.01	1,800.03
950	225,534	223,983	1,384,263	772,227	4,970	4,846	242.71	1,556.37
1,000	225,548	220,891	1,384,138	768,555	4,970	4,863	259.01	1,800.03
Average	248,270	235,614	1,287,761	946,872	4,878	4,905	471.13	907.02

6.4. Managerial Insights

A set of different sensitivity analyses were performed to obtain managerial insights that could be useful for the liner shipping companies. These sensitivity analyses include: (1) sensitivity analysis for the unit fuel cost; (2) sensitivity analysis for the unit emission cost; (3) sensitivity analysis for the unit inventory cost; (4) sensitivity analysis for the unit operational and chartering costs; (5) sensitivity analysis for the vessel availability; (6) sensitivity analysis for the unit late arrival cost; (7) sensitivity analysis for the unit freight rate; (8) sensitivity analysis for the availability of port arrival TWs; (9) sensitivity analysis for the availability of container HRs; (10) sensitivity analysis for the unit fuel cost and the unit emission cost; and (11) sensitivity analysis for the unit fuel cost and the unit inventory cost.

6.4.1. Sensitivity Analysis for the Unit Fuel Cost

A sensitivity analysis for the unit fuel cost is investigated in this section of the dissertation. A total of 20 scenarios were developed to conduct the sensitivity analysis for the unit fuel cost. With increments of 50 USD/ton, the unit fuel cost was increased from 50 USD/ton in scenario #1 to 1,000 USD/ton in scenario #20.

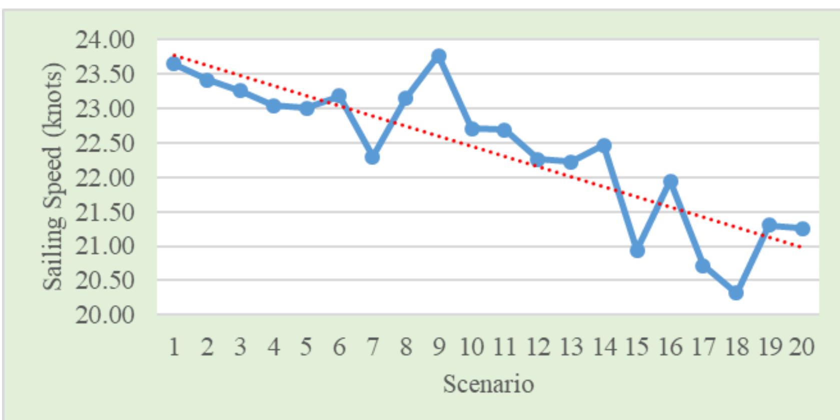


Figure 30 Sensitivity of the average sailing speed to the unit fuel cost.

Sensitivity of the average sailing speed to the unit fuel cost is presented in Figure 30. Note that the average sailing speed ($\boldsymbol{AvgWtSS}$) was weighted by the length of each voyage leg $\left(\boldsymbol{AvgWtSS} = \frac{\sum_{r\in R}\sum_{p\in P_r}\vartheta_{rp}l_{rp}}{\sum_{r\in R}\sum_{p\in P_r}l_{rp}}\right)$ in order to illustrate the impact of the voyage leg length. By decreasing the average sailing speed, the solution approach aimed to alleviate the effect of increments in the unit fuel cost. The maximum average sailing speed was observed in scenario #9, which was 23.76 knots. The minimum average sailing speed of 20.31 knots was observed in scenario #18.

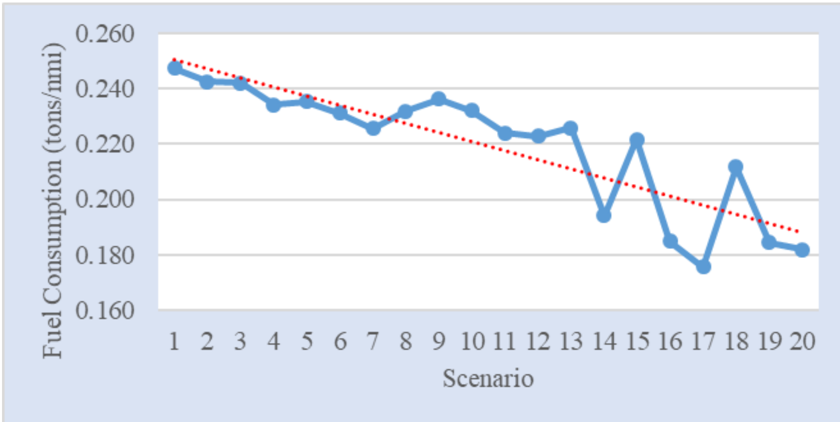


Figure 31 Sensitivity of the average fuel consumption to the unit fuel cost.

Sensitivity of the average fuel consumption to the unit fuel cost is shown in Figure 31. In order to mitigate the impact of increasing unit fuel cost, the solution approach aimed to decrease the fuel consumption cost by decreasing the average fuel consumption rate. The maximum average fuel consumption was observed in scenario #1, which was 0.247 tons/nmi. The minimum average fuel consumption of 0.175 tons/nmi was observed in scenario #17.

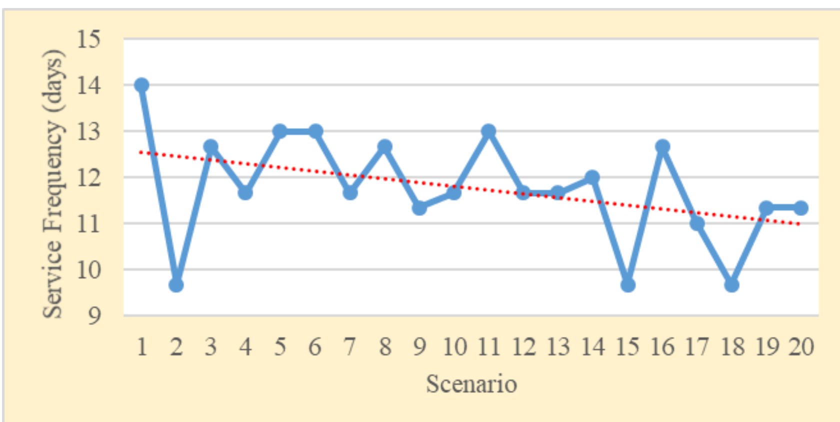


Figure 32 Sensitivity of the average port service frequency to the unit fuel cost.

Sensitivity of the average port service frequency to the unit fuel cost is presented in Figure 32. Since the sailing speed was decreased, the solution approach attempted to meet the demand by decreasing the port service frequency (i.e., the ports were visited more frequently). The maximum average port service frequency was observed in scenario #1, which was 14 days. The minimum average port service frequency of 9.67 days was observed in scenarios #2, #15, and #18.

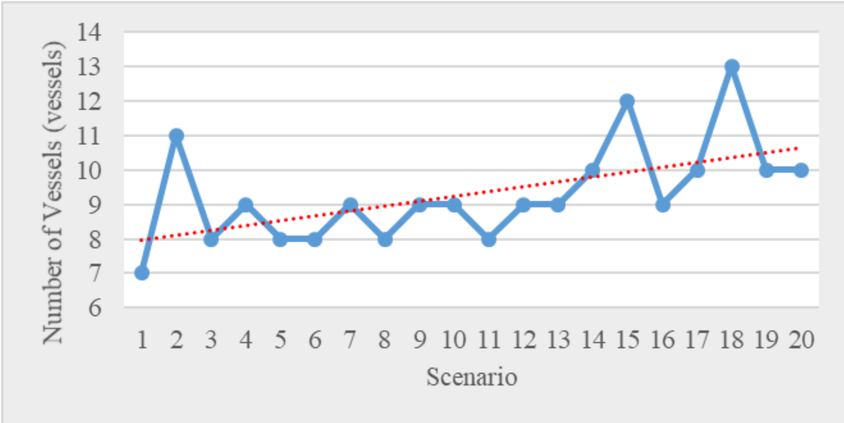


Figure 33 Sensitivity of the required number of vessels to the unit fuel cost.

Sensitivity of the required number of vessels to the unit fuel cost is highlighted in Figure 33. As the average port service frequency was decreased due to increments in the unit fuel cost, more vessels were required for deployment. Scenario #18 required the largest number of vessels to be deployed (13 vessels), while only 7 vessels were deployed in scenario #1.

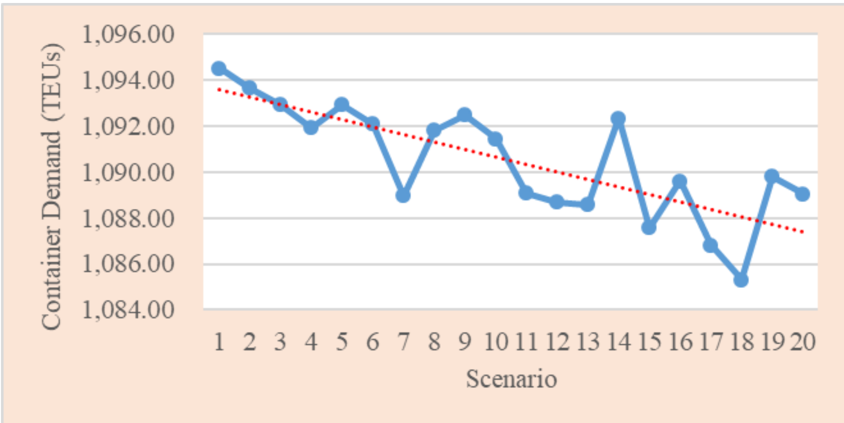


Figure 34 Sensitivity of the average container demand at ports to the unit fuel cost.

Sensitivity of the average container demand at ports to the unit fuel cost is presented in Figure 34. In the formulated mathematical model, the container demand at ports is inversely proportional to the sailing speed reciprocal. Since the sailing speed was decreased (i.e., sailing speed reciprocal was increased) with increasing unit fuel cost, the container demand at ports went through a decreasing trend. The maximum average container demand at ports was observed in scenario #1, which was 1,094.52 TEUs. The minimum average container demand at ports of 1,085.31 TEUs was observed in scenario #18.

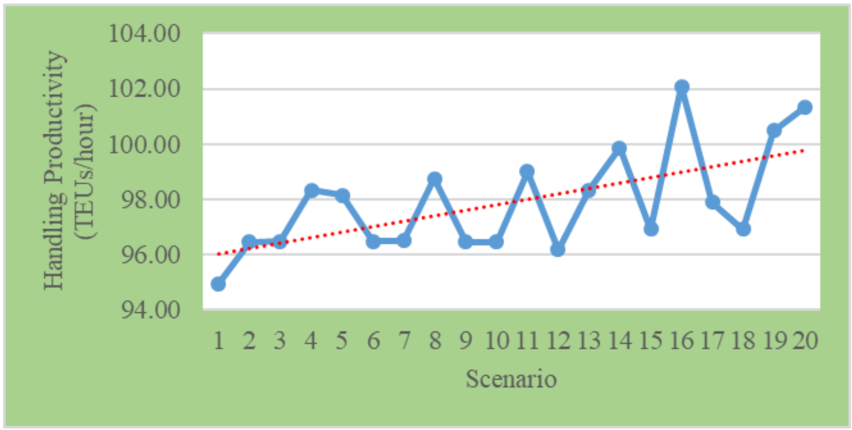


Figure 35 Sensitivity of the average handling productivity to the unit fuel cost.

Sensitivity of the average port handling productivity to the unit fuel cost is shown in Figure 35. It should be noted that in order to demonstrate the impact of the container demand, the average port handling productivity ($\boldsymbol{AvgWtHP}$) was weighted by container demand $\left(\boldsymbol{AvgWtHP} = \frac{\sum_{r\in R}\sum_{p\in P_r}\sum_{t\in T_{rp}}\sum_{h\in H_{rpt}}\sum_{v\in V} ph_{rpthv}\boldsymbol{QC}_{rp}^{PORT}\boldsymbol{x}_{rpthv}}{\sum_{r\in R}\sum_{p\in P_r}\boldsymbol{QC}_{rp}^{PORT}}\right)$. Due to increments in the unit fuel cost, the average port handling productivity experienced an increasing trend. Such pattern can be explained by the fact that the liner shipping company aimed to reduce the vessel handling time at ports of call (by requesting HRs with higher handling productivities) and use these time savings to compensate for the time losses in sea (since the vessel sailing speed generally decreased with increasing unit fuel cost from one scenario to another). The maximum average port handling productivity was observed in scenario #16, which was 102.08 TEUs/hour. The minimum average port handling productivity of 94.94 TEUs/hour was observed in scenario #1.

Sensitivity of the total quantity of emissions produced in sea to the unit fuel cost is presented in Figure 36. Since the quantity of emissions produced by the vessels in sea is proportional to the fuel consumption, and the fuel consumption was reduced because of an increase in the unit fuel cost, the quantity of emissions produced in sea was also decreased. The maximum quantity of emissions produced in sea was observed in scenario #1, which was 34,188.98 tons. The minimum quantity of emissions produced in sea of 22,795.80 tons was observed in scenario #17. Note that the total quantity of emissions produced due to handling of containers at ports, which was significantly less than the quantity of emissions produced in sea, also fluctuated due to an increase in the unit fuel cost (since the container demand at ports and port operations were impacted from changing the unit fuel cost).

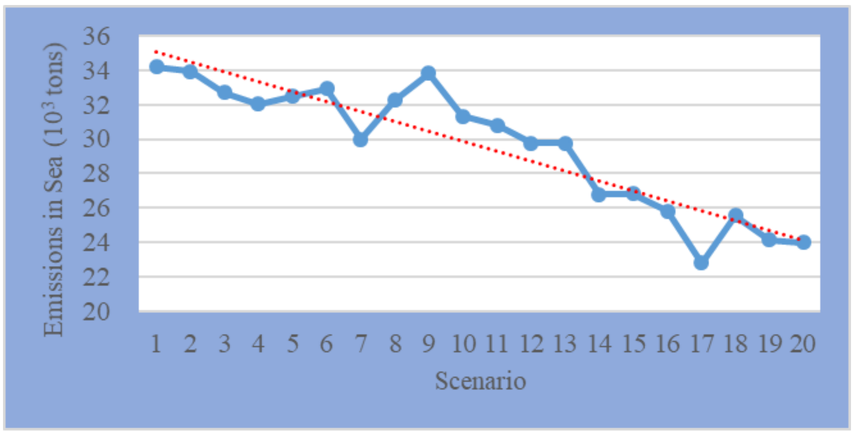


Figure 36 Sensitivity of the quantity of emissions produced in sea to the unit fuel cost.

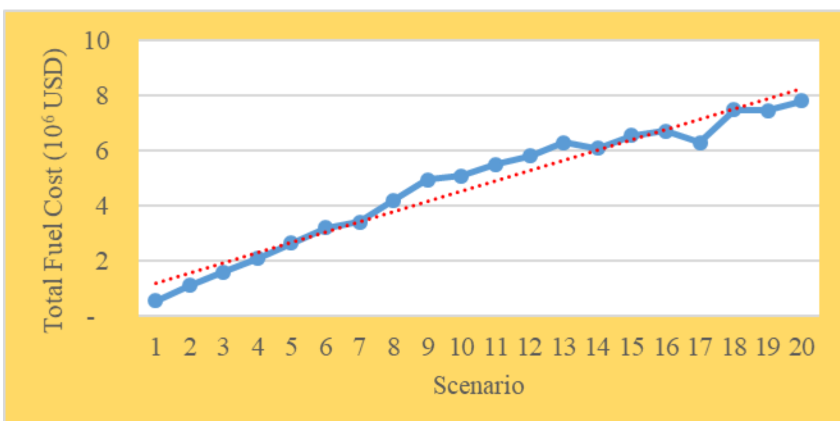


Figure 37 Sensitivity of the total fuel cost to the unit fuel cost.

Sensitivity of the total fuel cost to the unit fuel cost is highlighted in Figure 37. Even though the fuel consumption per unit length was decreased in order to mitigate the impact of an increase in the unit fuel cost, an increasing trend in the total fuel cost was still noted. The minimum total fuel cost was observed in scenario #1, which was 0.55 million USD. The maximum total fuel cost of 7.79 million USD was observed in scenario #20.

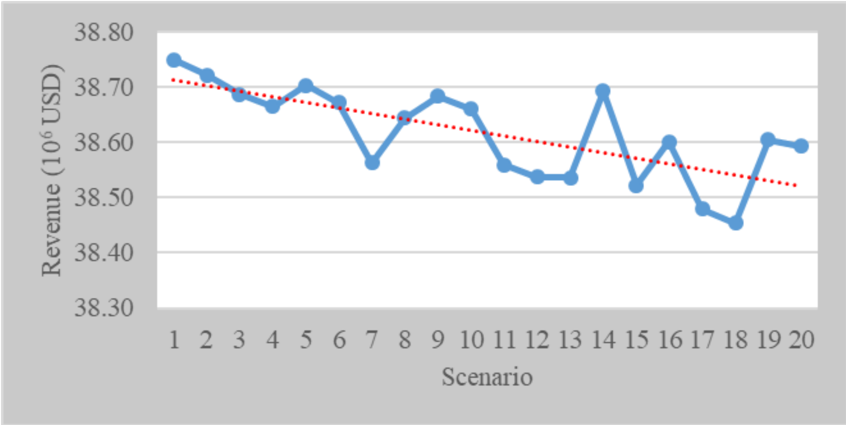


Figure 38 Sensitivity of the total revenue to the unit fuel cost.

Sensitivity of the total revenue to the unit fuel cost is presented in Figure 38. Due to increments in the unit fuel cost, the total revenue experienced an overall decreasing trend. The latter finding can be justified by a reduction in container demand at ports of call after increasing the unit fuel cost. The maximum revenue was observed in scenario #1, which was 38.75 million USD. The minimum revenue of 38.45 million USD was observed in scenario #18.

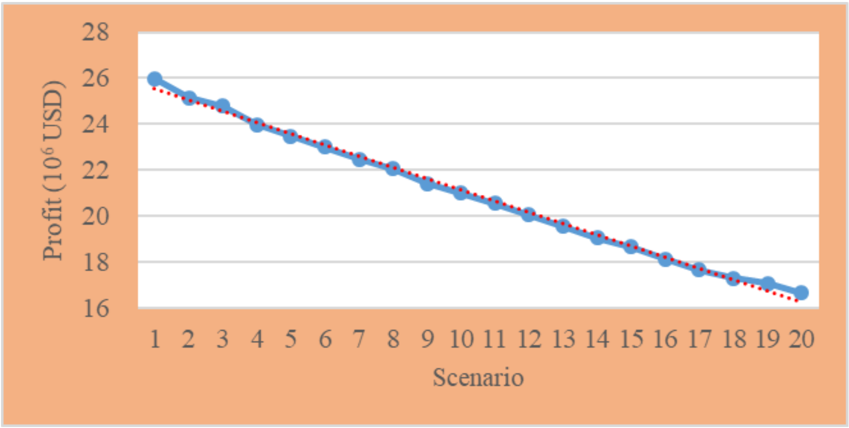


Figure 39 Sensitivity of the total profit to the unit fuel cost.

Sensitivity of the total profit to the unit fuel cost is shown in Figure 39. Due to increments in the unit fuel cost, the total profit experienced a decreasing pattern. The maximum profit was observed in scenario #1, which was 26.00 million USD. The minimum profit of 16.65 million USD was observed in scenario #20.

Table 9 presents changes in different variables of the mathematical model due to increments in the unit fuel cost. Apart from changes in the aforementioned variables, a number of other changes were noticed due to an increase in the unit fuel cost. Among the components of the route service cost, an overall reduction in the total vessel operational cost, the total container inventory cost at ports, and the total emission cost in sea was observed. On the other hand, the total vessel chartering cost, the total port handling cost, the total late arrival cost, and the total container inventory cost in sea experienced an increasing trend. The total emission cost at ports fluctuated from one scenario to another, but no clear increasing or decreasing trend was observed. In addition to the cost components, changes in other variables were also observed. The total quantity of emissions produced in sea and at ports followed trends similar to the total emission cost in sea and at ports, respectively. The quantity of containers transported by the vessels stayed the same. The required number of own vessels was decreased, and the required number of chartered vessels was increased. Moreover, increments in the average size of vessels were also observed. Last but not least, increments in the unit fuel cost increased the CPU times and the optimality gaps for the problem instances. The latter patterns can be explained by changes in the feasible space for the formulated optimization model.

6.4.2. Sensitivity Analysis for the Unit Emission Cost

A sensitivity analysis for the unit emission cost is investigated in this section of the dissertation. A total of 20 scenarios were developed to conduct the sensitivity analysis for the unit emission cost. With increments of 16 USD/ton, the unit emission cost was increased from 16 USD/ton in scenario #1 to 320 USD/ton in scenario #20. Sensitivity of the average sailing speed to the unit emission cost is presented in Figure 40. By decreasing the average sailing speed, the solution approach aimed to alleviate the effect of increments in the unit emission cost. The maximum average sailing speed was observed in scenario #1, which was 23.73 knots. The minimum average sailing speed of 20.27 knots was observed in scenario #20.

Table 9 Sensitivity analysis for the unit fuel cost.

Scenario	Unit Fuel Cost (USD/ton)	Profit (USD)	REV (USD)	VOC (USD)	VCC (USD)	FCC (USD)	PHC (USD)	LAC (USD)
1	50	25,996,602	38,749,966	3,500,000	910,000	554,656	3,443,941	0
2	100	25,143,479	38,721,539	3,117,000	1,560,000	1,100,834	3,366,075	58,426
3	150	24,783,290	38,687,198	3,578,000	910,000	1,591,520	3,395,006	65,247
4	200	23,972,668	38,665,094	3,320,000	1,430,000	2,077,763	3,392,594	58,426
5	250	23,476,984	38,703,132	3,242,000	1,430,000	2,633,573	3,525,881	35,409
6	300	23,001,720	38,671,980	3,242,000	1,430,000	3,204,926	3,361,950	58,426
7	350	22,474,838	38,562,605	3,523,000	1,300,000	3,403,347	3,352,182	58,426
8	400	22,059,693	38,644,054	3,578,000	910,000	4,182,913	3,496,738	66,235
9	450	21,423,258	38,683,334	3,234,000	1,300,000	4,934,434	3,407,119	50,853
10	500	20,999,366	38,660,921	3,320,000	1,430,000	5,083,846	3,404,073	35,409
11	550	20,540,033	38,559,109	3,695,000	910,000	5,497,029	3,449,747	58,426
12	600	20,047,032	38,537,802	3,523,000	1,300,000	5,792,896	3,373,890	58,426
13	650	19,549,612	38,536,119	3,523,000	1,300,000	6,276,660	3,381,713	58,426
14	700	19,047,799	38,693,067	2,408,000	3,120,000	6,085,253	3,650,832	67,294
15	750	18,652,898	38,522,580	3,351,000	1,950,000	6,527,763	3,429,259	63,028
16	800	18,131,498	38,601,325	2,408,000	3,250,000	6,698,807	3,691,360	69,603
17	850	17,651,259	38,479,903	2,021,000	4,160,000	6,286,966	3,858,151	75,820
18	900	17,302,996	38,454,303	3,523,000	1,950,000	7,460,173	3,422,484	153,565
19	950	17,080,235	38,604,420	2,236,000	3,640,000	7,438,512	3,802,141	35,409
20	1,000	16,658,997	38,593,099	2,236,000	3,640,000	7,792,783	3,820,670	76,261

Table 9 – Continued.

Scenario	$\boldsymbol{CIC^{SEA}}$ (USD)	$\boldsymbol{CIC^{PORT}}$ (USD)	$\boldsymbol{EC^{SEA}}$ (USD)	$\boldsymbol{EC^{PORT}}$ (USD)	$\boldsymbol{TotEP^{SEA}}$ (tons)	$\boldsymbol{TotEP^{PORT}}$ (tons)	$\boldsymbol{AvgQC^{SEA}}$ (TEUs)	$\boldsymbol{AvgQC^{PORT}}$ (TEUs)
1	3,007,535	238,310	1,094,047	4,875	34,188.98	152.33	5,594.65	1,094.52
2	3,039,382	245,775	1,085,686	4,882	33,927.70	152.55	5,595.09	1,093.64
3	3,076,600	236,200	1,046,414	4,920	32,700.44	153.76	5,595.08	1,092.92
4	3,104,889	279,275	1,024,586	4,894	32,018.32	152.93	5,594.77	1,091.92
5	3,088,181	227,208	1,038,934	4,963	32,466.69	155.09	5,594.19	1,092.92
6	3,080,036	234,439	1,053,609	4,875	32,925.27	152.33	5,594.50	1,092.10
7	3,253,115	233,831	959,005	4,861	29,968.90	151.91	5,593.81	1,088.97
8	3,085,345	228,749	1,031,339	5,044	32,229.34	157.61	5,594.84	1,091.82
9	3,012,798	234,516	1,081,453	4,904	33,795.39	153.24	5,593.67	1,092.49
10	3,146,190	234,361	1,002,778	4,898	31,336.82	153.08	5,593.45	1,091.45
11	3,192,042	226,202	985,707	4,923	30,803.35	153.85	5,595.18	1,089.09
12	3,248,930	236,568	952,198	4,862	29,756.18	151.92	5,594.76	1,088.70
13	3,262,839	226,638	952,353	4,878	29,761.02	152.45	5,594.28	1,088.58
14	3,187,644	263,934	857,360	4,951	26,792.50	154.73	5,594.24	1,092.33
15	3,451,481	233,800	858,392	4,959	26,824.75	154.97	5,594.36	1,087.58
16	3,302,178	219,130	825,829	4,921	25,807.15	153.79	5,594.72	1,089.60
17	3,457,409	235,000	729,466	4,833	22,795.80	151.03	5,595.41	1,086.83
18	3,586,170	233,464	817,502	4,948	25,546.95	154.64	5,594.14	1,085.31
19	3,371,067	223,983	772,227	4,846	24,132.10	151.45	5,594.69	1,089.80
20	3,374,078	220,891	768,555	4,863	24,017.36	151.98	5,594.15	1,089.06

Note:

$\boldsymbol{TotEP^{SEA}}$ – total quantity of emissions produced in sea (tons); $\boldsymbol{TotEP^{PORT}}$ – total quantity of emissions produced at ports (tons); $\boldsymbol{AvgQC^{SEA}}$ – average quantity of containers to be transported at each voyage leg (TEUs); $\boldsymbol{AvgQC^{PORT}}$ – average quantity of containers to be handled at each port (TEUs).

Table 9 – Continued.

Scenario	$Totq$ (vessels)	$Totq^{own}$ (vessels)	$Totq^{char}$ (vessels)	$Avgf$ (days)	$AvgRF$ (tons/nmi)	$AvgWtSpd$ (knots)	$AvgWtHP$ (TEUs/hour)	$AvgWtCCC$ (tons)	CPU Time (seconds)	Optimality Gap (%)
1	7	6	1	14.00	0.247	23.64	94.94	148,285.71	92.56	2.38%
2	11	7	4	9.67	0.243	23.41	96.43	148,363.64	386.78	3.00%
3	8	7	1	12.67	0.242	23.25	96.47	147,750.00	141.03	2.95%
4	9	7	2	11.67	0.234	23.04	98.32	148,000.00	308.50	3.00%
5	8	6	2	13.00	0.235	23.00	98.12	148,500.00	216.92	3.00%
6	8	6	2	13.00	0.231	23.17	96.47	148,500.00	236.50	2.82%
7	9	7	2	11.67	0.226	22.30	96.48	148,000.00	282.87	3.00%
8	8	7	1	12.67	0.232	23.15	98.74	147,750.00	272.54	3.00%
9	9	7	2	11.33	0.236	23.76	96.43	148,000.00	623.23	3.00%
10	9	7	2	11.67	0.232	22.71	96.44	148,000.00	611.18	3.00%
11	8	7	1	13.00	0.224	22.69	98.98	147,750.00	565.90	3.00%
12	9	7	2	11.67	0.223	22.26	96.16	148,000.00	1,001.03	3.00%
13	9	7	2	11.67	0.226	22.22	98.32	148,000.00	1,359.73	3.00%
14	10	4	6	12.00	0.194	22.46	99.86	150,000.00	1,500.40	3.00%
15	12	7	5	9.67	0.222	20.94	96.91	148,500.00	1,784.70	3.00%
16	9	4	5	12.67	0.185	21.94	102.08	150,000.00	1,800.04	3.62%
17	10	4	6	11.00	0.175	20.72	97.88	150,000.00	1,800.03	4.23%
18	13	7	6	9.67	0.212	20.31	96.91	148,615.38	1,800.03	3.97%
19	10	4	6	11.33	0.184	21.30	100.48	150,000.00	1,556.37	3.00%
20	10	4	6	11.33	0.182	21.26	101.34	150000.00	1,800.03	3.03%

Note:

$\boldsymbol{Totq}$ – total number of required vessels (vessels); $\boldsymbol{Totq^{own}}$ – total number of own vessels required (vessels); $\boldsymbol{Totq^{char}}$ – total number of chartered vessels required (vessels); $\boldsymbol{Avgf}$ – average port service frequency (days); $\boldsymbol{AvgRF}$ – average fuel consumption (tons/nmi); $\boldsymbol{AvgWtSpd}$ – average vessel sailing speed weighted by voyage leg length (knots); $\boldsymbol{AvgWtHP}$ – average requested handling productivity weighted by the number of containers handled at ports (TEUS/hour); $\boldsymbol{AvgWtCCC}$ – average weighted cargo carrying capacity of vessels (tons).

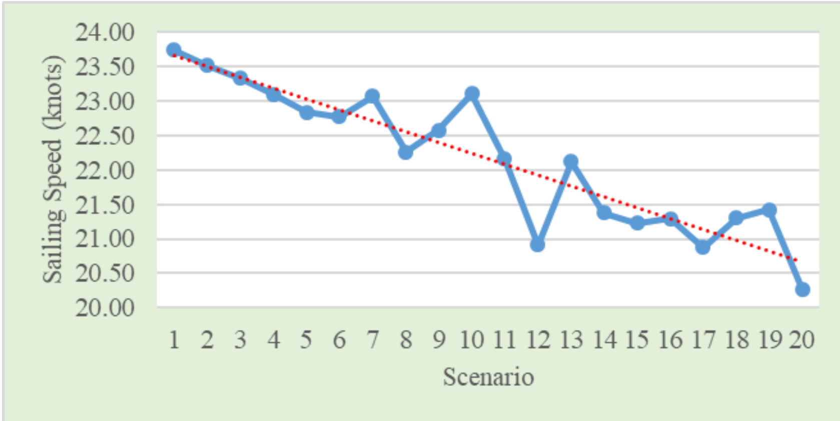


Figure 40 Sensitivity of the average sailing speed to the unit emission cost.

Sensitivity of the average fuel consumption to the unit emission cost is shown in Figure 41. In order to mitigate the impact of increasing unit emission cost, the solution approach aimed to decrease the fuel consumption cost by decreasing the average fuel consumption rate. The maximum average fuel consumption was observed in scenario #1, which was 0.250 tons/nmi. The minimum average fuel consumption of 0.174 tons/nmi was observed in scenario #20.

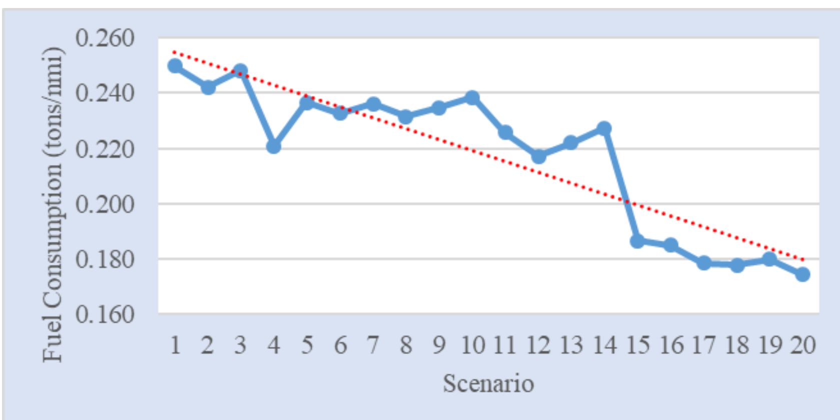


Figure 41 Sensitivity of the average fuel consumption to the unit emission cost.

Sensitivity of the average port service frequency to the unit emission cost is presented in Figure 42. Since the sailing speed was decreased, the solution approach attempted to meet the demand by decreasing the port service frequency (i.e., the ports were visited more frequently). The maximum average port service frequency was observed in scenarios #2 and #6, which was 13 days. The minimum average port service frequency of 11 days was observed in scenario #12.

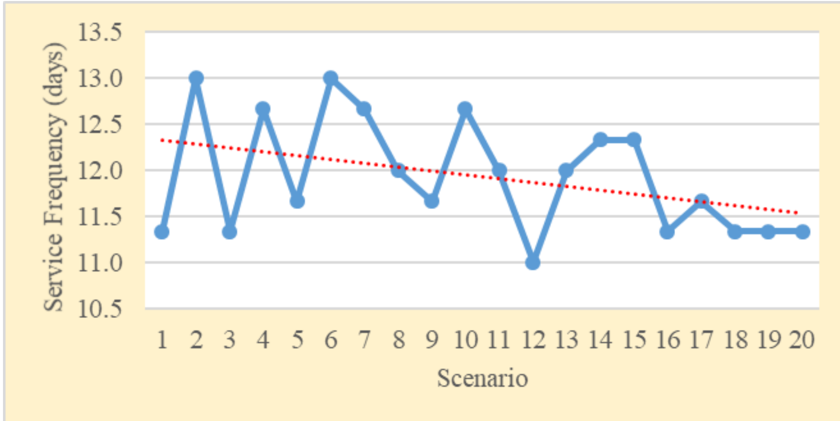


Figure 42 Sensitivity of the average port service frequency to the unit emission cost.

Sensitivity of the required number of vessels to the unit emission cost is highlighted in Figure 43. As the average port service frequency was decreased due to increments in the unit emission cost, more vessels were required for deployment. Scenarios #12, #16, #17, #18, #19, and #20 required the largest number of vessels to be deployed (10 vessels), while only 8 vessels were deployed in scenarios #2, #4, #6, #7, and #10.

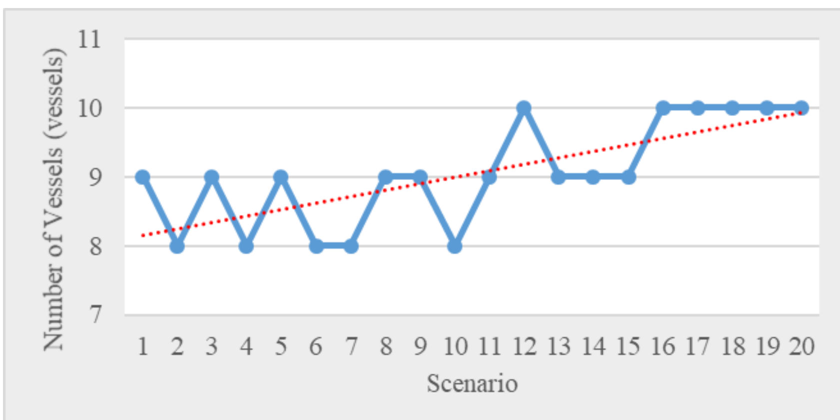


Figure 43 Sensitivity of the required number of vessels to the unit emission cost.

Sensitivity of the average port handling productivity to the unit emission cost is shown in Figure 44. Due to increments in the unit emission cost, the average port handling productivity experienced an increasing trend. Such pattern can be explained by the fact that the liner shipping company aimed to reduce the vessel handling time at ports of call (by requesting HRs with higher handling productivities) and use these time savings to compensate for the time losses in sea (since the vessel sailing speed generally decreased with increasing unit emission cost from one scenario to another). The maximum average port handling productivity was observed in scenario #18, which was 102.53 TEUs/hour. The minimum average port handling productivity of 94.21 TEUs/hour was observed in scenario #5.

