THE FLORIDA AGRICULTURAL AND MECHANICAL UNIVERSITY

COLLEGE OF ENGINEERING

DEVELOPMENT OF THE OPTIMIZATION MODELS AND SOLUTION ALGORITHMS FOR THE VESSEL SCHEDULE RECOVERY PROBLEM IN LINER SHIPPING

By

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A Dissertation submitted to the
Department of Civil and Environmental Engineering
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy in Civil Engineering

Tallahassee, FL

Fall, 2019

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DEDICATION

This dissertation is dedicated to God, the sustainer of my life, my late mother who always wanted me to be an engineer, and my family for nursing me with love and affection.

ACKNOWLEDGMENT

I want to express my most profound appreciation to my academic advisor and committee chair, Dr. Maxim A. Dulebenets (P.E.), who has the attitude and substance of a genius. He continually provided me with invaluable advice, consistent support, and guidance throughout this research. Without his persistence and thorough supervision, this dissertation would not have been possible.

Also, I would like to sincerely thank my committee members, Dr. Eren Erman Ozguven, Dr. Ren Moses (P.E.), and Dr. Hongmei Chi, for their generous support, constructive comments, advice, and recommendations during this research. Their valuable feedbacks assisted with improving the quality of this dissertation.

I want to acknowledge the Civil Engineering faculty at the FAMU-FSU College of Engineering. Some of the classes I enrolled in during my academic career, which were taught by Dr. Maxim Dulebenets, Dr. Ren Moses, and Dr. Eren Erman Ozguven, exposed me to the different aspects of transportation engineering.

Finally, I am thankful to my dad and siblings for their immeasurable moral support and encouragement throughout this dissertation.

RESUME

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JP3. Dulebenets, M.A., Pasha, J., **Abioye, O.F.**, Kavoosi, M., Ozguven, E.E., Moses, R., Boot, W.R., & Sando, T., 2019. Exact and Heuristic Solution Algorithms for Efficient Emergency Evacuation in Areas with Vulnerable Populations. *International Journal of Disaster Risk Reduction*, Elsevier, Vol. 39, pp. 1-18. DOI: 10.1016/j.ijdrr.2019.101114.
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JP7. Dulebenets, M.A., **Abioye, O.F.**, Ozguven, E.E., Moses, R., Boot, W.R., & Sando, T., 2019. Development of Statistical Models for Improving Efficiency of Emergency Evacuation in Areas with Vulnerable Population. *Reliability Engineering & System Safety*, Elsevier, Vol. 182, pp. 233-249. DOI: 10.1016/j.ress.2018.09.021.

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ABSTRACT

Over 80% of the global trade tonnage and 70% of global trade value are carried by oceangoing vessels around the world. However, vessel routing and scheduling is a challenging exercise in liner shipping because of uncertainties that may affect the planned operations. Delays caused by uncertainties, such as weather, natural hazards, labor strikes, and others, increase the complexity of liner shipping, related to schedule adherence and reliability of service. In the event of a delay, liner shipping companies take decisions to recover the schedule, aiming to deliver cargoes in a timely manner. Vessel operators may decide to increase the sailing speed of the ship, which will further increase bunker fuel consumption and the total operational cost of liner shipping operations. The vessel schedule recovery problem becomes even more difficult if the delay is large. The contributions of this dissertation to the state-of-the-art are as follows: 1) a set of operational-level vessel schedule recovery models in liner shipping; 2) the vessel schedule recovery models for the liner shipping routes that pass through Emission Control Areas; 3) consideration of multiple vessel schedule recovery alternatives (e.g., port skipping with and without cargo diversion, speed adjustment, handling rate adjustment); 4) application of the appropriate solution approaches for solving the vessel schedule recovery problem; 5) identification of the key factors that may influence vessel schedule recovery; and 6) presentation of the managerial insights and benefits of the developed vessel schedule recovery optimization models.

ABBREVIATIONS AND ACRONYMS

AIS – Automatic Identification System

BC – Black Carbon

CO – Carbon Monoxide

DP – Dynamic Programming

EA – Evolutionary Algorithm

ECA – Emission Control Area

ET – External Maritime Container Terminal

EU – European Union

GA – Genetic Algorithm

GRASP – Greedy Randomized Adaptive Search Procedure

GT – Gross Tons

GHG – Greenhouse Gas

HFO – Heavy Fuel Oil

IMO – International Maritime Organization

LNG – Liquefied Natural Gas

LP – Linear Programming

LPG – Liquefied Petroleum Gas

MGO – Marine Gas Oil

MINLP – Mixed-Integer Nonlinear Programming

MIP – Mixed-Integer Programming

MSC – Miscellaneous Costs

MUT – Multi-User Maritime Container Terminal

NGHG – Non-Greenhouse Gas

NLP – Nonlinear Programming

NP-hard – Non-Deterministic Polynomial-Time Hard

NSGA-II – A Non-Dominated Sorting Genetic Algorithm II

OR – Operations Research

PM – Particulate matter

REV – Total Revenue

SECA – Sulphur Emission Control Area

SPEA-II – Strength Pareto Evolutionary Algorithm II

S-VSRP – Speed-Based Vessel Schedule Recovery Problem

TEC – Total Vessel Emission Cost

TEU – Twenty-Foot-Equivalent Container Unit

TFC – Total Fuel Consumption Cost

TIC – Total Container Inventory Cost

TOC – Total Vessel Weekly Operational Cost

TPC – Total Port Handling Cost

TVC – Total Cost Associated with Violation of Service Time Windows

TW – Time Window

UNCTAD – United Nations Conference on Trade and Development

UNFCCC – United Nations Framework Convention on Climate Change

U.S. – United States

USD – United State Dollars

VSRP – Vessel Schedule Recovery Problem

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CHAPTER 1

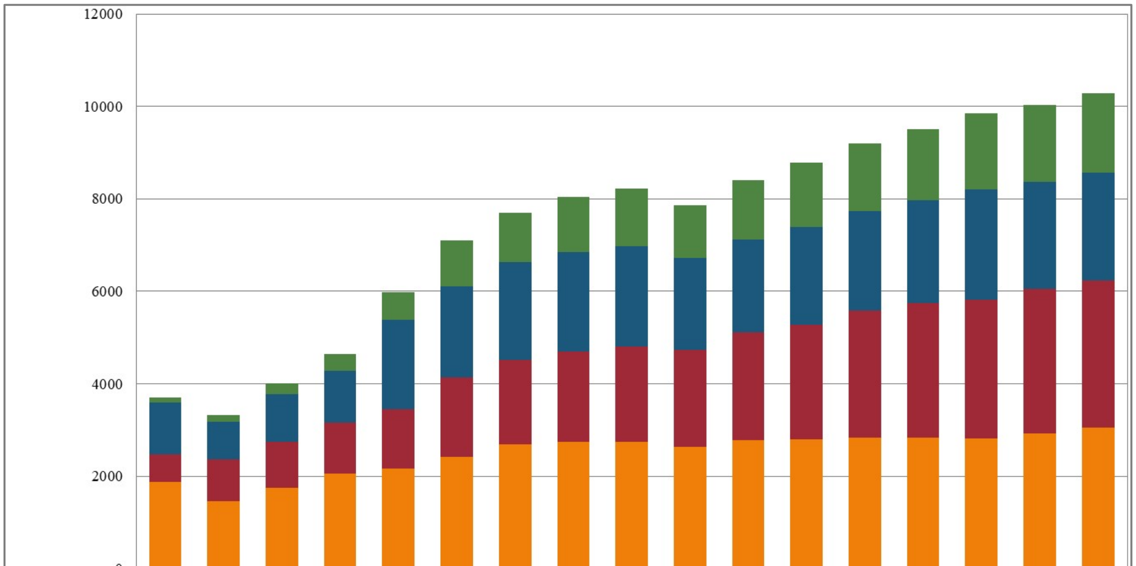
INTRODUCTION

1.1. Seaborne Trade Tendencies and Importance of Maritime Transportation

Recent trends have shown that maritime transportation is critical for global trade. Over 80% of the global trade tonnage and 70% of the global trade value are carried by oceangoing vessels around the world (UNCTAD, 2017). The United Nations Conference on Trade and Development (UNCTAD) report revealed that there has been an increase in the demand for shipping services over the last decade. The total volumes of the international trade, carried by vessels, reached 10.3 billion tons in 2016, which is a 1.8% increase as compared to the total seaborne international trade volumes recorded in 2015 (UNCTAD, 2017). According to statistical projections by UNCTAD (2017), an annual increase of 3.2% in total volume of world seaborne trade has been forecast between 2017 and 2022.

There has been a significant increase in the volumes of all forms of cargo, transported by vessels in the last decade. According to the statistical data, provided by UNCTAD (UNCTAD, 2017), a rapid growth in transported volumes of oil and gas cargo (4% increase in tonnage from 2015 to 2016), containerized trade (4% increase in tonnage from 2015 to 2016), and major bulk cargo (2% increase in tonnage from 2015 to 2016) has been reported (see Figure 1). The growth of international seaborne trade can be attributed to fast industrialization, improved standards of living, competitive markets, and population growth (Umang et al., 2011). The invention of container vessels with high container-carrying capacity of up to 20,000 twenty-foot-equivalent container units

(TEUs) has resulted in an increase in the number of megaships in the fleet of major world's container carriers to keep up with competition in the market and achieve economies of scale (Meng et al., 2014).



	1980	1985	1990	1995	2000	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Container	102	152	234	371	598	1001	1076	1193	1249	1127	1280	1393	1464	1544	1640	1661	1720
Other dry cargo	1123	819	1031	1125	1928	1975	2112	2141	2173	2004	2022	2112	2150	2218	2393	2310	2339
Five major bulks	608	900	988	1105	1295	1711	1814	1953	2065	2085	2335	2486	2742	2923	2985	3121	3172
Oil and gas	1871	1459	1755	2050	2163	2422	2698	2747	2742	2642	2772	2794	2841	2829	2825	2932	3055

Figure 1 International seaborne trade trends

Source: UNCTAD (2017)

Rodrigue et al. (2017) presented the maritime traffic per continent and on the sea in 1990. Europe accounted for the largest maritime traffic (28% of total maritime traffic), followed by Asia (25% of total maritime traffic) and North America (16% of total maritime traffic), respectively. Furthermore, other continents, including Africa, South America, and Australia recorded 8%, 6%, and 2.5%, respectively. A significant percentage of maritime traffic was moved on the Atlantic Ocean (40% of maritime traffic), while 25% of the maritime traffic was ferried across the Indian Ocean. Also, about 15% of maritime traffic was carried across the Pacific Ocean. The maritime traffic per continent and on the sea is presented in Figure 2.

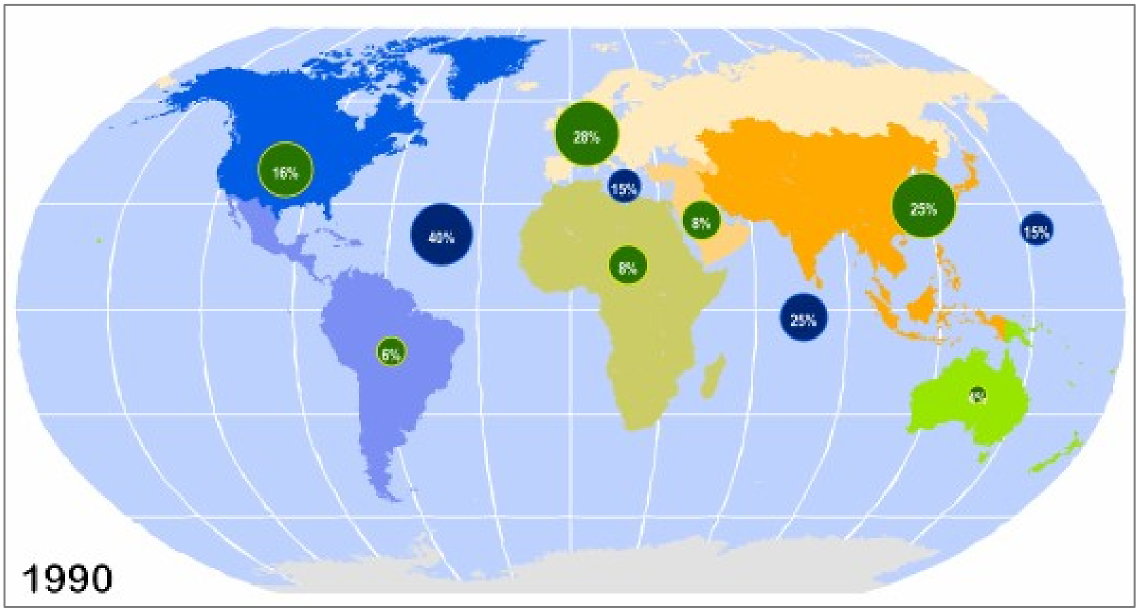


Figure 2 Maritime traffic per continent and on the sea

Source: Rodrigue et al. (2017)

The information, obtained from the World Shipping Council (2018a), revealed that seven of the top ten busiest container seaports in the world are in China. The Port of Shanghai (China) was ranked first (36.54 million TEUs) with a record of 8.69% growth in trade volume between 2013 and 2015 (see Table 1). The Port of Singapore (Singapore) was ranked second (30.92 million TEUs), while the Port of Shenzhen (China) was ranked third (24.20 million TEUs). The majority of the ports reported a growth in trade volume between 2013 and 2015, except the Ports of Singapore (lost 5.10% of trade) and Hong

Kong (lost 10.2% of trade). The Port of Los Angeles (USA) was reported as the busiest container seaport in North America and 19th in the world (8.16 million TEUs in 2015), followed by the Port of Long Beach (USA) (7.19 million TEUs in 2015), which was ranked as the second busiest seaport in North America and 21st in the world, and the Port of New York-New Jersey (USA) (6.37 million TEUs in 2015), which was ranked as the third busiest seaport in North America and 23rd in the world. Furthermore, it was observed that the Port of Rotterdam (the Netherlands) was ranked 11th with 12.23 million TEUs in 2015. Table 1 presents the top ten busiest container seaports in the world.

Table 1 Top 10 world seaports

Rank	**Port, Country**	**Volume, 10^6 TEUs**			**% growth in 3-years**
		2013	**2014**	**2015**	
1	Shanghai, China	33.62	35.29	36.54	8.69
2	Singapore, Singapore	32.60	33.87	30.92	-5.10
3	Shenzhen, China	23.28	24.03	24.20	3.90
4	Ningbo-Zhoushan, China	17.33	19.45	20.63	19.04
5	Hong Kong, S.A.R., China	22.35	22.23	20.07	-10.20
6	Busan, South Korea	17.69	18.65	19.45	9.99
7	Qingdao, China	15.52	16.62	17.47	12.56
8	Guangzhou Harbor, China	15.31	16.16	17.22	12.47
9	Jebel Ali, Dubai, United Arab Emirates	13.64	15.25	15.60	14.37
10	Tianjin, China	13.01	14.05	14.11	0.08

Source: World Shipping Council (2018)

Over the past three decades, there has been a continuous growth in container shipping. Such tendency has been predicted to be sustained. Shipping companies have been adopting several strategies, such as increasing their fleet size and forming alliances, to keep up with the increasing demand. Lawrence (1972) categorized the modes of operation in shipping into three: (1) industrial; (2) tramp; and (3) liner shipping. In industrial shipping, the vessels are controlled by the cargo owners, and they seek to minimize the cost of transporting the cargo. In tramp shipping, the vessel operator usually does not own the cargo, but selects the cargo to transport for a single customer at a time. The vessel operates only when there is a cargo demand and selects cargoes to be moved to maximize profit. Liner shipping involves transporting containerized cargoes for many customers based on a fixed schedule. Usually, liner shipping companies form a round trip and call at several ports during a voyage (a voyage refers to a single round-trip). Also, they publish their schedules and transit routes.