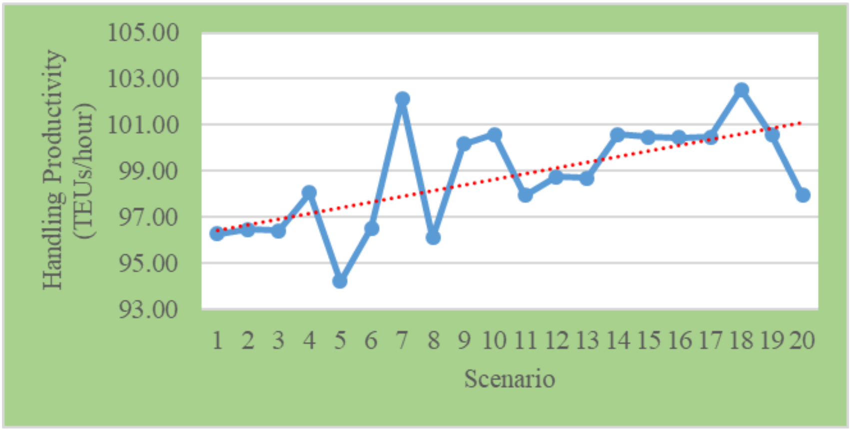


Figure 44 Sensitivity of the average handling productivity to the unit emission cost.

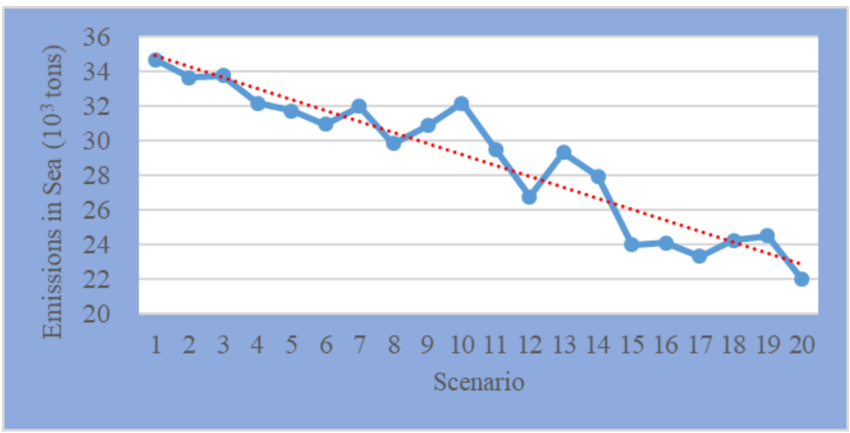


Figure 45 Sensitivity of the quantity of emissions produced in sea to the unit emission cost.

Sensitivity of the total quantity of emissions produced in sea to the unit emission cost is presented in Figure 45. Since the quantity of emissions produced by the vessels in sea is proportional to the fuel consumption, and the fuel consumption was reduced because of an increase in the unit emission cost, the quantity of emissions produced in sea was also decreased. The maximum quantity of emissions produced in sea was observed in scenario #1, which was 34,694.41 tons. The minimum quantity of emissions produced in sea of 21,971.50 tons was observed in scenario #20. Note that the total quantity of emissions produced due to handling of containers at ports, which was significantly less than the quantity of emissions produced in sea, also decreased due to an increase in the unit emission cost (since the container demand at ports and port operations were impacted from changing the unit emission cost).

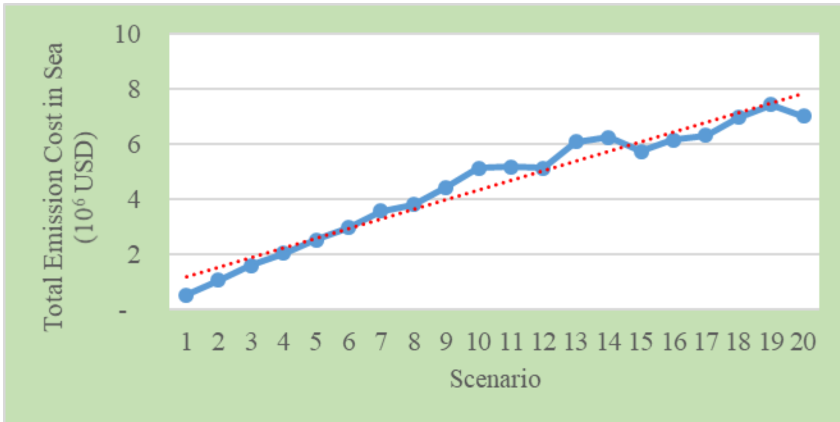


Figure 46 Sensitivity of the total emission cost in sea to the unit emission cost.

Sensitivity of the total emission cost in sea to the unit emission cost is highlighted in Figure 46. Even though the total quantity of emissions produced in sea was decreased in order to mitigate the impact of an increase in the unit emission cost, an increasing trend in total emission cost in sea was still noted. The minimum total emission cost in sea was observed in scenario #1, which was 0.55 million USD. The maximum total emission cost in sea of 7.44 million USD was observed in scenario #19.

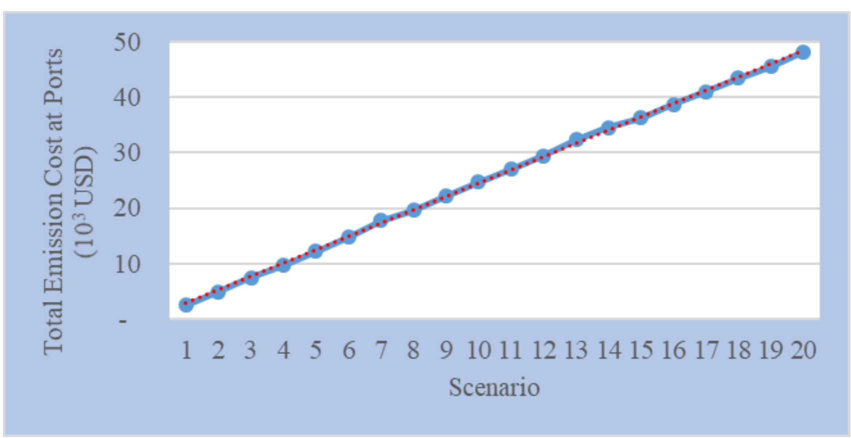


Figure 47 Sensitivity of the total emission cost at ports to the unit emission cost.

Sensitivity of the total emission cost at ports to the unit emission cost is highlighted in Figure 47. Even though total quantity of emissions produced at ports was decreased in order to mitigate the impact of an increase in the unit emission cost, an increasing trend in total emission cost at ports was still noted. The minimum total emission cost at ports was observed in scenario #1, which was 2,465 USD. The maximum total emission cost at ports of 48,257 USD was observed in scenario #20.

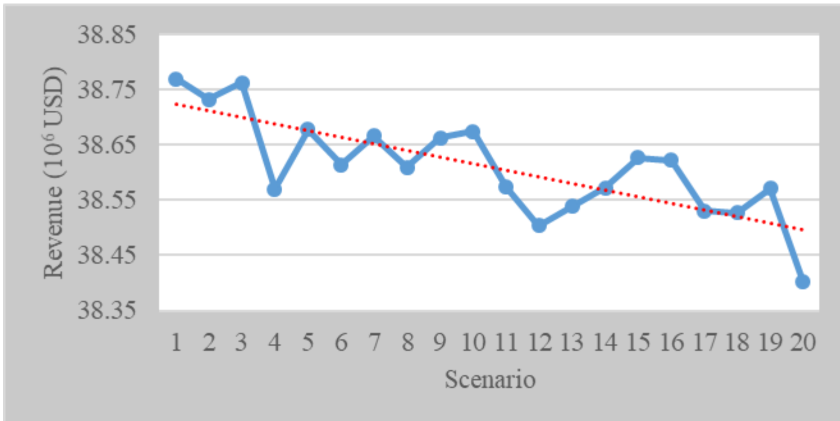


Figure 48 Sensitivity of the total revenue to the unit emission cost.

Sensitivity of the total revenue to the unit emission cost is presented in Figure 48. Due to increments in the unit emission cost, the total revenue experienced an overall decreasing trend. The latter finding can be justified by a reduction in container demand at ports of call after increasing the unit emission cost. The maximum revenue was observed in scenario #1, which was 38.77 million USD. The minimum revenue of 38.40 million USD was observed in scenario #20.

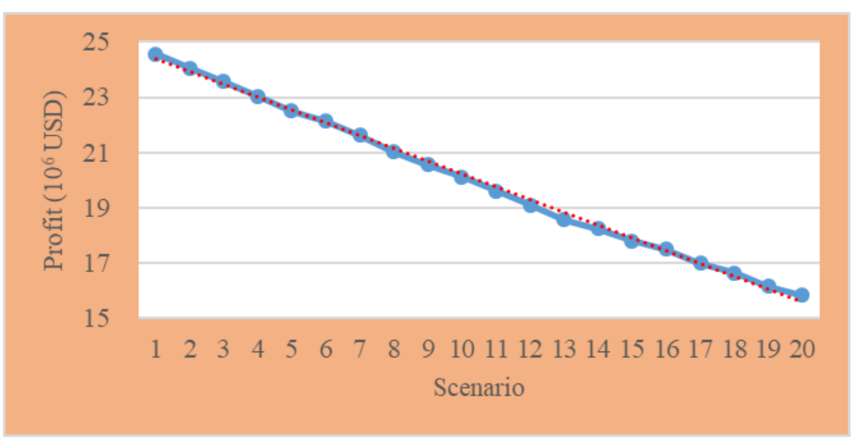


Figure 49 Sensitivity of the total profit to the unit emission cost.

Sensitivity of the total profit to the unit emission cost is shown in Figure 49. Due to increments in the unit emission cost, the total profit experienced a decreasing pattern. The maximum profit was observed in scenario #1, which was 24.57 million USD. The minimum profit of 15.82 million USD was observed in scenario #20.

Table 10 presents changes in different variables of the mathematical model due to increments in the unit emission cost. Apart from changes in the aforementioned variables, a number of other changes were noticed due to an increase in the unit emission cost. Among the components of the route service cost, an overall reduction in the total vessel operational cost, the total fuel cost, and the total container inventory cost at ports was observed. On the other hand, the total vessel chartering cost, the total port handling cost, the total late arrival cost, and the total container inventory cost in sea experienced an increasing trend.

In addition to the cost components, changes in other variables were also observed. The total quantity of emissions produced in sea and at ports followed trends similar to the total emission cost in sea and at ports, respectively. The container demand at ports was decreased, while the quantity of containers transported by the vessels stayed the same. The required number of own vessels was decreased, and the required number of chartered vessels was increased. Moreover, increments in the average size of vessels were also observed. Last but not least, increments in the unit emission cost increased the CPU times and the optimality gaps for the problem instances. The latter patterns can be explained by changes in the feasible space for the formulated optimization model.

6.4.3. Sensitivity Analysis for the Unit Inventory Cost

A sensitivity analysis for the unit inventory cost is investigated in this section of the dissertation. A total of 20 scenarios were developed to conduct the sensitivity analysis for the unit inventory cost. With increments of 0.05 USD/TEU/hour, the unit inventory cost was increased from 0.05 USD/TEU/hour in scenario #1 to 1.00 USD/TEU/hour in scenario #20.

Table 10 Sensitivity analysis for the unit emission cost.

Scenario	Unit Emission Cost (USD/ton)	Profit (USD)	REV (USD)	VOC (USD)	VCC (USD)	FCC (USD)	PHC (USD)	LAC (USD)
1	16	24,572,747	38,769,150	3,203,000	1,430,000	2,251,422	3,413,389	58,426
2	32	24,052,953	38,732,295	3,242,000	1,430,000	2,185,334	3,366,998	58,426
3	48	23,581,678	38,762,756	3,203,000	1,430,000	2,191,088	3,413,088	35,409
4	64	23,036,798	38,570,463	3,578,000	910,000	2,088,502	3,506,347	64,461
5	80	22,509,719	38,678,357	3,320,000	1,430,000	2,058,064	3,373,204	58,426
6	96	22,126,501	38,614,197	3,695,000	910,000	2,008,454	3,387,851	86,046
7	112	21,631,317	38,666,268	3,578,000	910,000	2,076,524	3,454,765	95,233
8	128	21,028,073	38,609,398	3,437,000	1,430,000	1,936,353	3,423,008	35,409
9	144	20,545,206	38,662,773	3,320,000	1,430,000	2,004,505	3,448,391	60,826
10	160	20,110,707	38,674,408	3,578,000	910,000	2,087,840	3,413,838	83,843
11	176	19,597,946	38,573,953	3,437,000	1,430,000	1,915,757	3,451,811	35,409
12	192	19,087,123	38,503,821	3,265,000	2,080,000	1,736,531	3,409,134	71,291
13	208	18,548,458	38,538,945	3,437,000	1,430,000	1,903,658	3,462,805	140,370
14	224	18,242,150	38,571,970	3,523,000	1,560,000	1,813,969	3,446,086	71,291
15	240	17,787,882	38,626,678	2,150,000	3,835,000	1,555,219	3,804,166	75,820
16	256	17,499,633	38,622,106	2,236,000	3,640,000	1,562,872	3,804,013	80,550
17	272	16,988,212	38,530,853	2,150,000	3,965,000	1,511,066	3,793,543	50,973
18	288	16,621,146	38,526,992	2,236,000	3,640,000	1,571,192	3,786,950	59,321
19	304	16,150,927	38,571,768	2,236,000	3,640,000	1,588,782	3,872,214	0
20	320	15,821,807	38,402,327	1,978,000	4,420,000	1,425,795	3,848,012	35,409

Table 10 – Continued.

Scenario	CIC^{SEA} (USD)	CIC^{PORT} (USD)	EC^{SEA} (USD)	EC^{PORT} (USD)	$TotEP^{SEA}$ (tons)	$TotEP^{PORT}$ (tons)	$AvgQC^{SEA}$ (TEUs)	$AvgQC^{PORT}$ (TEUs)
1	2,997,057	285,534	555,111	2,465	34,694.41	154.03	5,594.76	1,094.84
2	3,027,366	286,703	1,077,632	4,883	33,676.00	152.60	5,594.48	1,093.79
3	3,045,347	235,072	1,620,704	7,370	33,764.67	153.54	5,594.59	1,094.58
4	3,091,648	225,279	2,059,764	9,664	32,183.81	151.00	5,595.05	1,089.89
5	3,137,490	242,081	2,537,182	12,191	31,714.77	152.39	5,594.46	1,092.17
6	3,178,706	235,685	2,971,226	14,730	30,950.27	153.43	5,594.34	1,090.66
7	3,100,662	218,086	3,583,914	17,768	31,999.23	158.64	5,594.69	1,092.18
8	3,243,561	236,995	3,819,418	19,581	29,839.21	152.98	5,594.10	1,090.33
9	3,160,655	222,971	4,448,078	22,141	30,889.43	153.76	5,594.52	1,091.91
10	3,096,033	221,690	5,147,778	24,679	32,173.61	154.25	5,594.84	1,092.45
11	3,253,486	229,703	5,195,840	27,001	29,521.82	153.41	5,594.32	1,089.49
12	3,460,000	227,336	5,137,908	29,497	26,759.94	153.63	5,594.13	1,087.03
13	3,255,751	226,766	6,101,756	32,381	29,335.37	155.68	5,593.44	1,088.55
14	3,394,791	224,548	6,261,532	34,603	27,953.27	154.48	5,594.12	1,088.82
15	3,388,083	242,327	5,751,822	36,360	23,965.93	151.50	5,594.86	1,090.26
16	3,370,696	224,102	6,165,469	38,772	24,083.86	151.45	5,594.47	1,090.05
17	3,459,424	237,862	6,333,663	41,109	23,285.53	151.14	5,594.31	1,087.44
18	3,377,582	218,185	6,973,075	43,542	24,212.06	151.19	5,594.57	1,087.53
19	3,373,428	222,002	7,442,872	45,543	24,483.13	149.81	5,594.65	1,088.77
20	3,559,335	234,831	7,030,881	48,257	21,971.50	150.80	5,594.67	1,084.68

Note:

$TotEP^{SEA}$ – total quantity of emissions produced in sea (tons); $TotEP^{PORT}$ – total quantity of emissions produced at ports (tons); $AvgQC^{SEA}$ – average quantity of containers to be transported at each voyage leg (TEUs); $AvgQC^{PORT}$ – average quantity of containers to be handled at each port (TEUs).

Table 10 – Continued.

Scenario	$\boldsymbol{Totq}$ (vessels)	$\boldsymbol{Totq^{own}}$ (vessels)	$\boldsymbol{Totq^{char}}$ (vessels)	$\boldsymbol{Avgf}$ (days)	$\boldsymbol{AvgRF}$ (tons/nmi)	$\boldsymbol{AvgWtSpd}$ (knots)	$\boldsymbol{AvgWtHP}$ (TEUs/hour)	$\boldsymbol{AvgWtCCC}$ (tons)	**CPU Time (seconds)**	**Optimality Gap (%)**
1	9	7	2	11.33	0.250	23.73	96.27	148,000.00	121.14	3.00%
2	8	6	2	13.00	0.242	23.51	96.46	148,500.00	188.95	3.00%
3	9	7	2	11.33	0.248	23.32	96.41	148,000.00	144.29	3.00%
4	8	7	1	12.67	0.221	23.09	98.07	147,750.00	162.43	3.00%
5	9	7	2	11.67	0.237	22.84	94.21	148,000.00	338.75	3.00%
6	8	7	1	13.00	0.233	22.77	96.51	147,750.00	331.39	3.00%
7	8	7	1	12.67	0.236	23.07	102.11	147,750.00	284.67	2.66%
8	9	7	2	12.00	0.232	22.26	96.11	148,000.00	523.81	3.00%
9	9	7	2	11.67	0.235	22.57	100.18	148,000.00	721.93	3.00%
10	8	7	1	12.67	0.238	23.10	100.59	147,750.00	819.43	3.00%
11	9	7	2	12.00	0.226	22.16	97.95	148,000.00	804.48	3.00%
12	10	7	3	11.00	0.217	20.91	98.76	148,200.00	1,732.25	2.97%
13	9	7	2	12.00	0.222	22.12	98.70	148,000.00	1,800.01	3.69%
14	9	7	2	12.33	0.227	21.38	100.60	148,000.00	1,800.01	3.19%
15	9	4	5	12.33	0.187	21.23	100.47	150,000.00	1,800.03	3.64%
16	10	4	6	11.33	0.185	21.29	100.46	150,000.00	1,649.15	3.00%
17	10	4	6	11.67	0.178	20.88	100.47	150,000.00	1,800.01	3.79%
18	10	4	6	11.33	0.178	21.30	102.53	150,000.00	1,800.01	3.96%
19	10	4	6	11.33	0.180	21.42	100.56	150,000.00	1,800.01	12.38%
20	10	4	6	11.33	0.174	20.27	97.94	150,000.00	1,800.01	6.82%

Note:

$\boldsymbol{Totq}$ – total number of required vessels (vessels); $\boldsymbol{Totq^{own}}$ – total number of own vessels required (vessels); $\boldsymbol{Totq^{char}}$ – total number of chartered vessels required (vessels); $\boldsymbol{Avgf}$ – average port service frequency (days); $\boldsymbol{AvgRF}$ – average fuel consumption (tons/nmi); $\boldsymbol{AvgWtSpd}$ – average vessel sailing speed weighted by voyage leg length (knots); $\boldsymbol{AvgWtHP}$ – average requested handling productivity weighted by the number of containers handled at ports (TEUS/hour); $\boldsymbol{AvgWtCCC}$ – average weighted cargo carrying capacity of vessels (tons).

Sensitivity of the average sailing speed to the unit inventory cost is presented in Figure 50. When the unit inventory cost was increased, the solution approach decreased the vessel sailing speed reciprocal (i.e., sailing speed was increased). The maximum average sailing speed was observed in scenario #15, which was 24.68 knots. The minimum average sailing speed of 23.04 knots was observed in scenario #5.

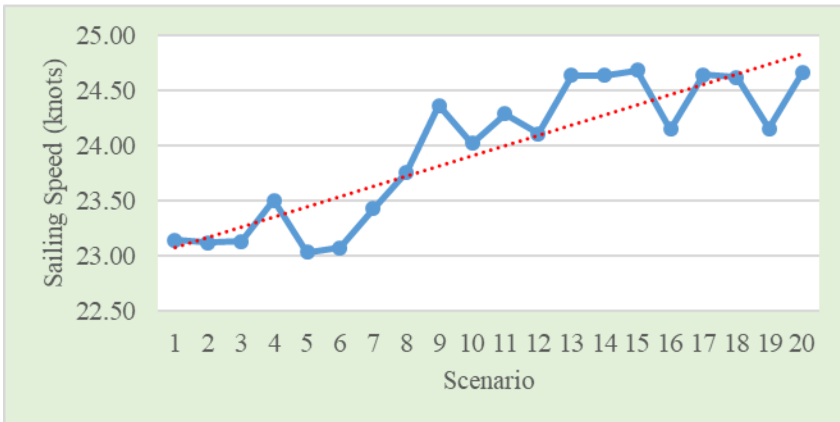


Figure 50 Sensitivity of the average sailing speed to the unit inventory cost.

Sensitivity of the average fuel consumption to the unit inventory cost is shown in Figure 51. As the sailing speed was increased due to an increase in the unit inventory cost, an increase in the average fuel consumption was noted as well. The maximum average fuel consumption was observed in scenarios #13, #14, and #18, which was 0.257 tons/nmi. The minimum average fuel consumption of 0.226 tons/nmi was observed in scenario #1.

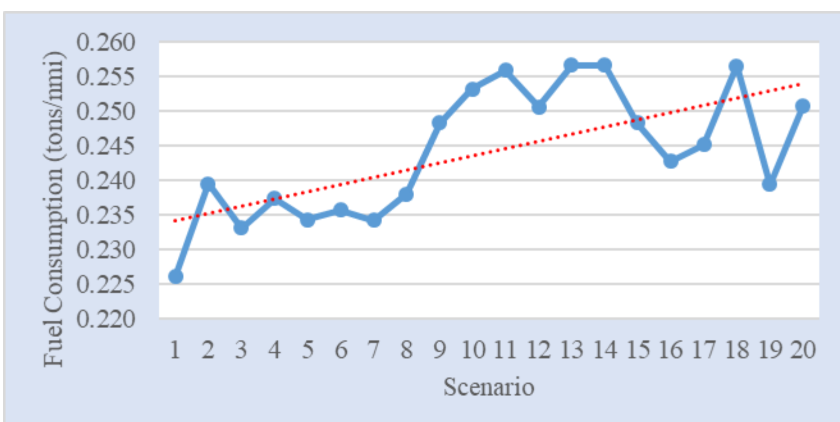


Figure 51 Sensitivity of the average fuel consumption to the unit inventory cost.

Sensitivity of the average port service frequency to the unit inventory cost is presented in Figure 52. Since the sailing speed was increased, there was no need to keep the same port service frequency. So, the average port service frequency was increased (i.e., the ports were visited less frequently). The maximum average port service frequency was observed in scenarios #11, #12, #16, and #19, which was 13.67 days. The minimum average port service frequency of 11 days was observed in scenario #9.

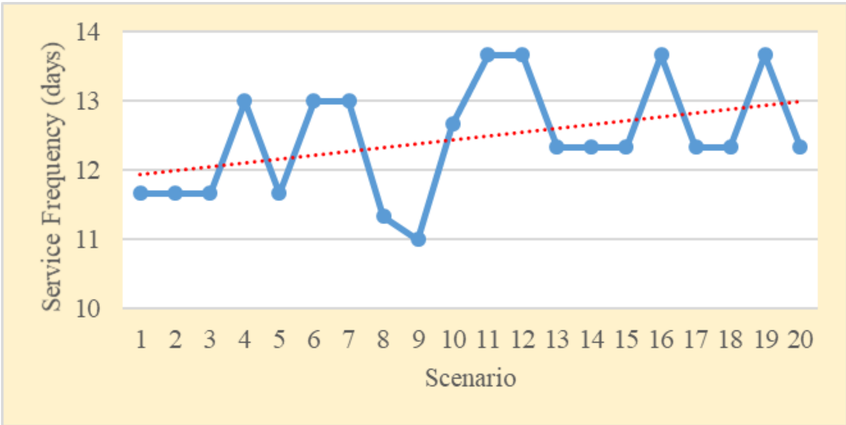


Figure 52 Sensitivity of the average port service frequency to the unit inventory cost.

Sensitivity of the required number of vessels to the unit inventory cost is highlighted in Figure 53. As the average port service frequency was increased due to increments in the unit inventory cost, less vessels were required for deployment. Scenarios #1, #2, #3, #5, #8, and #9 required the largest number of vessels to be deployed (9 vessels), while only 7 vessels were deployed in scenarios #11, #12, #16, and #19.

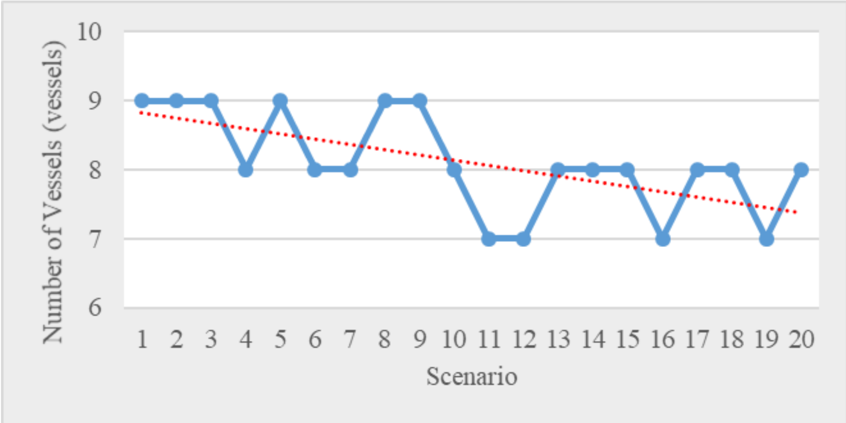


Figure 53 Sensitivity of the required number of vessels to the unit inventory cost.

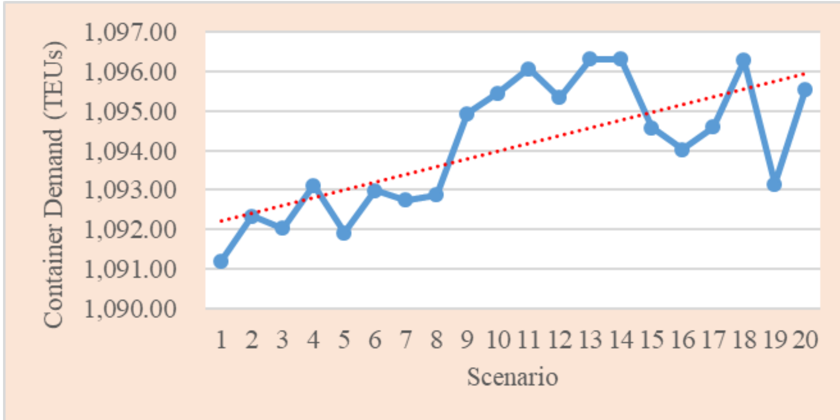


Figure 54 Sensitivity of the average container demand at ports to the unit inventory cost.

Sensitivity of the average container demand at ports to the unit inventory cost is presented in Figure 54. In the formulated mathematical model, the container demand at ports is inversely proportional to the sailing speed reciprocal. Since the sailing speed was increased (i.e., sailing speed reciprocal was decreased) with increasing unit inventory cost, the container demand at ports went through an increasing trend. The maximum average container demand at ports was observed in scenarios #13 and #14, which was 1,096.31 TEUs. The minimum average container demand at ports of 1,091.20 TEUs was observed in scenario #1.

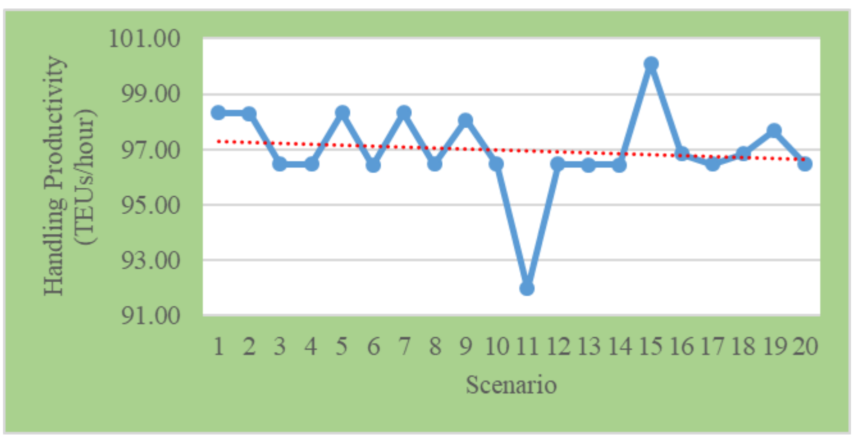


Figure 55 Sensitivity of the average handling productivity to the unit inventory cost.

Sensitivity of the average port handling productivity to the unit inventory cost is shown in Figure 55. As significant time savings were recorded due to increments in the average sailing speed (since the vessel sailing speed generally increased with increasing unit inventory cost from one scenario to another), the solution approach did not attempt to reduce the vessel handling time at ports of call (through requesting HRs with lower handling productivities) like before. Thus, a minor decrease in the average handling productivity was noted. The maximum average port handling productivity was observed in scenario #15, which was 100.11 TEUs/hour. The minimum average port handling productivity of 91.95 TEUs/hour was observed in scenario #11.

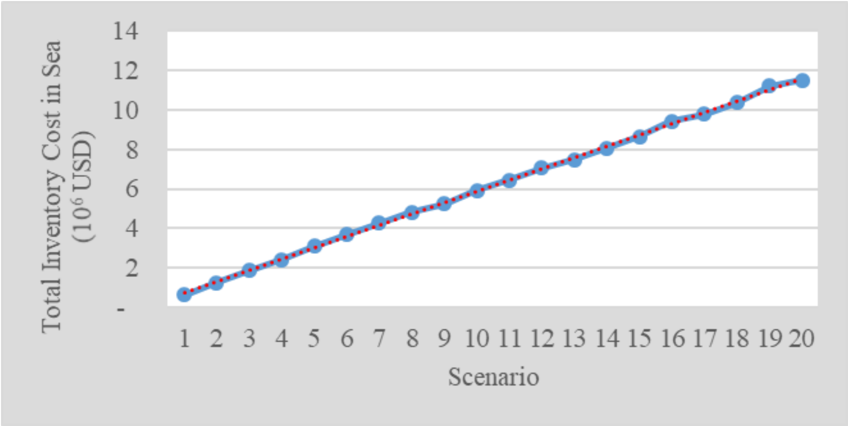


Figure 56 Sensitivity of the total inventory cost in sea to the unit inventory cost.

Sensitivity of the total inventory cost in sea to the unit inventory cost is highlighted in Figure 56. Due to an increase in the unit inventory cost, an increasing trend in the total inventory cost in sea was noted. The minimum total inventory cost in sea was observed in scenario #1, which was 0.62 million USD. The maximum total inventory cost in sea of 11.51 million USD was observed in scenario #20.

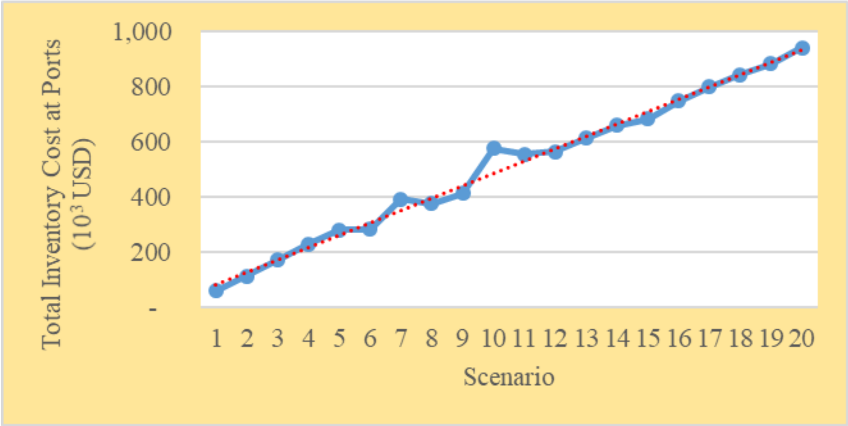


Figure 57 Sensitivity of the total inventory cost at ports to the unit inventory cost.

Sensitivity of the total inventory cost at ports to the unit inventory cost is highlighted in Figure 57. Due to an increase in the unit inventory cost, an increasing trend in the total inventory cost at ports was noted. The minimum total inventory cost at ports was observed in scenario #1, which was 59,813 USD. The maximum total inventory cost at ports of 939,709 USD was observed in scenario #20.

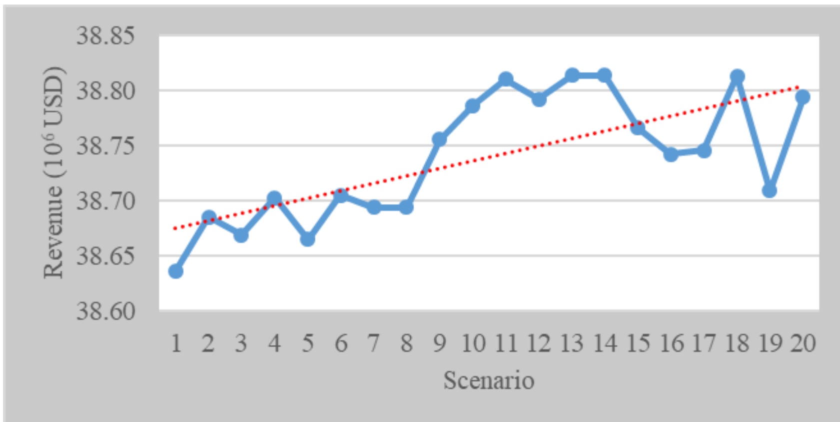


Figure 58 Sensitivity of the total revenue to the unit inventory cost.

Sensitivity of the total revenue to the unit inventory cost is presented in Figure 58. Due to increments in the unit inventory cost, the total revenue experienced an overall increasing trend. The latter finding can be justified by an increase in the container demand at ports of call after increasing the unit inventory cost. The maximum revenue was observed in scenarios #13 and #14, which was 38.81 million USD. The minimum revenue of 38.64 million USD was observed in scenario #1.

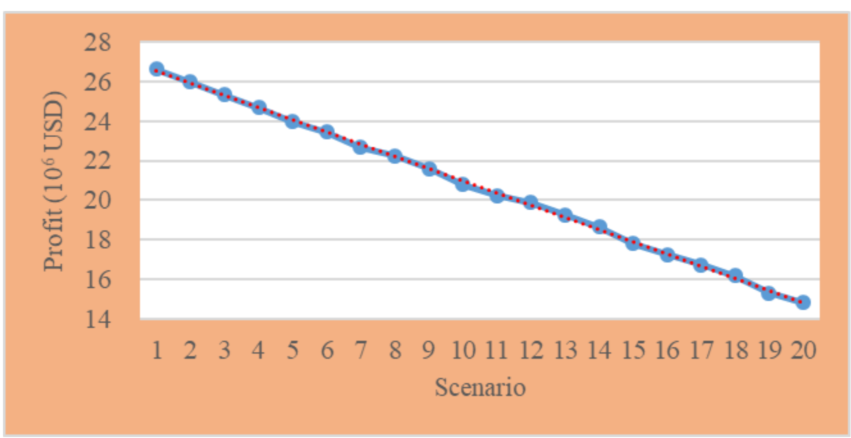


Figure 59 Sensitivity of the total profit to the unit inventory cost.

Sensitivity of the total profit to the unit inventory cost is shown in Figure 59. Due to increments in the unit inventory cost, the total profit experienced a decreasing pattern. The maximum profit was observed in scenario #1, which was 26.62 million USD. The minimum profit of 14.80 million USD was observed in scenario #20.

Table 11 presents changes in different variables of the mathematical model due to increments in the unit inventory cost. Apart from changes in the aforementioned variables, a number of other changes were noticed due to an increase in the unit inventory cost. Among the components of the route service cost, an overall reduction in the total vessel operational cost and the total vessel chartering cost was observed. On the other hand, the fuel consumption cost, the total port handling cost, and the total emission cost in sea as well as at ports experienced an increasing trend. The total late arrival cost fluctuated from one scenario to another, but no clear increasing or decreasing trend was observed.

In addition to the cost components, changes in other variables were also observed. The total quantity of emissions produced in sea and at ports followed trends similar to the total emission cost in sea and at ports, respectively. The quantity of containers transported by the vessels stayed the same. Similar to the required number of own vessels, the required number of chartered vessels was decreased. Moreover, increments in the average size of vessels were also observed. Last but not least, increments in the unit inventory cost reduced the CPU times and the optimality gaps for the problem instances. The latter patterns can be explained by changes in the feasible space for the formulated optimization model.

6.4.4. Sensitivity Analysis for the Unit Operational and Chartering Costs

A sensitivity analysis for the unit operational/chartering cost is investigated in this section of the dissertation. A total of 20 scenarios were developed to conduct the sensitivity analysis for the unit operational/chartering cost. From scenarios #1 to #20, the unit operational cost of type “1” vessels was increased from 10,000 USD/day to 200,000 USD/day (i.e., the increment rate was 10,000 USD/day), whereas the unit operational cost of type “2” vessels was increased from 9,000 USD/day to 180,000 USD/day (i.e., the increment rate was 9,000 USD/day).

Table 11 Sensitivity analysis for the unit inventory cost.

Scenario	Unit Inventory Cost (USD/TEU/hour)	Profit (USD)	REV (USD)	VOC (USD)	VCC (USD)	FCC (USD)	PHC (USD)	LAC (USD)
1	0.05	26,621,960	38,636,312	3,320,000	1,430,000	2,098,749	3,390,529	58,426
2	0.1	25,971,976	38,685,456	3,320,000	1,430,000	2,111,142	3,393,737	58,426
3	0.15	25,339,181	38,669,441	3,320,000	1,430,000	2,093,733	3,361,738	58,426
4	0.2	24,692,353	38,702,623	3,242,000	1,430,000	2,182,485	3,364,924	58,426
5	0.25	23,972,668	38,665,094	3,320,000	1,430,000	2,077,763	3,392,594	58,426
6	0.3	23,444,652	38,705,056	3,242,000	1,430,000	2,118,785	3,408,563	35,409
7	0.35	22,679,131	38,694,237	3,242,000	1,430,000	2,170,741	3,395,236	58,426
8	0.4	22,262,062	38,694,353	3,234,000	1,300,000	2,192,876	3,364,330	58,426
9	0.45	21,607,619	38,755,849	3,117,000	1,300,000	2,360,386	3,464,761	71,291
10	0.5	20,782,882	38,786,575	3,164,000	1,430,000	2,331,597	3,371,897	58,426
11	0.55	20,221,433	38,810,004	3,960,000	0	2,650,250	3,683,915	0
12	0.6	19,884,716	38,791,996	3,422,000	910,000	2,347,887	3,371,677	58,426
13	0.65	19,271,819	38,813,599	3,078,000	1,300,000	2,430,811	3,374,456	58,426
14	0.7	18,649,010	38,813,599	3,078,000	1,300,000	2,430,811	3,374,456	58,426
15	0.75	17,808,669	38,766,236	3,078,000	1,300,000	2,449,825	3,528,736	42,174
16	0.8	17,232,438	38,742,574	3,422,000	910,000	2,368,927	3,420,111	41,712
17	0.85	16,715,115	38,746,079	3,078,000	1,300,000	2,432,629	3,369,363	58,426
18	0.9	16,152,612	38,812,933	3,078,000	1,300,000	2,428,743	3,381,486	58,426
19	0.95	15,280,429	38,709,161	3,422,000	910,000	2,366,174	3,397,948	72,031
20	1	14,795,439	38,794,279	2,906,000	1,560,000	2,439,611	3,372,475	58,426

Table 11 – Continued.

Scenario	CIC^{SEA} (USD)	CIC^{PORT} (USD)	EC^{SEA} (USD)	EC^{PORT} (USD)	$TotEP^{SEA}$ (tons)	$TotEP^{PORT}$ (tons)	$AvgQC^{SEA}$ (TEUs)	$AvgQC^{PORT}$ (TEUs)
1	617,000	59,823	1,034,935	4,889	32,341.73	152.79	5,594.84	1,091.20
2	1,242,481	111,755	1,041,046	4,895	32,532.70	152.96	5,594.64	1,092.34
3	1,857,166	171,863	1,032,461	4,875	32,264.42	152.33	5,594.14	1,092.02
4	2,422,028	229,300	1,076,227	4,881	33,632.09	152.52	5,594.81	1,093.12
5	3,104,889	279,275	1,024,586	4,894	32,018.32	152.93	5,594.77	1,091.92
6	3,694,242	281,685	1,044,815	4,905	32,650.48	153.29	5,594.21	1,092.99
7	4,252,338	391,032	1,070,436	4,896	33,451.12	153.00	5,594.73	1,092.74
8	4,821,310	375,119	1,081,351	4,879	33,792.21	152.47	5,593.97	1,092.88
9	5,254,278	411,629	1,163,954	4,931	36,373.55	154.08	5,594.89	1,094.93
10	5,919,072	574,052	1,149,757	4,891	35,929.91	152.84	5,595.02	1,095.45
11	6,429,134	553,547	1,306,891	4,834	40,840.35	151.08	5,594.49	1,096.07
12	7,070,695	563,915	1,157,790	4,889	36,180.94	152.78	5,594.33	1,095.34
13	7,485,068	611,444	1,198,682	4,894	37,458.80	152.94	5,594.72	1,096.31
14	8,060,843	658,479	1,198,682	4,894	37,458.80	152.94	5,594.72	1,096.31
15	8,663,948	681,775	1,208,058	5,051	37,751.81	157.83	5,593.40	1,094.58
16	9,426,731	747,538	1,168,165	4,952	36,505.17	154.74	5,593.89	1,094.02
17	9,789,410	798,672	1,199,578	4,887	37,486.81	152.71	5,595.00	1,094.60
18	10,370,190	840,882	1,197,662	4,931	37,426.94	154.10	5,594.73	1,096.29
19	11,207,885	881,014	1,166,808	4,873	36,462.74	152.28	5,594.35	1,093.14
20	11,514,709	939,709	1,203,021	4,890	37,594.40	152.81	5,594.04	1,095.55

Note:

$TotEP^{SEA}$ – total quantity of emissions produced in sea (tons); $TotEP^{PORT}$ – total quantity of emissions produced at ports (tons); $AvgQC^{SEA}$ – average quantity of containers to be transported at each voyage leg (TEUs); $AvgQC^{PORT}$ – average quantity of containers to be handled at each port (TEUs).

Table 11 – Continued.

Scenario	$\boldsymbol{Totq}$ (vessels)	$\boldsymbol{Totq}^{own}$ (vessels)	$\boldsymbol{Totq}^{char}$ (vessels)	$\boldsymbol{Avgf}$ (days)	$\boldsymbol{AvgRF}$ (tons/nmi)	$\boldsymbol{AvgWtSpd}$ (knots)	$\boldsymbol{AvgWtHP}$ (TEUs/hour)	$\boldsymbol{AvgWtCCC}$ (tons)	CPU Time (seconds)	Optimality Gap (%)
1	9	7	2	11.67	0.226	23.15	98.32	148,000.00	190.45	3.00%
2	9	7	2	11.67	0.239	23.12	98.30	148,000.00	354.76	3.00%
3	9	7	2	11.67	0.233	23.13	96.46	148,000.00	404.93	3.00%
4	8	6	2	13.00	0.237	23.51	96.47	148,500.00	223.43	3.00%
5	9	7	2	11.67	0.234	23.04	98.32	148,000.00	310.37	3.00%
6	8	6	2	13.00	0.236	23.08	96.42	148,500.00	151.51	3.00%
7	8	6	2	13.00	0.234	23.43	98.32	148,500.00	194.14	3.00%
8	9	7	2	11.33	0.238	23.76	96.46	148,000.00	323.76	2.75%
9	9	7	2	11.00	0.248	24.36	98.06	148,000.00	153.73	3.00%
10	8	6	2	12.67	0.253	24.02	96.45	148,500.00	275.14	2.92%
11	7	7	0	13.67	0.256	24.29	91.95	147,428.57	299.25	3.00%
12	7	6	1	13.67	0.251	24.11	96.45	148,285.71	220.90	1.90%
13	8	6	2	12.33	0.257	24.64	96.43	148,500.00	311.68	1.72%
14	8	6	2	12.33	0.257	24.64	96.43	148,500.00	174.28	2.60%
15	8	6	2	12.33	0.248	24.68	100.11	148,500.00	213.70	3.00%
16	7	6	1	13.67	0.243	24.15	96.83	148,285.71	182.34	2.75%
17	8	6	2	12.33	0.245	24.64	96.45	148,500.00	163.71	1.98%
18	8	6	2	12.33	0.257	24.62	96.82	148,500.00	205.50	2.02%
19	7	6	1	13.67	0.239	24.16	97.66	148,285.71	295.51	3.00%
20	8	6	2	12.33	0.251	24.66	96.45	148,500.00	167.59	2.71%

Note:

$\boldsymbol{Totq}$ – total number of required vessels (vessels); $\boldsymbol{Totq}^{own}$ – total number of own vessels required (vessels); $\boldsymbol{Totq}^{char}$ – total number of chartered vessels required (vessels); $\boldsymbol{Avgf}$ – average port service frequency (days); $\boldsymbol{AvgRF}$ – average fuel consumption (tons/nmi); $\boldsymbol{AvgWtSpd}$ – average vessel sailing speed weighted by voyage leg length (knots); $\boldsymbol{AvgWtHP}$ – average requested handling productivity weighted by the number of containers handled at ports (TEUS/hour); $\boldsymbol{AvgWtCCC}$ – average weighted cargo carrying capacity of vessels (tons).

Furthermore, from scenarios #1 to #20, the unit chartering cost of type “1” vessels was increased from 15,000 USD/day to 300,000 USD/day (i.e., the increment rate was 15,000 USD/day), whereas the unit chartering cost of type “2” vessels was increased from 13,500 USD/day to 270,000 USD/day (i.e., the increment rate was 13,500 USD/day). Sensitivity of the average sailing speed to the unit operational/chartering cost is presented in Figure 60. By increasing the average sailing speed, the solution approach aimed to alleviate the effect of increments in the unit operational/chartering cost (through deployment of less vessels, which will be discussed later). The maximum average sailing speed was observed in scenario #16, which was 24.36 knots. The minimum average sailing speed of 22.40 knots was observed in scenario #1.

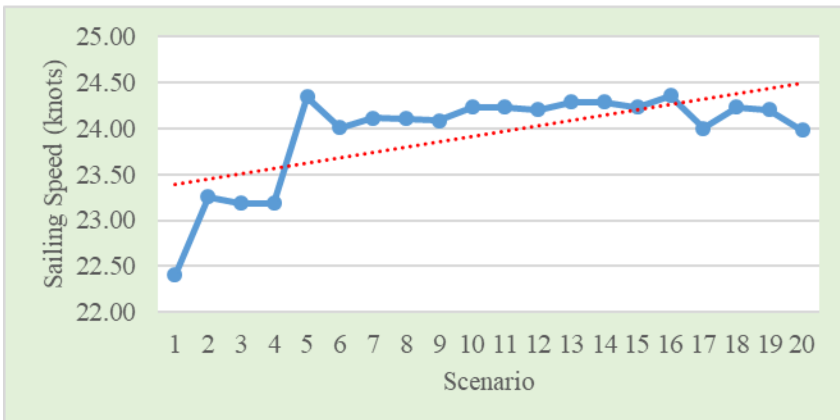


Figure 60 Sensitivity of the average sailing speed to the unit operational/chartering cost.

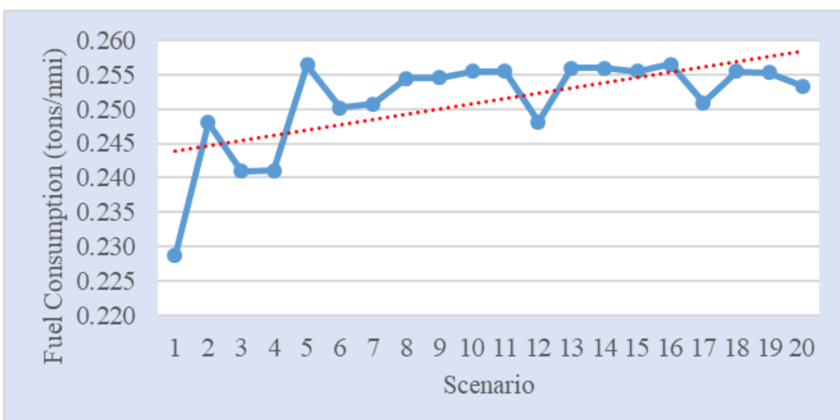


Figure 61 Sensitivity of the average fuel consumption to the unit operational/chartering cost.

Sensitivity of the average fuel consumption to the unit operational/chartering cost is shown in Figure 61. In order to mitigate the impact of increasing unit operational/chartering cost, the solution approach increased the average fuel consumption rate by increasing the average sailing speed. The maximum average fuel consumption was observed in scenario #16, which was 0.257 tons/nmi. The minimum average fuel consumption of 0.229 tons/nmi was observed in scenario #1.

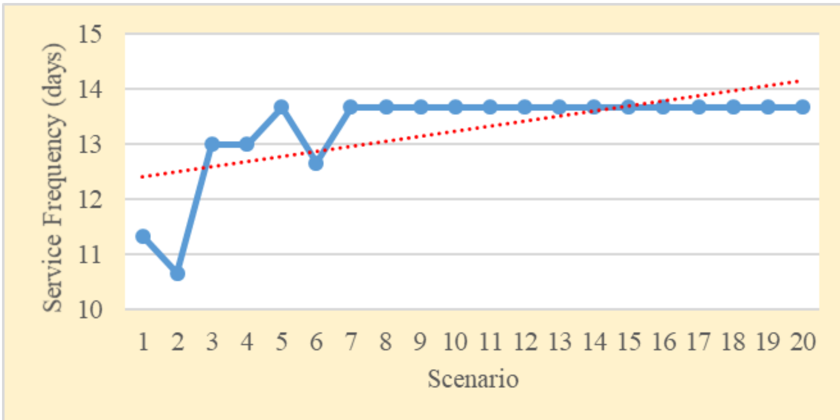


Figure 62 Sensitivity of the average port service frequency to the unit operational/chartering cost.

Sensitivity of the average port service frequency to the unit operational/chartering cost is presented in Figure 62. Since the sailing speed was increased, the solution approach increased the port service frequency as well (i.e., the ports were visited less frequently). The maximum average port service frequency was observed in scenarios #5 and #7 to #20, which was 13.67 days. The minimum average port service frequency of 10.67 days was observed in scenario #2.

Sensitivity of the total number of vessels required to the unit operational/chartering cost is highlighted in Figure 63. As the average port service frequency was increased due to increments in the unit operational/chartering cost, less vessels were required for deployment. Scenarios #1 and #2 required the largest number of vessels to be deployed (10 vessels), while only 7 vessels were deployed in scenarios #5 and #7 to #20. Note that the number of deployed vessels from the company’s own fleet stayed almost the same (6-7 vessels).

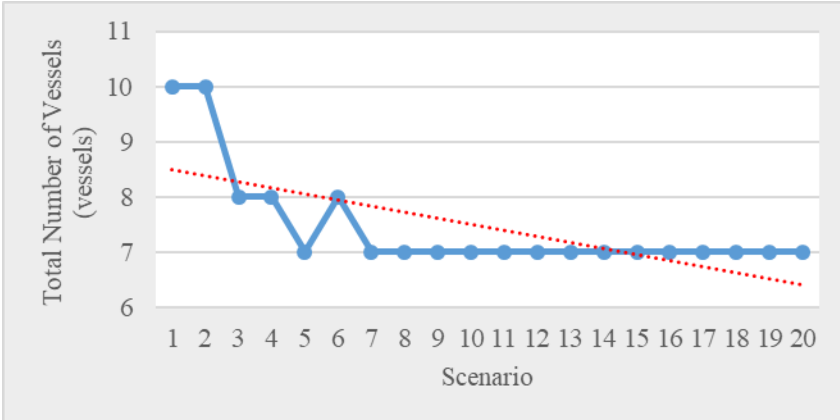


Figure 63 Sensitivity of the total number of vessels to the unit operational/chartering cost.

Sensitivity of the number of chartered vessels to the unit operational/chartering cost is highlighted in Figure 64. In the first few unit operational/chartering cost scenarios, the unit operational and chartering costs were comparatively lower; so, more vessels were deployed, which included both own and chartered vessels. In the later unit operational/chartering cost scenarios, there was a reduction in the number of chartered vessels. In fact, no chartering was done for scenarios #5 and #10 to #20.

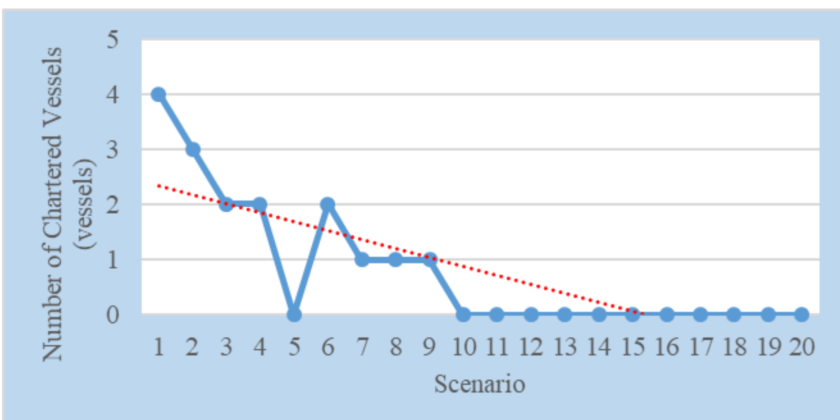


Figure 64 Sensitivity of the number of chartered vessels to the unit operational/chartering cost.

Sensitivity of the average cargo carrying capacity to the unit operational/chartering cost is shown in Figure 65. Note that in order to demonstrate the impact of the number of vessels on each port rotation, the average cargo carrying capacity ($\boldsymbol{AvgWtCCC}$) was weighted by the number of vessels on each port rotation $\left(\boldsymbol{AvgWtCCC} = \frac{\sum_{r\in R}\sum_{v\in V} TWC_v \boldsymbol{q}_r \boldsymbol{d}_{rv}}{\sum_{r\in R}\boldsymbol{q}_r}\right)$. Due to increments in the unit operational/chartering cost, the average cargo carrying capacity experienced a decreasing trend. Such pattern can be explained by the fact that smaller vessels had comparatively smaller unit operational and chartering costs. When the unit operation/chartering cost was increased, the liner shipping company tried to limit the increase in the total operational and chartering costs by deploying smaller vessels. The maximum average cargo carrying capacity was observed in scenarios #3, #4, and #6, which was 148,500 tons. The minimum average cargo carrying capacity of 147,429 tons was observed in scenarios #5 and #10 to #20.

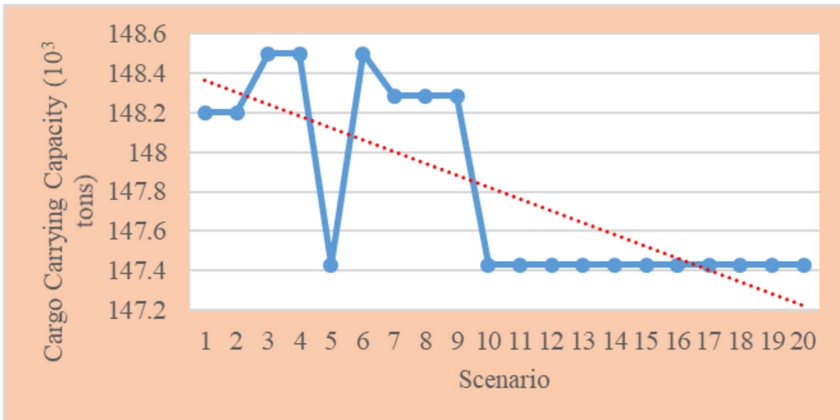


Figure 65 Sensitivity of the average cargo carrying capacity to the unit operational/chartering cost.

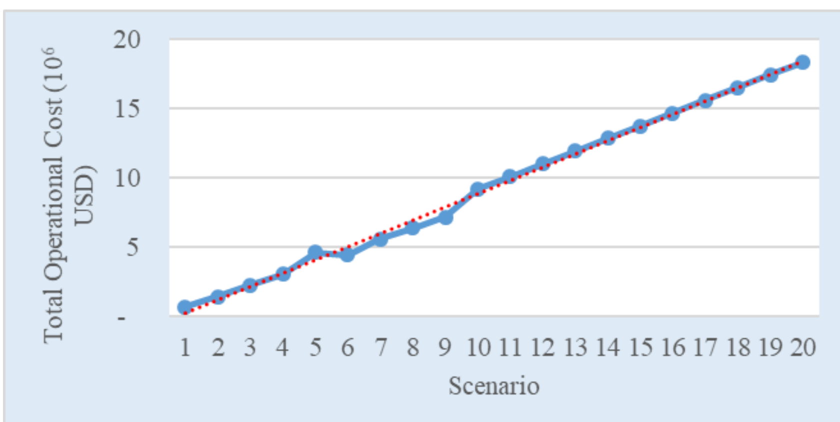


Figure 66 Sensitivity of the total operational cost to the unit operational/chartering cost.

Sensitivity of the total operational cost to the unit operational/chartering cost is highlighted in Figure 66. Even though the average vessel size was decreased in order to mitigate the impact of an increase in the unit operational/chartering cost, an increasing trend in the total operational cost was still noted. The minimum total operational cost was observed in scenario #1, which was 0.66 million USD. The maximum total operational cost of 18.36 million USD was observed in scenario #20.

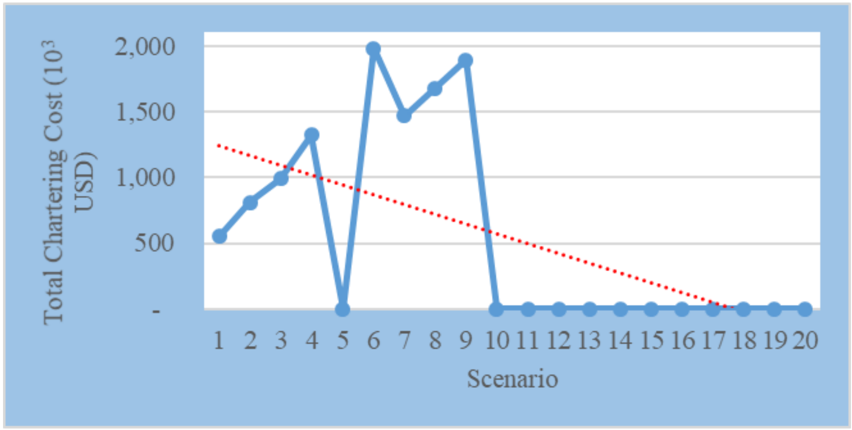


Figure 67 Sensitivity of the total chartering cost to the unit operational/chartering cost.

Sensitivity of the total chartering cost to the unit operational/chartering cost is highlighted in Figure 67. Even though the average vessel size and the number of chartered vessels were decreased in order to mitigate the impact of an increase in the unit operational/chartering cost, an increasing trend in the total chartering cost from scenarios #1 to #9 was still noted. However, no vessels were chartered for scenarios #10 to #20. Hence, an overall decreasing trend can be observed for the total chartering cost.

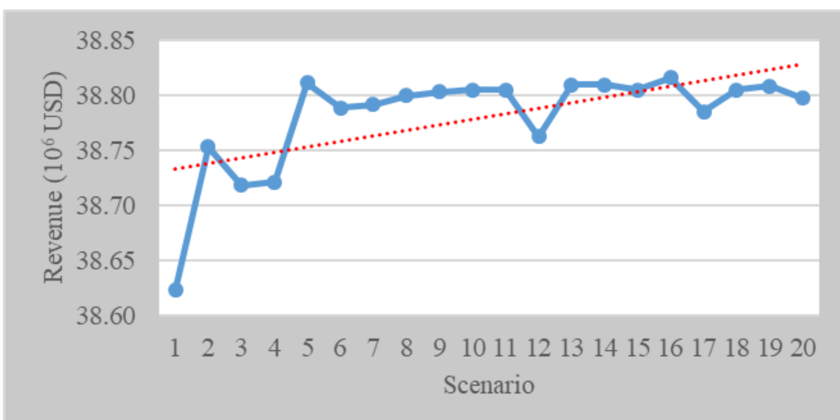


Figure 68 Sensitivity of the total revenue to the unit operational/chartering cost.

Sensitivity of the total revenue to the unit operational/chartering cost is presented in Figure 68. Due to increments in the unit operational/chartering cost, the total revenue experienced an overall increasing trend. The latter finding can be justified by an increase in the container demand at ports of call after increasing the unit operational/chartering cost. The maximum revenue was observed in scenario #16, which was 38.82 million USD. The minimum revenue of 38.62 million USD was observed in scenario #1.

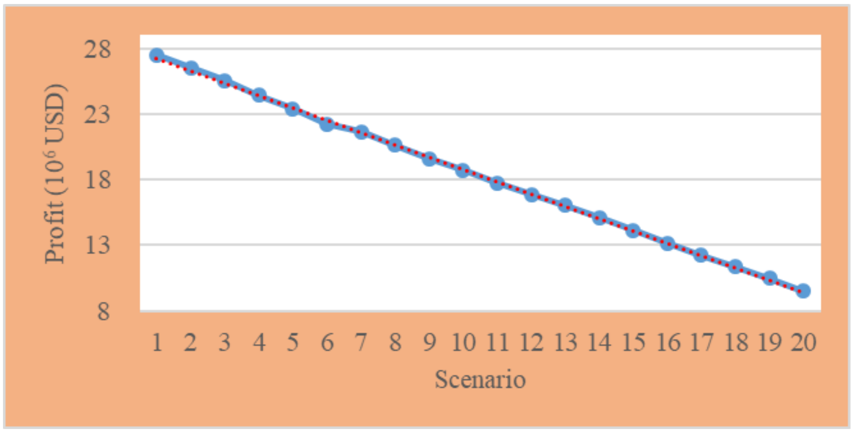


Figure 69 Sensitivity of the total profit to the unit operational/chartering cost.

Sensitivity of the total profit to the unit operational/chartering cost is shown in Figure 69. Due to increments in the unit operational/chartering cost, the total profit experienced a decreasing pattern. The maximum profit was observed in scenario #1, which was 27.49 million USD. The minimum profit of 9.49 million USD was observed in scenario #20.

Table 12 presents changes in different variables of the mathematical model due to increments in the unit operational/chartering cost. Apart from changes in the aforementioned variables, a number of other changes were noticed due to an increase in the unit operational/chartering cost. Among the components of the route service cost, an overall reduction in the total late arrival cost, the total container inventory cost in sea, the total container inventory cost at ports, and the total emission cost at ports was observed. On the other hand, the total fuel consumption cost, the total port handling cost, and the total emission cost in sea experienced an increasing trend.

In addition to the cost components, changes in other variables were also observed. The total quantity of emissions produced in sea and at ports followed trends similar to the total emission cost in sea and at ports, respectively. The quantity of containers transported by the vessels stayed the same, and the container demand at ports was slightly increased. Moreover, an overall reduction in the average handling productivity was observed. Last but not least, increments in the unit operational/chartering cost reduced the CPU times and the optimality gaps for the problem instances. The latter patterns can be explained by changes in the feasible space for the formulated optimization model.

6.4.5. Sensitivity Analysis for the Vessel Availability

A sensitivity analysis for the vessel availability is investigated in this section of the dissertation. A total of 20 scenarios were developed to conduct the sensitivity analysis for the vessel availability. For each type of vessel, the number of available vessels, including both own and chartered vessels, was increased from 2 vessels in scenario #1 to 21 vessels in scenario #20, with an increment of 1 vessel from one vessel availability scenario to another. Sensitivity of the average sailing speed to the vessel availability is presented in Figure 70. When the available number of vessels was increased, more vessels were deployed, which increased the total operational cost. To compensate for this increase, the solution approach decreased the total fuel consumption cost by reducing the sailing speed. The maximum average sailing speed was observed in scenario #20, which was 24.90 knots. The minimum average sailing speed of 22.02 knots was observed in scenario #10.

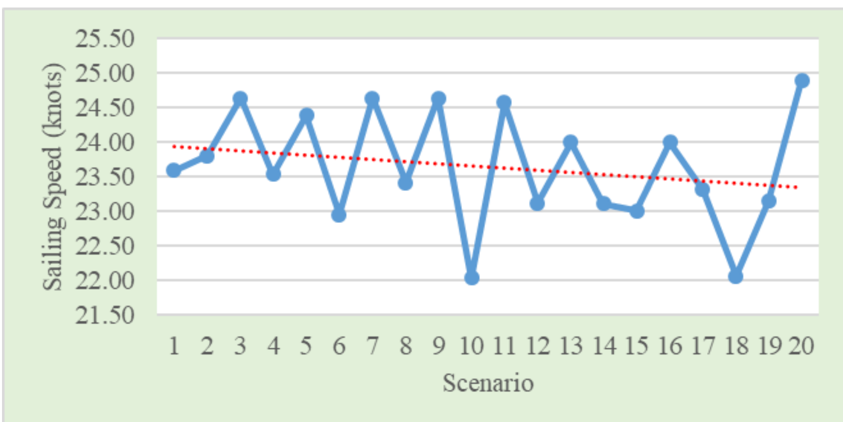


Figure 70 Sensitivity of the average sailing speed to the vessel availability.

Table 12 Sensitivity analysis for the unit operational/chartering cost.

Scenario	Unit Operational Cost for Vessel Type "1" (USD/day)	Unit Operational Cost for Vessel Type "2" (USD/day)	Unit Chartering Cost for Vessel Type "1" (USD)	Unit Chartering Cost for Vessel Type "2" (USD)	Profit (USD)	REV (USD)	VOC (USD)	VCC (USD)
1	10,000	9,000	15,000	13,500	27,487,642	38,623,627	658,000	553,500
2	20,000	18,000	30,000	27,000	26,526,027	38,753,591	1,406,000	810,000
3	30,000	27,000	45,000	40,500	25,530,482	38,718,825	2,256,000	990,000
4	40,000	36,000	60,000	54,000	24,451,336	38,721,778	3,008,000	1,320,000
5	50,000	45,000	75,000	67,500	23,395,917	38,811,325	4,590,000	0
6	60,000	54,000	90,000	81,000	22,243,813	38,789,086	4,404,000	1,980,000
7	70,000	63,000	105,000	94,500	21,642,239	38,791,996	5,558,000	1,470,000
8	80,000	72,000	120,000	108,000	20,644,720	38,800,172	6,352,000	1,680,000
9	90,000	81,000	135,000	121,500	19,622,358	38,803,168	7,146,000	1,890,000
10	100,000	90,000	150,000	135,000	18,728,031	38,804,842	9,180,000	0
11	110,000	99,000	165,000	148,500	17,756,726	38,804,942	10,098,000	0
12	120,000	108,000	180,000	162,000	16,874,388	38,762,542	11,016,000	0
13	130,000	117,000	195,000	175,500	16,056,168	38,810,004	11,934,000	0
14	140,000	126,000	210,000	189,000	15,138,168	38,810,004	12,852,000	0
15	150,000	135,000	225,000	202,500	14,138,031	38,804,842	13,770,000	0
16	160,000	144,000	240,000	216,000	13,178,367	38,816,192	14,688,000	0
17	170,000	153,000	255,000	229,500	12,234,162	38,785,331	15,606,000	0
18	180,000	162,000	270,000	243,000	11,384,031	38,804,842	16,524,000	0
19	190,000	171,000	285,000	256,500	10,500,801	38,808,329	17,442,000	0
20	200,000	180,000	300,000	270,000	9,486,793	38,797,454	18,360,000	0

Table 12 – Continued.

Scenario	FCC (USD)	PHC (USD)	LAC (USD)	CIC^{SEA} (USD)	CIC^{PORT} (USD)	EC^{SEA} (USD)	EC^{PORT} (USD)
1	1,978,366	3,387,619	58,426	3,222,029	297,589	975,572	4,885
2	2,186,950	3,367,848	58,426	3,077,614	237,413	1,078,429	4,884
3	2,142,693	3,365,471	58,426	3,079,703	234,565	1,056,605	4,881
4	2,142,491	3,365,562	58,426	3,079,993	234,585	1,056,505	4,881
5	2,666,522	3,600,243	67,077	2,915,080	256,718	1,314,915	4,853
6	2,330,015	3,371,280	58,426	2,960,686	287,000	1,148,977	4,888
7	2,347,887	3,371,677	58,426	2,946,123	234,965	1,157,790	4,889
8	2,348,350	3,372,622	58,426	2,946,068	235,076	1,158,018	4,891
9	2,349,099	3,417,020	35,409	2,944,677	235,299	1,158,388	4,919
10	2,640,160	3,754,353	19,904	2,930,602	245,052	1,301,916	4,825
11	2,640,278	3,807,004	20,427	2,930,507	245,148	1,301,974	4,879
12	2,638,066	3,711,118	40,853	2,932,273	244,115	1,300,883	4,845
13	2,650,250	3,683,915	0	2,922,334	251,612	1,306,891	4,834
14	2,650,250	3,683,915	0	2,922,334	251,612	1,306,891	4,834
15	2,640,160	3,754,353	19,904	2,930,602	245,052	1,301,916	4,825
16	2,662,171	3,765,618	32,178	2,912,569	259,797	1,312,770	4,723
17	2,573,029	3,825,630	87,657	2,962,206	222,930	1,268,812	4,905
18	2,640,160	3,754,353	19,904	2,930,602	245,052	1,301,916	4,825
19	2,624,820	3,765,275	0	2,933,487	242,761	1,294,351	4,834
20	2,571,116	3,834,014	87,657	2,963,634	221,427	1,267,869	4,944

Table 12 – Continued.

Scenario	$\boldsymbol{TotEP}^{SEA}$ (tons)	$\boldsymbol{TotEP}^{PORT}$ (tons)	$\boldsymbol{AvgQC}^{SEA}$ (TEUs)	$\boldsymbol{AvgQC}^{PORT}$ (TEUs)	$\boldsymbol{Totq}$ (vessels)	$\boldsymbol{Totq}^{own}$ (vessels)	$\boldsymbol{Totq}^{char}$ (vessels)	$\boldsymbol{Avgf}$ (days)
1	30,486.62	152.65	5,594.12	1,090.23	10	6	4	11.33
2	33,700.90	152.64	5,594.73	1,094.12	10	7	3	10.67
3	33,018.90	152.54	5,594.56	1,093.28	8	6	2	13.00
4	33,015.79	152.53	5,594.47	1,093.32	8	6	2	13.00
5	41,091.10	151.65	5,594.51	1,096.12	7	7	0	13.67
6	35,905.53	152.76	5,594.32	1,095.20	8	6	2	12.67
7	36,180.94	152.78	5,594.33	1,095.34	7	6	1	13.67
8	36,188.08	152.85	5,594.71	1,095.70	7	6	1	13.67
9	36,199.61	153.71	5,594.56	1,095.88	7	6	1	13.67
10	40,684.86	150.79	5,594.46	1,095.92	7	7	0	13.67
11	40,686.69	152.46	5,594.46	1,095.92	7	7	0	13.67
12	40,652.60	151.42	5,594.38	1,094.64	7	7	0	13.67
13	40,840.35	151.08	5,594.49	1,096.07	7	7	0	13.67
14	40,840.35	151.08	5,594.49	1,096.07	7	7	0	13.67
15	40,684.86	150.79	5,594.46	1,095.92	7	7	0	13.67
16	41,024.05	147.61	5,594.52	1,096.25	7	7	0	13.67
17	39,650.37	153.29	5,594.90	1,095.14	7	7	0	13.67
18	40,684.86	150.79	5,594.46	1,095.92	7	7	0	13.67
19	40,448.48	151.07	5,594.45	1,096.00	7	7	0	13.67
20	39,620.90	154.50	5,594.65	1,095.54	7	7	0	13.67

Note:

$\boldsymbol{TotEP}^{SEA}$ – total quantity of emissions produced in sea (tons); $\boldsymbol{TotEP}^{PORT}$ – total quantity of emissions produced at ports (tons); $\boldsymbol{AvgQC}^{SEA}$ – average quantity of containers to be transported at each voyage leg (TEUs); $\boldsymbol{AvgQC}^{PORT}$ – average quantity of containers to be handled at each port (TEUs); $\boldsymbol{Totq}$ – total number of required vessels (vessels); $\boldsymbol{Totq}^{own}$ – total number of own vessels required (vessels); $\boldsymbol{Totq}^{char}$ – total number of chartered vessels required (vessels); $\boldsymbol{Avgf}$ – average port service frequency (days).

Table 12 – Continued.