According to the World Shipping Council (2018b), there are more than 400 liner services around the world, which adopt a regular service frequency (mostly weekly). For a weekly service frequency, each port of call on the liner shipping route is visited the same day every week. Although shippers prefer a more frequent service (such as daily shipping service), the weekly service frequency has been adopted by most of liner shipping companies. The latter can be justified based on the fact that accumulating more cargo increases the revenue generated by the liner shipping companies. In addition, it is more convenient for marine container terminal operators to allocate fixed vessel service time windows for liner carriers that offer weekly service frequency (Meng et al., 2014). There are a few liner shipping companies that offer daily shipping service, such as Maersk Line (otherwise called Daily Maersk), which provides a competitive daily shipping service from Asia to Europe.

1.2. Existing Challenges Faced by Liner Shipping Companies

Liner shipping companies face numerous challenges at the decision-making level. Pesenti (1995) and (Meng et al., 2014) defined three decision-making levels for liner shipping companies, which include: (a) strategic; (b) tactical; and (c) operational. Liner shipping companies make long-term strategic level decisions regarding the fleet size and mix, network design, and alliance strategies. The frequency of service, deployment of vessels, sailing speed of vessels, and design of schedules are the tactical-level decisions made by liner shipping companies. Generally, the tactical-level decisions are revised every 3-6 months (Wang and Meng, 2012a). At the operational level, liner shipping carriers decide on the type of cargo to ship, the vessels to be used for cargo transport, and recovery of the schedule in the event of a delay. Liner container shipping is challenging and capital intensive due to the complex nature of logistics (such as routing and scheduling) involved. Figure 3 illustrates the decision-making levels for liner shipping companies. Some of the major challenges, affecting the operations of liner shipping companies, include: (1) bunker fuel consumption; (2) routing and scheduling; (3) speed optimization; (4) emissions; (5) uncertain port times; (6) network design; (7) schedule recovery; (8) alliance strategy, and others.

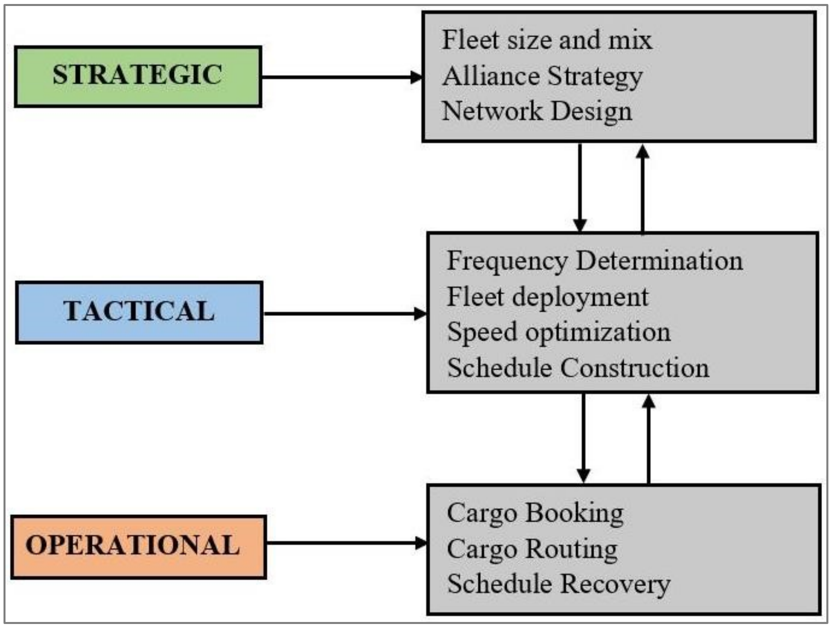


Figure 3 Levels of decision making for liner container shipping companies

Minimization of the total route service cost has been the main goal of shipping companies since the economic crisis in 2008 (Song et al., 2015). According to Ronen (2011), bunker costs account for about 75% of the total operating costs of container vessels. However, it has been identified that a positive correlation exists between the vessel sailing speed and fuel consumption (Notteboom and Vernimmen, 2009; Du et al., 2011; Wang and Meng, 2012b; Psaraftis and Kontovas, 2013). An increase in the vessel sailing speed by a few knots could result in a substantial increase in fuel consumption. Determining the optimal sailing speed to minimize the total operational cost has been a major challenge in liner shipping. Usually, researchers assume that the sailing speeds of a vessel are predetermined. Meng et al. (2014) attributed the assumption to the nonlinear relationship between bunker consumption rate and sailing speed. However, several factors may affect the bunker consumption along with the port handling times other than the sailing speed vessels, such as weather, uncertain port times, natural hazards, worker strike, among others.

Vessel routing and scheduling is a challenging exercise in liner shipping because of a number of factors, including the time sensitivity of some products being transported, additional costs incurred due to a missed connection, available vessel service time widows at ports, uncertainties (at ports of call and in sea), among others. Delays caused by uncertainties (such as weather, natural hazards, port congestion, uncertain port times, and others) increase the complexity of schedule adherence and reliability of service in liner shipping. In the event of a delay, liner shipping companies take decisions (at the operational decision-making level) to recover the schedule and deliver cargoes on time. Vessel operators may decide to increase the sailing speed of the vessel. The latter action may significantly increase bunker fuel consumption and consequently the total operational cost of liner shipping companies. The vessel schedule recovery problem becomes even more difficult in liner shipping if the delay extends over a long time period. Sometimes, liner shipping companies are not able to recover their schedule even if the maximum sailing speed of a vessel is selected.

Another major challenge faced by liner shipping companies is the minimization of emissions and associated costs. According to the International Maritime Organization (IMO), oceangoing vessels emitted approximately 2.2% of the world's anthropogenic carbon dioxide emissions in 2014 (IMO, 2014). Dulebenets (2016a) highlighted that greenhouse gases (GHGs), such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), are responsible for climate change. Moreover, non-greenhouse gases (NGHGs), including sulfur oxides (SO_X) (which cause acid rain and deforestation) and nitrogen oxides (NO_X) (that increase levels of GHG ozone and decrease GHG methane, which may give rise to warming and cooling, respectively), may negatively impact not only the environment, but also the health of living organisms (Dulebenets, 2016a).

Psaraftis and Kontovas (2013) underlined that the emissions produced by vessels affect the human health. Several corridors on the seas have been designated as “Sulfur Emission Control Areas” (SECA) by the IMO (e.g. the Baltic Sea, the North Sea, and the English Channel were designated as SECA in 2008). Also, the United States (U.S.) - Canadian coastal zone was designated as an “Emissions Control Area” (ECA) in 2010, with restrictions imposed on SO_X, NO_X, and particulate matter (PM) emissions. Vessels sailing through the ECAs are not allowed to burn fuel with a sulfur content of 0.10% m/m after 1 January 2015. Henderson (2015) suggested that the fuel chemical content standards might force liner shipping companies to switch from heavy oil to high-priced marine gas. In order to satisfy the demand, liner shipping companies are faced with the challenge of minimizing the total emission costs and maximizing profit, especially when navigating routes with ECAs. Also, liner shipping companies are faced with the challenge of minimizing the overall environmental impact throughout the design of efficient liner shipping networks and schedules.

Liner container shipping network design aims to determine the ports of call in a voyage and the sequence. Two types of networks are usually considered in liner shipping: hub-and-spoke (H&S) network and multi-port calling (MPC) network (Dulebenets et al., 2016). There are two groups of ports in the H&S network: hub ports and feeder ports. On the H&S network, the cargo between two hub ports is transported by larger vessels, which navigate the main route connecting the hub ports (see Figure 4A). Afterwards, the cargo is transported from the hub port to feeder ports via the feeder routes using smaller vessels. In an MPC network, ports are not categorized as main or feeder ports. Usually, a vessel can sail from one port to another along the shipping route (see Figure 4B). Ocean carriers, generally face the challenge of identifying the most efficient network for a given service route and the size of vessels to be deployed in order to achieve economies of scale. The decrease of the unit transportation cost resulting from an increase in the number of units (i.e., containers) is referred to as "economies of scale" (Silberston, 1972).

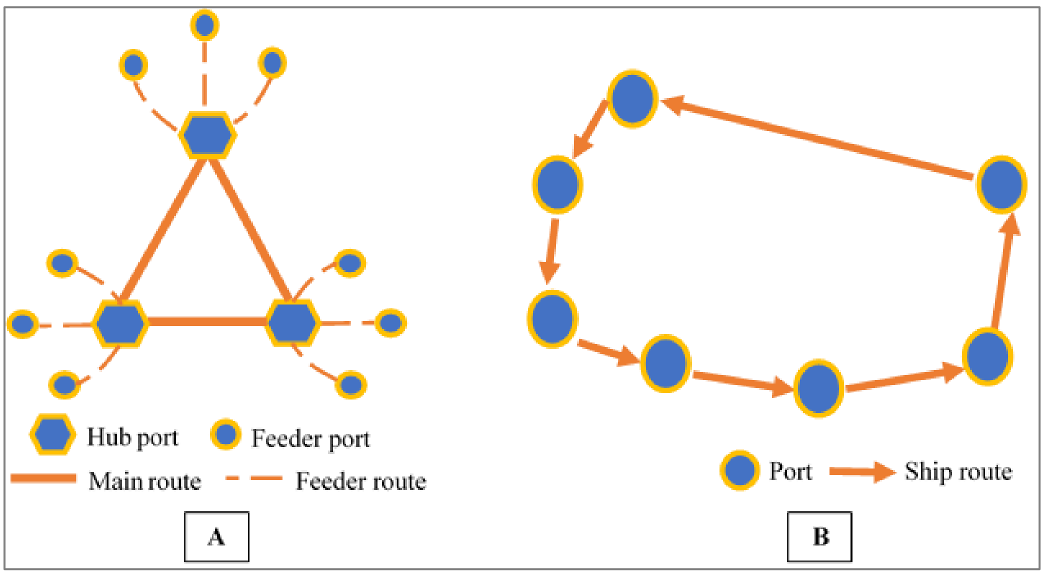


Figure 4 Hub-and-Spoke (A) and Multi-port Calling (B) Networks

Furthermore, the problem of network design in liner shipping overlaps with the vessel scheduling problem. Generally, liner shipping companies focus on itinerary design and vessel deployment, based on the assumption of a fixed vessel sailing speed and weekly service frequency without considering schedules (Meng et al., 2014). The liner shipping network design problem may involve more ports on the network and allow for container transshipment operations. Also, handling times at ports of call, vessel service time windows, and port congestion among other factors, affect vessel arrival times at subsequent ports of call, especially when the ports of call are close to one another. The latter may cause a delay, which propagates throughout the entire liner shipping network.

Liner shipping companies often choose to form strategic alliances, with the aim of minimizing the costs and maximizing the revenue (e.g. the establishment of M2 and Ocean Three alliances in 2014) (Brouer et al., 2014). Some researchers have suggested that developing capacity exchange mechanisms to achieve optimal vessel capacity allocation among multiple shipping lines in an alliance is a challenging task (Agarwal and Ergun, 2010; Zheng et al. 2015). Some other factors, such as strategy, governance, and culture, contribute to the success of alliances created by liner shipping companies (Meng et al., 2014). According to Dulebenets (2018a), the shippers forecast that formation of new alliances may negatively affect the reliability of liner shipping services. Also, shipping companies that are incapable of keeping up with existing competition are likely to bankrupt (in August 2016, the Hanjin liner shipping company filed for bankruptcy). Thus, liner shipping companies seek the optimal alliance strategies, where they can maximize their profit and transport cargoes at the minimal cost.

1.3. Strategies Used to Resolve the Existing Challenges

Liner shipping companies and researchers have adopted various strategies in different liner shipping decision problems. Generally, operations research (OR) methods have been used in addressing the majority of the problems associated with high fixed costs, high daily operational costs of container vessels, large fleet size, and alliances in liner shipping

(Meng et al., 2014). A number of researchers have highlighted the importance of optimizing the sailing speed of vessels, given the high price of fuel (Notteboom and Vernimmen, 2009; Ronen, 2011). According to Golias et al. (2010) liner shipping companies have adopted the strategy of slow steaming (the practice of reducing the sailing speed of vessels significantly below their design speeds). Slow steaming was introduced in 2008 by Maersk due to high bunker cost in order to reduce bunker consumption and total fuel costs (Notteboom and Vernimmen, 2009; Cariou, 2011; Ronen, 2011). Psaraftis and Kontovas (2014) and Kontovas (2014) showed that bunker consumption is proportional to the sailing speed and suggested that slow steaming is crucial to reduce bunker consumption significantly. Estimations from a vessel engine manufacturer indicated that reducing the sailing speed of a vessel from 27 knots to 18 knots could reduce bunker consumption by 59%; however, the reduction in sailing speed would increase the sailing time for Asia-Europe voyages by a week (Wartsila Technical Journal, 2010).

The decision to reduce vessel speed and bunker cost conflicts with the sailing time. The Journal of Commerce (2010) reported that slow steaming increases the sailing time for trans-Pacific voyages by 4-7 days. Notteboom and Vernimmen (2009) indicated that slow steaming would require the deployment of more megaships to meet the demand and service frequency at each port of call on the liner shipping network; dispatching more megaships increases the total operational costs. The problem of conflicting objectives has been addressed by some researchers. Meng et al. (2014) and Mansouri et al. (2015) underlined that most studies combine conflicting objectives into one objective function. To capture the conflicting nature of objectives effectively, Dulebenets (2018a) presented a mixed-integer programming (MIP) model, which separates conflicting objectives, associated with the total route service costs, into two conflicting groups. Along with slow steaming, Psaraftis and Kontovas (2014) underlined that some liner shipping companies have used another approach to reduce bunker consumption. Some of the ocean carriers order vessels with lower horsepower engine. The vessels are designed to sail at slow steaming speed, while travelling at their maximum speeds. According to the authors, Triple E vessels with a container carrying capacity of 18,000 TEUs have the maximum speed of 19 knots, which is 6.5 knots lower as compared to Emma Maersk vessels with lower capacity.

In practice, liner shipping companies build buffer time to manage uncertainties in sea for each leg of the voyage. At the beginning of the voyage, the sailing speed of the vessel can be increased to make sure that the vessel can recover from lost time at sea due to adverse weather or mechanical breakdowns. Another strategic and tactical decision, made by liner shipping companies to solve the scheduling problem, is the deployment of more vessels for the same service route, while maintaining the same service frequency (Song et al., 2015). The latter increases the buffer time of vessels at each leg of the voyage, which compensates for the lost time of vessels due to uncertainty. Furthermore, the vessel scheduling and routing problem has received a significant attention from researchers in the past years. Many studies proposed several mathematical models and solution algorithms to solve vessel routing and scheduling problems in liner shipping. Meng and Wang (2011) proposed an MIP model to minimize the total route service cost, and determine the service frequency, fleet deployment strategy, and vessel sailing speed for a long-haul liner service route. Some studies developed mathematical models, which consider the relationship between the connection times at transshipment ports and the schedules of liner services.

Reduction in emissions has been a major source of concern for liner shipping companies. The IMO (2013) indicated that sustainable maritime transportation is guided by economic, social, and environmental responsibilities. Several researchers have developed mathematical models and algorithms to reduce the cost of emissions, while optimizing the speed of vessels. A positive correlation has been established between the amount of emissions produced and the sailing speed of oceangoing vessels. In practice, liner shipping companies have been applying slow steaming and super slow steaming (reduction in sailing speed below 18 knots) strategies to minimize the emissions produced by vessels. Also, liner shipping companies use the technique of fuel switching when vessels are in ECAs. When a vessel enters the areas, designated as ECAs on the network, the operator switches the fuel supplied to the engine from Heavy Fuel Oil (HFO) to a cleaner Marine Gas Oil (MGO) with low sulfur content. Other techniques adopted to reduce emissions include berth scheduling and shipping route re-design.