Scenario	$AvgRF$ (tons/nmi)	$AvgWtSpd$ (knots)	$AvgWtHP$ (TEUs/hour)	$AvgWtCCC$ (tons)	CPU Time (seconds)	Optimality Gap (%)
1	0.229	22.40	98.35	148,200.00	278.32	2.83%
2	0.248	23.26	96.46	148,200.00	214.23	3.00%
3	0.241	23.18	96.48	148,500.00	210.53	3.00%
4	0.241	23.18	96.47	148,500.00	121.95	3.00%
5	0.256	24.34	90.25	147,428.57	296.04	3.00%
6	0.250	24.01	96.45	148,500.00	250.76	3.00%
7	0.251	24.11	96.45	148,285.71	209.31	2.18%
8	0.254	24.10	96.44	148,285.71	216.84	3.00%
9	0.255	24.09	96.39	148,285.71	209.59	2.99%
10	0.255	24.23	94.03	147,428.57	342.10	1.60%
11	0.255	24.23	94.30	147,428.57	132.62	3.00%
12	0.248	24.20	93.81	147,428.57	342.50	3.00%
13	0.256	24.29	91.95	147,428.57	148.56	2.45%
14	0.256	24.29	91.95	147,428.57	173.04	1.69%
15	0.255	24.23	94.03	147,428.57	246.54	1.49%
16	0.257	24.36	89.84	147,428.57	192.64	2.91%
17	0.251	24.00	99.23	147,428.57	144.07	3.00%
18	0.255	24.23	94.03	147,428.57	146.46	3.00%
19	0.255	24.20	93.99	147,428.57	142.71	3.00%
20	0.253	23.98	99.62	147,428.57	175.10	3.00%

Note:

$\boldsymbol{AvgRF}$ – average fuel consumption (tons/nmi); $\boldsymbol{AvgWtSpd}$ – average vessel sailing speed weighted by voyage leg length (knots); $\boldsymbol{AvgWtHP}$ – average requested handling productivity weighted by the number of containers handled at ports (TEUS/hour); $\boldsymbol{AvgWtCCC}$ – average weighted cargo carrying capacity of vessels (tons).

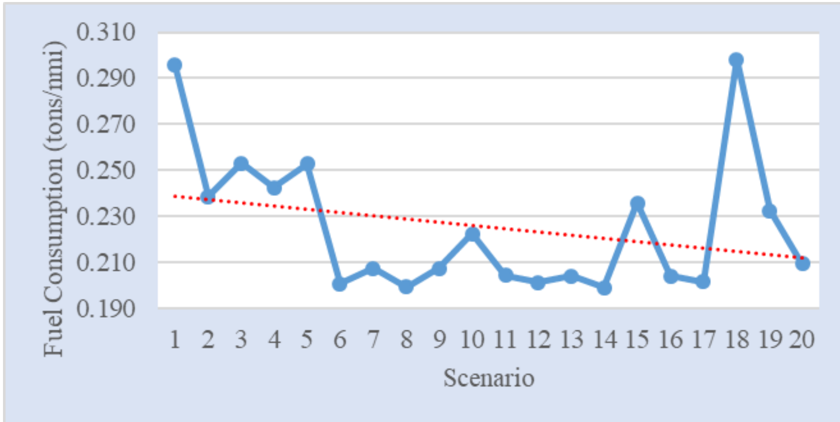


Figure 71 Sensitivity of the average fuel consumption to the vessel availability.

Sensitivity of the average fuel consumption to the vessel availability is shown in Figure 71. In order to mitigate the impact of increasing the total operational cost that was due to an increase in the available number of vessels, the solution approach aimed to decrease the fuel consumption cost by decreasing the average fuel consumption rate. The maximum average fuel consumption was observed in scenario #18, which was 0.298 tons/nmi. The minimum average fuel consumption of 0.199 tons/nmi was observed in scenarios #8 and #14.

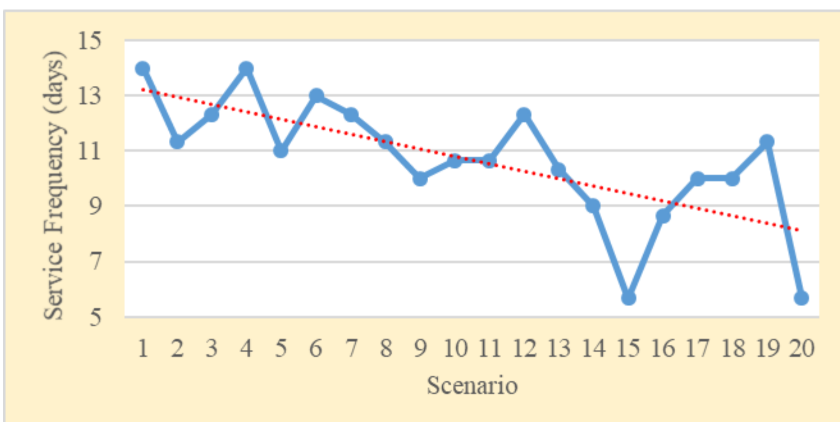


Figure 72 Sensitivity of the average port service frequency to the vessel availability.

Sensitivity of the average port service frequency to the vessel availability is presented in Figure 72. Since the sailing speed was reduced, the solution approach attempted to meet the demand by decreasing the port service frequency (i.e., the ports were visited more frequently). The maximum average port service frequency was observed in scenarios #1 and #4, which was

14 days. The minimum average port service frequency of 5.67 days was observed in scenarios #15 and #20.

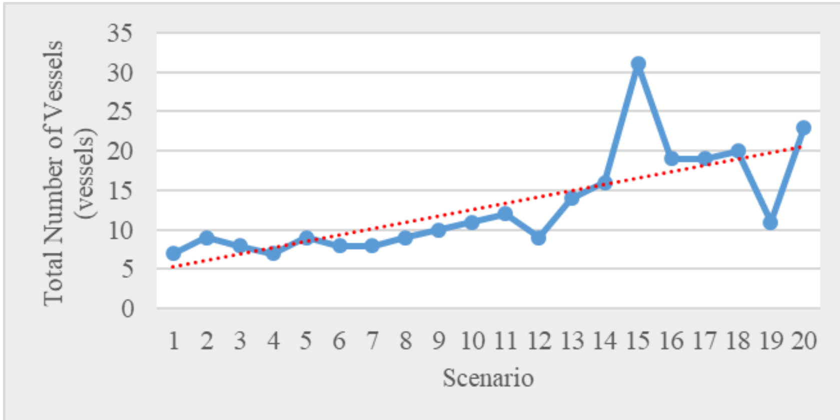


Figure 73 Sensitivity of the total number of vessels to the vessel availability.

Sensitivity of the total number of vessels required to the vessel availability is highlighted in Figure 73. As there was an increase in the number of vessels available for deployment, the solution approach deployed more vessels and decreased some variables, such as the sailing speed. Scenario #15 required the largest number of vessels to be deployed (31 vessels), while only 7 vessels were deployed in scenarios #1 and #4.

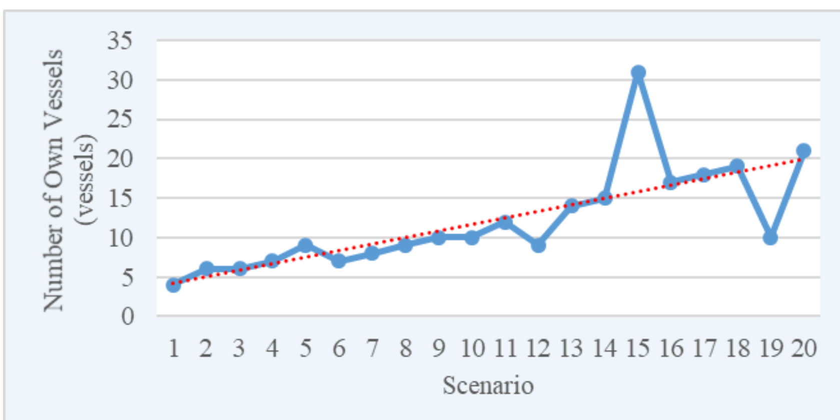


Figure 74 Sensitivity of the number of own vessels to the vessel availability.

Sensitivity of the number of vessels deployed from the company's own fleet to the vessel availability is highlighted in Figure 74. The number of vessels deployed in total was increased from one vessel availability scenario to another. At the same time, there were a number of vessels available in the company's own fleet. Thus, the deployed vessels consisted mostly of the company's own vessels, and an increase in the number of deployed vessels from own fleet was noted.

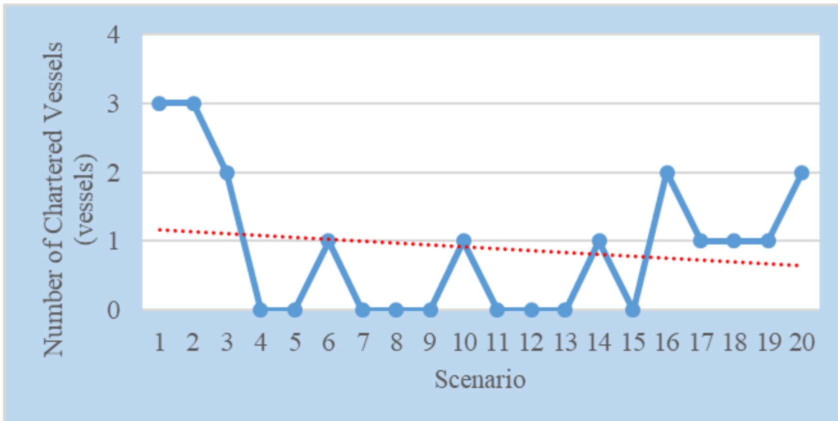


Figure 75 Sensitivity of the number of chartered vessels to the vessel availability.

Sensitivity of the number of chartered vessels to the vessel availability is highlighted in Figure 75. In the first two vessel availability scenarios, only a few vessels were available in the company's fleet. So, a significant portion of the deployed vessels were chartered. However, after the first two vessel availability scenarios, a decrease in the number of chartered vessels was observed, as more vessels were available in the company's own fleet. Furthermore, some fluctuations in the average vessel size (i.e., the average cargo carrying capacity) were observed, even though no clear increasing or decreasing pattern was noted (Figure 76).

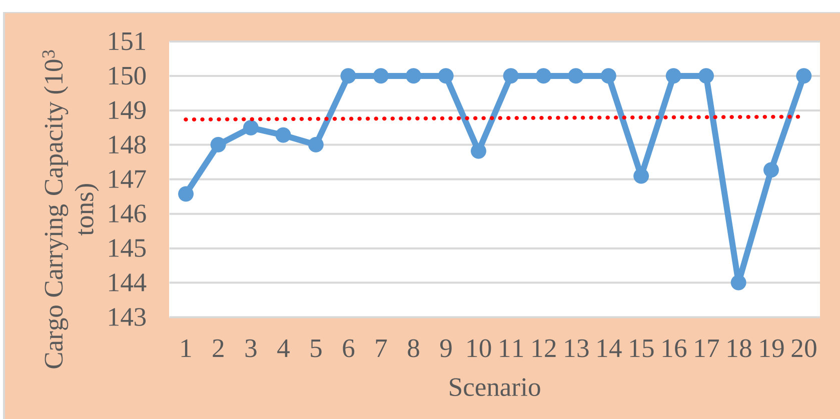


Figure 76 Sensitivity of the average cargo carrying capacity to the vessel availability.

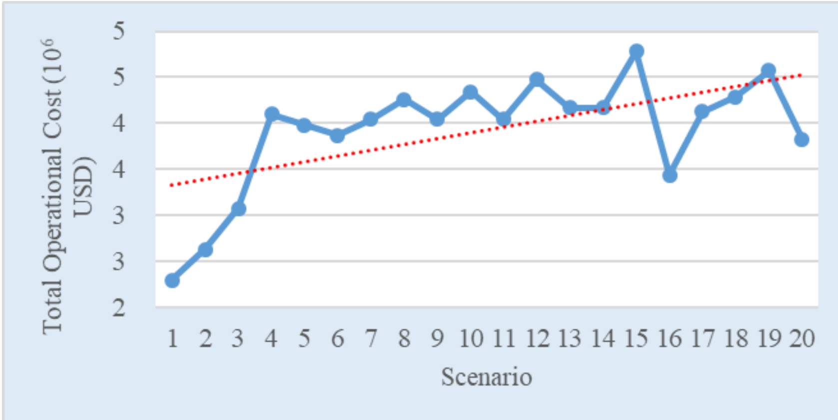


Figure 77 Sensitivity of the total operational cost to the vessel availability.

Sensitivity of the total operational cost to the vessel availability is highlighted in Figure 77. As there was a substantial increase in the number of deployed vessels, an increasing trend in the total operational cost was noted. The minimum total operational cost was observed in scenario #1, which was 2.30 million USD. The maximum total operational cost of 4.78 million USD was observed in scenario #15.

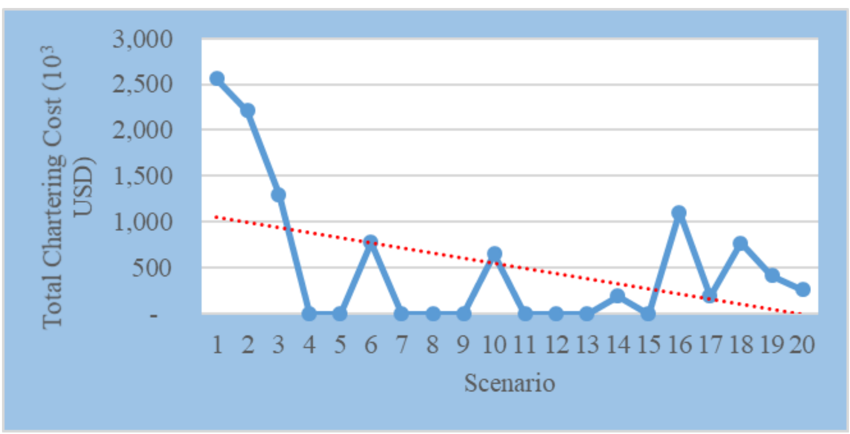


Figure 78 Sensitivity of the total chartering cost to the vessel availability.

Sensitivity of the total chartering cost to the vessel availability is highlighted in Figure 78. Even though the number of deployed vessels was increased, it consisted mostly of the company's own vessels. Moreover, for a number of scenarios after scenario #3, no vessels were chartered. Hence, an overall decreasing trend can be observed for the total chart141rring cost. The maximum total chartering cost was recorded in scenario #1, which was 2.56 million USD.

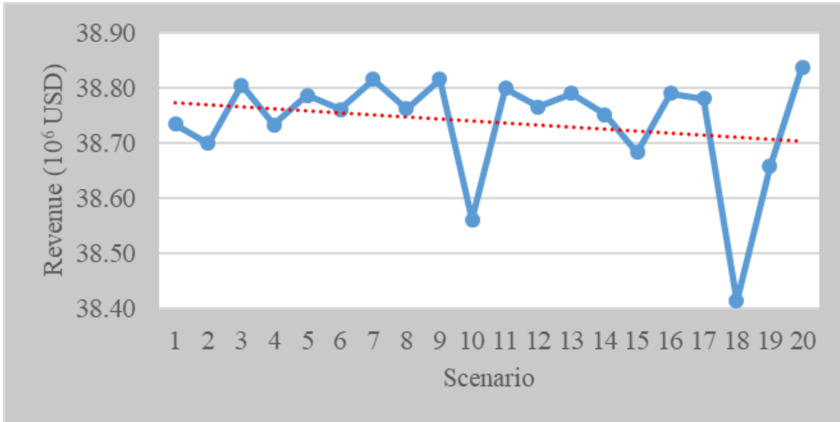


Figure 79 Sensitivity of the total revenue to the vessel availability.

Sensitivity of the total revenue to the vessel availability is presented in Figure 79. Due to increments in the available number of vessels, the total revenue experienced a slight decreasing trend. The latter finding can be justified by a slight decrease in the container demand at ports of call after increasing the available number of vessels. The maximum revenue was observed in scenario #20, which was 38.84 million USD. The minimum revenue of 38.41 million USD was observed in scenario #18.

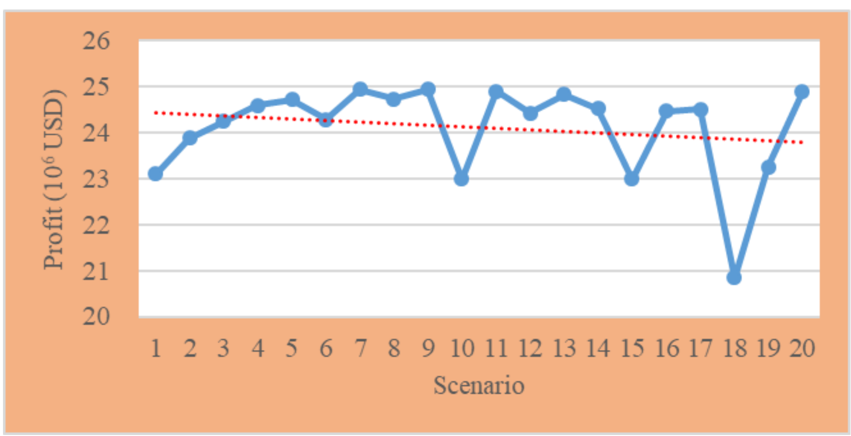


Figure 80 Sensitivity of the total profit to the vessel availability.

Sensitivity of the total profit to the vessel availability is shown in Figure 80. Frequent fluctuations in the total profit from one vessel availability scenario to another can be observed, which can be explained by the differences in the optimality gaps for the vessel availability scenarios due to differences in the complexity of the problem instances (i.e., vessel availability scenarios). Hence, due to different optimality gaps in the problem instances, there was a slight decrease in the total profit after increasing the available number of vessels. However, if the optimality gaps for all the vessel availability scenarios were the same, then a more definite pattern in the total profit would have been observed. The maximum profit was observed in scenarios #7 and #9, which was 24.94 million USD. The minimum profit of 20.85 million USD was observed in scenario #18.

Table 13 presents changes in different variables of the mathematical model due to increments in the available number of vessels. Apart from changes in the aforementioned variables, a number of other changes were noticed due to an increase in the available number of vessels. Among the components of the route service cost, an overall reduction in the total fuel consumption cost and the total emission cost in sea was observed. On the other hand, the total port handling cost, the total late arrival cost, the total container inventory cost in sea, the total container inventory cost at ports, and the total emission cost at ports experienced an increasing trend.

In addition to the cost components, changes in other variables were also observed. The total quantity of emissions produced in sea and at ports followed trends similar to the total emission cost in sea and at ports, respectively. The quantity of containers transported by the vessels stayed the same, and the container demand at ports was slightly decreased. In addition, an overall increase in the average handling productivity was observed. Last but not least, increments in the available number of vessels significantly increased the CPU times and the optimality gaps for the problem instances. The latter patterns can be explained by changes in the feasible space for the formulated optimization model.

6.4.6. Sensitivity Analysis for the Unit Late Arrival Cost

A sensitivity analysis for the unit late arrival cost is investigated in this section of the dissertation. A total of 20 scenarios were developed to conduct the sensitivity analysis for the unit late arrival cost. With increments of 500 USD/hour, the unit late arrival cost was increased from $U[500; 3{,}500]$ USD/hour in scenario #1 to $U[10{,}000; 13{,}000]$ USD/hour in scenario #20.

Table 13 Sensitivity analysis for the vessel availability.

Scenario	Available Number of Own Vessels of Type "1"	Available Number of Own Vessels of Type "2"	Available Number of Chartered Vessels of Type "1"	Available Number of Chartered Vessels of Type "2"	Profit (USD)	REV (USD)	VOC (USD)	VCC (USD)
1	2	2	2	2	23,102,802	38,734,237	2,296,000	2,562,000
2	3	3	3	3	23,877,954	38,699,527	2,632,000	2,210,000
3	4	4	4	4	24,247,807	38,805,424	3,078,000	1,300,000
4	5	5	5	5	24,591,337	38,733,831	4,102,000	0
5	6	6	6	6	24,709,863	38,786,615	3,977,000	0
6	7	7	7	7	24,277,874	38,761,751	3,870,000	780,000
7	8	8	8	8	24,935,991	38,816,148	4,042,000	0
8	9	9	9	9	24,735,843	38,763,009	4,257,000	0
9	10	10	10	10	24,935,991	38,816,148	4,042,000	0
10	11	11	11	11	22,982,950	38,562,324	4,344,000	650,000
11	12	12	12	12	24,899,187	38,800,292	4,042,000	0
12	13	13	13	13	24,425,988	38,766,437	4,472,000	0
13	14	14	14	14	24,834,073	38,790,761	4,171,000	0
14	15	15	15	15	24,523,177	38,752,401	4,171,000	195,000
15	16	16	16	16	22,991,544	38,683,788	4,782,000	0
16	17	17	17	17	24,460,073	38,790,761	3,440,000	1,105,000
17	18	18	18	18	24,508,497	38,780,964	4,128,000	195,000
18	19	19	19	19	20,845,351	38,414,962	4,290,000	767,000
19	20	20	20	20	23,253,376	38,657,776	4,575,000	413,000
20	21	21	21	21	24,881,869	38,837,700	3,827,000	260,000

Table 13 – Continued.

Scenario	FCC (USD)	PHC (USD)	LAC (USD)	CIC^{SEA} (USD)	CIC^{PORT} (USD)	EC^{SEA} (USD)	EC^{PORT} (USD)
1	2,672,506	3,471,403	58,426	3,015,325	232,987	1,317,866	4,923
2	2,201,268	3,381,899	60,706	3,005,171	240,120	1,085,489	4,921
3	2,430,348	3,373,511	58,426	2,878,927	235,059	1,198,453	4,892
4	2,194,926	3,448,255	58,426	3,021,529	230,112	1,082,362	4,884
5	2,355,256	3,372,358	58,426	2,912,358	235,038	1,161,424	4,892
6	1,820,217	3,728,484	0	3,149,199	233,528	897,585	4,863
7	2,061,411	3,582,424	58,426	2,880,827	233,660	1,016,523	4,887
8	1,870,586	3,651,462	40,853	3,035,343	244,634	922,423	4,865
9	2,061,411	3,582,424	58,426	2,880,827	233,660	1,016,523	4,887
10	1,929,697	3,587,772	302,299	3,314,781	494,404	951,572	4,849
11	2,051,733	3,614,985	58,426	2,889,130	228,143	1,011,751	4,937
12	1,844,576	3,624,156	36,665	3,129,568	319,010	909,597	4,877
13	1,960,767	3,579,497	58,426	2,962,780	252,441	966,894	4,883
14	1,822,481	3,745,244	74,793	3,075,925	241,119	898,702	4,960
15	2,109,026	3,421,835	535,367	3,110,702	688,370	1,040,003	4,939
16	1,960,767	3,579,497	58,426	2,962,780	252,441	966,894	4,883
17	1,859,032	3,846,339	39,333	3,055,148	227,982	916,726	4,907
18	2,895,213	3,596,471	478,353	3,269,937	840,045	1,427,688	4,904
19	2,089,413	3,360,843	58,426	3,102,645	769,868	1,030,332	4,873
20	2,102,931	3,585,036	58,426	2,846,811	233,741	1,036,997	4,890

Table 13 – Continued.

Scenario	$\boldsymbol{TotEP^{SEA}}$ (tons)	$\boldsymbol{TotEP^{PORT}}$ (tons)	$\boldsymbol{AvgQC^{SEA}}$ (TEUs)	$\boldsymbol{AvgQC^{PORT}}$ (TEUs)	$\boldsymbol{Totq}$ (vessels)	$\boldsymbol{Totq^{own}}$ (vessels)	$\boldsymbol{Totq^{char}}$ (vessels)	$\boldsymbol{Avgf}$ (days)
1	41,183.32	153.84	5,594.50	1,093.90	7	4	3	14.00
2	33,921.54	153.77	5,594.00	1,093.03	9	6	3	11.33
3	37,451.67	152.87	5,594.34	1,095.94	8	6	2	12.33
4	33,823.81	152.61	5,594.58	1,093.88	7	7	0	14.00
5	36,294.50	152.86	5,594.76	1,095.62	9	9	0	11.00
6	28,049.55	151.96	5,594.50	1,093.90	8	7	1	13.00
7	31,766.34	152.73	5,594.61	1,096.32	8	8	0	12.33
8	28,825.72	152.05	5,594.13	1,094.39	9	9	0	11.33
9	31,766.34	152.73	5,594.61	1,096.32	10	10	0	10.00
10	29,736.63	151.54	5,594.46	1,088.92	11	10	1	10.67
11	31,617.21	154.27	5,594.91	1,095.81	12	12	0	10.67
12	28,424.92	152.40	5,594.56	1,094.06	9	9	0	12.33
13	30,215.42	152.60	5,594.62	1,095.40	14	14	0	10.33
14	28,084.44	155.01	5,595.09	1,094.36	16	15	1	9.00
15	32,500.10	154.35	5,594.46	1,092.65	31	31	0	5.67
16	30,215.42	152.60	5,594.62	1,095.40	19	17	2	8.67
17	28,647.68	153.34	5,594.39	1,094.83	19	18	1	10.00
18	44,615.24	153.24	5,595.38	1,085.61	20	19	1	10.00
19	32,197.86	152.29	5,594.05	1,091.73	11	10	1	11.33
20	32,406.16	152.81	5,594.73	1,096.95	23	21	2	5.67

Note:

$\boldsymbol{TotEP^{SEA}}$ – total quantity of emissions produced in sea (tons); $\boldsymbol{TotEP^{PORT}}$ – total quantity of emissions produced at ports (tons); $\boldsymbol{AvgQC^{SEA}}$ – average quantity of containers to be transported at each voyage leg (TEUs); $\boldsymbol{AvgQC^{PORT}}$ – average quantity of containers to be handled at each port (TEUs); $\boldsymbol{Totq}$ – total number of required vessels (vessels); $\boldsymbol{Totq^{own}}$ – total number of own vessels required (vessels); $\boldsymbol{Totq^{char}}$ – total number of chartered vessels required (vessels); $\boldsymbol{Avgf}$ – average port service frequency (days).

Table 13 – Continued.

Scenario	$AvgRF$ (tons/nmi)	$AvgWtSpd$ (knots)	$AvgWtHP$ (TEUs/hour)	$AvgWtCCC$ (tons)	CPU Time (seconds)	Optimality Gap (%)
1	0.296	23.59	96.77	146,571.43	104.34	2.73%
2	0.238	23.80	94.98	148,000.00	449.50	3.00%
3	0.253	24.64	96.44	148,500.00	174.92	3.00%
4	0.242	23.53	100.49	148,285.71	221.70	3.00%
5	0.253	24.39	96.43	148,000.00	200.93	2.55%
6	0.201	22.95	97.78	150,000.00	661.21	3.00%
7	0.207	24.64	97.62	150,000.00	289.20	2.32%
8	0.199	23.41	96.13	150,000.00	204.29	2.24%
9	0.207	24.64	97.62	150,000.00	484.60	0.18%
10	0.222	22.02	101.33	147,818.18	1,800.01	8.38%
11	0.204	24.58	98.87	150,000.00	608.68	1.42%
12	0.201	23.11	96.44	150,000.00	665.65	3.00%
13	0.204	23.99	97.63	150,000.00	711.35	1.28%
14	0.199	23.10	98.69	150,000.00	441.35	2.19%
15	0.236	23.00	94.72	147,096.77	1,800.01	8.03%
16	0.204	23.99	97.63	150,000.00	703.68	3.00%
17	0.202	23.31	99.88	150,000.00	858.64	3.00%
18	0.298	22.05	96.33	144,000.00	1,800.01	17.93%
19	0.232	23.14	96.45	147,272.73	1,800.01	8.53%
20	0.209	24.90	97.63	150,000.00	593.62	0.39%

Note:

$\boldsymbol{AvgRF}$ – average fuel consumption (tons/nmi); $\boldsymbol{AvgWtSpd}$ – average vessel sailing speed weighted by voyage leg length (knots); $\boldsymbol{AvgWtHP}$ – average requested handling productivity weighted by the number of containers handled at ports (TEUS/hour); $\boldsymbol{AvgWtCCC}$ – average weighted cargo carrying capacity of vessels (tons).

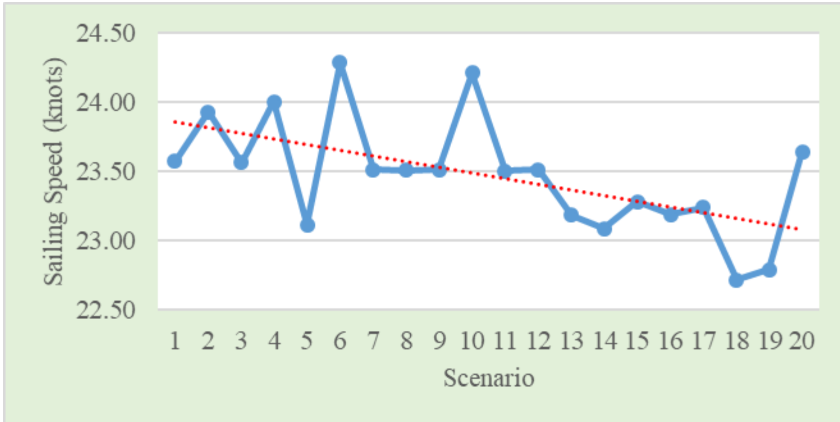


Figure 81 Sensitivity of the average sailing speed to the unit late arrival cost.

Sensitivity of the average sailing speed to the unit late arrival cost is presented in Figure 81. By decreasing the average sailing speed, the solution approach aimed to alleviate the effect of increments in the unit late arrival cost. The maximum average sailing speed was observed in scenario #6, which was 24.29 knots. The minimum average sailing speed of 22.79 knots was observed in scenario #18.

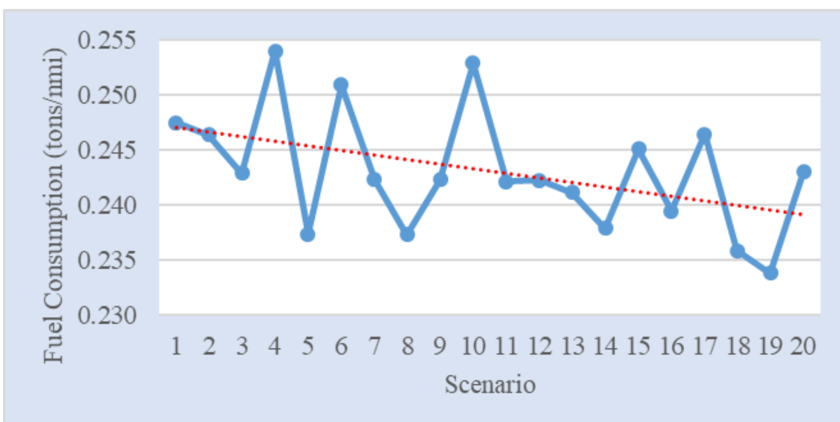


Figure 82 Sensitivity of the average fuel consumption to the unit late arrival cost.

Sensitivity of the average fuel consumption to the unit late arrival cost is shown in Figure 82. In order to mitigate the impact of increasing unit late arrival cost, the solution approach aimed to decrease the fuel consumption cost by decreasing the average fuel consumption rate. The maximum average fuel consumption was observed in scenario #4, which was 0.254 tons/nmi. The minimum average fuel consumption of 0.234 tons/nmi was observed in scenario #19.

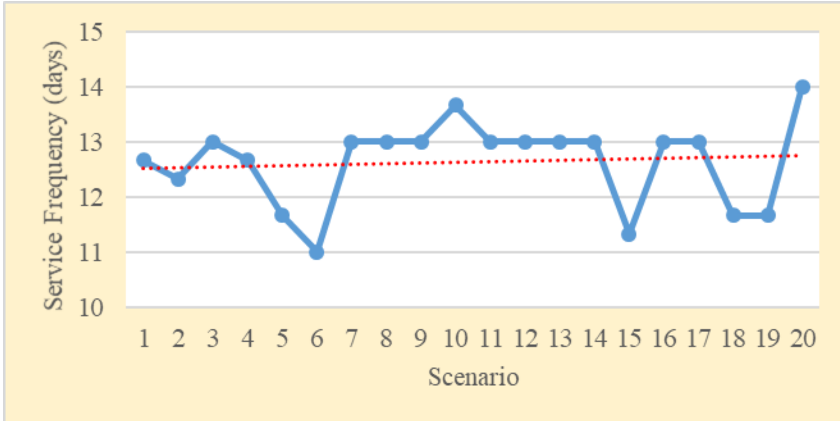


Figure 83 Sensitivity of the average port service frequency to the unit late arrival cost.

Sensitivity of the average port service frequency to the unit late arrival cost is presented in Figure 83. Even though the sailing speed was decreased, there was no clear pattern of increase or decrease in the average port service frequency. The maximum average port service frequency was observed in scenario #20, which was 14 days. The minimum average port service frequency of 11 days was observed in scenario #6.

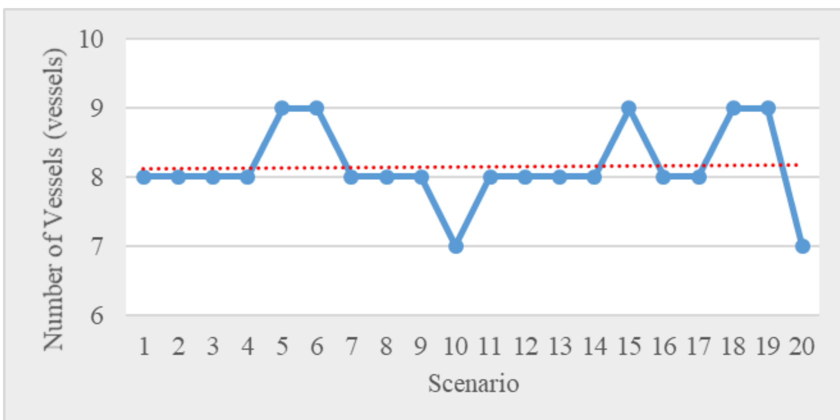


Figure 84 Sensitivity of the required number of vessels to the unit late arrival cost.

Sensitivity of the required number of vessels to the unit late arrival cost is highlighted in Figure 84. As the average port service frequency did not undergo significant change, the required number of vessels also stayed almost the same. Scenarios #5, #6, #15, #18, and #19 required the largest number of vessels to be deployed (9 vessels), while only 7 vessels were deployed in scenarios #10 and #20.

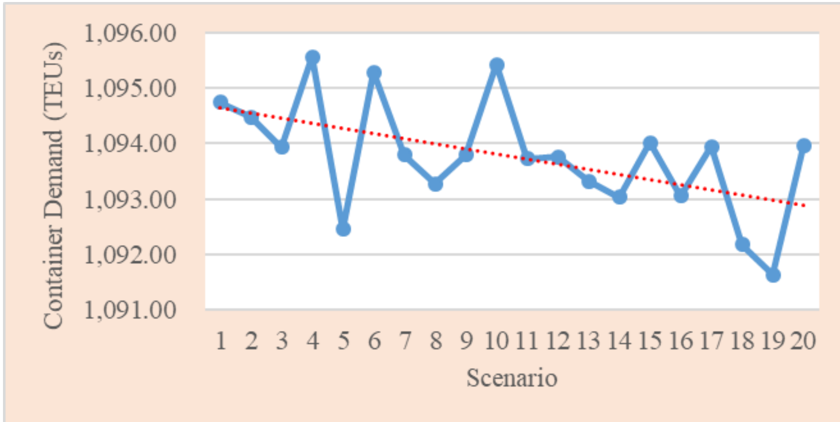


Figure 85 Sensitivity of the average container demand at ports to the unit late arrival cost.

Sensitivity of the average container demand at ports to the unit late arrival cost is presented in Figure 85. In the formulated mathematical model, the container demand at ports is inversely proportional to the sailing speed reciprocal. Since the sailing speed was decreased (i.e., sailing speed reciprocal was increased) with increasing unit late arrival cost, the container demand at ports went through a decreasing trend. The maximum average container demand at ports was observed in scenario #4, which was 1,095.57 TEUs. The minimum average container demand at ports of 1,091.62 TEUs was observed in scenario #19.

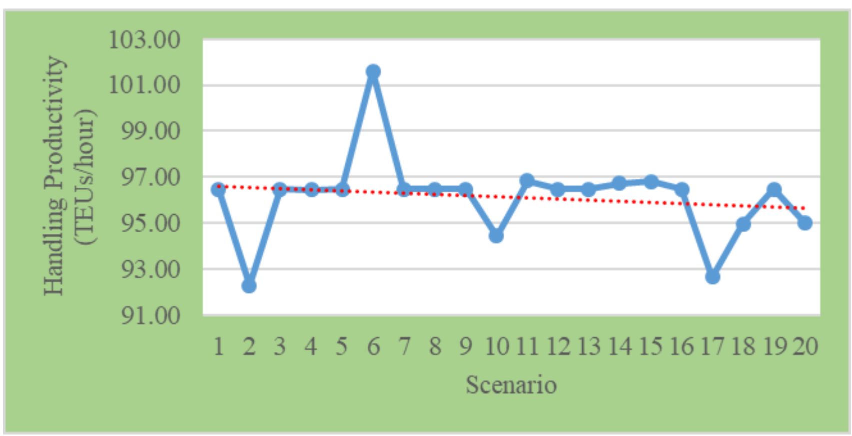


Figure 86 Sensitivity of the average handling productivity to the unit late arrival cost.

Sensitivity of the average port handling productivity to the unit late arrival cost is shown in Figure 86. Due to increments in the unit late arrival cost, the average port handling productivity experienced a decreasing trend. The maximum average port handling productivity was observed in scenario #6, which was 101.61 TEUs/hour. The minimum average port handling productivity of 92.29 TEUs/hour was observed in scenario #2.

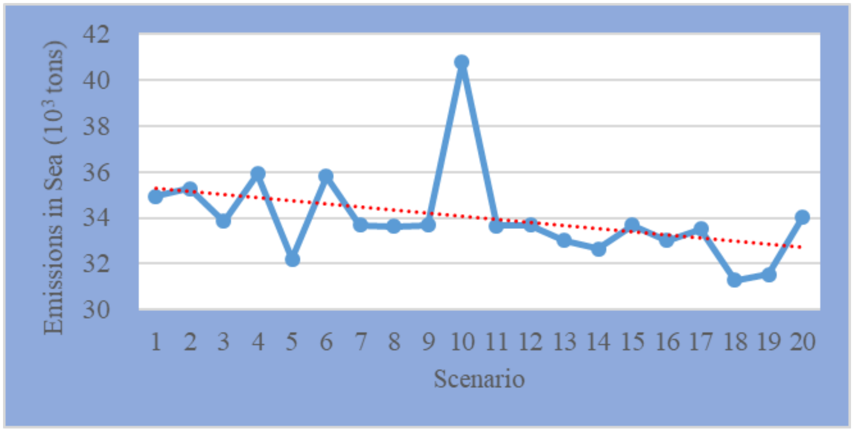


Figure 87 Sensitivity of the quantity of emissions produced in sea to the unit late arrival cost.

Sensitivity of the total quantity of emissions produced in sea to the unit late arrival cost is presented in Figure 87. Since the quantity of emissions produced by the vessels in sea is proportional to the fuel consumption, and the fuel consumption was reduced because of an increase in the unit late arrival cost, the quantity of emissions produced in sea was also decreased. The maximum quantity of emissions produced in sea was observed in scenario #10, which was 40,748 tons. The minimum quantity of emissions produced in sea of 31,299 tons was observed in scenario #18. Note that the total quantity of emissions produced due to handling of containers at ports, which was significantly less than the quantity of emissions produced in sea, also fluctuated due to an increase in the unit late arrival cost (since the container demand at ports and port operations were impacted from changing the unit late arrival cost).

Sensitivity of the total late arrival cost to the unit late arrival cost is highlighted in Figure 88. As the sailing speed and the fuel consumption per unit length were decreased in order to mitigate the impact of an increase in the unit late arrival cost, an overall decreasing trend in the total late arrival cost was noted. No late arrival was required for scenarios #14, #15, and #18. The maximum total late arrival cost of 197,525 USD was observed in scenario #6.

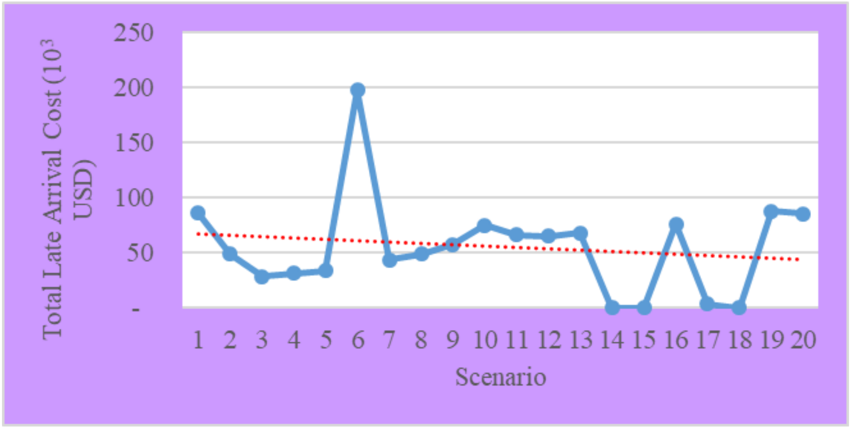


Figure 88 Sensitivity of the total late arrival cost to the unit late arrival cost.

Sensitivity of the total revenue to the unit late arrival cost is presented in Figure 89. Due to increments in the unit late arrival cost, the total revenue experienced an overall decreasing trend. The latter finding can be justified by reduction in container demand at ports of call after increasing the unit late arrival cost. The maximum revenue was observed in scenario #4, which was 38.80 million USD. The minimum revenue of 38.66 million USD was observed in scenario #19.

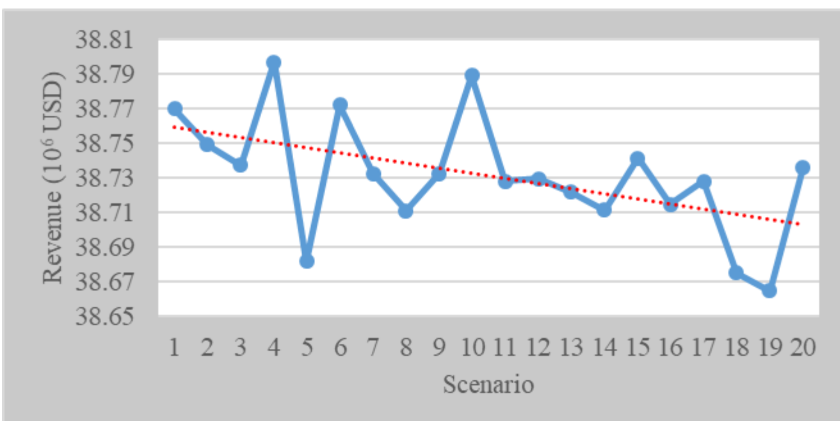


Figure 89 Sensitivity of the total revenue to the unit late arrival cost.

Sensitivity of the total profit to the unit late arrival cost is shown in Figure 90. No clear patterns for the total profit were observed, when the unit late arrival cost was increased. The maximum profit was observed in scenario #20, which was 24.29 million USD. The minimum profit of 23.87 million USD was observed in scenario #10.

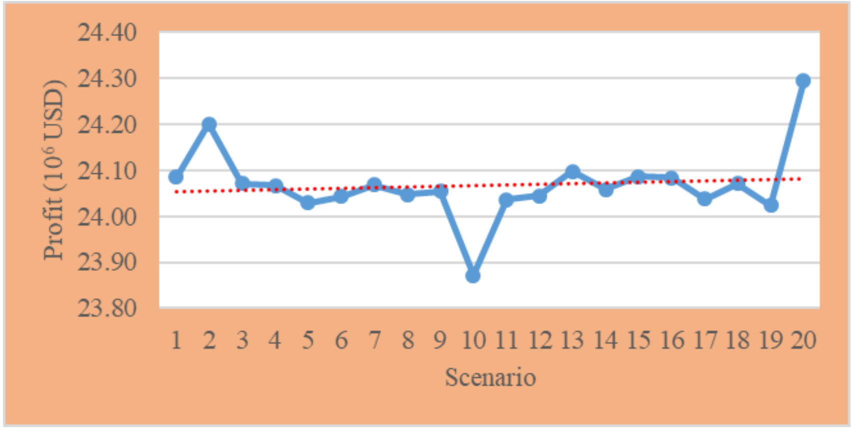


Figure 90 Sensitivity of the total profit to the unit late arrival cost.

Table 14 presents changes in different variables of the mathematical model due to increments in the unit late arrival cost. Apart from changes in the aforementioned variables, a number of other changes were noticed due to an increase in the unit late arrival cost. Among the components of the route service cost, an overall reduction in the total fuel cost, the total container inventory cost at ports, and the total emission cost in sea was observed. On the other hand, the total vessel operational cost, the total vessel chartering cost, the total port handling cost, and the total container inventory cost in sea experienced an increasing trend. The total emission cost at ports fluctuated from one scenario to another, but no clear increasing or decreasing trend was observed.

In addition to the cost components, changes in other variables were also observed. The total quantity of emissions produced in sea and at ports followed trends similar to the total emission cost in sea and at ports, respectively. The quantity of containers transported by the vessels stayed the same. The required number of own and chartered vessels fluctuated a little. Moreover, the average size of vessels stayed almost the same. Last but not least, increments in the unit late arrival cost decreased the CPU times and the optimality gaps for the problem instances. The latter patterns can be explained by changes in the feasible space for the formulated optimization model.

Table 14 Sensitivity analysis for the unit late arrival cost.

Scenario	Minimum Unit Late Arrival Cost (USD/hour)	Maximum Unit Late Arrival Cost (USD/hour)	Profit (USD)	REV (USD)	VOC (USD)	VCC (USD)	FCC (USD)	PHC (USD)	LAC (USD)
1	500	3,500	24,084,245	38,769,807	3,164,000	1,430,000	2,266,147	3,369,947	86,068
2	1,000	4,000	24,199,631	38,749,063	3,461,000	910,000	2,289,074	3,494,061	48,811
3	1,500	4,500	24,070,535	38,737,294	3,242,000	1,430,000	2,196,839	3,367,446	28,602
4	2,000	5,000	24,067,118	38,797,262	3,164,000	1,430,000	2,330,478	3,372,225	31,615
5	2,500	5,500	24,029,023	38,681,698	3,320,000	1,430,000	2,089,760	3,362,906	33,531
6	3,000	6,000	24,043,132	38,772,083	3,117,000	1,300,000	2,323,828	3,489,690	197,525
7	3,500	6,500	24,067,869	38,732,295	3,242,000	1,430,000	2,185,334	3,366,998	43,510
8	4,000	7,000	24,046,689	38,710,840	3,242,000	1,430,000	2,182,738	3,365,548	48,878
9	4,500	7,500	24,054,125	38,732,295	3,242,000	1,430,000	2,185,334	3,366,998	57,255
10	5,000	8,000	23,871,797	38,789,389	3,960,000	0	2,644,231	3,753,002	75,076
11	5,500	8,500	24,035,694	38,727,967	3,242,000	1,430,000	2,183,579	3,374,720	66,410
12	6,000	9,000	24,043,680	38,729,342	3,242,000	1,430,000	2,185,535	3,366,908	64,846
13	6,500	9,500	24,097,784	38,721,778	3,242,000	1,430,000	2,142,492	3,365,562	67,976
14	7,000	10,000	24,057,732	38,711,421	3,242,000	1,430,000	2,119,282	3,498,772	0
15	7,500	10,500	24,085,819	38,741,503	3,203,000	1,430,000	2,184,770	3,473,727	0
16	8,000	11,000	24,083,248	38,714,492	3,242,000	1,430,000	2,142,416	3,364,885	76,269
17	8,500	11,500	24,037,323	38,728,137	3,242,000	1,430,000	2,174,965	3,453,607	3,716
18	9,000	12,000	24,070,751	38,674,796	3,320,000	1,430,000	2,031,061	3,436,980	0
19	9,500	12,500	24,023,927	38,664,553	3,320,000	1,430,000	2,046,509	3,360,573	87,825
20	10,000	13,000	24,293,104	38,736,052	3,500,000	910,000	2,208,402	3,398,702	85,452

Table 14 – Continued.

Scenario	CIC^{SEA} (USD)	CIC^{PORT} (USD)	EC^{SEA} (USD)	EC^{PORT} (USD)	$TotEP^{SEA}$ (tons)	$TotEP^{PORT}$ (tons)	$AvgQC^{SEA}$ (TEUs)	$AvgQC^{PORT}$ (TEUs)
1	3,012,097	234,934	1,117,482	4,886	34,921	152.69	5,594.44	1,094.75
2	2,969,097	243,868	1,128,788	4,733	35,275	147.92	5,595.03	1,094.49
3	3,019,482	294,201	1,083,305	4,884	33,853	152.62	5,594.51	1,093.94
4	2,960,631	287,099	1,149,205	4,891	35,913	152.83	5,594.71	1,095.57
5	3,094,639	286,458	1,030,502	4,878	32,203	152.44	5,594.47	1,092.45
6	2,926,233	223,761	1,145,926	4,988	35,810	155.86	5,594.87	1,095.30
7	3,027,366	286,703	1,077,632	4,883	33,676	152.60	5,594.48	1,093.79
8	3,027,135	286,620	1,076,352	4,880	33,636	152.51	5,594.42	1,093.27
9	3,027,366	286,703	1,077,632	4,883	33,676	152.60	5,594.48	1,093.79
10	2,933,761	242,686	1,303,923	4,913	40,748	153.52	5,594.78	1,095.43
11	3,028,390	285,483	1,076,767	4,924	33,649	153.87	5,594.58	1,093.73
12	3,027,076	286,683	1,077,731	4,883	33,679	152.61	5,594.57	1,093.76
13	3,079,993	234,585	1,056,506	4,881	33,016	152.53	5,594.47	1,093.32
14	3,079,297	234,230	1,045,061	5,048	32,658	157.75	5,594.02	1,093.04
15	3,050,942	231,001	1,077,354	4,890	33,667	152.82	5,595.06	1,094.01
16	3,079,828	234,498	1,056,468	4,880	33,015	152.49	5,594.28	1,093.06
17	3,063,156	245,979	1,072,519	4,873	33,516	152.28	5,595.10	1,093.94
18	3,141,743	237,840	1,001,557	4,864	31,299	152.00	5,594.32	1,092.17
19	3,147,431	234,239	1,009,175	4,873	31,537	152.29	5,594.03	1,091.62
20	3,008,568	237,970	1,089,007	4,845	34,031	151.40	5,594.49	1,093.96

Note:

$\boldsymbol{TotEP^{SEA}}$ – total quantity of emissions produced in sea (tons); $\boldsymbol{TotEP^{PORT}}$ – total quantity of emissions produced at ports (tons); $\boldsymbol{AvgQC^{SEA}}$ – average quantity of containers to be transported at each voyage leg (TEUs); $\boldsymbol{AvgQC^{PORT}}$ – average quantity of containers to be handled at each port (TEUs).

Table 14 – Continued.

Scenario	$Totq$ (vessels)	$Totq^{own}$ (vessels)	$Totq^{char}$ (vessels)	$Avgf$ (days)	$AvgRF$ (tons/nmi)	$AvgWtSpd$ (knots)	$AvgWtHP$ (TEUs/hour)	$AvgWtCCC$ (tons)	CPU Time (seconds)	Optimality Gap (%)
1	8	6	2	12.67	0.247	23.57	96.44	148,500.00	307.84	3.00%
2	8	7	1	12.33	0.246	23.93	92.29	147,750.00	1,469.20	2.97%
3	8	6	2	13.00	0.243	23.56	96.46	148,500.00	210.12	3.00%
4	8	6	2	12.67	0.254	24.00	96.44	148,500.00	192.53	3.00%
5	9	7	2	11.67	0.237	23.11	96.47	148,000.00	345.35	3.00%
6	9	7	2	11.00	0.251	24.29	101.61	148,000.00	291.21	3.00%
7	8	6	2	13.00	0.242	23.51	96.46	148,500.00	216.57	3.00%
8	8	6	2	13.00	0.237	23.51	96.46	148,500.00	276.01	2.69%
9	8	6	2	13.00	0.242	23.51	96.46	148,500.00	336.25	3.00%
10	7	7	0	13.67	0.253	24.21	94.44	147,428.57	289.73	3.00%
11	8	6	2	13.00	0.242	23.50	96.85	148,500.00	207.23	3.00%
12	8	6	2	13.00	0.242	23.51	96.47	148,500.00	278.28	3.00%
13	8	6	2	13.00	0.241	23.18	96.47	148,500.00	217.60	3.00%
14	8	6	2	13.00	0.238	23.08	96.74	148,500.00	177.40	3.00%
15	9	7	2	11.33	0.245	23.28	96.81	148,000.00	138.82	3.00%
16	8	6	2	13.00	0.239	23.19	96.48	148,500.00	287.21	2.48%
17	8	6	2	13.00	0.246	23.24	92.66	148,500.00	318.64	2.47%
18	9	7	2	11.67	0.236	22.71	94.97	148,000.00	319.78	2.87%
19	9	7	2	11.67	0.234	22.79	96.49	148,000.00	111.04	3.00%
20	7	6	1	14.00	0.243	23.64	94.99	148,285.71	113.28	3.00%

Note:

$Totq$ – total number of required vessels (vessels); $Totq^{own}$ – total number of own vessels required (vessels); $Totq^{char}$ – total number of chartered vessels required (vessels); $Avgf$ – average port service frequency (days); $AvgRF$ – average fuel consumption (tons/nmi); $AvgWtSpd$ – average vessel sailing speed weighted by voyage leg length (knots); $AvgWtHP$ – average requested handling productivity weighted by the number of containers handled at ports (TEUS/hour); $AvgWtCCC$ – average weighted cargo carrying capacity of vessels (tons).

6.4.7. Sensitivity Analysis for the Unit Freight Rate

A sensitivity analysis for the unit freight rate is investigated in this section of the dissertation. A total of 20 scenarios were developed to conduct the sensitivity analysis for the unit freight rate. With increments of 250 USD/TEU, the unit freight rate was increased from $U[250; 1{,}750]$ USD/TEU in scenario #1 to $U[5{,}000; 6{,}500]$ USD/TEU in scenario #20. Sensitivity of the average sailing speed to the unit freight rate is presented in Figure 91, where it can be seen that when the unit freight rate was increased, the average sailing speed experienced an overall decrease. The maximum average sailing speed was observed in scenario #19, which was 24.30 knots. The minimum average sailing speed of 22.03 knots was observed in scenario #8.

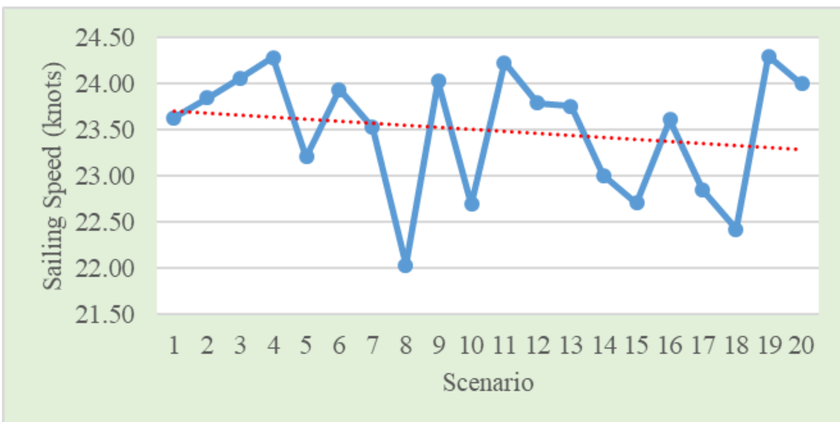


Figure 91 Sensitivity of the average sailing speed to the unit freight rate.

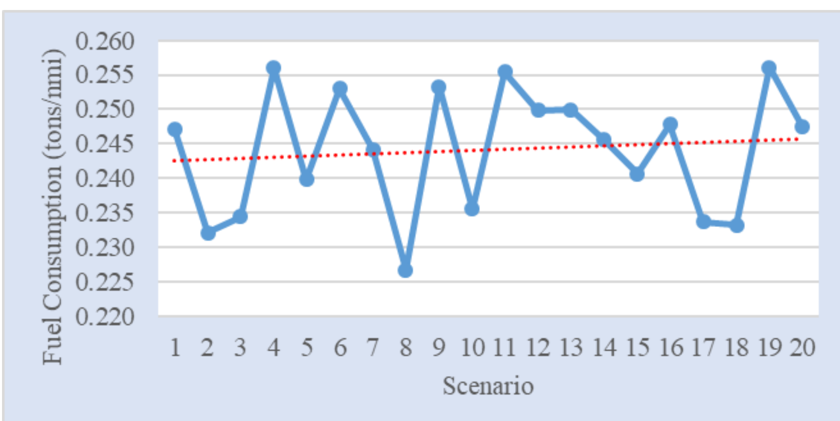


Figure 92 Sensitivity of the average fuel consumption to the unit freight rate.

Sensitivity of the average fuel consumption to the unit freight rate is shown in Figure 92. Even though the average sailing speed experienced a decrease, there was an increase in the average fuel consumption rate. However, no clear increase in the average fuel consumption can be observed from one scenario to another due to fluctuations in the vessel sailing speed. The maximum average fuel consumption was observed in scenarios #4 and #19, which was 0.256 tons/nmi. The minimum average fuel consumption of 0.227 tons/nmi was observed in scenario #8.

Sensitivity of the average port service frequency to the unit freight rate is presented in Figure 93. Since the sailing speed was decreased, the solution approach attempted to meet the demand by decreasing the port service frequency (i.e., the ports were visited more frequently). The maximum average port service frequency was observed in scenarios #1 and #7, which was 14 days. The minimum average port service frequency of 10.33 days was observed in scenario #14.

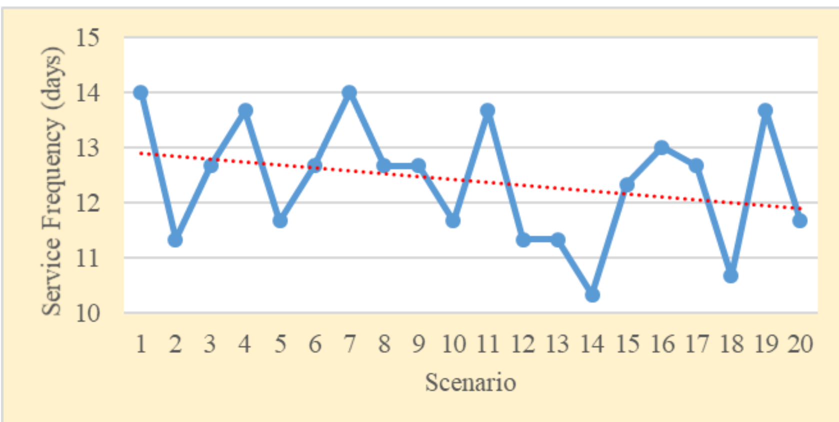


Figure 93 Sensitivity of the average port service frequency to the unit freight rate.

Sensitivity of the required number of vessels to the unit freight rate is highlighted in Figure 94. As the average port service frequency was decreased due to increments in the unit freight rate, more vessels were required for deployment. Scenario #18 required the largest number of vessels to be deployed (11 vessels), while only 7 vessels were deployed in scenarios #1, #4, #7, #11, and #19.

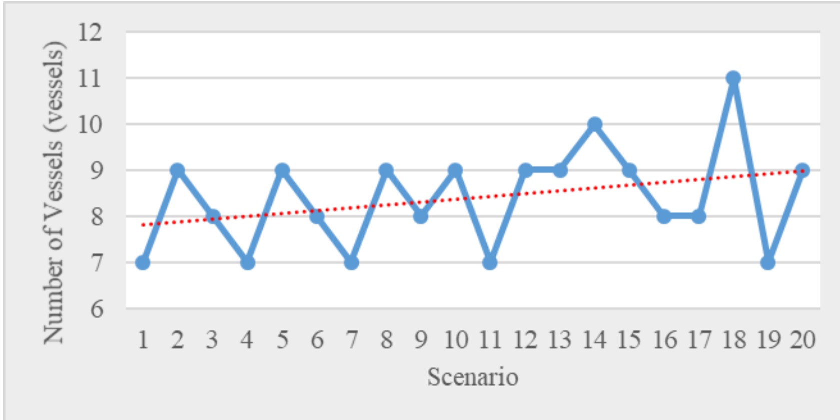


Figure 94 Sensitivity of the required number of vessels to the unit freight rate.

Sensitivity of the average container demand at ports to the unit freight rate is presented in Figure 95. Since the unit freight rate was increased, more containers were transported to obtain a higher profit. However, no clear increase in the container demand can be observed from one scenario to another due to fluctuations in the vessel sailing speed. The maximum average container demand at ports was observed in scenario #19, which was 1,096.11 TEUs. The minimum average container demand at ports of 1,090.14 TEUs was observed in scenario #8.

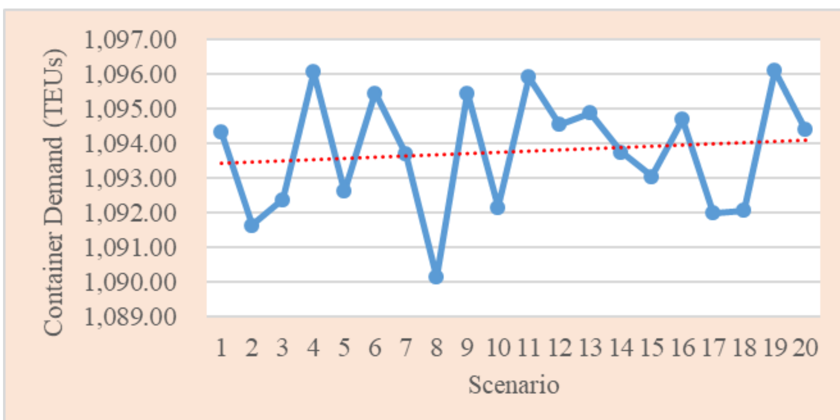


Figure 95 Sensitivity of the average container demand at ports to the unit freight rate.

Sensitivity of the average port handling productivity to the unit freight rate is shown in Figure 96. Due to increments in the unit freight rate, the average port handling productivity experienced an increasing trend. Such pattern can be explained by the fact that the liner shipping company aimed to reduce the vessel handling time at ports of call (by requesting HRs with higher handling productivities) and use these time savings to compensate for the time losses in sea (since the vessel sailing speed generally decreased with increasing unit freight rate from one scenario to another). The maximum average port handling productivity was observed in scenario #15, which was 104.28 TEUs/hour. The minimum average port handling productivity of 91.95 TEUs/hour was observed in scenarios #4 and #19.

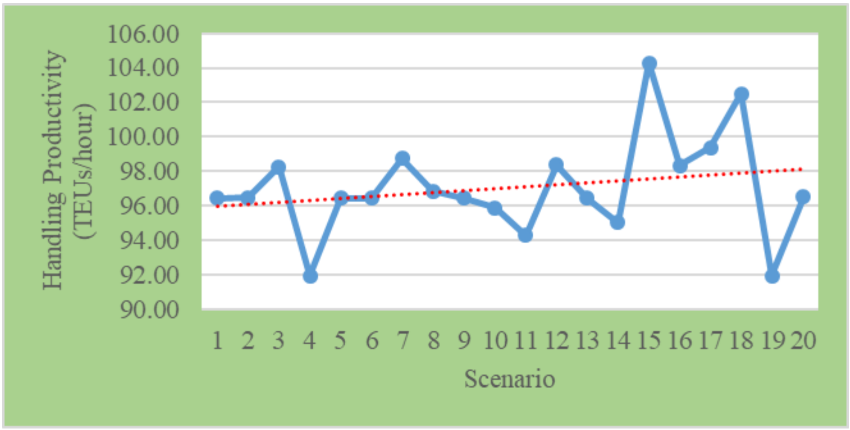


Figure 96 Sensitivity of the average handling productivity to the unit freight rate.

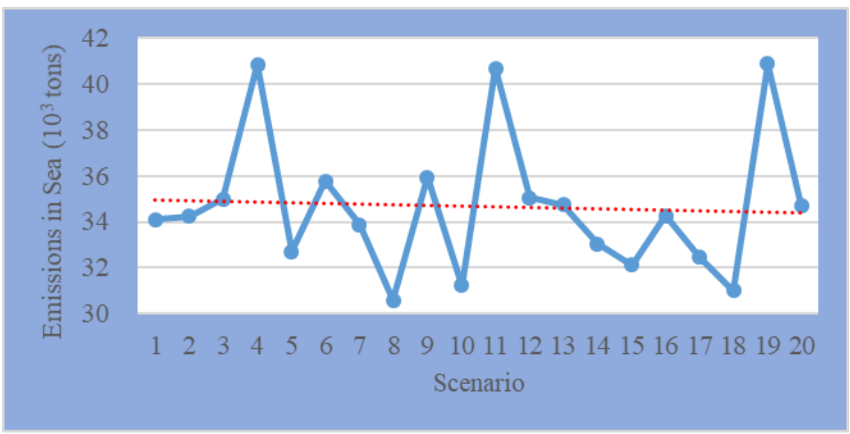


Figure 97 Sensitivity of the quantity of emissions produced in sea to the unit freight rate.

Sensitivity of the total quantity of emissions produced in sea to the unit freight rate is presented in Figure 97. Due to an increase in the unit freight rate, the quantity of emissions produced in sea was decreased. The maximum quantity of emissions produced in sea was observed in scenario #19, which was 40,867 tons. The minimum quantity of emissions produced in sea of 30,579 tons was observed in scenario #8. Note that the total quantity of emissions produced due to handling of containers at ports, which was significantly less than the quantity of emissions produced in sea, also fluctuated due to an increase in the unit freight rate (since the container demand at ports and port operations were impacted from changing the unit freight rate).

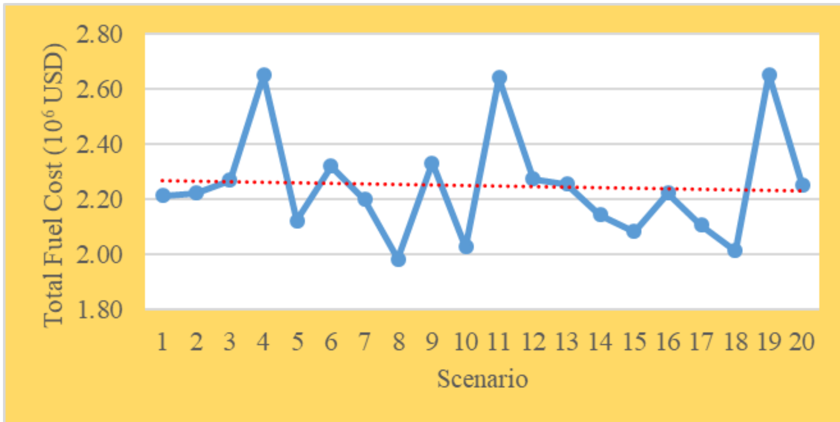


Figure 98 Sensitivity of the total fuel cost to the unit freight rate.

Sensitivity of the total fuel cost to the unit freight rate is highlighted in Figure 98. Even though the fuel consumption per unit length was increased, a slight decreasing trend in the total fuel cost was noted. However, no clear decrease in the total fuel cost can be observed from one scenario to another due to fluctuations in the vessel sailing speed. The minimum total fuel cost was observed in scenario #8, which was 1.98 million USD. The maximum total fuel cost of 2.65 million USD was observed in scenario #19.

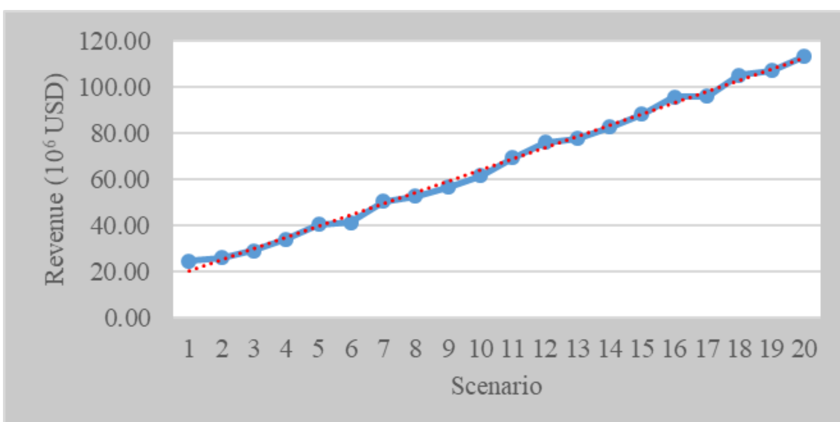


Figure 99 Sensitivity of the total revenue to the unit freight rate.

Sensitivity of the total revenue to the unit freight rate is presented in Figure 99. Due to increments in the unit freight rate, the total revenue experienced an overall increasing trend. The latter finding can be justified by an increase in container demand at ports of call after increasing the unit freight rate. The maximum revenue was observed in scenario #20, which was 113.46 million USD. The minimum revenue of 24.49 million USD was observed in scenario #1.

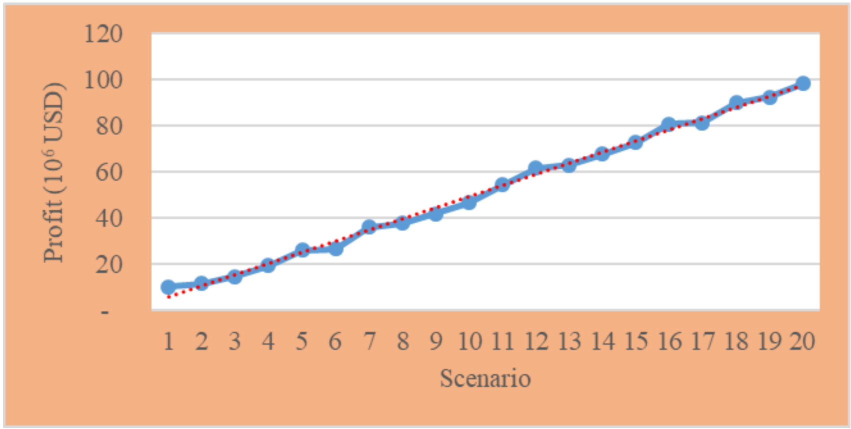


Figure 100 Sensitivity of the total profit to the unit freight rate.

Sensitivity of the total profit to the unit freight rate is shown in Figure 100. As the total revenue was substantially increased due to an increase in the unit freight rate, the total profit was also increased. The maximum profit was observed in scenario #20, which was 98.44 million USD. The minimum profit of 10.09 million USD was observed in scenario #1.

Table 15 presents changes in different variables of the mathematical model due to increments in the unit freight rate. Apart from changes in the aforementioned variables, a number of other changes were noticed due to an increase in the unit freight rate. Among the components of the route service cost, an overall reduction in the total vessel operational cost and the total emission cost in sea was observed. On the other hand, the total vessel chartering cost, the total port handling cost, the total late arrival cost, and the total container inventory cost in sea and at ports experienced an increasing trend. The total emission cost at ports fluctuated from one scenario to another, but no clear increasing or decreasing trend was observed.

In addition to the cost components, changes in other variables were also observed. The total quantity of emissions produced in sea and at ports followed trends similar to the total emission cost in sea and at ports, respectively. The quantity of containers transported by the vessels stayed the same. The required number of own vessels also stayed almost the same, while the required number of chartered vessels was increased. Moreover, reductions in the average size of vessels were also observed. Last but not least, increments in the unit freight rate decreased the CPU times and the optimality gaps for the problem instances. The latter patterns can be explained by changes in the feasible space for the formulated optimization model.

6.4.8. Sensitivity Analysis for the Availability of Port Arrival TWs

A sensitivity analysis for the availability of port arrival TWs is investigated in this section of the dissertation. A total of 4 scenarios were developed to conduct the sensitivity analysis for the availability of TWs, where a total of 3 TWs (i.e., TWs "1", "2", and "3") were considered. In scenarios #1, #2, and #3, TWs "1", "2", and "3" were available, respectively, while in scenario #4, all the TWs (i.e., TWs "1", "2", and "3") were made available. Sensitivity of the average sailing speed to the availability of TWs is presented in Figure 101. The maximum average sailing speed was observed in scenario #1, which was 23.76 knots. The minimum average sailing speed of 22.81 knots was observed in scenario #2.