Kontovas and Psaraftis (2011) conducted an extensive review of literature to assess the impact of sailing speed on the sustainability of liner shipping and suggested that slow steaming is the link to sustainable maritime transportation. In addition, some researchers have also demonstrated that a reduction in the sailing speed of vessels will reduce the amount of emissions produced (Psaraftis and Kontovas, 2013; Kontovas, 2014). Others have recommended that although sustainability considerations in liner shipping involve many conflicting objectives, there is the need to reduce the maximum sailing speed of vessels to minimize emissions.

The reduction in operating cost has been the primary consideration in the design of liner shipping networks. However, as indicated earlier, the environmental issues have also become a major source of concern in the design of an efficient liner shipping network. Liner shipping companies consider the number of routes, the sailing speed of vessels along the routes, and the allocation of cargoes in the service network. In the design of an efficient network, liner shipping companies account for some tactical-level decisions, such as fleet deployment and service frequency, to determine the vessels to be deployed in the network and the service frequency (such as daily or weekly service frequency), without considering schedules (Meng et al., 2014). Also, some researchers have used mathematical models to address network design problems in liner shipping.

1.4. Outline of Contributions of This Dissertation

Over the past decade, a lot of research efforts have been devoted to vessel scheduling, uncertainty in liner shipping, collaborative agreements between liner shipping companies, agreements between liner shipping companies and marine container terminal operators, and green vessel scheduling. However, only a few studies addressed the vessel schedule recovery problem in liner shipping. Moreover, the studies dedicated to vessel schedule recovery have primarily focused on the option of speeding up in solving the vessel schedule recovery problem. Only a few models have considered other alternatives. Also, the studies, addressing the vessel schedule recovery problem presented in the state-of-the-art, have focused on minimizing the total route service cost, and do not consider other important objectives, such as minimization of emissions, minimization of delay, etc., in the mathematical models proposed.

Furthermore, the effects of disruptions on vessels sailing through ECAs, where the sailing speed of the vessel is reduced due to the environmental regulations (and the speeding up approach might not be applicable), have not been accounted for in the literature. In practice, many ports also have restrictions for vessel arrivals. The uncertainty at the ports throughout disruption modeling has not been captured by studies that have addressed the vessel schedule recovery problem. To fill the gaps in the state-of-the-art, the contributions of this study include the following:

i. Propose a set of operational-level vessel schedule recovery models in liner shipping.
ii. Consider the environmental regulations for the liner shipping routes that pass through the areas, which are designated as ECAs.
iii. Consider multiple vessel schedule recovery alternatives (e.g., port skipping, speed adjustment, handling rate adjustment).
iv. Apply the appropriate solution approaches for solving the vessel schedule recovery problem in a reasonable computational time.
v. Conduct the numerical experiments to determine the key factors that may influence vessel schedule recovery.
vi. Present managerial insights and benefits of applying the developed vessel schedule recovery optimization models.

CHAPTER 2

LITERATURE REVIEW

An extensive literature search was performed through several databases and major academic publishers (Elsevier, Springer, Taylor and Francis Online, Springer Verlag, John Wiley, etc.), conference proceedings, and scientific manuscripts (i.e., Master theses and Dissertations) to capture relevant publications in the state-of-the-art. The following keywords and phrases were used to guide the search and return only publications that are relevant to the present work: vessel scheduling, vessel, ship, vessel schedule recovery, shipping collaborative agreements, green vessel, sustainable shipping, shipping uncertainty, ship/vessel routing, ship/vessel scheduling and liner shipping. Next, all articles collected were separated by various topics: 1) General vessel scheduling; 2) Uncertainty in liner shipping operations; 3) Collaborative agreements; 4) Environmental considerations and green vessel scheduling; and 5) Vessel schedule recovery. A statistical analysis of the collected studies revealed that the conducted search captured the most recent studies (approximately 80% of the studies were published between 2008 and 2018).

Figure 5 shows the distribution of studies collected by year. This section of the dissertation provides a detailed review of the collected studies based on the aforementioned topics, presents a critical evaluation of the existing work, and discusses the existing gaps in the state-of-the-art.

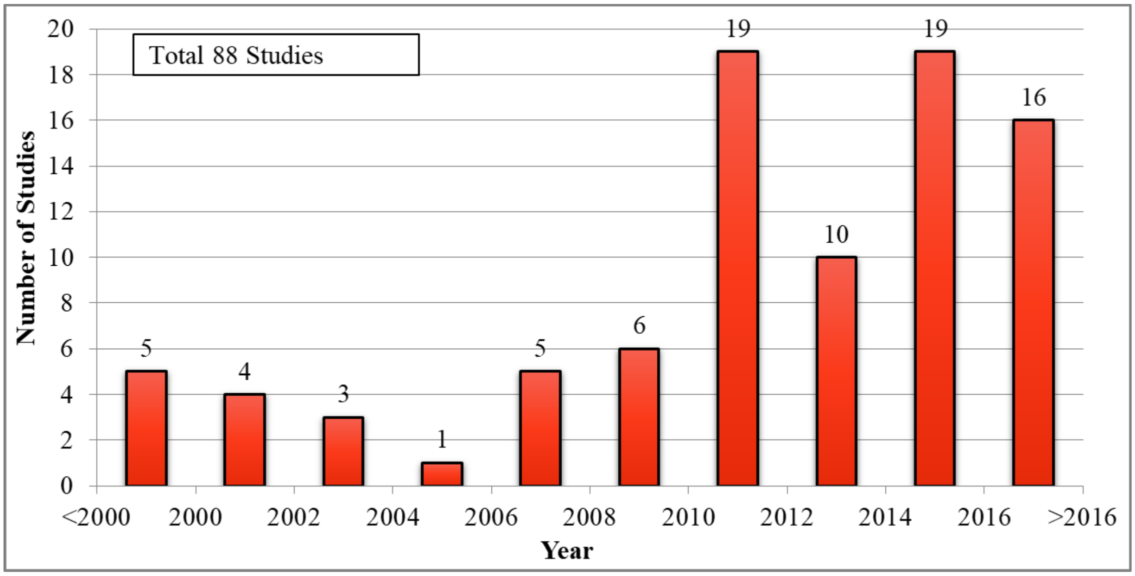


Figure 5 Distribution of studies by year

2.1. Review of the Collected Studies

This section of the present work provides a detailed review of studies collected from the literature survey. As indicated earlier, the collected studies were classified in the following groups: (1) general vessel scheduling – the studies that account for certain characteristics that are typically considered by liner shipping companies throughout design of vessel schedules, such as sailing speed, port handling cost, port handling productivity, total delay, vessel operational cost, and others; (2) uncertainty in liner shipping operations – the studies that focus on modeling uncertainty in liner shipping operations and evaluation of strategies for improving the degree of schedule reliability; (3) collaborative agreements – the studies that propose and evaluate collaborative agreements between liner shipping companies to achieve certain objectives (which may include minimization of transportation costs, maximization of the profit, market control, etc.), as well as agreements between liner shipping companies and marine container terminal operators to achieve certain objectives (which may include minimization of the total vessel handling time and delayed departures); (4) environmental considerations and green vessel scheduling – the studies that consider environmental concerns (i.e. vessel emissions) in vessel scheduling; and (5) vessel schedule recovery – the studies that model man-made and/or natural disruptions in vessel scheduling.

2.1.1. General Vessel Scheduling

Ronen (1982) indicated that vessel routing and scheduling problems are complex due to a high level of uncertainty associated with liner shipping operations. The author suggested that the complex nature of scheduling problems requires the use of mathematical programming models, which are limited. The short-term, medium-term, and long-term vessel scheduling frameworks were evaluated. Findings revealed that medium-term schedules are used as guidelines and are updated often. Furthermore, the major objectives considered were found to be dependent on the mode of operation. The study indicated that industrial shippers focus on cost minimization (port entry charge, the cost of loading and discharge times), liner shipping companies aim to maximize the profit, while in tramp shipping the objective depends on the type of cargo, which is usually not known in advance.

Lane et al. (1987) proposed a deterministic vessel scheduling problem, which imposed penalties on late handling time and total idle time. The objective minimized the total route service cost. Several problem instances were generated for six ports serving the Australia/North America West Coast trade, and an iterative optimization heuristic was designed to solve the problem. The authors highlighted that the major advantage of the shipping model proposed is flexibility, as it permits the liner shipping companies to evaluate only the alternatives, which are relevant to the objective. Ronen (1993) evaluated the vessel scheduling problems and the existing quantitative models, which have been used in resolving various issues related to vessel scheduling. Moreover, several mathematical models (including MIP, Nonlinear programming, and Liner programming models), which have been widely used to formulate vessel scheduling problems, were considered as well. It was found that the majority of studies focused on minimization of the total cost and maximization of the revenue. The author also underlined that heuristic algorithms have been frequently utilized in solving the formulated optimization problems.

Bendall and Stent (2001) examined the factors influencing the demand for fast cargo delivery service. The authors also assessed the profitability of a short-haul hub-and-spoke feeder operation. A fast feeder hub and spoke scheduling problem was formulated as an MIP optimization model. The objective minimized the total annual revenue. The problem was applied to six ports, handling short sea trades in East Asia, specifically, Singapore based hub-and-spoke regional feeder services. Computational experiments were conducted, and results indicated that operating costs depended on the technology (high speed vessels), while other factors, including transit time, frequency of service, freight rates and volume of containers carried, affected the total revenue.

Fagerholt (2001) investigated the factors that may result in violation of service time windows (TWs) (otherwise known as soft TWs) of vessels arriving at a port of call. The author formulated a vessel scheduling problem, which imposed inconvenience costs on vessels arriving outside the service TWs in order to control violations. The study suggested that allowing controlled violations might reduce transportation costs and generate a better schedule. The objective minimized the total route service cost, which included the transportation cost (e.g., the vessel operational cost, the fuel consumption cost, the chartering cost, etc.) and the inconvenience cost. A set partitioning algorithm was designed to solve the problem. Results from numerical experiments revealed that for large problem size instances the computational time significantly increased. Moreover, the proposed methodology was found to be promising when compared with the vessel scheduling problems with fixed TWs (otherwise known as hard TWs).

Ting and Tzeng (2003) presented a vessel scheduling problem with terminal berth time-window constraints. A dynamic programming algorithm was applied to solve the problem. A Taiwan liner shipping company, navigating the Asia – U.S. West Coast service route, was used as a case study. Computational results demonstrated that the algorithm reduced the bunker costs and port handling time. In addition, the algorithm solved large problem instances within acceptable computational time.

Christiansen et al. (2004) assessed the use of optimization-based decision-support systems for vessel routing and scheduling. The study suggested that applying optimization techniques in fleet utilization could substantially improve vessel routing and scheduling. From the analysis of the state-of-the-art, it was found that while tactical/operational vessel scheduling has received significant attention in the literature, only a few studies considered a wide range of issues in strategic liner shipping. The authors underlined that the use of optimization techniques has proven to be effective in solving various vessel scheduling problems in liner shipping. Furthermore, the majority of studies related to vessel scheduling, aimed to minimize the total cost or maximize the total profit.

Chen et al. (2007) formulated an *NP*-hard MIP vessel scheduling problem with bi-directional flows. The authors proved that a special case of this problem is totally unimodular and designed a three-step heuristic vessel scheduling algorithm based on the latter property. The problem was also solved using CPLEX, and the optimality gap was computed. A total of five numerical experiments were conducted for 270 problem instances, and the results showed that the optimality gap ranged between 0.41% and 3.74%. Moreover, the problems were solved within a reasonable computational time. Fagerholt and Linstad (2007) presented an optimization-based decision support tool for solving vessel scheduling and routing problems in industrial and tramp shipping. The objective aimed to minimize the total route service cost. The tool relied on a local search heuristic, and the results from computational experiments showed that the algorithm returned near-optimal solutions within reasonable computational time. Furthermore, the total route service cost was reduced by approximately 5%.

Argawal and Ergun (2008) considered the vessel scheduling and cargo-routing problem in liner shipping. The authors formulated an MIP model, which aimed to maximize the total revenue. A total of three algorithms were developed for the vessel scheduling problem: 1) a greedy heuristic; 2) a column generation-based algorithm; and 3) a two-phase Bender's decomposition-based algorithm. In addition, an iterative search algorithm was proposed to generate vessel schedules. Problem size instances were generated for 100 vessels calling at 20 ports, and the computational experiments were conducted. The results suggested that the solution approach could minimize the total route service cost for liner shipping companies with a fleet of up to 100 vessels.

Boros et al. (2008) investigated the problem of vessel and marine container terminal operations scheduling with conflicting objectives. The objectives aimed to maximize the total profit and minimize the cycle time. The authors indicated that while liner shipping companies prefer a longer cycle time, which gives the vessel more time to transport profitable cargo, marine container terminal operators prefer a shorter cycle time as it reduces the cost of overflows. A heuristic was designed to solve the problem. Moreover, CPLEX was used to solve the problem to optimality. Results from numerical experiments, conducted for 300 randomly generated problem size instances, indicated that the proposed methodology optimized the cycle time and the total profit.

Lei et al. (2008) conducted an analysis to assess performance of vessel schedules under three management policies: 1) non-collaborative policy; 2) the slot-sharing (partial collaboration) policy; and 3) total collaboration policy. A mixed-integer programming model was proposed, where the objective minimized the total operating cost. Empirical results from 2040 randomly generated problem instances revealed that the benefits of collaborative planning are fully utilized without the commitment of partners in resource sharing and demand.

Based on the work of Gatica and Miranda (2011), Angel and Hayden (2007) evaluated a network-based model for the vessel routing and scheduling problem with discretized TWs for a heterogeneous tramp fleet. The objective minimized the total operating cost of serving a set of trip cargo contracts. TW constraints were considered at both origins and destinations of the cargoes. Three sets of fifteen problem size instances were generated for 30, 40 and 50 cargoes per instance, respectively. Results from numerical computations indicated that the solution methodology presented a better trade-off between solution quality and computational time than a similar constant speed continuous model.

Korsvik et al. (2011) addressed the vessel routing and scheduling problem by incorporating split load strategy, which allows a carrier to transport cargo using more than one vessel. An MIP model was presented, and the objective aimed to maximize the profit. A large neighborhood search heuristic was proposed to solve the problem. Computational results showed that the heuristic provided good-quality solutions for all the problem size instances. Furthermore, the results suggested that introducing split loads improved utilization of the fleet capacity; however, such approach increased the problem complexity.

Ronen (2011) analyzed the effects of bunker price, sailing speed, service frequency and fleet size on the vessel schedule. This study proposed a strategy for estimating the optimal speed, cycle time and fleet size in order to minimize the total route service cost. A minimal-cost speed model was developed for liner shipping companies with constant service frequency. The author found that although a reduction in sailing speed reduced the total route service cost, reduction in sailing speeds would require deployment of more vessels on the liner shipping route.

Christiansen et al. (2013) conducted a detailed review of the literature to identify and analyze the existing vessel scheduling and routing problems in the millennium. The authors found that a large number of studies considered problems related to liner network design, maritime inventory routing and maritime supply chains. However, some complex problems have not been properly addressed, some of which include: 1) potential economic impact on network design; 2) vessel routing and scheduling problems considering port management issues. Findings from the analysis suggested that the majority of the relevant studies focused on theoretical contributions rather than practical operations.

Halvorsen-Weare and Fagerholt (2013) studied the vessel routing and scheduling problem, considering inventory and berth capacity constraints. The problem was formulated as an MIP model, and the objective minimized the total route service cost. A penalty was imposed if the service TW was violated. The authors used an exact optimization algorithm (Xpress-MP) to solve the problem as well as a heuristic routing algorithm. Computational experiments were conducted, and results showed that the developed solution method could be used to solve realistic problem size instances within a reasonable computational time. Hvattum et al. (2013) proposed a vessel sailing speed optimization problem, which minimized the total route service cost. The problem was formulated as a nonlinear model and then was linearized. The problem instances were generated considering seven ports of call. The problem was solved using a heuristic. Findings from numerical experiments indicated that optimal speeds could be found in a quadratic time.

de Armas et al. (2015) formulated the vessel routing and scheduling problem with discretized TWs. The objective minimized the total route service cost. The authors applied a heuristic algorithm (which combines the Greedy Randomized Adaptive Search Procedure (GRASP) and a Variable Neighborhood Search) to solve the problem. Computational experiments were conducted, and results demonstrated that the quality of the solutions was affected by the level of discretization. In addition, the optimality gap increased as the level of discretization increased. However, the problem was solved with an acceptable optimality gap in a reasonable computational time.