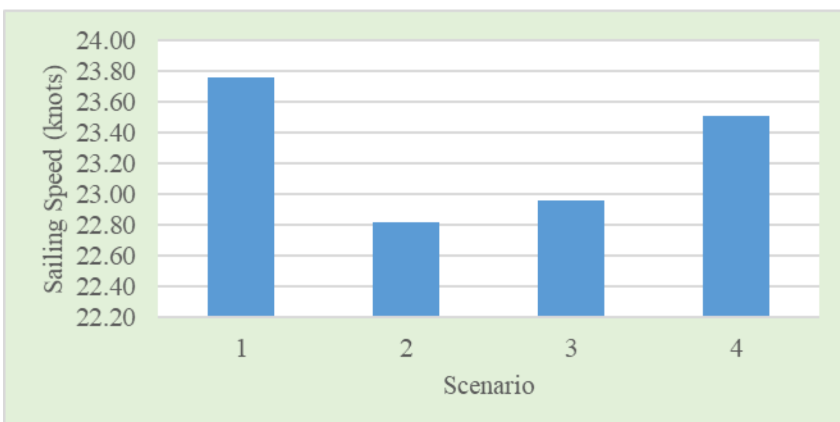


Figure 101 Sensitivity of the average sailing speed to the availability of TWs.

Sensitivity of the average fuel consumption to the availability of TWs is shown in Figure 102. Scenario #1 required the highest average sailing speed, and it also made the fuel consumption rate to be the highest, which was 0.252 tons/nmi. The minimum average fuel consumption of 0.231 tons/nmi was observed in scenario #3.

Table 15 Sensitivity analysis for the unit freight rate.

Scenario	**Minimum Unit Freight Rate (USD/TEU)**	**Maximum Unit Freight Rate (USD/TEU)**	**Profit (USD)**	REV **(USD)**	VOC **(USD)**	VCC **(USD)**	FCC **(USD)**	PHC **(USD)**	LAC **(USD)**
1	250	1,750	10,092,413	24,485,903	3,500,000	910,000	2,212,738	3,368,431	58,426
2	500	2,000	11,401,513	25,925,872	3,234,000	1,300,000	2,222,440	3,360,854	58,426
3	750	2,250	14,488,683	28,975,020	3,156,000	1,300,000	2,270,140	3,394,048	58,426
4	1,000	2,500	19,195,530	33,975,366	3,960,000	0	2,650,250	3,683,915	0
5	1,250	2,750	25,757,362	40,486,158	3,320,000	1,430,000	2,122,657	3,363,401	58,426
6	1,500	3,000	26,333,948	41,107,763	3,164,000	1,430,000	2,320,790	3,371,934	89,975
7	1,750	3,250	35,857,096	50,354,841	3,500,000	910,000	2,198,547	3,551,448	0
8	2,000	3,500	37,479,367	52,513,531	3,156,000	1,950,000	1,984,329	3,408,228	37,670
9	2,250	3,750	41,761,983	56,519,159	3,164,000	1,430,000	2,331,560	3,371,920	58,426
10	2,500	4,000	46,448,725	61,466,471	2,930,000	2,020,000	2,026,789	3,631,083	27,620
11	2,750	4,250	54,339,701	69,249,917	3,960,000	0	2,640,278	3,807,004	20,427
12	3,000	4,500	61,423,736	76,182,956	3,203,000	1,430,000	2,274,141	3,381,226	64,602
13	3,250	4,750	62,906,370	77,620,810	3,203,000	1,430,000	2,254,886	3,370,150	58,426
14	3,500	5,000	67,674,869	82,871,400	2,945,000	2,145,000	2,144,413	3,402,426	40,020
15	3,750	5,250	72,594,998	88,198,118	3,070,000	1,755,000	2,084,116	3,725,009	581,794
16	4,000	5,500	80,788,671	95,942,625	3,242,000	1,625,000	2,222,761	3,501,792	35,409
17	4,250	5,750	81,375,853	96,232,194	3,609,000	910,000	2,105,788	3,827,294	0
18	4,500	6,000	89,937,578	105,378,114	2,898,000	2,340,000	2,012,882	3,632,682	35,409
19	4,750	6,250	92,327,296	107,109,886	3,960,000	0	2,651,966	3,684,037	0
20	5,000	6,500	98,438,361	113,458,964	2,922,000	1,949,000	2,252,898	3,373,344	58,426

Table 15 – Continued.

Scenario	CIC^{SEA} (USD)	CIC^{PORT} (USD)	EC^{SEA} (USD)	EC^{PORT} (USD)	$TotEP^{SEA}$ (tons)	$TotEP^{PORT}$ (tons)	$AvgQC^{SEA}$ (TEUs)	$AvgQC^{PORT}$ (TEUs)
1	3,013,053	234,811	1,091,146	4,886	34,098	152.69	5,594.78	1,094.32
2	3,006,323	241,515	1,095,930	4,873	34,248	152.27	5,593.52	1,091.63
3	2,956,100	227,277	1,119,452	4,895	34,983	152.97	5,594.58	1,092.38
4	2,922,334	251,612	1,306,891	4,834	40,840	151.08	5,594.49	1,096.07
5	3,096,152	286,558	1,046,725	4,878	32,710	152.42	5,594.02	1,092.62
6	2,968,364	279,435	1,144,428	4,890	35,763	152.81	5,594.61	1,095.46
7	3,023,768	224,903	1,084,147	4,933	33,880	154.14	5,594.79	1,093.71
8	3,281,390	233,102	978,512	4,931	30,579	154.11	5,593.95	1,090.14
9	2,959,618	287,023	1,149,739	4,891	35,929	152.85	5,595.02	1,095.46
10	3,142,637	235,210	999,450	4,957	31,233	154.89	5,594.50	1,092.15
11	2,930,507	245,148	1,301,974	4,879	40,687	152.46	5,594.46	1,095.92
12	2,998,008	281,930	1,121,424	4,888	35,045	152.76	5,595.31	1,094.56
13	2,994,199	286,963	1,111,929	4,888	34,748	152.75	5,594.75	1,094.88
14	3,102,525	354,823	1,057,453	4,870	33,045	152.18	5,594.98	1,093.76
15	3,143,057	211,464	1,027,719	4,959	32,116	154.97	5,593.94	1,093.04
16	3,008,757	417,236	1,096,088	4,911	34,253	153.48	5,594.77	1,094.70
17	3,136,290	224,727	1,038,406	4,834	32,450	151.06	5,594.98	1,091.99
18	3,169,014	354,987	992,592	4,971	31,019	155.34	5,594.35	1,092.07
19	2,921,009	253,006	1,307,738	4,835	40,867	151.08	5,594.48	1,096.11
20	2,974,900	374,172	1,110,949	4,913	34,717	153.53	5,594.70	1,094.40

Note:

$TotEP^{SEA}$ – total quantity of emissions produced in sea (tons); $TotEP^{PORT}$ – total quantity of emissions produced at ports (tons); $AvgQC^{SEA}$ – average quantity of containers to be transported at each voyage leg (TEUs); $AvgQC^{PORT}$ – average quantity of containers to be handled at each port (TEUs).

Table 15 – Continued.

Scenario	$\boldsymbol{Totq}$ (vessels)	$\boldsymbol{Totq^{own}}$ (vessels)	$\boldsymbol{Totq^{char}}$ (vessels)	$\boldsymbol{Avgf}$ (days)	$\boldsymbol{AvgRF}$ (tons/nmi)	$\boldsymbol{AvgWtSpd}$ (knots)	$\boldsymbol{AvgWtHP}$ (TEUs/hour)	$\boldsymbol{AvgWtCCC}$ (tons)	CPU Time (seconds)	Optimality Gap (%)
1	7	6	1	14.00	0.247	23.63	96.45	148,285.71	241.87	2.60%
2	9	7	2	11.33	0.232	23.85	96.48	148,000.00	549.40	3.00%
3	8	6	2	12.67	0.234	24.06	98.27	148,500.00	539.20	2.23%
4	7	7	0	13.67	0.256	24.29	91.95	147,428.57	347.81	3.00%
5	9	7	2	11.67	0.240	23.20	96.45	148,000.00	289.89	3.00%
6	8	6	2	12.67	0.253	23.93	96.44	148,500.00	147.03	3.00%
7	7	6	1	14.00	0.244	23.52	98.75	148,285.71	197.56	3.00%
8	9	6	3	12.67	0.227	22.03	96.84	148,666.67	194.53	3.00%
9	8	6	2	12.67	0.253	24.02	96.46	148,500.00	136.73	3.00%
10	9	6	3	11.67	0.236	22.69	95.89	148,000.00	321.81	3.00%
11	7	7	0	13.67	0.255	24.23	94.30	147,428.57	429.21	3.00%
12	9	7	2	11.33	0.250	23.79	98.38	148,000.00	261.87	2.85%
13	9	7	2	11.33	0.250	23.75	96.45	148,000.00	114.85	2.22%
14	10	7	3	10.33	0.246	23.00	95.05	148,200.00	141.20	3.00%
15	9	6	3	12.33	0.241	22.70	104.28	148,666.67	279.12	3.00%
16	8	6	2	13.00	0.248	23.61	98.34	148,500.00	216.29	2.34%
17	8	7	1	12.67	0.234	22.84	99.39	147,750.00	257.95	3.00%
18	11	6	5	10.67	0.233	22.42	102.51	148,909.09	117.81	3.00%
19	7	7	0	13.67	0.256	24.30	91.95	147,428.57	241.15	2.12%
20	9	6	3	11.67	0.247	24.00	96.50	148,000.00	92.78	2.22%

Note:

$\boldsymbol{Totq}$ – total number of required vessels (vessels); $\boldsymbol{Totq^{own}}$ – total number of own vessels required (vessels); $\boldsymbol{Totq^{char}}$ – total number of chartered vessels required (vessels); $\boldsymbol{Avgf}$ – average port service frequency (days); $\boldsymbol{AvgRF}$ – average fuel consumption (tons/nmi); $\boldsymbol{AvgWtSpd}$ – average vessel sailing speed weighted by voyage leg length (knots); $\boldsymbol{AvgWtHP}$ – average requested handling productivity weighted by the number of containers handled at ports (TEUS/hour); $\boldsymbol{AvgWtCCC}$ – average weighted cargo carrying capacity of vessels (tons).

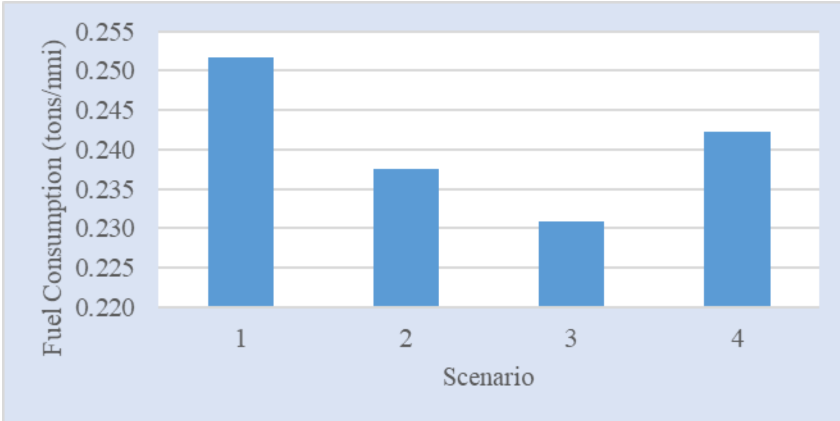


Figure 102 Sensitivity of the average fuel consumption to the availability of TWs.

Sensitivity of the average port service frequency to the availability of TWs is presented in Figure 103. The maximum average port service frequency was observed in scenario #4, which was 13 days. The minimum average port service frequency of 10 days was observed in scenario #3.

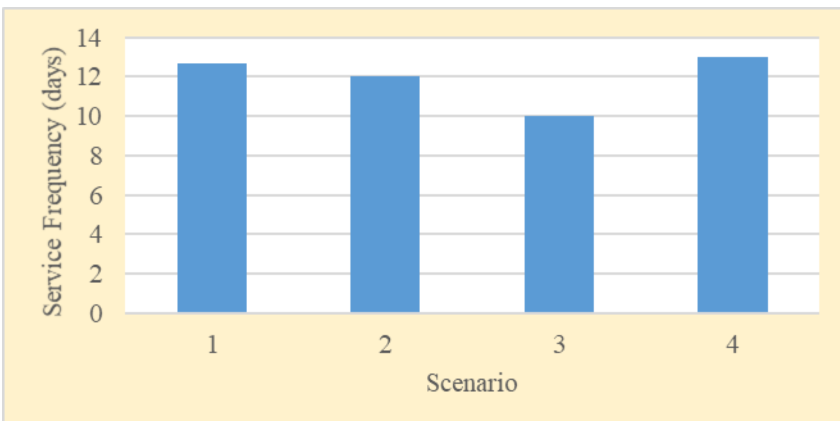


Figure 103 Sensitivity of the average port service frequency to the availability of TWs.

Sensitivity of the required number of vessels to the availability of TWs is highlighted in Figure 104. Scenario #3 required the largest number of vessels to be deployed (13 vessels), as the lowest port service frequency was observed in this scenario. Scenarios #1 and #4 required the highest port service frequency, and so, the lowest number of vessels (8 vessels) were observed in these scenarios.

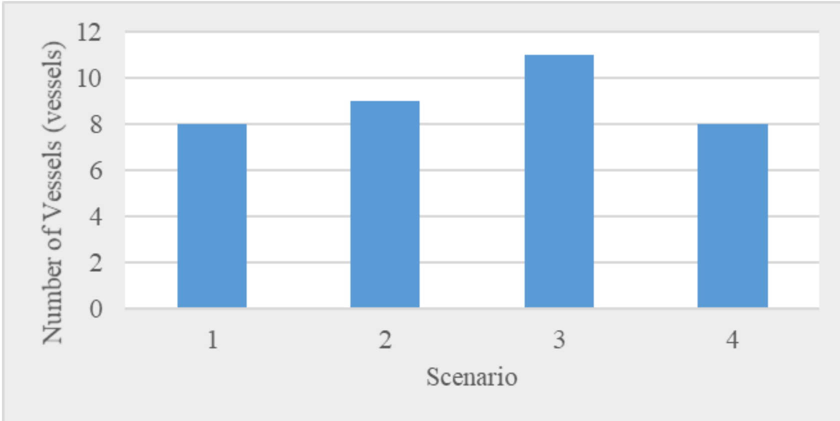


Figure 104 Sensitivity of the required number of vessels to the availability of TWs.

Sensitivity of the average container demand at ports to the availability of TWs is presented in Figure 105. The maximum average container demand at ports was observed in scenario #1, which was 1,095.20 TEUs. The minimum average container demand at ports of 1,090.67 TEUs was observed in scenario #3.

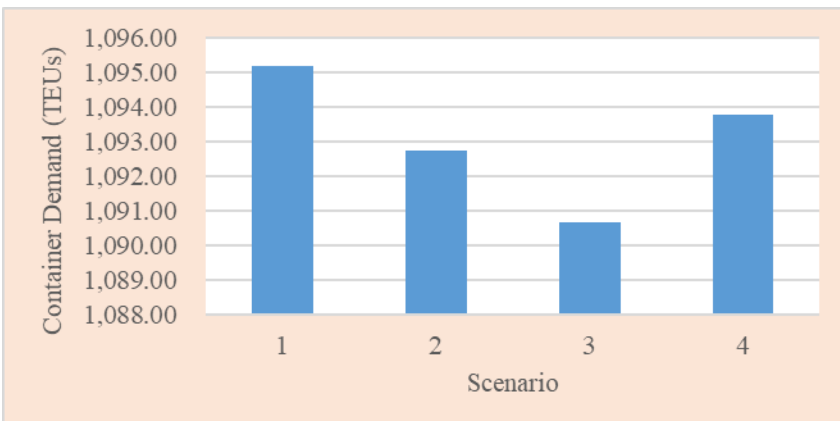


Figure 105 Sensitivity of the average container demand at ports to the availability of TWs.

Sensitivity of the average port handling productivity to the availability of TWs is shown in Figure 106. The maximum average port handling productivity was observed in scenario #2, which was 103.35 TEUs/hour. The minimum average port handling productivity of 91.72 TEUs/hour was observed in scenario #3.

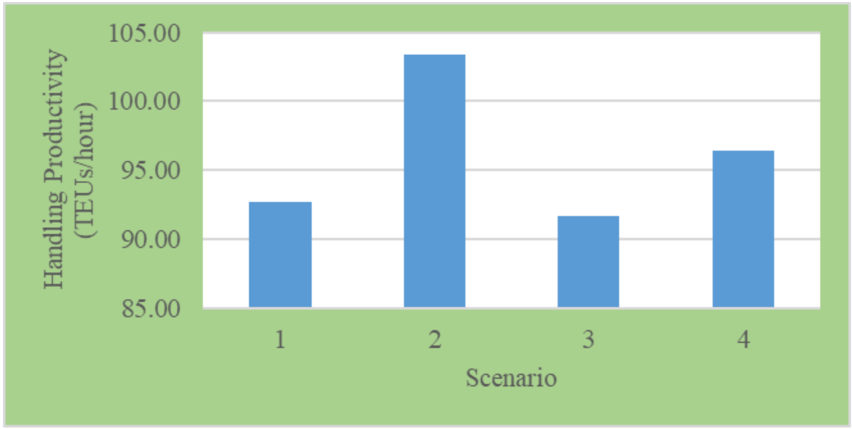


Figure 106 Sensitivity of the average handling productivity to the availability of TWs.

Sensitivity of the total quantity of emissions produced in sea to the availability of TWs is presented in Figure 107. Since the quantity of emissions produced by the vessels in sea is proportional to the fuel consumption, and highest fuel consumption was recorded in scenario #1, the highest amount of emissions produced in sea was also observed in scenario #1, which was 38,635 tons. The minimum quantity of emissions produced in sea (32,257 tons) was observed in scenario #2. Note that the total quantity of emissions produced due to handling of containers at ports, which was significantly less than the quantity of emissions produced in sea, also fluctuated due to a change in the availability of TWs (since the container demand at ports and port operations were impacted from changing the availability of TWs).

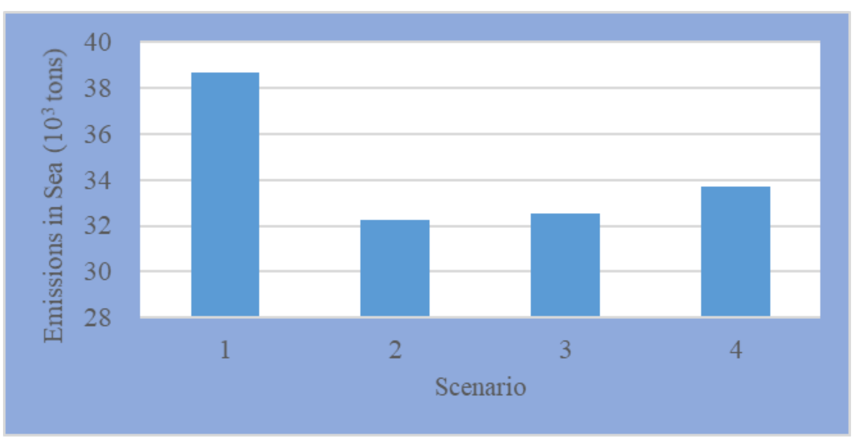


Figure 107 Sensitivity of the quantity of emissions produced in sea to the availability of TWs.

Sensitivity of the total fuel cost to the availability of TWs is highlighted in Figure 108. The highest average sailing speed and the highest average fuel consumption were recorded in scenario #1. So, scenario #1 incurred the highest value of the total fuel cost, which was 2.51 million USD. The minimum total fuel cost was observed in scenario #2, which was 2.09 million USD.

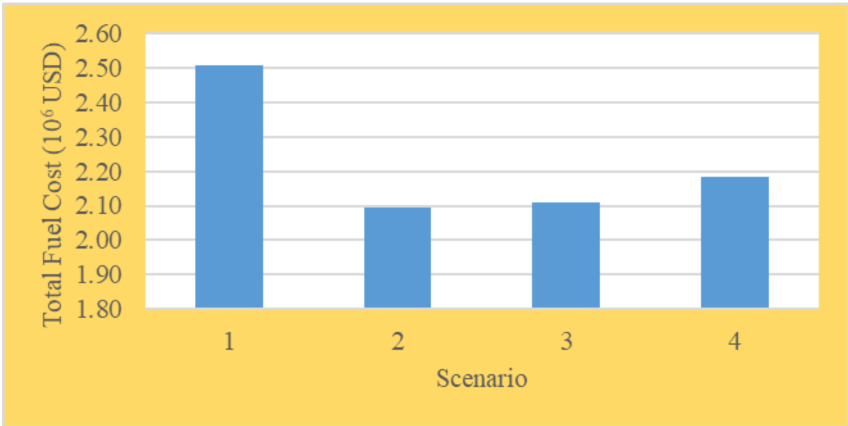


Figure 108 Sensitivity of the total fuel cost to the availability of TWs.

Sensitivity of the total revenue to the availability of TWs is presented in Figure 109. The maximum revenue was observed in scenario #1, which was 38.79 million USD. The latter finding can be justified by the fact that the revenue was generated from transportation of containers, and the container demand at ports was the highest in scenario #1. The minimum revenue of 38.61 million USD was observed in scenario #3, which recorded the lowest container demand.

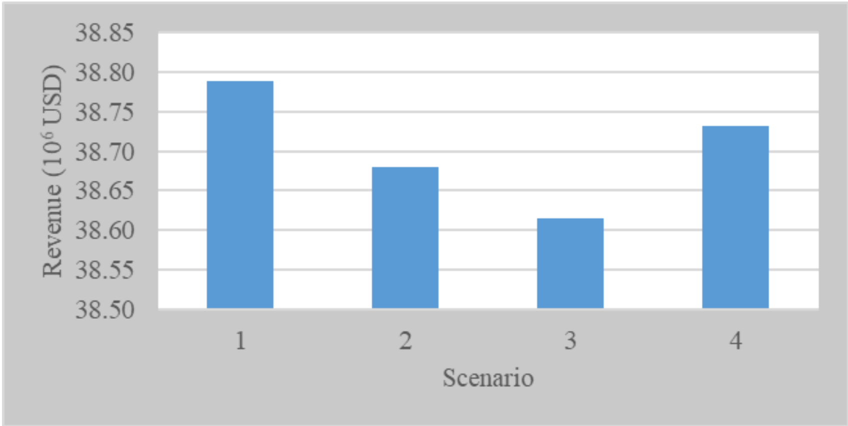


Figure 109 Sensitivity of the total revenue to the availability of TWs.

Sensitivity of the total profit to the availability of TWs is shown in Figure 110. The minimum profit of 22.64 million USD was observed in scenario #1. The maximum profit (24.05 million USD) was recorded in scenario #4, where all 3 TWs were made available. The latter finding highlights that availability of more TWs led to the highest total profit (i.e., the best value of the objective function).

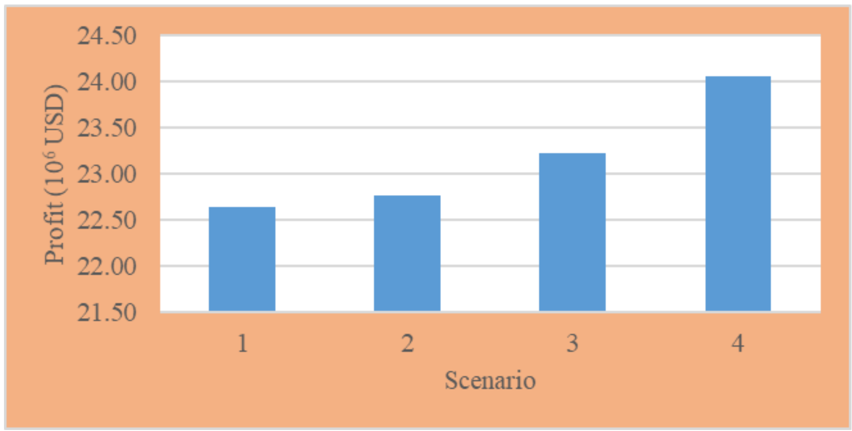


Figure 110 Sensitivity of the total profit to the availability of TWs.

Table 16 presents changes in different variables of the mathematical model due to changes in the availability of TWs. Apart from the aforementioned variables, the other variables highlighted in this table include the total vessel operational cost, the total vessel chartering cost, the total port handling cost, the total late arrival cost, the total container inventory cost in sea and at ports, the total emission cost in sea and at ports, the quantity of containers transported in sea, the total number of own and chartered vessels required, the average weighted cargo carrying capacity of vessels, CPU time, and optimality gap.

6.4.9. Sensitivity Analysis for the Availability of Container HRs

A sensitivity analysis for the availability of container HRs is investigated in this section of the dissertation. A total of 5 scenarios were developed to conduct the sensitivity analysis for the availability of HRs, where a total of 4 HRs (i.e., HRs “1”, “2”, “3”, and “4”) were considered. In scenarios #1, #2, #3, and #4, HRs “1”, “2”, “3”, and “4” were available, respectively, while in scenario #5, all the HRs (i.e., HRs “1”, “2”, “3”, and “4”) were made available.

Table 16 Sensitivity analysis for the availability of TWs.

Scenario	1	2	3	4
Available TWs	1	2	3	All
Profit (USD)	22,637,692	22,763,426	23,221,716	24,052,953
$\boldsymbol{REV}$ **(USD)**	38,788,705	38,680,266	38,614,874	38,732,295
$\boldsymbol{VOC}$ **(USD)**	3,609,000	3,242,000	3,234,000	3,242,000
$\boldsymbol{VCC}$ **(USD)**	649,000	1,560,000	1,560,000	1,430,000
$\boldsymbol{FCC}$ **(USD)**	2,507,152	2,093,254	2,111,179	2,185,334
$\boldsymbol{PHC}$ **(USD)**	4,415,595	4,546,180	4,048,420	3,366,998
$\boldsymbol{LAC}$ **(USD)**	484,590	46,695	12,408	58,426
$\boldsymbol{CIC}^{SEA}$ **(USD)**	2,999,049	3,124,230	3,134,286	3,027,366
$\boldsymbol{CIC}^{PORT}$ **(USD)**	245,365	267,336	246,940	286,703
$\boldsymbol{EC}^{SEA}$ **(USD)**	1,236,327	1,032,226	1,041,064	1,077,632
$\boldsymbol{EC}^{PORT}$ **(USD)**	4,934	4,918	4,860	4,883
$\boldsymbol{TotEP}^{SEA}$ **(tons)**	38,635	32,257	32,533	33,676
$\boldsymbol{TotEP}^{PORT}$ **(tons)**	154.20	153.68	151.87	152.60
$\boldsymbol{AvgQC}^{SEA}$ **(TEUs)**	5,594.70	5,595.17	5,593.90	5,594.48
$\boldsymbol{AvgQC}^{PORT}$ **(TEUs)**	1,095.20	1,092.74	1,090.67	1,093.79
$\boldsymbol{Totq}$ **(vessels)**	8	9	11	8
$\boldsymbol{Totq}^{own}$ **(vessels)**	7	6	7	6
$\boldsymbol{Totq}^{char}$ **(vessels)**	1	3	4	2
$\boldsymbol{Avgf}$ **(days)**	12.67	12.00	10.00	13.00
$\boldsymbol{AvgRF}$ **(tons/nmi)**	0.252	0.238	0.231	0.242
$\boldsymbol{AvgWtSpd}$ **(knots)**	23.76	22.81	22.96	23.51
$\boldsymbol{AvgWtHP}$ **(TEUs/hour)**	92.71	103.35	91.72	96.46
$\boldsymbol{AvgWtCCC}$ **(tons)**	147,000.00	148,666.67	148,363.64	148,500.00
CPU Time (seconds)	363.76	178.04	124.95	192.39
Optimality Gap (%)	2.33%	3.00%	3.00%	3.00%

Note:

$\boldsymbol{TotEP}^{SEA}$ – total quantity of emissions produced in sea (tons); $\boldsymbol{TotEP}^{PORT}$ – total quantity of emissions produced at ports (tons); $\boldsymbol{AvgQC}^{SEA}$ – average quantity of containers to be transported at each voyage leg (TEUs); $\boldsymbol{AvgQC}^{PORT}$ – average quantity of containers to be handled at each port (TEUs); $\boldsymbol{Totq}$ – total number of required vessels (vessels); $\boldsymbol{Totq}^{own}$ – total number of own vessels required (vessels); $\boldsymbol{Totq}^{char}$ – total number of chartered vessels required (vessels); $\boldsymbol{Avgf}$ – average port service frequency (days); $\boldsymbol{AvgRF}$ – average fuel consumption (tons/nmi); $\boldsymbol{AvgWtSpd}$ – average vessel sailing speed weighted by voyage leg length (knots); $\boldsymbol{AvgWtHP}$ – average requested handling productivity weighted by the number of containers handled at ports (TEUS/hour); $\boldsymbol{AvgWtCCC}$ – average weighted cargo carrying capacity of vessels (tons).

Sensitivity of the average sailing speed to the availability of HRs is presented in Figure 111. The maximum average sailing speed was observed in scenario #2, which was 23.73 knots. The minimum average sailing speed of 23.51 knots was observed in scenario #5.

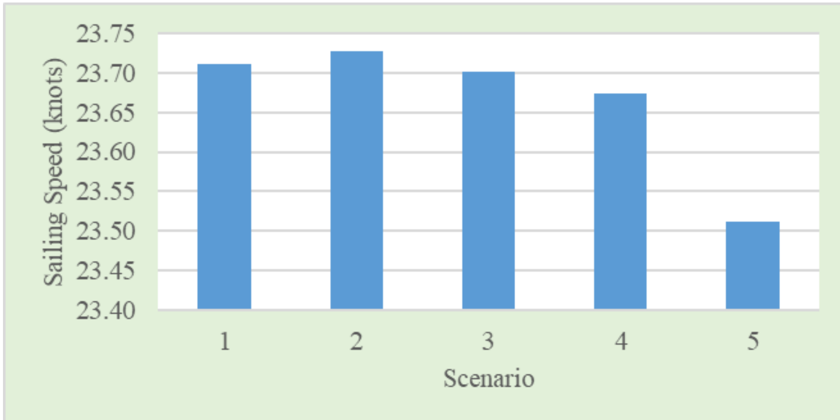


Figure 111 Sensitivity of the average sailing speed to the availability of HRs.

Sensitivity of the average fuel consumption to the availability of HRs is shown in Figure 112. Scenario #5 required the lowest average sailing speed, and it also made the fuel consumption rate to be the lowest, which was 0.242 tons/nmi. The maximum average fuel consumption of 0.250 tons/nmi was observed in scenario #2.

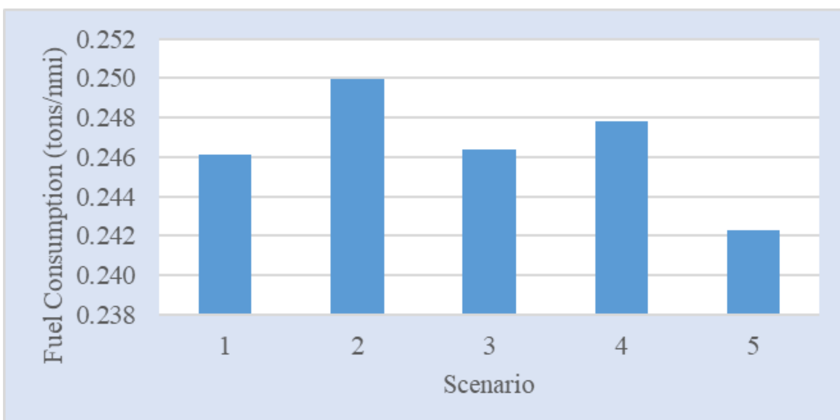


Figure 112 Sensitivity of the average fuel consumption to the availability of HRs.

Sensitivity of the average port service frequency to the availability of HRs is presented in Figure 113. The maximum average port service frequency was observed in scenarios #3 and #5, which was 13 days. The minimum average port service frequency of 9.67 days was observed in scenario #2.

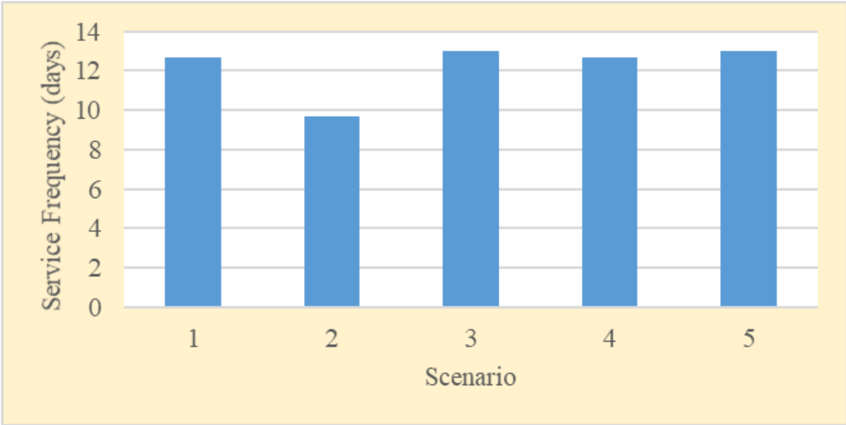


Figure 113 Sensitivity of the average port service frequency to the availability of HRs.

Sensitivity of the required number of vessels to the availability of HRs is highlighted in Figure 114. Scenario #2 required the largest number of vessels to be deployed (11 vessels), as the lowest port service frequency was observed in this scenario. All the other scenarios required 8 vessels to be deployed.

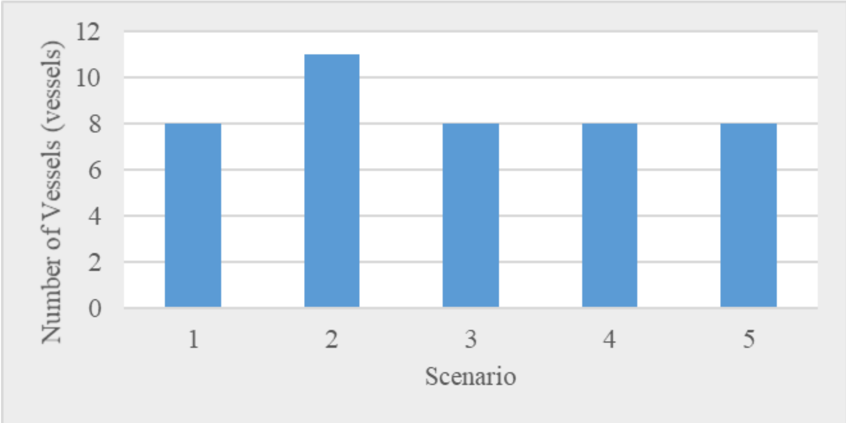


Figure 114 Sensitivity of the required number of vessels to the availability of HRs.

Sensitivity of the average container demand at ports to the availability of HRs is presented in Figure 115. The maximum average container demand at ports was observed in scenario #3, which was 1,095.11 TEUs. The minimum average container demand at ports of 1,093.79 TEUs was observed in scenario #5.

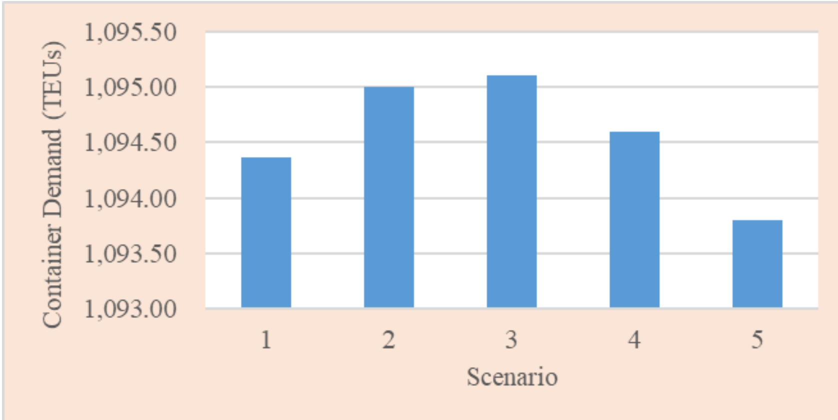


Figure 115 Sensitivity of the average container demand at ports to the availability of HRs.

Sensitivity of the average port handling productivity to the availability of HRs is shown in Figure 116. The maximum average port handling productivity was observed in scenario #4, which was 97.38 TEUs/hour. The minimum average port handling productivity of 83.87 TEUs/hour was observed in scenario #2.

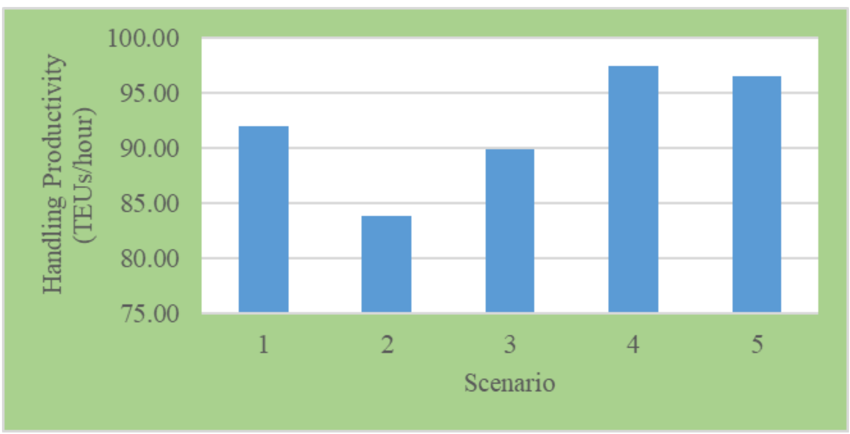


Figure 116 Sensitivity of the average handling productivity to the availability of HRs.

Sensitivity of the total quantity of emissions produced in sea to the availability of HRs is presented in Figure 117. Since the quantity of emissions produced by the vessels in sea is proportional to the fuel consumption, and the lowest fuel consumption was recorded in scenario #5, the lowest amount of emissions produced in sea was also observed in scenario #5, which was 33,676 tons. The maximum quantity of emissions produced in sea (37,673 tons) was observed in scenario #3. Note that the total quantity of emissions produced due to handling of containers at ports, which was significantly less than the quantity of emissions produced in sea, also fluctuated due to a change in the availability of HRs (since the container demand at ports and port operations were impacted from changing the availability of HRs).

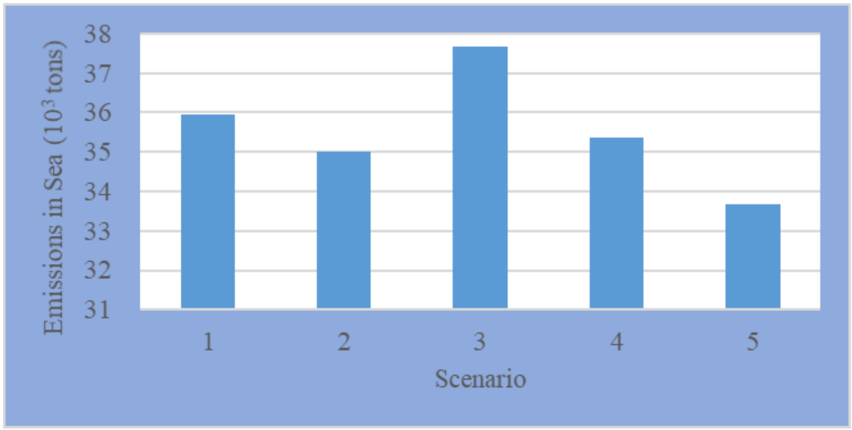


Figure 117 Sensitivity of the quantity of emissions produced in sea to the availability of HRs.

Sensitivity of the total fuel cost to the availability of HRs is highlighted in Figure 118. The lowest average sailing speed and the lowest average fuel consumption were recorded in scenario #5. So, scenario #5 incurred the lowest value of the total fuel cost, which was 2.19 million USD. The maximum total fuel cost was observed in scenario #3, which was 2.44 million USD.

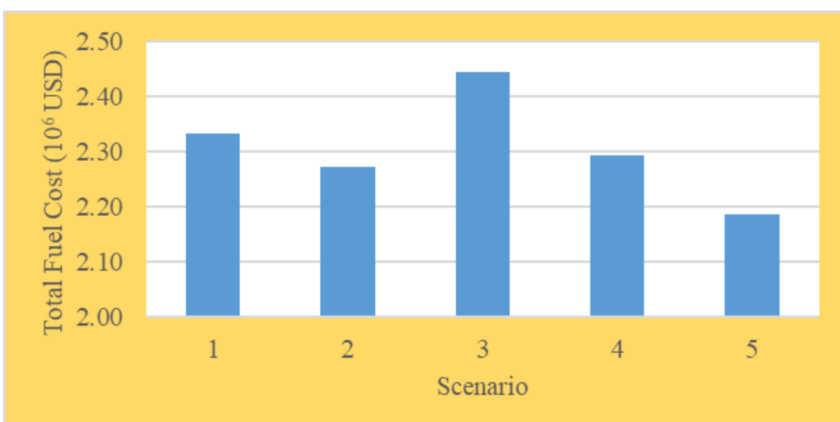


Figure 118 Sensitivity of the total fuel cost to the availability of HRs.

Sensitivity of the total revenue to the availability of HRs is presented in Figure 119. The maximum revenue was observed in scenario #3, which was 38.78 million USD. The latter finding can be justified by the fact that the revenue was generated from transportation of containers, and the container demand at ports was the highest in scenario #3. The minimum revenue of 38.73 million USD was observed in scenario #5, which recorded the lowest container demand.

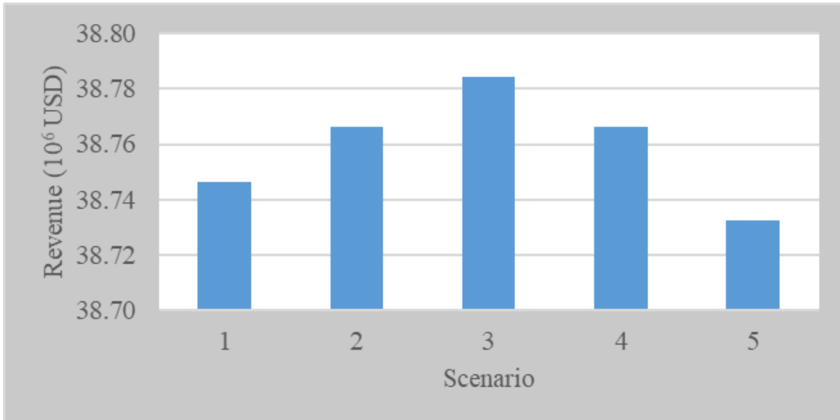


Figure 119 Sensitivity of the total revenue to the availability of HRs.

Sensitivity of the total profit to the availability of HRs is shown in Figure 120. The minimum profit of 22.21 million USD was observed in scenario #1. The maximum profit (24.05 million USD) was recorded in scenario #5, where all 4 HRs were made available. The latter finding highlights that availability of more HRs led to the highest total profit (i.e., the best value of the objective function).

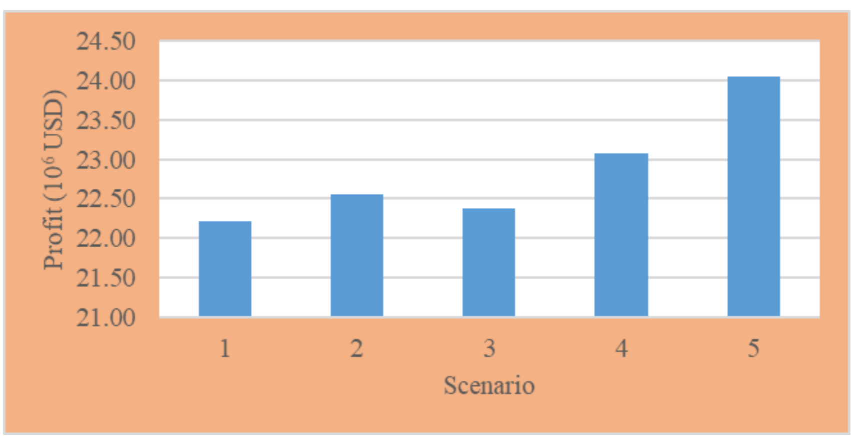


Figure 120 Sensitivity of the total profit to the availability of HRs.

Table 17 Sensitivity analysis for the availability of HRs.

Scenario	1	2	3	4	5
Available TWs	1	2	3	4	All
Profit (USD)	22,209,303	22,555,061	22,375,934	23,071,623	24,052,953
$\boldsymbol{REV}$ **(USD)**	38,746,394	38,766,162	38,784,513	38,766,409	38,732,295
$\boldsymbol{VOC}$ **(USD)**	3,578,000	3,117,000	3,726,000	3,164,000	3,242,000
$\boldsymbol{VCC}$ **(USD)**	910,000	1,560,000	708,000	1,430,000	1,430,000
$\boldsymbol{FCC}$ **(USD)**	2,331,975	2,272,391	2,444,711	2,294,232	2,185,334
$\boldsymbol{PHC}$ **(USD)**	5,233,030	4,792,881	4,863,977	4,365,263	3,366,998
$\boldsymbol{LAC}$ **(USD)**	17,892	73,826	81,370	58,426	58,426
$\boldsymbol{CIC^{SEA}}$ **(USD)**	2,994,021	2,992,965	3,003,345	3,010,642	3,027,366
$\boldsymbol{CIC^{PORT}}$ **(USD)**	317,680	276,994	370,980	235,739	286,703
$\boldsymbol{EC^{SEA}}$ **(USD)**	1,149,944	1,120,561	1,205,536	1,131,331	1,077,632
$\boldsymbol{EC^{PORT}}$ **(USD)**	4,549	4,483	4,659	5,153	4,883
$\boldsymbol{TotEP^{SEA}}$ **(tons)**	35,936	35,018	37,673	35,354	33,676
$\boldsymbol{TotEP^{PORT}}$ **(tons)**	142.17	140.08	145.60	161.02	152.60
$\boldsymbol{AvgQC^{SEA}}$ **(TEUs)**	5,594.58	5,595.01	5,594.45	5,594.66	5,594.48
$\boldsymbol{AvgQC^{PORT}}$ **(TEUs)**	1,094.36	1,095.01	1,095.11	1,094.60	1,093.79
$\boldsymbol{Totq}$ **(vessels)**	8	11	8	8	8
$\boldsymbol{Totq^{own}}$ **(vessels)**	7	7	7	6	6
$\boldsymbol{Totq^{char}}$ **(vessels)**	1	4	1	2	2
$\boldsymbol{Avgf}$ **(days)**	12.67	9.67	13.00	12.67	13.00
$\boldsymbol{AvgRF}$ **(tons/nmi)**	0.246	0.250	0.246	0.248	0.242
$\boldsymbol{AvgWtSpd}$ **(knots)**	23.71	23.73	23.70	23.67	23.51
$\boldsymbol{AvgWtHP}$ **(TEUs/hour)**	91.97	83.87	89.83	97.38	96.46
$\boldsymbol{AvgWtCCC}$ **(tons)**	147,750.00	148,363.64	147,000.00	148,500.00	148,500.00
CPU Time (seconds)	111.54	224.17	79.29	133.75	193.21
Optimality Gap (%)	3.00%	2.27%	3.00%	3.00%	3.00%

Note:

$\boldsymbol{TotEP^{SEA}}$ – total quantity of emissions produced in sea (tons); $\boldsymbol{TotEP^{PORT}}$ – total quantity of emissions produced at ports (tons); $\boldsymbol{AvgQC^{SEA}}$ – average quantity of containers to be transported at each voyage leg (TEUs); $\boldsymbol{AvgQC^{PORT}}$ – average quantity of containers to be handled at each port (TEUs); $\boldsymbol{Totq}$ – total number of required vessels (vessels); $\boldsymbol{Totq^{own}}$ – total number of own vessels required (vessels); $\boldsymbol{Totq^{char}}$ – total number of chartered vessels required (vessels); $\boldsymbol{Avgf}$ – average port service frequency (days); $\boldsymbol{AvgRF}$ – average fuel consumption (tons/nmi); $\boldsymbol{AvgWtSpd}$ – average vessel sailing speed weighted by voyage leg length (knots); $\boldsymbol{AvgWtHP}$ – average requested handling productivity weighted by the number of containers handled at ports (TEUS/hour); $\boldsymbol{AvgWtCCC}$ – average weighted cargo carrying capacity of vessels (tons).

Table 17 presents changes in different variables of the mathematical model due to changes in the availability of HRs. Apart from the aforementioned variables, the other variables highlighted in this table include the total vessel operational cost, the total vessel chartering cost, the total port handling cost, the total late arrival cost, the total container inventory cost in sea and at ports, the total emission cost in sea and at ports, the quantity of containers transported in sea, the total number of own and chartered vessels required, the average weighted cargo carrying capacity of vessels, CPU time, and optimality gap.

6.4.10. Sensitivity Analysis for the Unit Fuel Cost and the Unit Emission Cost

A sensitivity analysis for the unit fuel cost and the unit emission cost is investigated in this section of the dissertation. A total of 100 scenarios were developed to conduct the sensitivity analysis for the unit fuel cost and the unit emission cost. For every 10 scenarios, the unit fuel cost was increased from 50 USD/ton to 500 USD/ton, with increments of 50 USD/ton. After every 10 scenarios, the unit fuel cost was reset to 50 USD/ton and again increased to 500 USD/ton, with increments of 50 USD/ton. On the other hand, the unit emission cost was assumed to be the same for every 10 scenarios. After every 10 scenarios, the unit emission cost was increased by 16 USD/ton. Overall, the unit emission cost was increased from 16 USD/ton to 160 USD/ton. The unit fuel cost value and the unit emission cost value for each scenario are presented in Table 18.

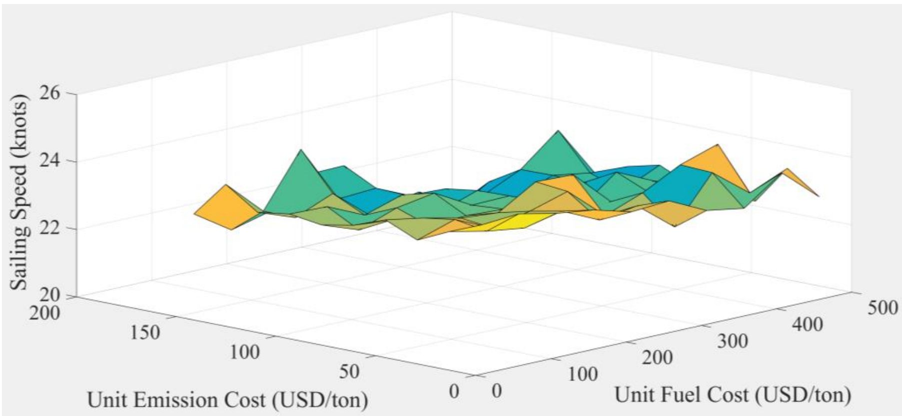


Figure 121 Sensitivity of the average sailing speed to the unit fuel cost and the unit emission cost.

Sensitivity of the average sailing speed to the unit fuel cost and the unit emission cost is presented in Figure 121. By decreasing the average sailing speed, the solution approach aimed to alleviate the effect of increments in the unit fuel cost and the unit emission cost. The maximum average sailing speed was observed in scenario #83, which was 24.29 knots. The minimum average sailing speed of 20.87 knots was observed in scenario #99.

Table 18 Unit fuel costs and unit emission costs for different scenarios.

Scenario	1	2	3	4	5	6	7	8	9	10
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Emission Cost (USD/ton)	16	16	16	16	16	16	16	16	16	16
Scenario	11	12	13	14	15	16	17	18	19	20
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Emission Cost (USD/ton)	32	32	32	32	32	32	32	32	32	32
Scenario	21	22	23	24	25	26	27	28	29	30
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Emission Cost (USD/ton)	48	48	48	48	48	48	48	48	48	48
Scenario	31	32	33	34	35	36	37	38	39	40
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Emission Cost (USD/ton)	64	64	64	64	64	64	64	64	64	64
Scenario	41	42	43	44	45	46	47	48	49	50
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Emission Cost (USD/ton)	80	80	80	80	80	80	80	80	80	80
Scenario	51	52	53	54	55	56	57	58	59	60
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Emission Cost (USD/ton)	96	96	96	96	96	96	96	96	96	96
Scenario	61	62	63	64	65	66	67	68	69	70
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Emission Cost (USD/ton)	112	112	112	112	112	112	112	112	112	112
Scenario	71	72	73	74	75	76	77	78	79	80
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Emission Cost (USD/ton)	128	128	128	128	128	128	128	128	128	128
Scenario	81	82	83	84	85	86	87	88	89	90
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Emission Cost (USD/ton)	144	144	144	144	144	144	144	144	144	144
Scenario	91	92	93	94	95	96	97	98	99	100
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Emission Cost (USD/ton)	160	160	160	160	160	160	160	160	160	160

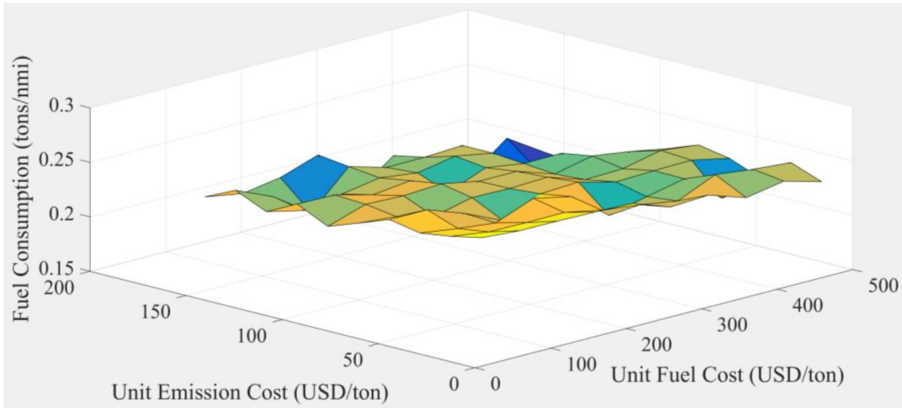


Figure 122 Sensitivity of the average fuel consumption to the unit fuel cost and the unit emission cost.

Sensitivity of the average fuel consumption to the unit fuel cost and the unit emission cost is shown in Figure 122. In order to mitigate the impact of increasing the unit fuel cost and the unit emission cost, the solution approach aimed to decrease the fuel consumption cost by decreasing the average fuel consumption rate. The maximum average fuel consumption was observed in scenario #1, which was 0.253 tons/nmi. The minimum average fuel consumption of 0.182 tons/nmi was observed in scenario #98.

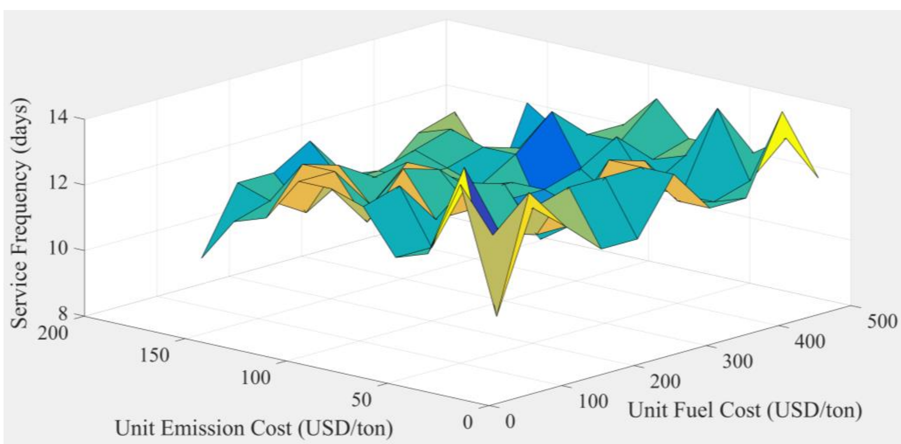


Figure 123 Sensitivity of the average port service frequency to the unit fuel cost and the unit emission cost.

Sensitivity of the average port service frequency to the unit fuel cost and the unit emission cost is presented in Figure 123. Since the sailing speed was decreased, the solution approach attempted to meet the demand by decreasing the port service frequency (i.e., the ports were visited more frequently). The maximum average port service frequency was observed in scenarios #9, #11, and #22, which was 14 days. The minimum average port service frequency of 9.33 days was observed in scenario #99.

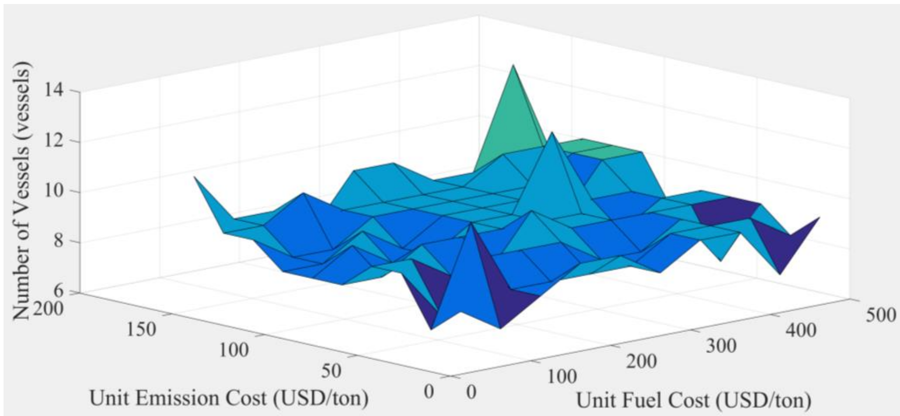


Figure 124 Sensitivity of the required number of vessels to the unit fuel cost and the unit emission cost.

Sensitivity of the required number of vessels to the unit fuel cost and the unit emission cost is highlighted in Figure 124. As the average port service frequency was decreased due to increments in the unit fuel cost and the unit emission cost, more vessels were required for deployment. Scenario #99 required the largest number of vessels to be deployed (13 vessels), while only 7 vessels were deployed in scenarios #2, #9, #11, #22, and #29.

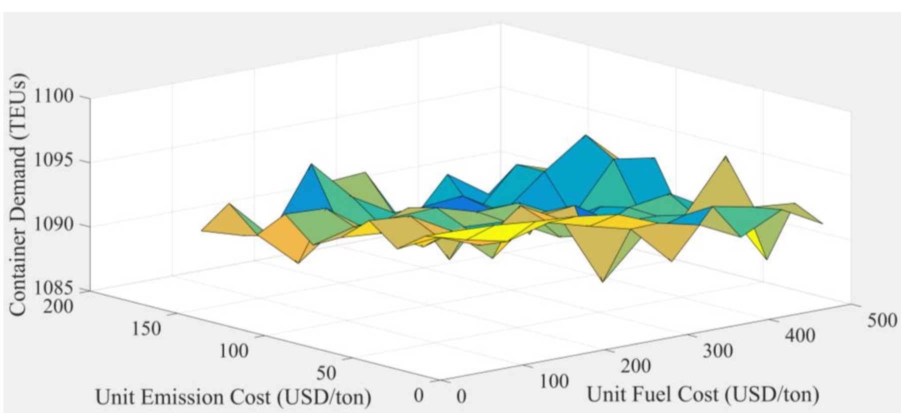


Figure 125 Sensitivity of the average container demand at ports to the unit fuel cost and the unit emission cost.

Sensitivity of the average container demand at ports to the unit fuel cost and the unit emission cost is presented in Figure 125. In the formulated mathematical model, the container demand at ports is inversely proportional to the sailing speed reciprocal. Since the sailing speed was decreased (i.e., sailing speed reciprocal was increased) with increasing unit fuel cost and the unit emission cost, the container demand at ports went through a decreasing trend. The maximum average container demand at ports was observed in scenario #29, which was 1,095.49 TEUs. The minimum average container demand at ports of 1,085.46 TEUs was observed in scenario #99.

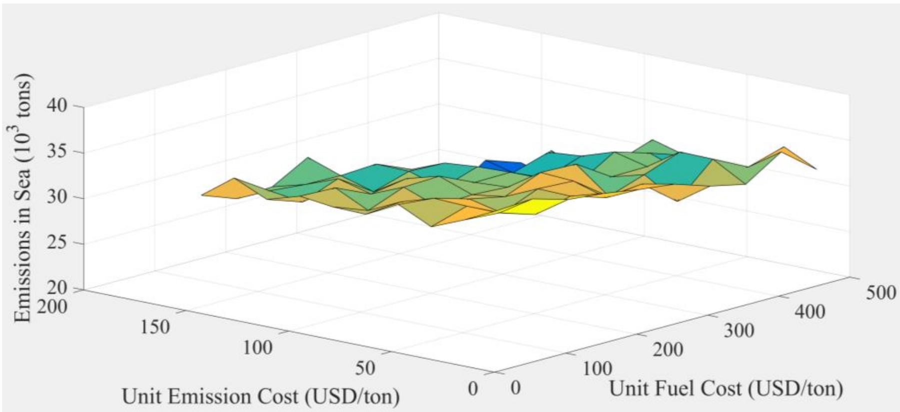


Figure 126 Sensitivity of the quantity of emissions produced in sea to the unit fuel cost and the unit emission cost.

Sensitivity of the total quantity of emissions produced in sea to the unit fuel cost and the unit emission cost is presented in Figure 126. Since the quantity of emissions produced by the vessels in sea is proportional to the fuel consumption, and the fuel consumption was reduced because of an increase in the unit fuel cost and the unit emission cost, the quantity of emissions produced in sea was also decreased. The maximum quantity of emissions produced in sea was observed in scenario #2, which was 36,180.94 tons. The minimum quantity of emissions produced in sea of 23,877.08 tons was observed in scenario #98. Note that the total quantity of emissions produced due to handling of containers at ports, which was significantly less than the quantity of emissions produced in sea, also fluctuated due to an increase in the unit fuel cost and the unit emission cost (since the container demand at ports and port operations were impacted from changing the unit fuel cost and the unit emission cost).

Sensitivity of the total fuel cost to the unit fuel cost and the unit emission cost is highlighted in Figure 127. Even though the fuel consumption per unit length was decreased in order to mitigate the impact of an increase in the unit fuel cost and the unit emission cost, an increasing trend in the total fuel cost was still noted. Moreover, it was observed that changes in the total fuel cost were mostly governed by modifications in the unit fuel cost. The minimum total fuel cost was observed in scenario #91, which was 0.51 million USD. The maximum total fuel cost of 5.33 million USD was observed in scenario #20.

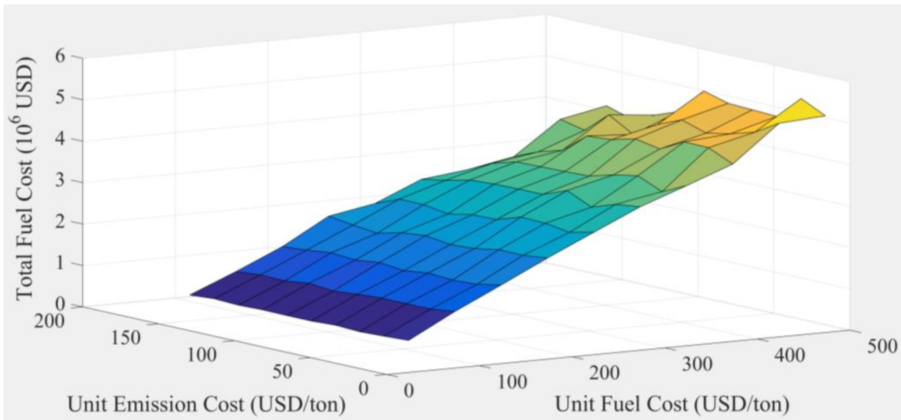


Figure 127 Sensitivity of the total fuel cost to the unit fuel cost and the unit emission cost.

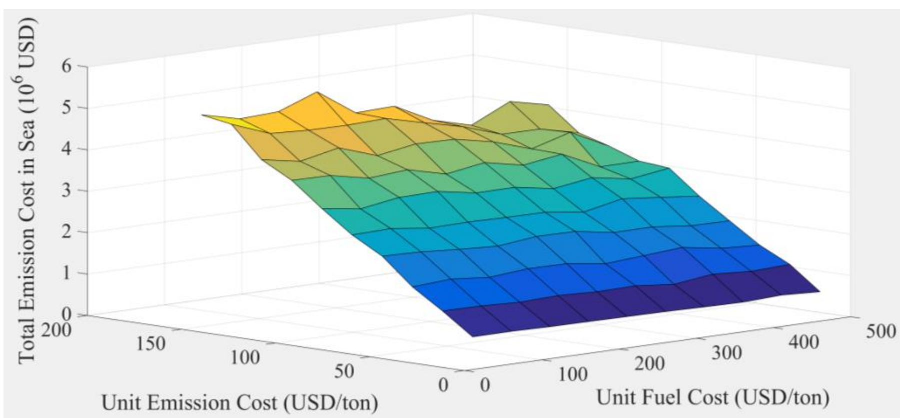


Figure 128 Sensitivity of the total emission cost in sea to the unit fuel cost and the unit emission cost.

Sensitivity of the total emission cost in sea to the unit fuel cost and the unit emission cost is highlighted in Figure 128. Even though the quantity of emissions produced in sea was decreased in order to mitigate the impact of an increase in the unit fuel cost and the unit emission cost, an increasing trend in the total emission cost in sea was still noted. Moreover, it was observed that changes in the total emission cost in sea were mostly governed by modifications in the unit emission cost. The minimum total emission cost in sea was observed in scenario #10, which was 0.50 million USD. The maximum total emission cost in sea of 5.15 million USD was observed in scenario #94. Note that the total emission cost at ports, which was significantly less than the total emission cost in sea, also experienced an increase.

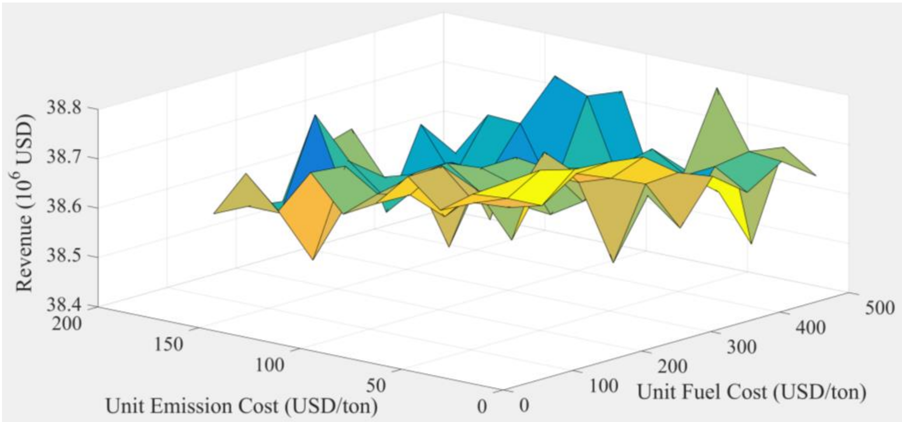


Figure 129 Sensitivity of the total revenue to the unit fuel cost and the unit emission cost.

Sensitivity of the total revenue to the unit fuel cost and the unit emission cost is presented in Figure 129. Due to increments in the unit fuel cost and the unit emission cost, the total revenue experienced an overall decreasing trend. The latter finding can be justified by a reduction in container demand at ports of call after increasing the unit fuel cost and the unit emission cost. The maximum revenue was observed in scenario #29, which was 38.80 million USD. The minimum revenue of 38.43 million USD was observed in scenario #99.

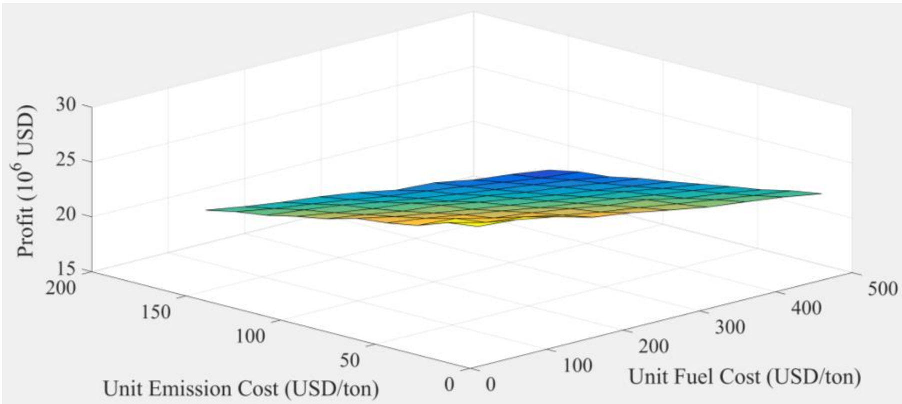


Figure 130 Sensitivity of the total profit to the unit fuel cost and the unit emission cost.

Sensitivity of the total profit to the unit fuel cost and the unit emission cost is shown in Figure 130. Due to increments in the unit fuel cost and the unit emission cost, the total profit experienced a decreasing pattern. The maximum profit was observed in scenario #1, which was 26.36 million USD. The minimum profit of 17.30 million USD was observed in scenario #100.

Apart from changes in the aforementioned variables, a number of other changes were noticed due to an increase in the unit fuel cost and the unit emission cost. Among the components of the route service cost, an overall reduction in the total vessel operational cost, the total late arrival cost, and the total container inventory cost at ports was observed. On the other hand, the total vessel chartering cost, the total port handling cost, and the total container inventory cost in sea experienced an increasing trend.

In addition to the cost components, changes in other variables were also observed. The quantity of containers transported by the vessels stayed almost the same. The required number of own vessels was decreased, and the required number of chartered vessels was increased. Moreover, increments in the average handling productivity and the average size of vessels were observed. Last but not least, increments in the unit fuel cost and the unit emission cost increased the CPU times and the optimality gaps for the problem instances. The latter patterns can be explained by changes in the feasible space for the formulated optimization model.

6.4.11. Sensitivity Analysis for the Unit Fuel Cost and the Unit Inventory Cost

A sensitivity analysis for the unit fuel cost and the unit inventory cost is investigated in this section of the dissertation. A total of 100 scenarios were developed to conduct the sensitivity analysis for the unit fuel cost and the unit inventory cost. For every 10 scenarios, the unit fuel cost was increased from 50 USD/ton to 500 USD/ton, with increments of 50 USD/ton. After every 10 scenarios, the unit fuel cost was reset to 50 USD/ton and again increased to 500 USD/ton, with increments of 50 USD/ton. On the other hand, the unit inventory cost was assumed to be the same for every 10 scenarios. After every 10 scenarios, the unit inventory cost was increased by 0.05 USD/TEU/hour. Overall, the unit inventory cost was increased from 0.05 USD/TEU/hour to 0.50 USD/TEU/hour. The unit fuel cost value and the unit inventory cost value for each scenario are presented in Table 19.

Table 19 Unit fuel costs and unit inventory costs for different scenarios.

Scenario	1	2	3	4	5	6	7	8	9	10
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Inventory Cost (USD/TEU/hour)	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Scenario	11	12	13	14	15	16	17	18	19	20
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Inventory Cost (USD/TEU/hour)	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Scenario	21	22	23	24	25	26	27	28	29	30
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Inventory Cost (USD/TEU/hour)	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
Scenario	31	32	33	34	35	36	37	38	39	40
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Inventory Cost (USD/TEU/hour)	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Scenario	41	42	43	44	45	46	47	48	49	50
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Inventory Cost (USD/TEU/hour)	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Scenario	51	52	53	54	55	56	57	58	59	60
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Inventory Cost (USD/TEU/hour)	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
Scenario	61	62	63	64	65	66	67	68	69	70
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Inventory Cost (USD/TEU/hour)	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35
Scenario	71	72	73	74	75	76	77	78	79	80
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Inventory Cost (USD/TEU/hour)	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
Scenario	81	82	83	84	85	86	87	88	89	90
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Inventory Cost (USD/TEU/hour)	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
Scenario	91	92	93	94	95	96	97	98	99	100
Unit Fuel Cost (USD/ton)	50	100	150	200	250	300	350	400	450	500
Unit Inventory Cost (USD/TEU/hour)	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50

Sensitivity of the average sailing speed to the unit fuel cost and the unit inventory cost is presented in Figure 131. By decreasing the average sailing speed, the solution approach aimed to alleviate the effect of increments in the unit fuel cost. So, the average sailing speed was found to be low, when the unit fuel cost was high, and the unit inventory cost was low. The maximum average sailing speed was observed in scenario #93, which was 24.64 knots. The minimum average sailing speed of 21.23 knots was observed in scenario #20.