Dulebenets (2015a) suggested a metaheuristic approach for solving the vessel scheduling problem. The author presented an MIP formulation of the problem, which aimed to minimize the total route service cost. The problem was solved using a Memetic Algorithm. The study underlined that the advantages of using metaheuristic for the problem include: 1) allows for variation in sailing speed throughout the voyage; 2) considers the entire search space; 3) estimates bunker consumption using the nonlinear function without generating approximations; and 4) does not require any specific solvers. Results from the conducted numerical experiments demonstrated that the proposed algorithm produced good-quality solutions within an acceptable computational time.

Wang et al. (2015) presented a methodology, which could be used to estimate the perceived value of container transit times. The objective of the mathematical model minimized the total cost, associated with the bunker consumption and inventory cost. Numerical experiments suggested that the proposed methodology could assist liner shipping companies with the design of the optimal transit time between consecutive ports, prediction of the market share for various fuel types, and decision on the vessel sailing speed. Aydin et al. (2017) investigated the sailing speed optimization and the bunker management problem in liner shipping, considering stochastic port times and TWs. The objective of the mathematical model minimized the total route service cost, including the fuel consumption cost and the cost of late vessel arrivals at ports. The model accounted for the fuel consumption throughout the voyage between consecutive ports and the fuel consumption during waiting and service at ports. A dynamic programming model was applied to solve the problem. Results from computational experiments revealed that consideration of the port time uncertainty in the selection of the vessel sailing speed reduced the fuel consumption cost.

Dulebenets and Ozguven (2017) focused on the vessel scheduling problem in a liner shipping route with perishable assets. The authors proposed a nonlinear programming model for the problem. The objective minimized the total route service cost, including the cost associated with deterioration of perishable cargo throughout the voyage. The original model was linearized using piecewise secant approximations and solved using CPLEX. Results demonstrated that maintaining freshness of perishable assets might cause an increase in the route service cost. Moreover, deployment of small-size vessels would be more advantageous for liner shipping routes with perishable assets.

Lee and Song (2017) conducted a review of the state-of-the-art to assess current shipping practices. The authors examined a wide range of strategic, tactical and operational issues in maritime transport. Some of the strategic planning issues identified include: i) competition and cooperation between carriers, ports, and terminals; and ii) pricing and contracting. The major tactical planning issues found include: a) network design and routing; b) vessel scheduling; and c) slow steaming. Moreover, the key operations management issues discovered include: 1) empty container repositioning; and 2) safety and disruption management.

Dulebenets (2018a) studied the vessel scheduling problem, taking into account all major route service cost components. The author formulated a multi-objective mixed-integer nonlinear optimization model, which was linearized. The objective minimized the total route service cost. A Global Multi-Objective Optimization Algorithm was designed to solve the linearized vessel scheduling problem. Results from computational experiments, conducted for the Asia-Mediterranean Express Service liner shipping route showed that vessel schedules were more sensitive to the unit bunker cost as compared to the unit carbon dioxide emission cost.

Dulebenets (2018b) proposed a mixed-integer nonlinear mathematical model for the vessel scheduling problem, considering heterogeneous nature of the vessel fleet. The objective minimized the total route service cost. A total of 24 instances were developed, and the problem was solved using BARON. Results from numerical experiments indicated that schedules were more sensitive to introduction of larger vessels in the fleet as compared to an increase in the unit bunker cost. Furthermore, the adopted solution approach solved the problem instances within a reasonable computational time.

Mallidis et al. (2018) investigated the impact of slow steaming on the total route service cost and the total operational cost. The proposed model was used in assessing the impact of speed adjustment strategies used by carriers and the potential cost savings from adopting slow steaming strategies. The resulting delay at ports of call was considered in the model, developed using the historical delay data. Results from numerical examples showed that adopting slow steaming on the last voyages leg significantly increased the logistics cost as well as the total route service cost. The authors also underlined that slow steaming did not significantly impact the voyage cost as the sailing distance decreased.

2.1.2. Uncertainty in Liner Shipping Operations

Over the past decades, liner shipping companies have focused on designing liner services with short transit times and a high degree of schedule reliability. Complex logistic networks, high frequency of service, low transit times, high schedule reliability, and minimum operational costs are the major factors, which directly impact timely delivery of cargo to the customers. In order to provide an excellent service to their customers, liner shipping companies endeavor to keep up with their published schedules. However, waiting times and delays at ports of call may significantly affect schedule reliability and increase the customer logistic cost. Moreover, shipping lines may incur additional operating costs related to unproductive vessel service time and the rescheduling of vessels.

Notteboom (2006) classified the causes of delays in liner shipping into the following: 1) terminal operations; 2) port access; 3) maritime passages; and 4) chance. The author underlined that increasing port volumes and capacity constraints at ports around the world result in port congestion, which could disrupt liner service schedules. The study highlighted that port congestion was the main source of schedule unreliability. Carriers negotiate vessel handling rates and capacity with marine container terminal operators to mitigate delays that may arise due to the risk of port congestion. Furthermore, disruptions in port access due to bottlenecks at channels could increase the waiting times and result in irregularities of other services (such as towage services). Previously conducted studies reported that there has been no significant improvement in service reliability over the years.

Drewry (2010) highlighted that the top-20 liners only reached an on-time performance of up to 60% (the statistic was based on the same-day arrival criterion). Fuzzy sets have been frequently used by researchers to address the problems related to uncertainty. Chuang et al. (2010) proposed a mathematical model for the vessel routing and scheduling problem, considering the uncertainty in port handling times, sailing times, and demand at ports of call. The objective aimed to maximize the total revenue. The authors solved the problem using a fuzzy Evolutionary Algorithm. The algorithm was able to find the solutions through continuous copy, crossover, and mutation, taking into account the market demand, shipping and berthing time of vessels. Computational experiments were conducted, and the results showed that the solution algorithm suggested promising routes and schedules for the container vessels.

Qi and Song (2012) focused on the vessel scheduling problem, considering the effects of uncertain port handling time and constraints of vessel sailing speeds. The objective minimized the total expected fuel consumption and the total delays at ports of call. The problem was solved using a stochastic approximation procedure. A set of numerical experiments were performed, and the results indicated that the shortest leg in a voyage was the most complex leg in the vessel schedule design. The results also demonstrated that port time uncertainty could significantly affect the fuel consumption, optimal schedule, and the service levels.

Wang and Meng (2012a) presented a mixed-integer nonlinear vessel scheduling problem, which accounted for uncertain port handling time and vessel sailing time. The objective minimized the total route service cost. An exact cutting-plane based algorithm was applied to solve the problem. Numerical experiments demonstrated that allowing a small number of vessels to violate the transit time requirements reduced the total cost and provided feasible schedules. Furthermore, reducing the sailing speeds of vessels, when the price of bunker fuel was high, minimized the total route service cost. The authors suggested that uncertain port and sailing times might require liner shipping companies to deploy more vessels to maintain their schedules.

Wang and Meng (2012c) developed a mixed-integer nonlinear vessel scheduling problem, where the port waiting and container handling times were subject to uncertainty. The objective of the proposed model minimized the total route service cost. The sample average approximation approach was used to solve the problem. In addition, the solution methodology adopted linearization techniques (to linearize the nonlinear constraints) and a decomposition scheme (to improve the computational efficiency). Computational experiments were conducted for the Asia–America–Europe vessel route, and the results suggested that deploying more vessels for service could enhance the reliability of vessel schedules on a given liner shipping route. However, the latter action would increase the total operational cost of the carrier.

Halvorsen-Weare et al. (2013) formulated a mixed-integer programming model for the vessel routing and scheduling problem, which accounted for uncertain port handling times. The objective minimized the costs of violating the time windows at every port of call. A total of five problem instances were described using the LNG data, and then were solved by applying exact optimization (Xpress-Optimizer) algorithms. Results from the computational experiments showed that the schedule was resistant to small amount of delays, and the proposed solution approach could be used to solve real-life problem instances within a reasonable computational time.

Song et al. (2015) applied the NSGA II algorithm to solve multi-objective vessel scheduling problem with port time uncertainty. A total of three objectives were minimized, including: (a) the total vessel operational costs (sum of the fuel consumption and chartering costs); (b) service unreliability (i.e., probability of late vessel arrivals at ports); and (c) the total carbon dioxide emissions. Numerical experiments were conducted, and results revealed that the objectives were conflicting in nature. Moreover, the least amount of emissions could only be achieved simultaneously either with the least cost or with the least service unreliability.

Gürel and Shadmand (2018) presented a chance-constrained mixed-integer nonlinear programming model for the vessel scheduling problem. The model took into account uncertain waiting and handling times at ports of call for a liner shipping service with a heterogeneous fleet. The objective of the proposed model aimed to minimize the total fuel cost and attain the intended service level, which was set based on the probabilities of on-time vessel departure. CPLEX was used to solve the problem. Results from computational experiments suggested that allocating distinct service levels to port-vessel pairs could be more advantageous to the liner shipping company than assigning the same service levels to all port-vessel pairs.

2.1.3. Collaborative Agreements

2.1.3.1. Liner shipping alliances

Collaborative agreements between liner shipping companies, often referred to as “alliances”, are generally formed by liner shipping companies at the strategic level, aiming to maximize the total profit, outperform competitors, and achieve other related business objectives. According to Cariou (2000), the major reasons for alliance formation between liner shipping companies are: 1) to achieve economies of scale; 2) to achieve better allocation of vessels; and 3) market control. The first liner shipping alliance, called the “Global Alliance”, was formed in 1994 by four mega-carriers, including APL, OOCL, MOL, and Royal Nedlloyd Lines. By 1996, three other major liner shipping alliances had been formed, namely Grand Alliance, Maersk/Sea-Land, and Tricon (Cariou, 2000). Usually, the liner shipping companies in an alliance agree on a standard price rate for moving cargo on a given route at conferences.

Evangelista and Morvillo (1999) explored the effects of alliance formation between liner shipping companies on the efficiency of the supply chain processes. The authors explored the response of various carriers to alliance formation and the implications for maritime transportation. Results from the conducted empirical survey revealed that many carriers were forming strategic alliances based on the strategic options, which include: 1) improvement in local and global logistical capabilities; 2) intermodal and logistical integration of services; and 3) geographical spread and market exclusion.

Cariou (2000) studied the two major reasons why liner shipping companies start forming alliances: economies of scale and operational synergy. The author stressed that fleet characteristics of vessel owners are important in the formation of strategic alliances. Factors, such as adaptation of ports to new market conditions and the impact of an alliance on the logistical chain, were found to impact the formation of alliances in liner shipping. Heaver et al. (2000) studied various liner shipping alliances in Europe, such as alliances between shipping companies and merges among shipping lines, conferences, alliances between shipping companies and marine container terminal operators, and alliances between shipping companies and inland transport companies. The authors suggested that the formation of alliances might result in preferential treatment, conflicts of interests, and market dominance.

Slack et al. (2002) examined the transformation of services, the evolution of fleets (fleet size and fleet mix), and adjustments made at ports of call due to the formation of strategic alliances. According to the authors, some of the major changes caused by the formation of alliances include a deployment of the largest vessels on the alliance route and an increase in service frequency at various ports of call. Findings from a global analysis of liner shipping alliances between the years 1989 and 1999, conducted in that study, showed that although liner shipping companies in an alliance served more ports than before, the total number of ports served remained constant.

Lu et al. (2006) evaluated a strategic alliance formed between liner shipping carriers in Asia (CKYH). It was suggested that carriers followed the tendency of international trades, especially in the integration of global logistics systems into alliances. Some of the critical issues of concern for the carriers include how to choose well-matched partners, extent of co-operation, and how to assure the success of the alliance. Pyanides and Wiedmer (2011) conducted an empirical analysis of three major alliances. Findings indicated that service characteristics, including the number of port calls visited, average number of vessels deployed, and the average sailing time, do not differ substantially among the major alliances. Furthermore, it was found that carriers in major alliances have a high number of vessels in order books.

Researchers have suggested various strategies to improve collaborative agreements between liner shipping companies. Song and Panayides (2002) underlined that while the majority of liners have sought extensive cooperation by forming alliances, some carriers do not form alliances and achieve relative success. To improve the formation of strategic alliances, the authors applied a cooperative game theory, an approach widely used in the field of economics, to analyze cooperation among members of liner shipping strategic alliances. The adopted framework highlighted the inter-organizational relationships and decision-making behavior in the liner shipping sector. The strengths of the applied methodology were justified based on the ability to assess individual partner's current capabilities, potential joint capabilities of two or more carriers, as well as the possibility of utilizing third parties.

Agarwal and Ergun (2010) applied inverse programming and game theory and design to develop a model for optimizing collaboration strategies in liner shipping. The authors studied alliance formation among carriers in liner shipping and transportation networks that operate as an alliance among different carriers. A tactical problem, associated with the design of large-scale networks, as well as operational problems, related to the allocation of the limited capacity of a transportation network among the carriers in an alliance, were addressed. The mechanism, suggested in the study, provided side payments to the liner shipping companies as an added incentive to motivate them to act in the best interest of the alliance, whereas maximizing their own profits. Results of computational experiments for various problem instances suggested that factors, such as similar mission, strategy, governance, culture, organization, management, and others, contribute significantly to the success of an alliance.

Collaborative agreements in berth scheduling have been proposed by some studies. Karafa et al. (2011) modeled a collaborative agreement, where vessels from a dedicated maritime container terminal could be diverted for service at the external maritime container terminal during pre-determined time windows. The authors presented an MIP mathematical model for the proposed problem. The objective of the presented model minimized the total vessel service cost (including the total handling and delayed departures cost). The authors applied an Evolutionary Algorithm to solve the problem, and several numerical experiments were conducted to test the efficiency of the solution methodology. Results demonstrated that the developed solution algorithm efficiently solved the problem.

Dulebenets et al. (2018a) extended an existing berth allocation policy, proposed by Imai et al. (2008), Karafa et al. (2011), and Peng et al. (2015). The authors considered a collaborative agreement, where demand could be diverted from a multi-user terminal to an external terminal at an additional cost. The berth allocation policy was formulated as a nonlinear mixed-integer mathematical model. The objective minimized the total service cost of vessels calling at the multi-user terminal. A Memetic Algorithm was developed to solve the problem due to its high complexity. Results from numerical experiments showed that the proposed berth allocation policy yielded substantial cost savings during high vessel service demand periods at ports.

2.1.3.2. Agreements between liner shipping companies and marine container terminal operators

A large number of studies have been dedicated to collaborative agreements between liner shipping companies; however, only a few researchers have modeled various types of agreements between liner shipping companies and marine container terminal operators. Golias et al. (2007) considered the contractual agreements between the marine container terminal operator and the liner shipping company. The authors presented the discrete dynamic berth allocation problem as a linear mixed-integer problem, which aimed to minimize the cost incurred from the vessel late departures and maximize the total benefits from early and timely departures at ports of call. Computational experiments were conducted, and findings from the results showed that consideration of the vessel service priority in contractual agreements minimized the total vessel handling time and delay penalties.

Imai et al. (2008) studied a discrete dynamic berth allocation problem at a dedicated multi-user maritime container terminal (MUT), where vessels with excessive waiting times were diverted for service at the external maritime container terminal (ET). The problem was formulated as an MIP mathematical model, and the objective minimized the total service time of vessels at the external terminal. An Evolutionary Algorithm was developed to solve the problem. The computational experiments demonstrated that the proposed berth allocation policy would improve efficiency of operations at maritime container terminals with high demand.

Similar to the work of Golias et al. (2007), Golias and Haralambides (2010) assumed that marine container terminal operators could be imposed a penalty for delayed vessel service based on contractual agreements with liner shipping companies. The authors proposed a berth scheduling problem based on the agreements, which aimed to minimize the cost of vessel's waiting time and late departures and maximize the total benefit from early departures. The problem was solved using a genetic algorithm-based heuristic, and a several computational experiments were performed for various costs based on the policies. The studies described (Golias et al., 2007; Imai et al., 2008; and Golias and Haralambides, 2010) primarily focused on the berth scheduling aspect, not the vessel scheduling aspect.

Several studies considered collaborative agreements between liner shipping companies and marine container terminal operators in vessel scheduling. Wang et al. (2014) formulated a mixed-integer nonlinear optimization model for the vessel scheduling problem, where the vessel service time windows were negotiated between the marine container terminal operators and the liner shipping company. The objective of the model was to minimize the total route service cost. The problem was linearized, and an iterative optimization algorithm was used to solve it. The solution methodology was applied to the trans-Atlantic shipping route (AGM route of OOCL), and computational experiments revealed that the availability of port arrival TWs, unit fuel cost, unit inventory cost, and port handling efficiency significantly affected the total route service cost. In addition, it was found that the aforementioned factors could substantially influence the design of vessel schedules.

Alharbi et al. (2015) proposed a mixed-integer nonlinear optimization model, which adopted a similar collaborative approach, proposed by Wang et al. (2014), between the marine container terminal operators and the liner shipping company. The original model was reformulated as an integer linear optimization model and was solved using an iterative optimization approach. When the solution approach was applied to two networks, consisting of six ports and 21 ports, the results demonstrated that the number of vessels arriving at the port, selected sailing speed of vessels, port handling efficiency, and the price of bunker fuel affected the total route service cost, the number of vessels deployed, as well as the optimal schedule. The availability of multiple service TWs, shorter vessel handling time, and lower unit fuel cost significantly reduced the total route service cost of the liner shipping company considered.

Dulebenets (2015b) presented a service policy agreement, between several marine container terminal operators and liner shipping companies, whereby each terminal operator provided a set of handling rates to the liner shipping company. The author formulated a mixed-integer nonlinear mathematical programming model, which aimed to minimize the total route service cost. The mathematical model was linearized, and CPLEX was adopted to solving it. Results from numerical experiments demonstrated that the proposed collaborative agreement could reduce the total route service cost by approximately 14%.

Peng et al. (2015) formulated a mathematical model for a collaborative agreement, where the berthing space and the storage yard capacity could be shared among multiple terminals. The objective function minimized the total service time of vessels. The problem was solved using an Evolutionary Algorithm. Moreover, CPLEX was used to solve the problem to optimality for the small-size problem instances. Results from computational experiments revealed that the objective function values, suggested by the developed solution algorithm, were close to the optimal solutions for the small-size problem instances. Furthermore, the results also indicated that the port service schedule was significantly improved.

Dulebenets (2018a) proposed a novel collaborative agreement policy between liner shipping companies and marine container terminal operators. The agreement allowed liner shipping companies to negotiate both handling rates as well as service time windows. A multi-objective mixed-integer nonlinear model was formulated. The objectives aimed to: (i) minimize the total route service cost components, which generally increase with the total vessel turnaround time (including total vessel weekly operational cost, total container inventory cost, and total vessel late arrival cost); and (ii) minimize the total route service cost components, which generally decrease with the total vessel turnaround time (including the total fuel consumption cost, total port handling cost, and total cost of CO_2 emissions produced in sea and at ports of call). The problem was solved using an ε-constraint-based Global Multi-Objective Optimization Algorithm. Results from computational experiments suggested that the proposed agreement could improve the efficiency of liner shipping operations and reduce operational costs.

2.1.4. Environmental Considerations and Green Vessel Scheduling

To date, IMO designated four distinct "Emission Control Areas" (ECAs), including the following (IMO, 2016):

1) Baltic Sea area with established restrictions on SO_X (effective since 2005);
2) North Sea area with established restrictions on SO_X (effective since 2005);
3) The English Channel (effective since 2005)

4) North American area (U.S. - Canadian coastal zone) with established restrictions on NO_X, SO_X and PM (effective since 2012); and
5) USA, Caribbean Sea area with established restrictions on NO_X, SO_X and PM (effective since 2014).

IMO also plans to designate Norway, Japan and Mediterranean as ECAs (Marine Urea, 2014). According to the IMO regulations 14.1 and 14.4 (IMO, 2016), the percentage of fuel sulfur should not exceed 3.50 per cent m/m after January 01, 2012, and 0.50 per cent m/m after January 01, 2020, for the vessels sailing outside ECAs. The percentage of fuel sulfur is limited to 1.00 per cent m/m after July 01, 2010, and to 0.10 per cent m/m after January 01, 2015, for the vessels sailing within ECAs. From the review of the state-of-the-art, it was observed that many researchers have focused on the environmental concerns in liner shipping. Findings showed that the impact of emissions and slow steaming strategies (which have been widely adopted by liner shipping companies to minimize emissions) have been considered by several studies.

Corbett et al. (2009) investigated the effects of fuel tax and reduction in vessel sailing speed on emissions for the vessels calling the U.S. ports. The authors adopted the profit-maximizing function, which considered the losses associated with the speed reduction. It was observed that reducing the design speed of a vessel by 40% could result in a 40–60% reduction in CO_2 emissions. Further analysis showed that the fuel tax of about \$150/ton of fuel led to speed related CO_2 emission reduction ranging between 20 and 30%. To maintain the scheduled frequency, the number of vessels deployed was increased, and the results revealed that although there was a significant reduction in CO_2

emissions, the option was not cost-effective. The authors suggested that the reduction in sailing speed is an efficient strategy in reducing emissions. However, the reduction in emissions is dependent on the route characteristics.

Psaraftis and Kontovas (2009) conducted an analysis to determine the CO_2 emissions of the world commercial fleet using data from the Lloyds Fairplay database. The study also developed a tool for estimating the emissions (CO_2, NO_X, and SO_X) produced by several types of vessels, including bulk carriers, crude oil tankers, container vessels, product/chemical carriers, LNG carriers, LPG carriers, reefer vessels, Ro-Ro vessels, general cargo vessels, small vessels, and passenger vessels. Emission estimates showed 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). Smaller vessels, with less than 400 gross tons (GTs), produce approximately 9.82 million tons of CO_2 emissions per year. The authors highlighted that additional information about vessel movements and accurate bunker consumption values could improve the accuracy of the results. Moreover, it was suggested that vessel size and type might significantly affect the amount of emissions produced.

Eyring et al. (2010) studied the impact of emissions, generated by oceangoing vessels on atmospheric composition, air quality, ecosystems, human health, and climate. The study indicated that the emissions, produced by vessels, significantly contribute to the total emissions, produced in the transportation sector, and have negatively impacted the environment (increase in global warming) and human health (increase in mortality from cardiopulmonary diseases and lung cancer). Findings suggested that many models, used in estimating the effects of emissions, do not accurately predict the amount of emissions produced and the effects on the environment due to incomplete observational data. The authors demonstrated the benefits of introducing new technologically feasible and economically efficient policy actions to reduce emissions produced by vessels.

Golias et al. (2010) formulated a discrete space berth scheduling problem at the marine container terminal using an environmentally friendly berth-scheduling policy. The problem formulation accounted for the vessel bunker consumption and emissions produced by vessels, when sailing to the next port of call, and minimized the total service time and delayed departure of vessels while maximizing the berth productivity. An evolutionary algorithm (EA) was used in solving the problem. Results from computational experiments showed that the proposed algorithm was efficient and provided near-optimal solutions in acceptable computational time. The vessel emissions produced and the total bunker consumption were reduced.

Psaraftis and Kontovas (2010) considered the effects of emission reduction policies on maritime logistics. The authors suggested that the measures, such as efficient vessel hulls, energy-saving engines, efficient propulsion, use of alternative fuels (such as fuel cells, biofuels, and others), could be used to reduce GHGs produced by vessels. Furthermore, slow steaming was underlined as an efficient strategy for reducing vessel emissions. However, the authors underlined that slow steaming might require increasing the fleet size to maintain the service frequency due to an increase in transit time of cargo.

Cariou (2011) investigated the impact of slow steaming strategies on CO_2 emissions in liner shipping. The author reported that slow steaming strategy has been widely adopted by liner shipping companies to reduce bunker consumption and emissions produced for larger vessels with capacity of over 8,000 TEUs. Analysis showed that if the bunker fuel price is sustained between \$350 and \$400, a 15% reduction in emissions could be achieved by 2018 due to slow steaming. Although the environmental benefit and cost savings associated with slow steaming were demonstrated by the study, it was suggested that an increase in inventory costs and freight rates, and a decrease in bunker cost might cause liner shipping companies to increase the sailing speed.

Heitmann and Khalilian (2011) highlighted that CO_2 emissions in maritime shipping were unregulated and forecasted a significant increase if regulatory guidelines and policies were not introduced. Various emission control strategies, which have been suggested by the Body for Scientific and Technological Advice, a subsidiary of the United Nations Framework Convention on Climate Change (UNFCCC), were considered based on their effectiveness in reducing the levels of pollutants in the atmosphere, possibility of implementation, fairness, and burden sharing. It was found that none of the allocation options satisfied the condition of being environmentally effective, legally effective, and allowed for fair burden sharing. The authors concluded that allocation of vessel emissions should be performed on the basis of the operating company.

Kontovas and Psaraftis (2011) modeled the effects of sailing speed on bunker cost savings and vessel emissions. The authors indicated that the aim of shipping companies is to increase fuel efficiency in order to minimize bunker costs, which is the biggest portion of total route service cost. Slow steaming strategies were suggested as a feasible alternative to significantly minimize bunker costs, and since bunker costs and emissions are directly proportional to one another, slow steaming strategies prove to effectively achieve both objectives.

Lindstad et al. (2011) studied the effects of reduction in the sailing speed of vessels on CO_2 emissions and total operational costs in liner shipping. The authors used the data, obtained from the container and Ro-Ro vessels for trade between Asia and Europe in their analysis. The results showed that reducing the sailing speed by 59% for Ro-Ro vessels and by 67% for container vessels yielded emission reductions of 46% and 62%, respectively, for both vessel types. Further analysis revealed that a reduction in sailing speed of vessels could decrease CO_2 emissions by 28% for cases with zero cost of emissions. Computational experiments showed that imposing an emission cost of 20 USD/ton reduced CO_2 emissions by 33% and by 36% when an emission cost of 50 USD/ton was used. It was underlined that the reduction in emissions was estimated based on a reduction in sailing speed of vessels; thus, the authors suggested that imposing a speed limit on oceangoing vessels is the most efficient method of reducing emissions.

Miola and Ciuffo (2011) analyzed different strategies, used in modeling vessel emissions, by classifying them into four groups based on the vessel characteristics and geographic location of shipping routes. By comparing several emission modeling methods, they found that there is a wide variation in emission values reported by different studies. The authors attributed the variation in emission estimates to unreliability of the input data, used in calculating vessel emissions, and proposed a tool, which combines the data from various sources. It was underlined that the combination of data might produce more accurate results. The study also suggested that Automatic Identification System (AIS) data, obtained from space satellites, might provide a more accurate and comprehensive data required for calculating emissions from vessels.

Cariou and Cheaitou (2012) evaluated the effectiveness of two measures to reduce CO_2 emissions in maritime transportation: 1) bunker levies approach; and 2) mandatory speed limit for vessels. The mandatory speed limit policy was suggested by the European Commission in 2011 for all the vessels, calling at European Union ports. Using examples of emissions produced by container vessels, the study compared the emission reductions from bunker-levy to the emission reductions if a mandatory speed limit approach was adopted. Results showed that imposing a mandatory speed limit does not automatically reduce the amount of CO_2 emissions from vessels globally. Furthermore, it was suggested that the bunker levy approach was the preferable option.

Psaraftis (2012) assessed ten different market-based measures to minimize GHG emissions from vessels submitted to the IMO for consideration. A review of the measures suggested that there are different opinions about the market-based approach that should be implemented to reduce emissions produced by vessels. It was also found that stakeholders shared contradicting opinions and failed to agree on a strategy to be implemented. Moreover, it was indicated that some developing countries (such as China, India, Brazil, and others) were against the market-based measures and frustrated the process due to lack of agreement. Psaraftis and Kontovas (2013) presented a detailed survey of speed models that have been used in maritime transportation. The authors classified the speed models into: general, non-emission, and emission speed models. Although several bunker consumption functions and emission coefficients were used in the studies, the emission speed models indicated that the amount of emissions produced by vessels is affected by the sailing speed of vessels. The effects of imposing speed limits were also discussed in the paper. The study underlined that imposing the speed limit could cause distortions in the market and result in the overall costs exceeding the benefits.

Chang and Wang (2014) conducted a comprehensive assessment of the approaches used in commercial maritime transportation to determine the optimal sailing speed of vessels. Reduction in emissions and significant cost savings were identified as some of the advantages of selecting an optimal vessel sailing speed. Numerical experiments were performed for four scenarios to show the effect of speed reduction on emissions and total operational costs: 1) High fuel prices and high charter rates; 2) High fuel prices and low charter rates; 3) Low fuel prices and high charter rates; and 4) Low fuel prices and low charter rates. The results demonstrated that speed reduction was the most efficient for the cases with high bunker costs and low charter rates; thus, the optimum speed reduction is substantially affected with charter rates and fuel prices.

Cullinane and Bergqvist (2014) underlined that emissions from the vessels, which are not environmentally friendly, are highly correlated to its fuel consumption. The study indicated that IMO, EU, the U.S., and Canada have designated certain coastal areas as ECAs to reduce the emissions produced from the maritime transport sector. The authors forecasted that due to the socioeconomic benefits of the emission regulations, tougher regulations could be imposed in the future to further reduce gaseous emissions, such as NO_X and SO_X. The authors also suggested that modal shift effects from introducing ECAs were limited.

Kontovas (2014) presented a generalized formulation for the green vessel routing and scheduling problem and discussed the need to adopt more accurate models in estimating vessel emissions and bunker consumption. The model presented a combined green vessel scheduling and routing problem in maritime transportation. Also, the paper underlined that the following approaches could be used to capture vessel emissions in the green vessel routing and scheduling mathematical model: (1) emissions cost as the objective function, (2) emissions cost as a component in the objective function, (3) emissions produced as a constraints set, and (4) emissions cost as one of the objective functions. It was suggested that there is a need to incorporate vessel sailing speed into the models because there is a strong correlation between the emissions produced and the sailing speed. It was suggested that the problem formulation presented did not increase the computational complexity.

Psaraftis and Kontovas (2014) investigated several factors affecting the choice of vessel sailing speed. Some of the factors, identified as critical in determining vessel sailing speed selection, include bunker price, state of the market, freight rates, inventory costs, and dependency of the bunker consumption on payload. It was found that vessels carrying expensive cargoes increase their sailing speed, thus, increasing the amount of emissions produced. Furthermore, the paper indicated that environmentally friendly decisions might affect the optimal economic performance in commercial maritime shipping.

Zis et al. (2014) estimated the reduction in CO_2, SO_2, NO_X, and black carbon (BC) emissions from vessels near the ports using vessel-call data and examined the effectiveness of emission reduction policies at ports. Computational examples demonstrated that the emission reduction schemes could decrease CO_2, SO_X, and NO_X emissions by 8–20%, 9–40%, and 9–17%, respectively. The study indicated that speed reduction policies near the ports might increase BC emissions by 10%. In addition, the factors, such as vessel fleet, vessel service time, and emission intensity of electricity supply, affected the amount of emissions produced by vessels near the ports.

Fagerholt et al. (2015) evaluated the impacts of restrictions regarding the production of SO_X emissions in ECAs on sailing paths, sailing speed, and operational costs in maritime shipping. It was found that shipping companies choose to sail longer routes in order to avoid sailing at a lower speed through ECAs. The authors underlined that shipping companies sail at higher speeds outside ECAs and burn a large amount of cheaper high-sulfur fuel (which produces more emissions).