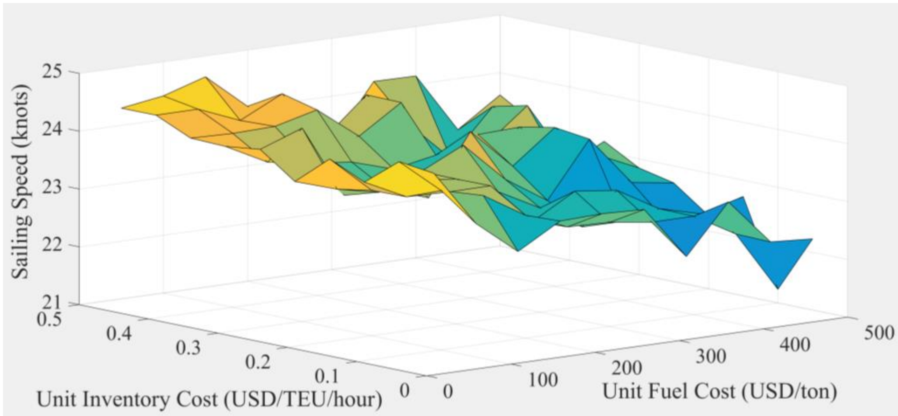


Figure 131 Sensitivity of the average sailing speed to the unit fuel cost and the unit inventory cost.

Sensitivity of the average fuel consumption to the unit fuel cost and the unit inventory cost is shown in Figure 132. In order to mitigate the impact of increasing the unit fuel cost, the solution approach aimed to decrease the fuel consumption cost by decreasing the average fuel consumption rate. So, the average fuel consumption was found to be low, when the unit fuel cost was high, and the unit inventory cost was low. The maximum average fuel consumption was observed in scenario #93, which was 0.257 tons/nmi. The minimum average fuel consumption of 0.214 tons/nmi was observed in scenario #28.

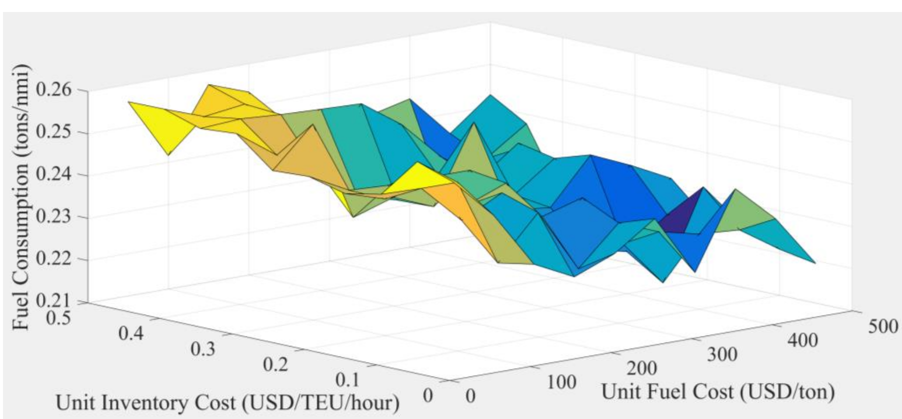


Figure 132 Sensitivity of the average fuel consumption to the unit fuel cost and the unit inventory cost.

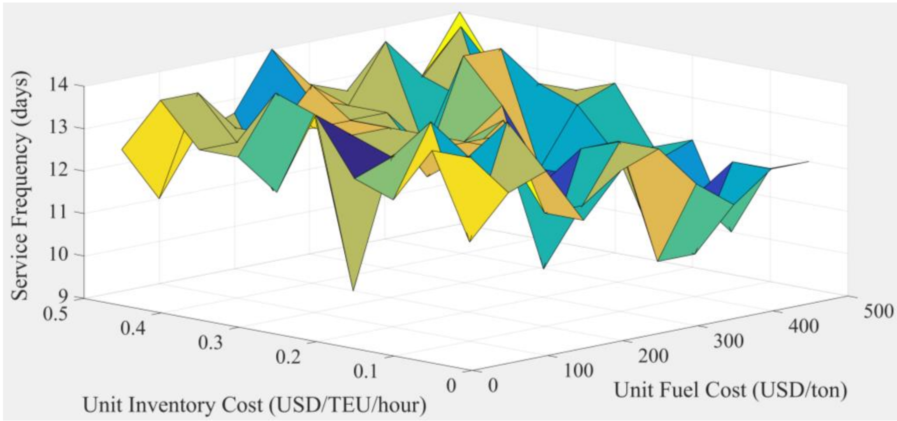


Figure 133 Sensitivity of the average port service frequency to the unit fuel cost and the unit inventory cost.

Sensitivity of the average port service frequency to the unit fuel cost and the unit inventory cost is presented in Figure 133. The lowest values of the average port service frequency were observed, when the unit fuel cost was high, and the unit inventory cost was low. Such finding can be supported by the fact that since the sailing speed was decreased (while increasing the unit fuel cost), the solution approach attempted to meet the demand by decreasing the port service frequency (i.e., the ports were visited more frequently). The maximum average port service frequency was observed in scenarios #13, #22, #41, #62, #67, #68, #87, #89, #95, and #100, which was 14 days. The minimum average port service frequency of 9.67 days was observed in scenario #42.

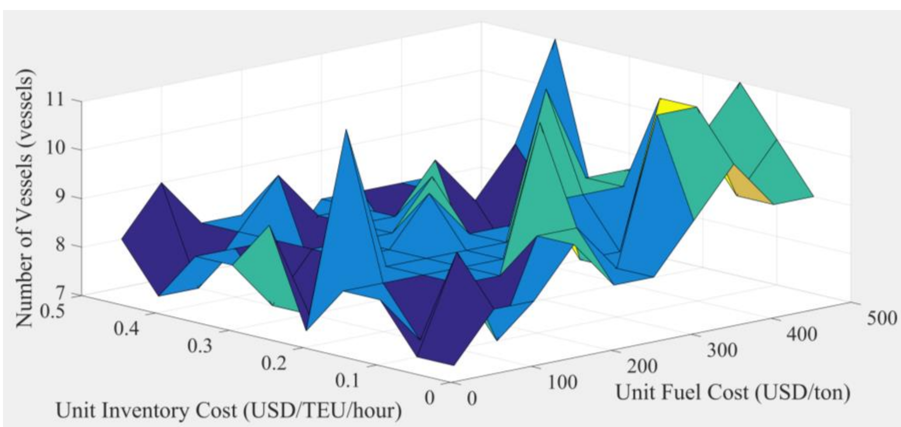


Figure 134 Sensitivity of the required number of vessels to the unit fuel cost and the unit inventory cost.

Sensitivity of the required number of vessels to the unit fuel cost and the unit inventory cost is highlighted in Figure 134. The highest values of the required number of vessels were observed, when the unit fuel cost was high, and the unit inventory cost was low. Such finding can be supported by the fact that since the average port service frequency was decreased due to increments in the unit fuel cost, more vessels were required for deployment. Scenarios #17, #18, #25, #28, #30, #42, #47, and #80 required the largest number of vessels to be deployed (11 vessels), while only 7 vessels were deployed in scenarios #1, #11, #13, #22, #41, #52, #62, #67, #68, #74, #81, #82, #87, #89, #95, and #100.

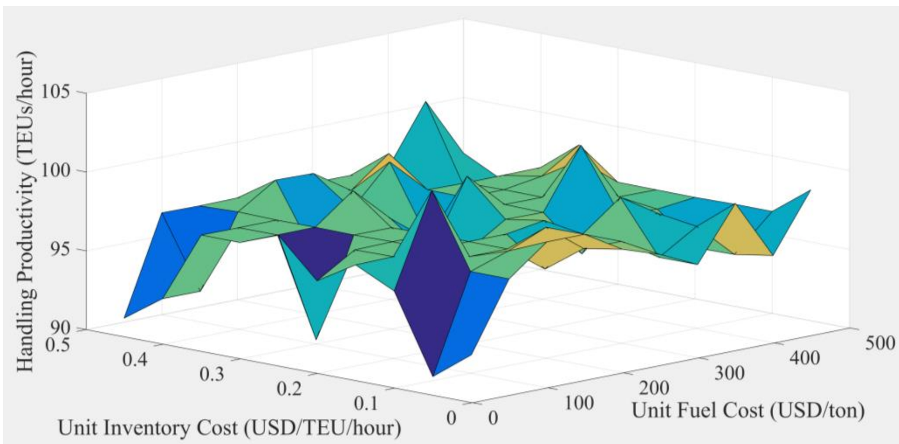


Figure 135 Sensitivity of the average handling productivity to the unit fuel cost and the unit inventory cost.

Sensitivity of the average port handling productivity to the unit fuel cost and the unit inventory cost is shown in Figure 135. The highest values of the average handling productivity were found, when the unit fuel cost was high, and the unit inventory cost was low. Such finding can be explained by the fact that the liner shipping company aimed to reduce the vessel handling time at ports of call (by requesting HRs with higher handling productivities) and use these time savings to compensate for the time losses in sea (since the vessel sailing speed generally decreased with increasing the unit fuel cost). The maximum average port handling productivity was observed in scenario #22, which was 101.13 TEUs/hour. The minimum average port handling productivity of 90.25 TEUs/hour was observed in scenario #91.

Sensitivity of the total fuel cost to the unit fuel cost and the unit inventory cost is highlighted in Figure 136. Even though the fuel consumption per unit length was decreased in order to mitigate the impact of an increase in the unit fuel cost, an increasing trend in the total fuel cost was still noted. Moreover, it was observed that changes in the unit inventory cost had little impact on the total fuel cost. The minimum total fuel cost was observed in scenario #41, which was 0.55 million USD. The maximum total fuel cost of 5.51 million USD was observed in scenario #100.

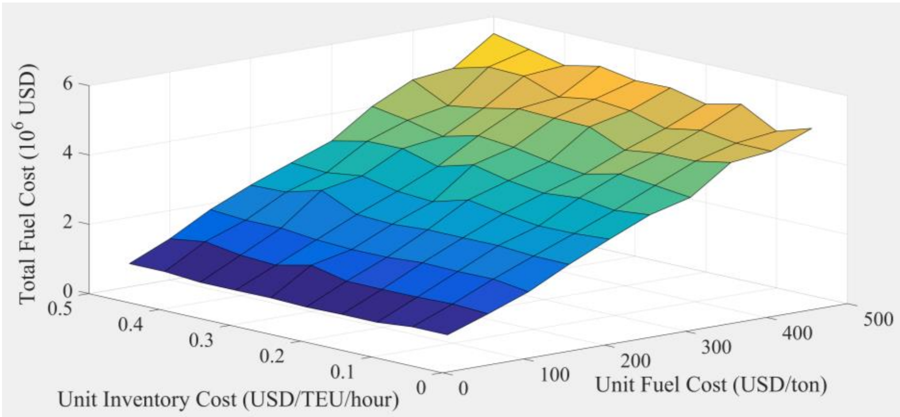


Figure 136 Sensitivity of the total fuel cost to the unit fuel cost and the unit inventory cost.

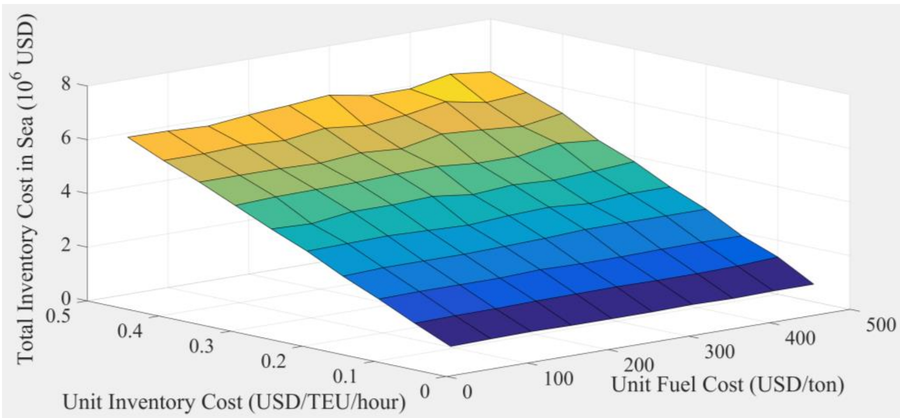


Figure 137 Sensitivity of the total inventory cost in sea to the unit fuel cost and the unit inventory cost.

Sensitivity of the total inventory cost in sea to the unit fuel cost and the unit inventory cost is highlighted in Figure 137. Due to an increase in the unit inventory cost, an increasing trend in the total inventory cost in sea was noted. Moreover, it was observed that changes in the unit fuel cost had little impact on the total inventory cost in sea. The minimum total inventory cost in sea was observed in scenario #1, which was 0.58 million USD. The maximum total inventory cost in sea of 6.19 million USD was observed in scenario #99.

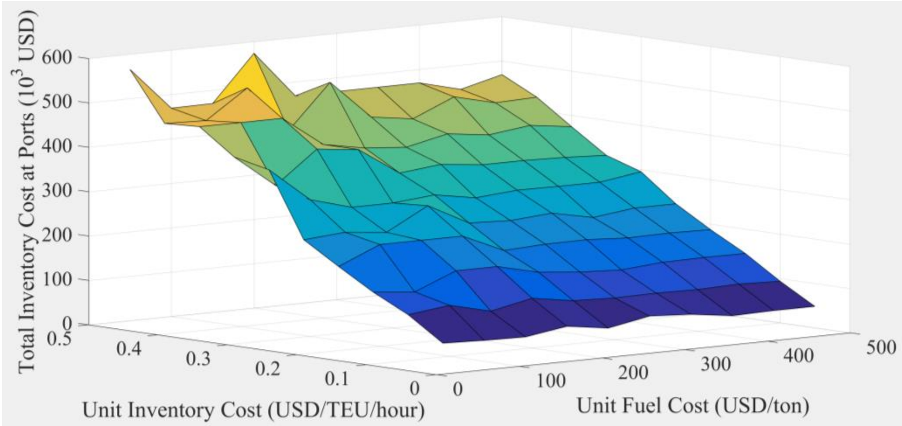


Figure 138 Sensitivity of the total inventory cost at ports to the unit fuel cost and the unit inventory cost.

Sensitivity of the total inventory cost at ports to the unit fuel cost and the unit inventory cost is highlighted in Figure 138. Due to an increase in the unit inventory cost, an increasing trend in the total inventory cost at ports was noted. Moreover, it was observed that changes in the unit fuel cost had little impact on the total inventory cost at ports. The minimum total inventory cost at ports was observed in scenario #3, which was 45,366 USD. The maximum total inventory cost at ports of 574,052 USD was observed in scenario #94.

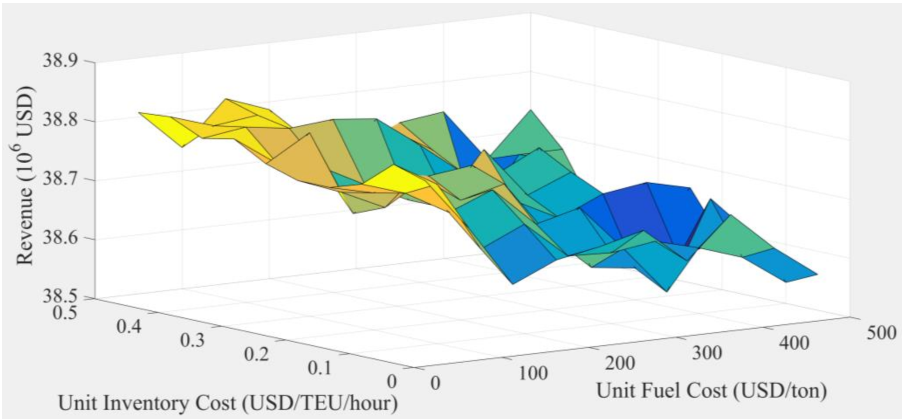


Figure 139 Sensitivity of the total revenue to the unit fuel cost and the unit inventory cost.

Sensitivity of the total revenue to the unit fuel cost and the unit inventory cost is presented in Figure 139. High revenues were generated, when the unit fuel cost was low, and the unit inventory cost was high. On the other hand, low revenues were generated, when the unit fuel cost was high, and the unit inventory cost was low. The maximum revenue was observed in scenario #93, which was 38.81 million USD. The minimum revenue of 38.52 million USD was observed in scenario #28.

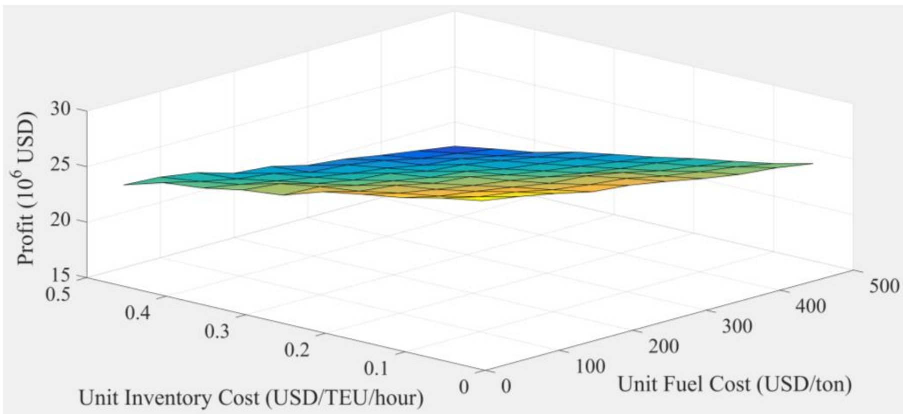


Figure 140 Sensitivity of the total profit to the unit fuel cost and the unit inventory cost.

Sensitivity of the total profit to the unit fuel cost and the unit inventory cost is shown in Figure 140. Due to increments in the unit fuel cost and the unit inventory cost, the total profit experienced a decreasing pattern. The maximum profit was observed in scenario #1, which was 28.53 million USD. The minimum profit of 17.81 million USD was observed in scenario #100.

Apart from changes in the aforementioned variables, a number of other changes were noticed due to an increase in the unit fuel cost and the unit inventory cost. Among the components of the route service cost, an overall reduction in the total port handling cost, the total late arrival cost, and the total emission cost in sea was observed. On the other hand, the total vessel operational cost, the total vessel chartering cost, and the total emission cost at ports experienced an increasing trend.

In addition to the cost components, changes in other variables were also observed. The total quantity of emissions produced in sea and at ports followed trends similar to the total emission cost in sea and at ports, respectively. The quantity of containers transported by the vessels and the container demand at ports stayed almost the same. The required number of own vessels and the required number of chartered vessels fluctuated from one scenario to another. Moreover, increments in the average size of vessels were observed. Last but not least, increments in the unit fuel cost and the unit inventory cost decreased the CPU times and the optimality gaps for the problem instances. The latter patterns can be explained by changes in the feasible space for the formulated optimization model.

CHAPTER 7

CONCLUDING REMARKS

Supply chain management focuses on a systematic coordination of business functions in order to improve the performance of the supply chain. It deals with three major areas, which are purchasing, manufacturing, and transportation. Freight transportation is an integral part of supply chain management, and its magnitude has been increasing day by day. Maritime transportation covers a significant portion of freight transportation, as the largest portion (in terms of volume) of the global merchandise trade is carried out by maritime transportation. Liner shipping plays a colossal role for the global seaborne trade. Liner shipping is operated on fixed schedules along fixed routes.

Liner shipping companies face three levels of decision problems, namely strategic level, tactical level, and operational level. The strategic-level decisions are taken for more than six months to several years. These decisions include: (1) fleet size and mix; (2) alliance strategy; and (3) network design. The tactical-level decisions are effective for three months to six months. These decisions include: (1) service frequency determination; (2) fleet deployment; (3) sailing speed optimization; and (4) vessel scheduling. Finally, the operational level decisions are taken for a couple of weeks to less than three months. These decisions include: (1) cargo booking; (2) cargo routing; and (3) rescheduling vessels.

This dissertation encompasses the tactical-level decisions in liner shipping (i.e., service frequency determination, fleet deployment, sailing speed optimization, and vessel scheduling). The service frequency determination problem deals with determining the time headway between consecutive vessels along a liner shipping route. If a high frequency is selected, the waiting time of containers at the origin ports becomes short; however, this results in the requirement of a large number of vessels to be deployed. The fleet deployment problem assigns vessels from the liner shipping company's fleet (and sometimes, from other liner shipping companies' fleets) to liner shipping routes. At this level, the liner shipping company decides if a homogeneous or heterogeneous vessel fleet is to be assigned to a route. The sailing speed optimization problem deals with selecting sailing speeds along different voyage legs of a given port rotation. A number of considerations are incorporated in this problem, the first of which is the price of fuel. Fuel prices primarily govern the selection of vessel sailing speeds. Then, other factors are considered, such as emissions from vessel engines. If vessels sail at high speeds, a large amount of harmful substances emit from vessel engines (e.g., carbon dioxide). Moreover, emission control areas are also accounted for in sailing speed selection. Within the emission control areas, vessels have to use low-sulfur fuel, which is expensive. Hence, vessels adjust their speed within the emission control areas. The vessel scheduling problem lists the schedules (e.g., arrival time, handling time, departure time) at different ports. The sailing speeds are adjusted after the vessel schedules are set.

As a part of the dissertation, a detailed review of the concurrent liner shipping literature was carried out. From the literature review, it was revealed that the existing literature on the tactical-level decisions focused on the problems individually. Some of the tactical-level problems were combined by a few studies. However, no study combined all four of them. Solutions from different solution methodologies, for the separate problems, may have compatibility problems. Moreover, they are not attractive to the liner shipping companies, who look for integrated solutions. Hence, this research focused on the development of a combined mathematical model that encompassed the four tactical-level decisions in liner shipping. This mathematical model was named the Holistic Optimization Model for Tactical-Level Planning in Liner Shipping (**HOMTLP**).

The **HOMTLP** mathematical model focused on maximization of the total profit from transport of cargo. So, the objective function had two main components: (1) the total revenue and (2) the total route service cost. The major route service cost components, found from the literature, were covered by the model, which include: (I) total late arrival cost; (II) total port handling cost; (III) total fuel consumption cost; (IV) total vessel operational cost; (V) total vessel chartering cost; (VI) total container inventory cost in sea; (VII) total container inventory cost at ports of call; (VIII) total emission cost in sea; and (IX) total emission cost at ports of call. In addition to the integration of all tactical-level decisions in liner shipping, the mathematical model boasted several key features. First, the model helped to achieve a flexible relationship between the liner shipping company and the marine container terminal operators by offering multiple time windows and handling rates at each port of call. Second, the fuel consumption function considered the payload carried by the vessels. Third, customer preference was integrated by modifying the container demand at different sailing speeds. Fourth, container inventory was accounted for at ports of call and in sea. Fifth, emissions from liner shipping operations were also accounted for to achieve sustainable liner shipping.

The **HOMTLP** model was solved with BARON to the global optimality. Moreover, this dissertation carried out a set of numerical experiments to test the performance of the mathematical model. These experiments include: (1) sensitivity analysis for the unit fuel cost; (2) sensitivity analysis for the unit emission cost; (3) sensitivity analysis for the unit inventory cost; (4) sensitivity analysis for the unit operational and chartering costs; (5) sensitivity analysis for the vessel availability; (6) sensitivity analysis for the unit late arrival cost; (7) sensitivity analysis for the unit freight rate; (8) sensitivity analysis for the availability of port arrival time windows; (9) sensitivity analysis for the availability of container handling rates; (10) sensitivity analysis for the unit fuel cost and the unit emission cost; and (11) sensitivity analysis for the unit fuel cost and the unit inventory cost.

The experiments revealed that the sailing speed was reduced, when there was an increase in the unit fuel cost, the unit emission cost, vessel availability, the unit late arrival cost, and the unit freight rate. On the contrary, the sailing speed was increased, when there was an increase in the unit inventory cost, the unit operational cost, as well as the unit chartering cost. The service frequency was reduced, when there was an increase in the unit fuel cost, the unit emission cost, vessel availability, and the unit freight rate. On the contrary, the service frequency was increased, when there was an increase in the unit inventory cost, the unit operational cost along with the unit chartering cost, and the unit late arrival cost.

Moreover, the total required number of vessels was increased, when there as an increase in the unit fuel cost, the unit emission cost, vessel availability, the unit late arrival cost, and the unit freight rate. On the contrary, the total required number of vessels was decreased, when there was an increase in the unit inventory cost, the unit operational cost, as well as the unit chartering cost. Sensitivity analyses for the availability of port arrival time windows and container handling rates revealed that the total profit was increased, when more choices were available for port arrival time windows and container handling rates, respectively. Several other findings were gleaned from the numerical experiments. These experiments showed that the mathematical model provided effective decisions. Hence, **HOMTLP** model could assist liner shipping companies with taking tactical-level decisions, which are effective and profitable.

CHAPTER 8

FUTURE RESEARCH DIRECTIONS

This dissertation has covered all the tactical-level problems in liner shipping and developed a holistic optimization model. However, there are many aspects, which could be incorporated by future research. In particular, the following aspects could be captured by future studies:

- A number of liner shipping companies have formed strategic alliances to strengthen their positions and to optimize their operations. These strategic alliances could be studied by future research.
- Tactical-level decisions could be tailored for different kinds of liner shipping networks, such as hub-and-spoke networks.
- Liner shipping companies are using mega vessels to exploit economies of scale. Although these vessels have the advantage of economies of scale, some special considerations should be made for them. For example, the fuel consumption cost of auxiliary engines is traditionally included in the vessel operating cost. However, such cost could be very high and fluctuate significantly in different scenarios for mega vessels. These special considerations should be incorporated in future research.
- The model developed by this dissertation allows a liner shipping company to have a homogeneous vessel fleet. However, this model has a limitation of allocating only one type of vessel to a port rotation. So, future studies could develop holistic models, similar to the one proposed herein, which could allow assigning different types of vessels to a single port rotation. In such models, the estimation of different entities would be more complicated. For example, the sailing times, fuel consumption rates, etc., should be estimated for different types of vessels. Moreover, some vessels might be run on only a specific type of fuel. So, fuel compatibility should also be considered in such models.
- Transshipment of containers could be thoroughly investigated by future research.

- Fuel price is one of the major parameters considered at the tactical level. Fuel price has fluctuated substantially in the recent years due to a wide variety of reasons, such as labor issues, political problems, trade wars, and others. Moreover, fuel price might also fluctuate with the passage of time without any abnormal reasons. Therefore, fuel price forecasting models could be designed by future research to use while making tactical-level decisions.
- Currently, little data is available for modeling emissions from liner shipping. Thus, the currently used parameter values for modeling emissions of harmful pollutants may not be very accurate. Hence, more data is required for estimating these parameter values. Moreover, using more data, more accurate emission models could be developed for the liner shipping industry.
- Several emission control areas have been enforced in the past decade. These emission control areas require use of special fuel. Moreover, sailing speeds are likely to be adjusted in these areas. So, emission control areas should be considered by holistic models tackling the tactical-level decisions.
- Multi-objective models could be developed for the tactical-level decisions, which would allow value trade-offs between different objectives.

8.1. Addressing Uncertainties in Liner Shipping

Several uncertainties are associated with liner shipping, which need to be addressed by future studies. First, container demands are not fixed, as assumed by most models that address the tactical-level decisions in liner shipping. Hence, uncertainties in container demand should be modeled by future holistic models tackling the tactical-level decisions. Second, a wide variety of time periods are associated with liner shipping, such as vessel handling times, waiting times at ports, transit times, and others, which should be modeled. Third, uncertainties in several other factors, such as weather conditions, fuel consumption, mechanical issues, berthing availability, etc. should also be studied. Uncertainties in liner shipping could be addressed with several approaches, such as minimax regret approach, application of upper and lower bounds, cardinality-constrained method, scenario analysis, sample average approximation, and others. The future research may focus on a comprehensive comparison of the aforementioned methods, aiming to determine their potential advantages and disadvantages for the **HOMTLP** mathematical model. The following sections of the dissertation elaborate on some of the approaches that can be used for modeling uncertainties in liner shipping operations.

8.1.1. Minimax Regret Approach

The minimax regret approach was introduced by Savage (1951). Under the approach, the maximum regret is minimized. Note that the regret in this case is defined as the difference between the payoff for a given action and the payoff for the optimal action. The approach is useful in addressing various uncertainties, such as fuel price uncertainty. Let's consider a case, where the price of fuel is uncertain; it can increase, stay the same, or decrease. The liner shipping company can take one of the three following actions: (1) increase the sailing speed; (2) decrease the sailing speeds and (3) not change the sailing speed.

Table 20 Payoff for each action and state.

Action/State	**Fuel Price Increased**	**Fuel Price Unchanged**	**Fuel Price Decreased**
Increase Speed	-$5	$0	$9
Decrease Speed	$0	$1	-$7
Not Change Speed	-$6	$0	$3

The payoff for each action is highlighted in Table 20. In case of increasing the speed, the optimal payoff is $9, when the fuel price decreases. Hence, the regret for fuel price decrease is ($9 - $9) = $0, as it is the optimal payoff. The regret for fuel price increase and no change in the fuel price are ($9-(-$5)) = $14 and ($9 - $0) = $9, respectively. Hence, the maximum regret, when the liner shipping company increases the sailing speed, is $14. The regrets for the other actions (i.e., decreasing the speed and not changing the speed) are presented in Table 21, where it can be seen that the maximum regret for increasing the speed, decreasing the speed, and not changing the speed are $14, $8, and $9, respectively. The minimax regret approach dictates that the liner shipping company should decrease the sailing speed, as this action would incur the minimum loss (i.e., regret), which is $8.

Table 21 Regret for each action and state.

Action/State	Fuel Price Increased	Fuel Price Unchanged	Fuel Price Decreased
Increase Speed	\$14	\$9	\$0
Decrease Speed	\$1	\$0	\$8
Not Change Speed	\$9	\$3	\$0

8.1.2. Application of Upper and Lower Bounds

Uncertain parameters in robust optimization can be modeled by polyhedral, cardinality-constrained, ellipsoidal, and norm uncertainty sets. A popular method of obtaining uncertainty sets is the use of upper and lower bounds. A solution is then constructed, which is feasible for any value in the uncertainty set (e.g., the solution is feasible for the worst-case value) (Ben-Tal et al., 2009). The robust counterpart of a linear optimization problem can be formulated as follows (Bertsimas et al., 2011):

$$\min c^T \boldsymbol{x} \tag{65}$$

Subject to:

$$A\boldsymbol{x} \leq b \ \forall a_1 \in u_1, \ldots, a_n \in u_n \tag{66}$$

$$\boldsymbol{x} \in \mathbb{R} \tag{67}$$

where:

a_i – is the i-th row of uncertain matrix A, and its value is from the uncertainty set u_i. Therefore,

$$a_i^T \boldsymbol{x} \leq b_i \Leftrightarrow \max_{\{a_i \in u_i\}} a_i^T \boldsymbol{x} \leq b_i \ \forall i \tag{68}$$

8.1.3. Cardinality-Constrained Method

Due to various reasons, a parameter may be subject to uncertainty. However, in many cases, it is assumed that the parameter will not hold the worst value for all the elements. For example, not all the ports in a liner shipping port rotation are expected to undergo congestion within the same time frame. Hence, the cardinality-constrained method assumes that only a subset or bounded number of parameter elements will have the worst-case values, which results in less-conservative and more practical solutions (Raith et al., 2018).

Let's consider a set E. Each $e \in E$ and each scenario $i = 1, \ldots, k$ are associated with two real values $\hat{c}_{ei}$ and δ_{ei}. The uncertain parameter c_{ei} must be within the interval $[\hat{c}_{ei}; \hat{c}_{ei} + \delta_{ei}]$, where $\hat{c}_{ei}$ is the nominal value. A positive integer $b_i < |E|$ must be given for each scenario i. Then, the cardinality-constrained set would include all scenarios, where a maximum of b_i elements can vary from the nominal value for each scenario i, as follows:

$$u = \{c \in \mathbb{R}^{|E| \times \mathrm{k}}: c_{ei} \in [\hat{c}_{ei}; \hat{c}_{ei} + \delta_{ei}]\ \forall e \in E, \forall i = 1, \ldots, k,$$
$$|\{e: c_{ei} > \hat{c}_{ei}\}| < b_i\ \forall i = 1, \ldots, k \tag{69}$$

8.1.4. Scenario Analysis

The process of scenario analysis has some similarities with the enumeration method. When the number of uncertain scenarios is not large, scenario analysis is used to assess each of the potential scenarios, which is similar to the enumeration method. It should be noted that scenario analysis should not be interpreted as prediction or forecasting. It is merely a way to imitate a set of plausible futures or possibilities for future development (Roxburgh, 2009; Quiceno et al., 2019). Each scenario involves a set of future events along with their cause and effect. Through a comprehensive analysis of the scenarios, the decision makers address uncertainties.

8.1.5. Sample Average Approximation

Sample average approximation can be very useful, when the set of plausible scenarios is large. Monte Carlo Simulation is used by the sample average approximation technique in order to solve stochastic optimization problems (Wang and Meng, 2012a). Let's consider the following stochastic optimization problem, where ξ is an uncertain parameter.

$$\min f(\boldsymbol{x}) = c^T \boldsymbol{x} + E(Q(\boldsymbol{x}, \xi)) \tag{70}$$

Subject to:

$$A\boldsymbol{x} = b \tag{71}$$

$$\boldsymbol{x} \in \mathbb{R}^{+} \tag{72}$$

In the sample average approximation method, N random replications of the uncertain parameter ξ are generated. Then, the expected value of the function containing the uncertain parameter ξ (i.e., $E(Q(\boldsymbol{x},\xi))$) is approximated using the following equation:

$$E_N\big(Q(\boldsymbol{x},\xi)\big) = \frac{1}{N}\sum_{i=1}^{N} Q(\boldsymbol{x},\xi_i) \tag{73}$$

Therefore, the optimization problem is given by:

$$\min f_N(\boldsymbol{x}) = c^T x + \frac{1}{N}\sum_{i=1}^{N} Q(\boldsymbol{x},\xi_i) \tag{74}$$

Subject to:

$$A\boldsymbol{x} = b \tag{75}$$

$$\boldsymbol{x} \in \mathbb{R}^{+} \tag{76}$$

Deterministic solution approaches are then used to solve the problem. The aforementioned process is repeated multiple times with various samples, until a satisfactory candidate solution as well as a statistical estimate of the optimality gap are obtained.

8.2. Solving the Model within a Reasonable Time

The **HOMTLP** mathematical model is a mixed-integer nonlinear programming model with a number of continuous and discrete decision variables. This model has high computational complexity, as increasing the number of variables and/or parameters drastically increases the computational time required. Although it has been solved with a commercial exact optimization solver in this work, it might not be solved in realistic time limits with exact optimization approaches for large-scale liner shipping networks. So, there is a need to solve this model in a reasonable computational time. However, solving this model in a short time would likely compromise the solution quality. Therefore, it needs to be solved in a considerable amount of time without losing the solution quality to a high degree. Heuristic and metaheuristic approaches could be employed to solve this model.

In contrast to heuristics that are typically problem-specific, metaheuristics can be applied to a wide range of problems. Metaheuristics can be categorized into the following classes: (1) local search metaheuristics; (2) constructive metaheuristics; (3) population-based metaheuristics; and (4) hybrid metaheuristics. Local search metaheuristics are focused on a single solution, which is often referred to as the current solution. The current solution is improved by iterative changes until a good-quality solution is reached (some other termination criteria can be imposed as well – for example, the maximum allowable computational time and/or the maximum allowable number of iterations). Examples of local search metaheuristics include Simulated Annealing, Iterated Local Search, Multi-Start Local Search, Variable Neighborhood Search, Tabu Search, Guided Local Search, and others.

Instead of improving complete solutions, constructive metaheuristics build solutions from constituting elements. The building/construction process is conducted through addition of one element to the partial solution at a time. Several constructive metaheuristics have been developed by researchers, which include Greedy Randomized Adaptive Search Procedure and Large Neighborhood Search. Rather than focusing on a single solution, population-based metaheuristics consider a set of solutions, which is called a population. In population-based metaheuristic approaches, good-quality solutions are found by iteratively selecting and combining the existing solutions from the population of solutions. Population-based metaheuristics include Evolutionary Computation-based algorithms (e.g., Genetic Algorithms, Evolutionary Programming, Evolutionary Strategies, Structured Genetic Algorithms, Messy Genetic Algorithms, Island Evolutionary Algorithms, Differential Evolution, among many others), Particle Swarm Optimization, Artificial Bee Colony Optimization, Ant Colony Optimization, Estimation of Distribution Algorithm, and others.

In addition to the aforementioned classes, another class of metaheuristics has been developed over the recent years, which are called hybrid metaheuristics. Hybrid metaheuristics are inspired by ideas from different metaheuristics. Moreover, unlike typical metaheuristics that rely on stochastic procedures (e.g., crossover operations and mutation operations that are commonly used within the Evolutionary Computation-based algorithms), hybrid metaheuristics deploy local search heuristics and optimization procedures that directly capture properties of the problem at hand. Such a feature of hybrid metaheuristics typically allows improving the quality of solutions produced towards convergence.

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