Fagerholt and Psaraftis (2015) presented two speed optimization models for the vessels sailing through ECAs. The first model considered vessel speed optimization inside and outside ECAs, while the second model considered the vessel optimal crossover point in and out of the ECA boundary. Numerical computations revealed that the best alternative for vessels would be sailing through the shortest route while in an ECA, regardless the price of bunker to minimize bunker costs and associated emissions.

Mansouri et al. (2015) examined the use of multi-objective optimization models to estimate emission reductions in maritime transportation. The authors indicated that simulation modeling and optimization modeling are good approaches to address emission reduction problems in maritime shipping. The study identified that uncertain port times are a major factor affecting slow steaming and emission reduction. Furthermore, it was suggested that there is a need to conduct further research, which adequately considers trade-offs to improve decision-making by shipping companies.

Song et al. (2015) formulated a stochastic multi-objective vessel scheduling problem with uncertain port times in liner shipping. Three objectives were modeled, which included: (i) minimization of the annual vessel operational costs; (ii) minimization of the average schedule unreliability; and (iii) minimization of the annual total CO_2 emissions. A Non-Dominated Sorting Genetic Algorithm (NSGA-II) was developed to solve the mathematical model. Numerical experiments indicated that about of 5-10% reduction in CO_2 emissions could be achieved when the operating cost is minimized. Moreover, the results suggested that the schedule unreliability and costs are insensitive to emission reductions.

Dulebenets (2016a) assessed the benefits and drawbacks of introducing restrictions on the emissions, produced by oceangoing vessels within ECAs. The study compared the existing IMO regulation regarding bunker fuel sulfur content within ECAs with an alternative environmental policy, which imposed emission restrictions within ECAs along with the existing IMO regulations. Two mathematical models were proposed with the aim of minimizing the total route service cost, and an iterative optimization algorithm was presented to solve the models. Results from computational experiments demonstrated that emission restrictions reduced SO_2 emissions by 40%. However, there was an increase in vessel turnaround time and total route service cost.

Dulebenets et al. (2017a) proposed a mathematical model for the green vessel scheduling problem, imposing constraints on the emissions produced by a vessel at each voyage leg of the liner shipping route. The objective minimized the total route service cost, which was composed of the total vessel weekly operating cost, the total bunker consumption cost, the total port handling costs, the total late arrival penalty, and the total inventory cost. CPLEX was applied to solve the linearized problem. Results from numerical experiments indicated that the introduction of emission constraints might reduce the vessel sailing speed at each voyage leg.

Some studies considered vessel emissions in formulating berth scheduling problems. For example, Dulebenets et al. (2017b) applied a Hybrid Evolutionary Algorithm in solving an MIP model for a berth scheduling problem. The objective was to minimize the total carbon dioxide emission cost due to container handling and the total service cost. Results from numerical experiments indicated that the optimality gap of the developed algorithm was less than 1.62%. The authors underlined that the application of local search heuristic improved the search process without significantly increasing the computational time.

Dulebenets (2018c) presented a green vessel scheduling problem at the liner shipping route with ECAs and transit time constraints. The author designed a mixed-integer nonlinear programming model, which minimized the overall route service cost and emissions. The model captured changes in the vessel schedule due to switching from Heavy Fuel Oil (HFO) to Marine Gas Oil (MGO) with low sulfur content within ECAs. The problem was linearized, and an iterative optimization algorithm was used to solve the problem. Computational experiments revealed that imposing emission constraints led to a reduction in vessel sailing speeds on voyage legs with ECAs at the liner shipping route. Also, it was found that the emission restrictions and the transit time requirements resulted in changes of the vessel schedule design.

Dulebenets (2018d) designed a mixed-integer nonlinear programming (MINLP) model, which accounted for CO_2 emission costs of oceangoing vessels in sea and at ports of call. The author linearized the MINLP model and solved the green vessel scheduling problem using CPLEX. Results from computational experiments showed that an increase in CO_2 tax from 32.0 USD to 1060.4 USD reduced the quantity of carbon dioxide emissions produced in sea by 64.3%. Findings also indicated that carbon dioxide tax value might significantly change the schedule of vessels in liner shipping. Although a reduction in the sailing speed of vessels reduced CO_2 emissions produced, many vessels arrived at the ports of call late.

Giovannini and Psaraftis (2018) underlined that liner shipping companies tend to increase vessel sailing speeds when freight rates are high and reduce vessel sailing speeds during depressed market conditions. The authors also examined the effects of the decisions made by liner shipping companies on the total amount of CO_2 emissions produced by vessels. The study developed a mathematical model, which aimed to maximize the total profit of a liner shipping company, taking into account a number of factors, including bunker price, freight rate, daily operating fixed costs, and cargo inventory costs. Results from computational experiments revealed that flexible service frequencies could significantly reduce the total operating costs. Moreover, maintaining a fixed service frequency could increase the fuel cost and result in loss of revenue.

2.1.5. Vessel Schedule Recovery

Several studies developed a number of deterministic vessel scheduling optimization models, which assumed that the vessel service time, waiting time, sailing distance, sailing speed, among other significant parameters, were known. However, in practice, there are lots of disruptions that affect the planned schedule of a vessel voyage. Some of the disruptions include severe weather, port congestion, mechanical failures, port strikes, and natural hazards. According to Brouer at al. (2013), piracy and crew strikes on vessels are some of the unusual causes of disruptions in liner shipping. Notteboom (2006) found that about 70% and 80% of vessel round trips, recorded late arrivals at one or multiple port(s) of call along their routes. The latter affected the planned schedule of vessels, and shipping companies faced the challenge of recovering the delayed schedule of vessels in sea. The disruption of the vessel schedules in liner shipping usually results in late arrivals of vessels for connection, and, in some cases, the whole network could be affected by the delay at a point on the network.

Timely delivery is important in liner shipping, as the delay in the cargo delivery results in an excessive cost for the customers. Therefore, in the event of a disruption in the planned schedule of a vessel, the liner shipping companies examine the scenario and determine the most feasible action in order to recover the schedule. For delayed vessels, the operator of a vessel may decide to increase the sailing speed. However, researchers have established that bunker fuel consumption increases with vessel sailing speed (Alderton, 2004; Du et al., 2011; Wang and Meng, 2012b; Psaraftis and Kontovas, 2013); thus, increasing the sailing speed results in an increase in the fuel costs. Also, vessels have the design maximum speeds. Hence, selecting the maximum speed does not guarantee the schedule recovery. Disruption management has become a primary source of discussion by liner shipping companies, given the prohibitive costs associated with schedule recovery. Although some studies considered uncertainties associated with the liner shipping operations, only a few studies examined the vessel schedule recovery problem in liner shipping.

Paul and Maloni (2010) presented a nonlinear programming model for disruptions at seaports due to a disaster. The objective aimed to minimize the total operational cost (including transportation, inventory and port handling costs). The Dijkstra's shortest path algorithm was applied to obtain the optimal routes and allocation of vessels to ports. Moreover, a more robust algorithm was also developed to continuously update the vessel to port allocation and port capacity. The algorithm was applied to assess the effect of disasters (e.g., weather, labor, terrorist attack, etc.) on the North American container port network. Results from numerical experiments, conducted for one-year time period single and multiple port shutdown scenarios, suggested high additional costs.

Brouer et al. (2013) conducted a pioneering research in vessel schedule recovery. The authors proposed an MIP vessel schedule recovery problem (VSRP) to evaluate the effects of disruptions, which include: (1) delays (due to inclement weather); (2) port closure (due to strikes); (3) berth prioritization (decision to service a vessel because of its size); and (4) port congestion (port maintenance may result in congestion). The study presented a space-time network model with an objective function, which minimized the total operational cost and penalties imposed due to delayed or missed cargo connection. The presented model indicated that the VSRP is of *NP*-hard complexity. Four real-life problem instances were generated and were solved using CPLEX. The considered vessel schedule recovery strategies included: (i) omit a port of call; (ii) swap port calls; and (iii) adjust vessel sailing speeds. The results of computational experiments, which were solved within a reasonable CPU time, showed a 58% cost reduction when the operator decided to omit a port of call or swap ports of call, and ensured timely delivery of cargo. Furthermore, the authors suggested other recovery strategies, which could be considered, e.g. reducing the time spent in a port of call unloading but not loading, merging port of calls or adding protection arcs, rerouting cargoes on the network, and others.

Lee at al. (2015) proposed a model that incorporated port time uncertainty and slow steaming in determining service reliability, bunker consumption, and emissions. The authors found that delay and uncertain port times reduced the service quality and increased bunker consumption as well as emissions. This study underlined that delay at ports might cause vessel operators to speed up to recover the schedule. The decision to implement the latter strategy could increase bunker consumption and associated emissions.

Li et al. (2015) studied the vessel schedule recovery problem for a single vessel in liner shipping route. The problem was formulated and divided into three aspects, based on possible actions that could be taken by the vessel operator, which include: (a) speeding up only; (b) port skipping only; and (c) pork skipping and port swapping. The objective of the mathematical model formulated was to minimize the total route service cost. A set of discrete dynamic programming (DP) algorithms were developed to solve the nonlinear optimization problem. Results from computational experiments showed that the DP algorithms solved the problem instances within a reasonable computational time for the cases with the options of speeding up and port skipping. Also, the results showed that if the delay was not too large, the option of speeding was preferred for the vessel schedule recovery as the vessel might not need to sail at the maximum speed to recover the schedule. In addition, it was found that for the vessels with low maximum sailing speeds (e.g. sailing speeds less than 20 knots), the option of port skipping was found to be more effective. Furthermore, port swapping and port skipping were found to be better alternatives with significant cost savings if the delay was large. It was also found that additional buffer time reduced the cost of scheduled recovery. Wang and Meng (2012a) and Qi and Song (2012) highlighted that short segments on a liner shipping route require more buffer time due to weak flexibility.

Li et al. (2016) focused on a real time schedule recovery problem in a liner shipping service. Two types of uncertainties in liner shipping were defined: (1) regular uncertainties (recurring probabilistic activities at the port and sea, such as port congestion); and (2) disruptive events (occasional or one-off events, which may be forecasted but are not usually planned, e.g. labor strikes and inclement weather). The authors proposed a multi-stage stochastic model, where the liner shipping route was represented by several sea legs. The optimal travel time at each segment was computed by considering the uncertainties in sailing times due to a disruption. The objective of the formulated mathematical model minimized the total route service cost (which included the vessel delay penalty, cost of vessel handling at ports, and fuel consumption cost), the service unreliability and emissions. The DP algorithm was applied to solve the problem. Results from numerical experiments indicated that, for scenarios without earliest handling time constraints, skipping the disruption port might allow the carrier to recover the schedule.

Cheraghchi et al. (2018) formulated the VSRP as a bi-objective optimization problem. The authors presented a speed-based vessel schedule recovery problem (S-VSRP). The first objective minimized the total monetary losses, associated with bunker consumption and late arrival penalty. Moreover, slow steaming and normal steaming policies were considered to minimize the bunker consumption. The second objective minimized the total delay due to disruption (considering the scheduled time of arrival at the port and the time of arrival after the recovery plan). This study used the delay as a measure of the service reliability in the problem formulation. Problem instances were generated using a list of major ports in the world, and numerical experiments were conducted for the scenarios, which considered: 1) scalability of the metaheuristics applied; 2) two vessel steaming policies (slow steaming and normal steaming); and 3) voyage distance. The Non-Dominated Sorting Genetic Algorithm (NSGA-II), GA, Strength Pareto Evolutionary Algorithm II (SPEA-II), and other metaheuristics were applied to solve the problems. Results from the computational experiments showed that the NSGA-II algorithm performed better than other metaheuristics used. Furthermore, the results demonstrated that delays in long-distance voyages are easier to mitigate as compared to short-distance voyages. It was also found that the models performed better under normal steaming as compared to slow steaming.

2.2. Literature Summary

A concise summary of the collected studies is provided in Table 2. The presented information includes: (i) author(s); (ii) year; (iii) objective considered; (iv) objective components (if applicable); (v) solution approach used (if applicable); and (vi) notes/important considerations.

Table 2 Literature summary

a/a	Author(s)	Objective	Objective Components	Solution Approach	Notes/Important Considerations
			General Vessel Scheduling		
1	Ronen (1982)	Review vessel scheduling models	N/A	N/A	Underlined that uncertainty associated with vessel operations limits the applicability of deterministic models
2	Lane et al. (1987)	Minimize the total cost	TOC; TPC; TVC	Heuristic	Considered port service times
3	Ronen (1993)	Review vessel scheduling models	N/A	N/A	Majority of studies focused on cost minimization and revenue maximization
4	Bendall and Stent (2001)	Maximize the total revenue	TOC; TPC; TVC; TFV; MSC	Heuristic	Estimated the optimum number of vessels required to meet a given demand
5	Fagerholt (2001)	Minimize the total cost	TOC; TPC; TFC	Heuristic	Allowed controlled time window violation to obtain better schedules
6	Ting and Tzeng (2003)	Minimize the schedule unreliability	TPC; TVC	Dynamic programming	Modeled the optimal vessel cruising speed
7	Christiansen et al. (2004)	Review vessel routing and scheduling models	N/A	N/A	Highlighted that optimization-based decision-support systems have been widely adopted
8	Chen et al. (2007)	Minimize the total cost	TOC; TIC; TPC; TVC	Heuristic	Considered containers with load on one way and empty containers on the return trip
9	Fagerholt and Linstad (2007)	Maximize the total profit	TOC; TIC	Heuristic	Developed a decision support system for vessel planning and scheduling
10	Argawal and Ergun (2008)	Maximize the total profit	TOC; REV; TIC	Heuristic	Solution approach improved utilization of vessel capacities
11	Boros et al. (2008)	Maximize the total profit; Minimize the total cost	TOC; REV; TIC; TPC; TVC	Iterative optimization algorithm	Considered port availability, port times, and seasonality in the demand
12	Lei et al. (2008)	Minimize the total cost	TOC; TPC; TIC; TVC	Heuristic	Emphasized the need for partners with full commitment to share the demand and the resources

Table 2 Literature summary – continued

a/a	Author(s)	Objective	Objective Components	Solution Approach	Notes/Important Considerations
			General Vessel Scheduling		
13	Gatica and Miranda (2011)	Minimize the total cost	TOC; TPC; TVC	Heuristic	Network based model allowed the inclusion of features, such as soft time windows, port service costs, etc.
14	Korsvik et al. (2011)	Maximize the total profit	TOC; TPC; TVC; REV	Heuristic	Indicated that introducing split loads could yield significant improvements
15	Ronen (2011)	Minimize the total cost	TOC; TFC; TIC	Analytical method	Determined the optimal sailing speed of vessels
16	Christiansen et al. (2013)	Review problems in vessel routing and scheduling	N/A	N/A	Complex vessel routing and scheduling problems still exist, which have not been addressed
17	Halvorsen-Weare and Fagerholt (2013)	Minimize the total cost	TOC; TFC; TPC; TVC; REV	Heuristic	Considered fixed and flexible vessel service times
18	Hvattum et al. (2013)	Minimize the total cost	TOC; TFC; TPC	Iterative optimization algorithm	Determined the optimal sailing speed
19	de Armas et al. (2015)	Minimize the total cost	TOC; TFC; TPC	Heuristic	Use of discretized time windows allows for the consideration of several features
20	Dulebenets (2015a)	Minimize the total cost	TOC; TFC; TPC; TVC	CPLEX	Proposed a Memetic Algorithm to model bunker consumption
21	Wang et al. (2015)	Minimize the total cost	TFC; TIC	Iterative optimization algorithm	Estimated the perceived value of container transit times
22	Aydin et al. (2017)	Minimize the total cost	TOC; TFC; TPC; TVC	Dynamic programming	Considered uncertain port times, bunkering problem, and speed optimization in liner shipping
23	Dulebenets and Ozguven (2017)	Minimize the total cost	TOC; TFC; TPC; TVC; TIC; MSC	CPLEX	Transportation of perishable assets
24	Lee and Song (2017)	Review current practices and issues in container transport	N/A	N/A	Highlighted the strategic planning, tactical planning and operations management issues

Table 2 Literature summary – continued

a/a	Author(s)	Objective	Objective Components	Solution Approach	Notes/Important Considerations
			General Vessel Scheduling		
25	Dulebenets (2018a)	Minimize the total cost	TOC; TIC; TPC; TVC; TFC	CPLEX	Vessel schedules are more sensitive to the unit fuel cost as compared to the unit carbon dioxide emission cost
26	Dulebenets (2018b)	Minimize the total cost	TOC; TFC; TPC; TVC; TIC	BARON	Vessel schedules were more sensitive to larger vessels in the fleet, compared to increase in the unit bunker cost
27	Mallidis et al. (2018)	Minimize the total cost	TOC; TFC; TPC; TVC; TIC; TEC; MSC	Analytical method	Slow steaming significantly reduced the vessel's fuel costs, and shipping CO2 emissions
			Collaborative Agreements		
28	Evangelista and Morvillo (1999)	Review the performance of existing alliances	N/A	N/A	Found that most of the alliances in liner shipping are in maritime transport rather than inland transport
29	Cariou (2000)	Analyze various fleet allocation models	TOC; TIC; REV; MSC	Analytical method	Composition of a strategic alliance may impact its effectiveness
30	Heaver et al. (2000)	Examine the consequences of evolution of market structures	TOC; TIC; REV; MSC	N/A	Indicated that port operators play a significant role in the European market
31	Slack et al. (2002)	Analyze strategic alliances in container shipping	TOC; TIC	N/A	Emphasized the need to impose greater standardization in the container shipping industry
32	Lu et al. (2006)	Explore success factors within a specific alliance group	N/A	N/A	Mutual trust between partners is the most important factor for success of alliances
33	Pyanides and Wiedmer (2011)	Analyze collaboration among liner shipping companies	N/A	N/A	Several studies made qualitative assessments of horizontal alliances but not quantitative evaluations
34	Song and Panayides (2002)	Minimize the total cost	TOC; TIC; REV; MSC	Analytical method	The theory explains the liner shipping market
35	Agarwal and Ergun (2010)	Maximize the total profit	TOC; TIC; REV	CPLEX	Considered alliance formation among three and four carriers

Table 2 Literature summary – continued

a/a	Author(s)	Objective	Objective Components	Solution Approach	Notes/Important Considerations
			Collaborative Agreements		
36	Golias et al. (2007)	Minimize the total cost	TOC; TPC; TVC	Evolutionary Algorithm	Considered priority in handling vessels
37	Imai et al. (2008)	Minimize the total cost	TOC; TPC; TVC	Evolutionary Algorithm	Additional costs were considered for external terminal utilization
38	Golias and Haralambides (2010)	Minimize the total cost	TOC; TFC; TPC; TVC	Evolutionary Algorithm	Proposed berth scheduling policy with different cost functions
39	Karafa et al. (2011)	Minimize the total cost	TOC; TFC; TPC; TVC	Evolutionary Algorithm	Considered the total handling and delayed departure cost
40	Wang et al. (2014)	Minimize the total cost	TOC; TFC; TPC; TVC	Iterative optimization algorithm	Considered multiple service time windows in liner shipping schedule
41	Alhrabi et al. (2015)	Minimize the total cost	TOC; TFC; TPC; TVC	Iterative optimization algorithm	Considered the effects of service time windows, port handling efficiency, bunker price, and unit inventory cost in liner shipping
42	Dulebenets (2015b)	Minimize the total cost	TOC; TFC; TPC; TVC	Heuristic	Modeled multiple port handling rates
43	Peng et al. (2015)	Minimize the total service time	TOC; TPC; TVC	Evolutionary Algorithm	Port scheduling scheme was significantly improved
44	Dulebenets (2018a)	Minimize the total cost	TOC; TIC; TPC; TVC; TFC	CPLEX	Vessel schedules are more sensitive to the unit fuel cost as compared to the unit carbon dioxide emission cost
45	Dulebenets et al. (2018a)	Minimize the total cost	TOC; TPC; TVC	Memetic Algorithm	The proposed policy demonstrated greater savings for the scenarios with higher demand
			Uncertainty in Liner Shipping Operations		
46	Notteboom (2006)	Assess the causes of schedule unreliability	TOC; TPC; TVC	Analytical method	Discussed measures to maximize schedule reliability
47	Drewry (2010)	Addressed schedule unreliability	TOC; TPC; TVC	Analytical method	Analyzed the historical data in order to assess the schedule unreliability
48	Chuang et al. (2010)	Maximize the total revenue	REV; TOC; TFC; TPC	Fuzzy genetic algorithm	Modeled uncertainty in market demand, port times, and sailing times

Table 2 Literature summary – continued

a/a	Author(s)	Objective	Objective Components	Solution Approach	Notes/Important Considerations
			Uncertainty in Liner Shipping Operations		
49	Qi and Song (2012)	Minimize the total cost	TFC; TVC	Sample average approximation algorithm	Considered uncertainty in port times in optimizing vessel schedule
50	Wang and Meng (2012a)	Minimize the total cost	TOC; TFC	Cutting-plane algorithm	Considered the effects of uncertainty in port times and sailing times on costs and liner shipping schedule
51	Wang and Meng (2012c)	Minimize the total cost	TOC; TFC; TVC	Sample average approximation algorithm	Modeled uncertain waiting time and uncertain container handling time due to port congestion
52	Halvorsen-Weare et al. (2013)	Minimize the total cost	TOC; TPC; TVC	Xpress-IVE	Considered uncertainty in sailing times due to changing weather conditions
53	Song et al. (2015)	Minimize the annual vessel operational cost; Minimize the schedule unreliability; Minimize the total carbon dioxide emissions	TFC; TVC; TEC; MSC	Heuristic	Modeled uncertainty in port times
54	Gürel and Shadmand (2018)	Minimize the total fuel cost	TFC	CPLEX	Modeled uncertainty in vessel waiting and handling times for a heterogeneous fleet
			Green Vessel Scheduling		
55	Corbett et al. (2009)	Maximize the total profit	TFC; TEC	N/A	Speed reduction was the best option to mitigate CO_2 emissions
56	Psaraftis and Kontovas (2009)	Determine CO_2 emission of world commercial fleet	TFC; TEC	N/A	Vessel size and type may affect bunker consumption
57	Eyring et al. (2010)	Assess the impact of emission control strategies	N/A	N/A	Demonstrated the benefits of introducing new technologically feasible and economically efficient policy actions to reduce emissions produced by oceangoing vessels

Table 2 Literature summary – continued

a/a	Author(s)	Objective	Objective Components	Solution Approach	Notes/Important Considerations
			Green Vessel Scheduling		
58	Golias et al. (2010)	Maximize berth productivity; Minimize the total cost	TFC; TEC; TPC; TVC	Evolutionary Algorithm	Proposed a berth-scheduling policy that considered bunker consumption and vessel emissions
59	Psaraftis and Kontovas (2010)	Determine optimum sailing speed	TFC; TEC	Analytical method	Determined the trade-offs between vessel sailing speed and emissions
60	Cariou (2011)	Estimate CO_2 emissions rate and the bunker break-even price	TFC; TEC	Analytical method	Demonstrated that slow steaming reduced emissions by 11% - 15%
61	Heitmann and Khalilian (2011)	Investigate various options for allocating CO_2 emissions to shipping companies	N/A	N/A	No option was environmentally effective, legally effective and allowed fair burden sharing
62	Kontovas and Psaraftis (2011)	Minimize the total cost	TOC; TEC	Analytical method	Modeled the effects of sailing speed on bunker cost savings, and vessel emissions
63	Lindstad et al. (2011)	Minimize the total cost	TOC; TFC; TEC	Analytical method	Demonstrated that speed reduction could reduce emission costs
64	Miola and Ciuffo (2011)	Analyzed vessel emission modeling strategies	TOC; TFC; TEC; REV	Analytical method	Highlights the uncertainty of results from the different methods due to uncertainty of data sources
65	Cariou and Cheaitou (2012)	Minimize the total cost; Maximize the revenue	TOC; TEC; REV	Analytical method	An increase in sailing speed increased the total emissions produced
66	Psaraftis (2012)	Review several proposals for market-based measures under consideration by IMO for GHGs	N/A	N/A	None of the considered measures were selected due to lack of agreement between countries
67	Psaraftis and Kontovas (2013)	Review various vessel speed models	N/A	N/A	Underlined that vessel speed is a key determinant of total cost and emissions produced
68	Chang and Wang (2014)	Assess the strategies to minimize costs and reduce emissions	TOC; TEC; TFC	Analytical method	Compared the cost of speed reduction against the environmental benefits

Table 2 Literature summary – continued

a/a	Author(s)	Objective	Objective Components	Solution Approach	Notes/Important Considerations
			Green Vessel Scheduling		
69	Cullinane and Bergqvist (2014)	Evaluate alternatives for complying with the regulations relating to emission control areas	TEC; TFC	Analytical method	Highlighted the socio-economic benefits of the ECA regulations
70	Kontovas (2014)	Minimize the total cost	TOC; TFC; TPC; TEC; MSC	Analytical method	Modeled the effects of sailing speed and weight of cargoes on bunker consumption and emission
71	Psaraftis and Kontovas (2014)	Develop models that optimize vessel speed for various routing scenarios	TOC; TFC; TEC	Analytical method	Expensive cargoes induce more CO_2, as they encourage higher vessel speeds
72	Zis et al. (2014)	Examine emission reduction port policies based on ship-call data	N/A	N/A	Larger vessels offer greater potential for emission reduction
73	Fagerholt et al. (2015)	Minimize the total cost	TOC; TFC; TEC; MSC	Xpress-MP	Determined sailing paths and speeds using low sulfur fuel to reduce emission in ECAs
74	Fagerholt and Psaraftis (2015)	Maximize the total profit	REV; TEC; TFC	Analytical method	Considered speed optimization using fuel switching to reduce emissions within ECAs
75	Mansouri et al. (2015)	Assess the use of multi-objective optimization to improving sustainability in maritime shipping	N/A	N/A	Indicated that multi-objective optimization and environmental sustainability have received attention over time
76	Song et al. (2015)	Minimize emissions; Minimize annual operational costs	TOC; TPC; TFC; TVC; TEC	NSGA II	Modeled uncertainty in optimizing cost, service reliability and carbon dioxide emissions
77	Dulebenets (2016a)	Minimize the total cost	TOC; TPC; TFC; TVC; TIC	Iterative optimization algorithm	Effects of restrictions on vessel emissions produced within ECAs
78	Dulebenets et al. (2017a)	Minimize the total cost	TOC; TPC; TFC; TVC; TIC	CPLEX	Emission constraints required liner shipping companies to reduce vessel sailing speeds at voyage legs

Table 2 Literature summary – continued

a/a	Author(s)	Objective	Objective Components	Solution Approach	Notes/Important Considerations
			Green Vessel Scheduling		
79	Dulebenets et al. (2017b)	Minimize the total cost	TPC; TEC; TVC	Hybrid EAs and CPLEX	Hybrid EAs were applied to solve the problem due to its *NP*-hard complexity
80	Dulebenets (2018c)	Minimize the total cost	TOC; TIC; TFC; TPC; TVC; MSC	Dynamic secant approximation	Emission constraints resulted in decreasing vessel sailing speeds
81	Dulebenets (2018d)	Minimize the total cost	TOC; TFC; TPC; TVC; TIC; REV; TEC	CPLEX	Increasing carbon dioxide tax value lead to a reduction in vessel sailing speed to reduce fuel consumption and carbon dioxide emissions, produced by vessels
82	Giovannini and Psaraftis (2018)	Maximize the total profit	REV; TFC; TOC; TPC; TIC; MSC	Analytical method	Flexible port service frequency; carbon dioxide emissions, produced by vessels in sea
			Vessel Schedule Recovery		
83	Paul and Maloni (2010)	Minimize the total cost	TOC; TPC; TIC	Dijkstra algorithm	Dynamically model cargo processing times and port capacities
84	Brouer et al. (2013)	Minimize the total cost	TOC; TFC; TPC; TVC; MSC	CPLEX	Model accepts the delay and catch up the schedule
85	Lee at al. (2015)	Minimize the total cost	TOC; TPC; TFC; TVC; MSC	Analytical method	Quantified the effect of slow steaming strategies on service quality, bunker cost and shipping time
86	Li et al. (2015)	Minimize the total cost	TFC; TPC; TVC; MSC	Dynamic programming	Showed that speeding up could effectively handle a small delay
87	Li et al. (2016)	Minimize the total cost	TFC; TVC	Dynamic programming	Considered skipping the disruption port
88	Cheraghchi et al. (2018)	Minimize the total loss; Minimize the total delay	TFC; TVC	Metaheuristics	Sensitivity of the optimizers in different scenarios to parameter tuning

Notes: TOC – total vessel weekly operational cost.
TFC – total fuel consumption cost.
TPC – total port handling cost.
TVC – total cost associated with violation of service TWs.
TIC – total container inventory cost.
TEC – total vessel emission cost.
ECA – "*Emission Control Area*".
REV – total revenue.
MSC – miscellaneous costs.

A review of the state-of-the-art reveals that the majority of the studies proposed the mathematical models, which aimed to minimize the total route service cost. The objective components of the total route service cost, considered in various mathematical models presented in the literature, include: (1) total vessel weekly operational cost – TOC; (2) total fuel consumption cost – TFC; (3) total port handling cost – TPC; (4) total service TW violation cost – TVC; (5) total vessel emission cost – TEC; (6) total container inventory cost – TIC; (7) miscellaneous costs – MSC; and (8) total revenue – REV. Figure 6 presents the distribution of the collected studies by the considered cost components.

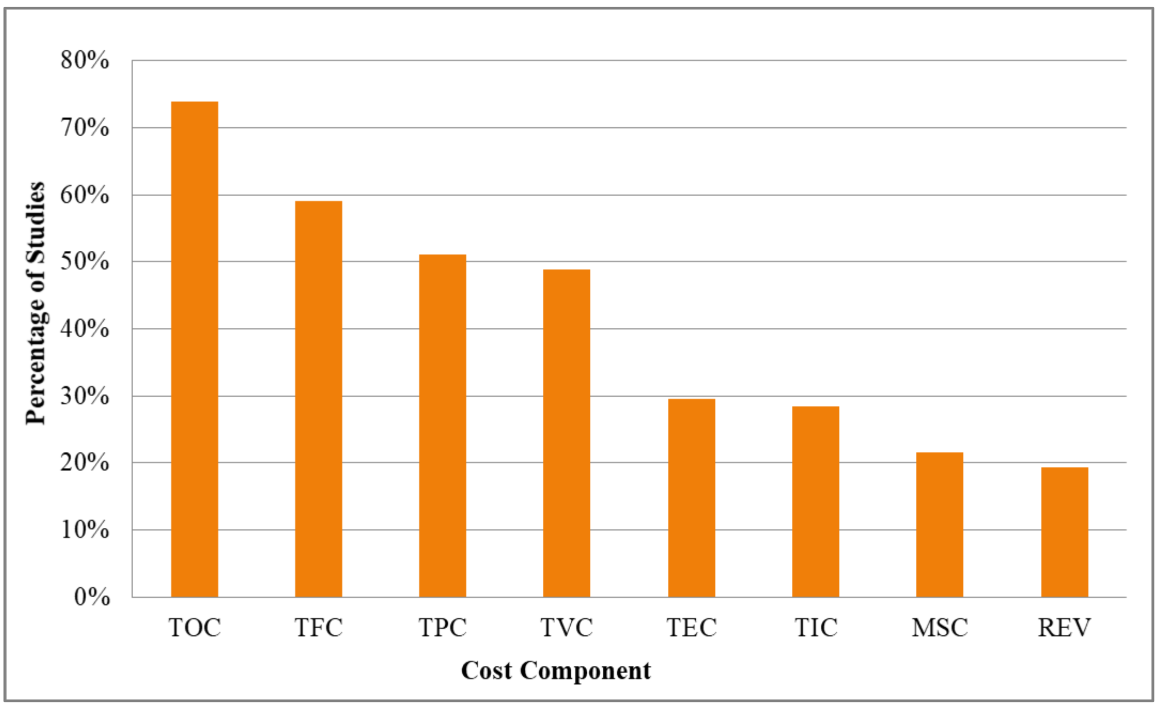


Figure 6 Distribution of studies by the considered cost components

Some of the studies presented the mathematical models, aiming to minimize the total operational cost (65 studies or 74% of studies), minimize the total fuel consumption cost (52 studies or 59% of studies), minimize the total port handling cost (45 studies or 51% of studies), minimize the total cost associated with violation of service TWs (43 studies or 49% of studies), and minimize total emission costs (26 studies or 30% of studies). A number of studies also focused on minimizing the total inventory cost (25 studies or 28% of studies), minimizing miscellaneous costs (19 studies or 22% of studies), and maximizing the total revenue of the carriers (17 studies or 19% of studies).

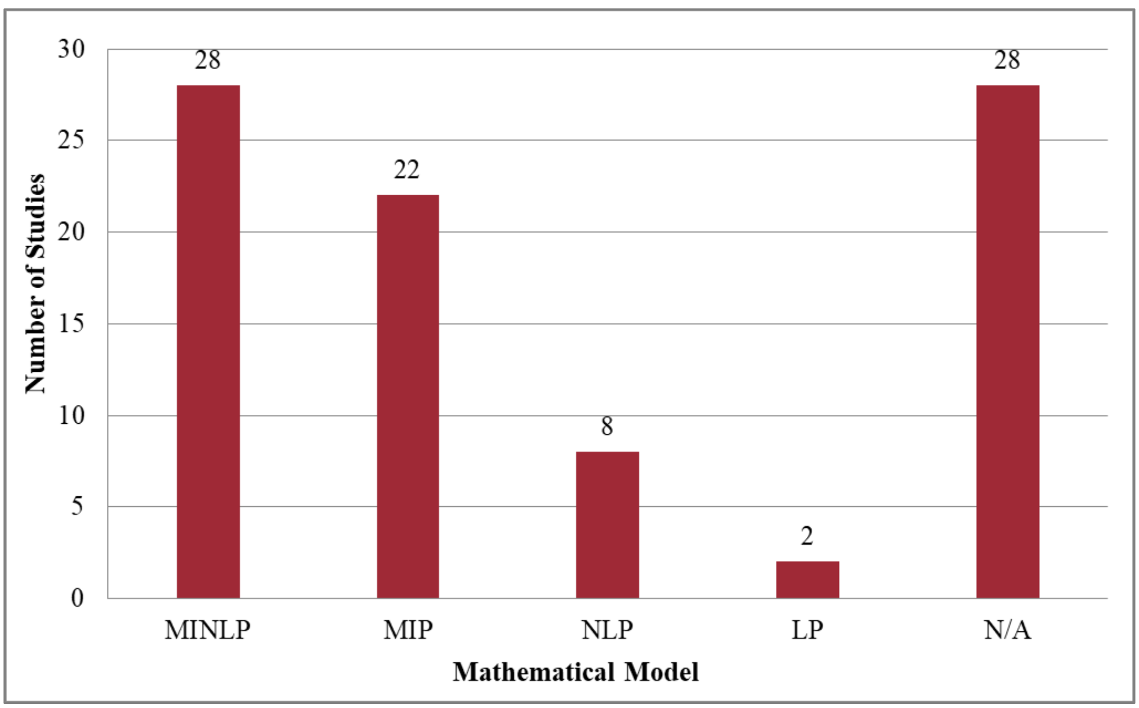


Figure 7 Distribution of studies by mathematical model used

Figure 7 presents the distribution of reviewed studies by the mathematical model used. The mathematical models, examined by the collected studies, were categorized based on the type of mathematical programming considered. It was found that the majority of the studies (31.8% of studies) used mixed-integer nonlinear programming (MINLP), in which the relationships between certain variables are nonlinear, and some of the variables are constrained to be integers, as well as mixed-integer programming (MIP) (25.0% of studies), where some of the decision variables are constrained to be integer values. Moreover, certain studies (9.1% of studies) adopted the nonlinear programming (NLP) (some of the constraints are nonlinear or the objective function is nonlinear), while a small number of studies (2.3% of studies) used linear programming (LP), in which the relationship between variables is represented by linear constraint sets. Some studies (31.8% of studies) did not use mathematical models but used other analytical models or theoretical approaches.

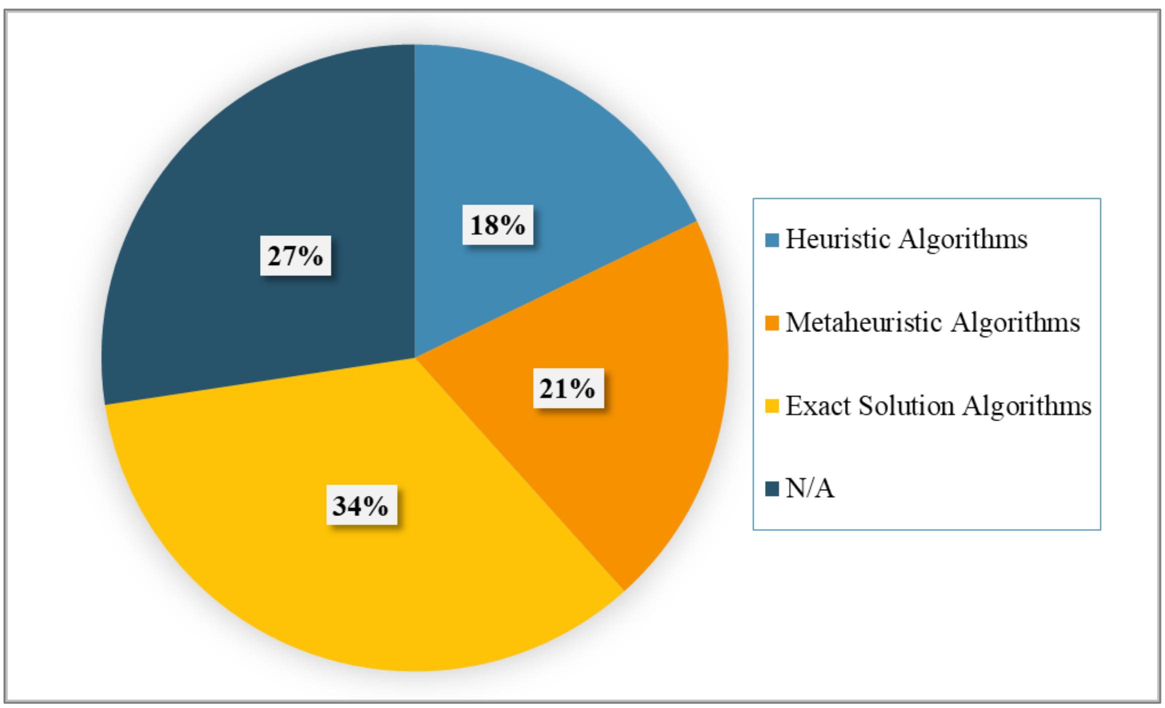


Figure 8 Distribution of studies by the algorithm type

The types of algorithms adopted by the collected studies were also extracted throughout the literature review. Figure 8 illustrates the distribution of studies by the types of algorithms. It was found that 25 studies (or 34.0% of studies) adopted exact solution algorithms, while 15 studies (or 21.0% of studies) developed metaheuristic algorithms. Moreover, 13 studies (or 18.0% of studies) developed heuristic algorithms. A relatively frequent utilization of exact optimization algorithms indicates that a large number of the mathematical models formulated in liner shipping scheduling could be solved to the global optimality within a reasonable computational time. Although most of the studies proposed a solution algorithm, some other studies focused on the alternative methods, such as statistical modeling, review of models, fuzzy logic, and others. A total of 20 studies (or 27.0% of studies) did not use any solution algorithm and adopted analytical/theoretical approaches, aiming to solve various problems in liner shipping scheduling.

The reviewed studies were classified based on the research methodology adopted in the following categories:

1) ***Theoretical or conceptual method*** - this approach may suggest a new concept related to the topic by using a conceptual framework. The conclusions made by the studies that use this approach are not supported with any mathematical calculations or models.
2) ***Analytical method*** - this approach uses mathematical calculations, statistical analysis, and other analytical methods to evaluate a new approach to a topic.

Inferences drawn are based on the results obtained from the method of analysis used.

3) ***Survey based method*** - questionnaire surveys or interviews, administered to a specific or random sample, are used to obtain the information about the subject, which can be an existing topic, a proposed topic, an invention, policy, among others. Inferences drawn from the survey are used in making conclusions about the subject topic.
4) ***Literature review method*** - involves the collection and detailed analysis of scientific studies to examine the extent of existing work on a particular subject, review of various approaches that have been established and determine potential future research works in the same area.
5) ***Modeling method*** - this approach relies on development of different models in order to solve a specific problem (e.g., optimization models, simulation models, agent-based models). Findings are based on mathematical and computational experiments, which may require the development of an algorithm, simulation and/or optimization models.

The distribution of reviewed studies by research method is presented in Figure 9. It was found that the majority of studies (69.3%) were based on the modeling method. The latter finding can be justified by the fact that the majority of the problems in liner shipping scheduling are solved using an optimization approach (which involves formulation of the mathematical models, solved using various solution algorithms). Furthermore, some studies (18.2% of studies) used the analytical method, while a few studies used the literature review method (9.1% of studies). Approximately 3.4% of studies used the theoretical method.

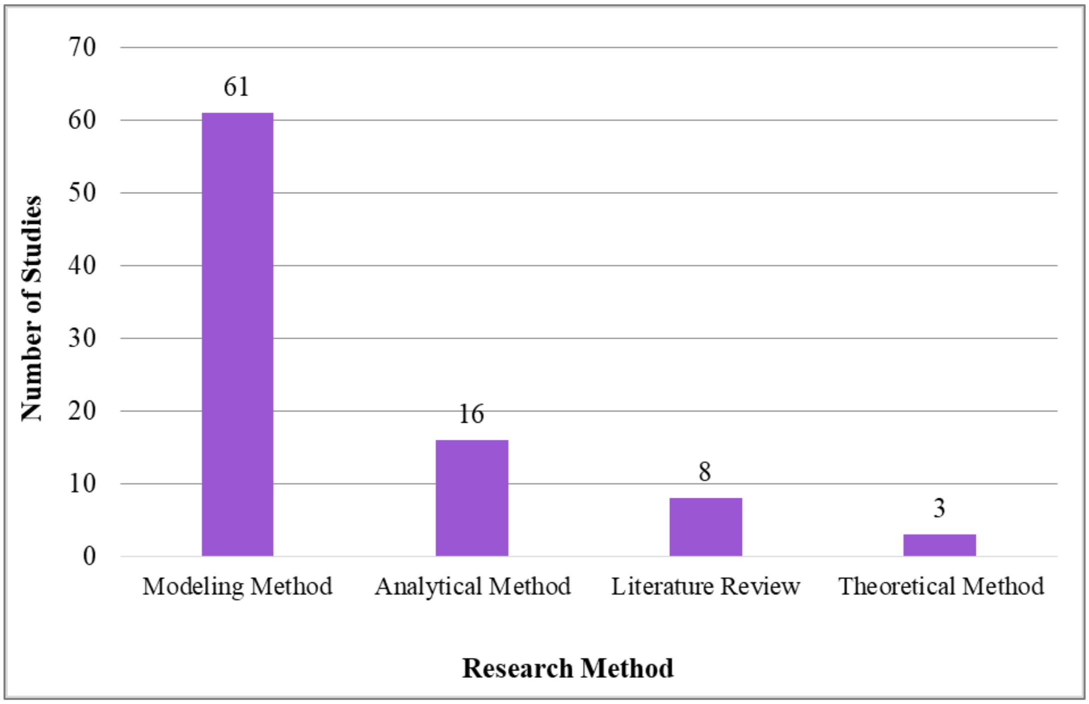


Figure 9 Distribution of studies by research method

2.3. Existing Gaps in the State-of-the-Art

Based on the analysis of the collected studies, some of the gaps in the state-of-the-art with a primary focus on the vessel schedule recovery are outlined as follows:

a) The majority of studies investigated the speed-based vessel schedule recovery problem. However, other recovery alternatives (e.g., port of call omission, port of call swap) other than the speed-based recovery option considered may ensure timely delivery of cargo without having to increase speed.

b) The vessel schedule recovery problem should be considered simultaneously with the green vessel schedule problem. There is a need for researchers to take into account emission constraints and/or environmental regulations, which are imposed to vessels, in solving the vessel schedule recovery problem

c) There is a need to account for the changes in original berth scheduling that may arise due to disruptions in fixed schedule services at the ports with and without soft TWs.

d) Many vessel schedule recovery models developed to date do not explicitly model uncertainty at ports. There is a need to consider how to manage uncertainty in ports operations.

e) There is a need to develop mathematical models, which focus on multiple objective components, such as TOC, TFC, TPC, TIC, TEC, and others.

f) There is a need to develop mathematical models, which account for conflicting nature of certain objectives in vessel schedule recovery.

As it was highlighted in section 1.4 of this dissertation, some of the identified limitations of the state-of the-art will be directly addressed in this dissertation.

CHAPTER 3

VESSEL SCHEDULE RECOVERY FOR THE LINER SHIPPING ROUTES WITH EMISSION CONTROL AREAS

3.1. Background

As discussed in section 1.2 of this manuscript, the service network is planned by the liner shipping company at the strategic tier of decision-making over a specified time-period (Meng et al., 2014). Other critical components of liner shipping operations, such as arrival, departure, and waiting times of vessels at ports, sailing speed, and service frequency, are planned at the tactical level (i.e., every 3-6 months). However, in practice, various disruptions may occur that will negatively impact the planned vessel schedules. Disruptions that may occur in sea include inclement weather, mechanical failures, piracy attacks, crew strikes on vessels, while port congestion, port strikes, natural hazards, handling equipment breakdowns, etc. are some of the disruptive events that may occur at ports.

Brouer at al. (2013) underlined that piracy and crew strikes on vessels as some of the uncommon causes of disruptions in liner shipping. According to Notteboom (2006), about 70% – 80% of liner shipping routes recorded late arrivals at one or multiple port(s) of call during their voyage. The latter negatively affected the planned operations, and liner shipping companies faced the challenge of recovering the planned vessel schedules. Disruptions in vessel schedules often cause late arrivals of vessels at the consecutive ports of call. In some instances, the whole network could be impacted by the delay at only one port or voyage leg of the liner shipping route. Disruptions in the planned schedule of vessels can substantially increase the total operational cost for the liner shipping company, and, thus, result in enormous monetary losses.

In the case of a disruption in the planned vessel schedule, the liner shipping company has to identify the most feasible strategy that could be implemented in order to recover the schedule and ensure timely delivery of cargo or at least minimize the delays in the delivery of cargo at ports. If a disruptive event occurs in sea and/or at ports, the vessel operator may increase the vessel sailing speed at voyage legs. However, several studies have established that bunker fuel consumption increases with the vessel sailing speed (Wang and Meng, 2012b; Psaraftis and Kontovas, 2013), consequently, the decision to increase the sailing speed in order to recover the schedule may significantly increase the total fuel cost. Moreover, there is a limit on the maximum speed of a vessel, which is based on the capacity of the main engine; therefore, selecting the maximum speed of a vessel does not guarantee the schedule recovery. Also, liner shipping companies may add "buffers" at certain voyage legs to account for uncertain events that may cause a delay in the planned operations. However, for significantly large delays caused by disruptions in sea and/or at ports, the buffers are usually not enough to recover the vessel schedule. Generally, the introduction of many buffers in the liner shipping network affects the network efficiency.

Several corridors of the sea have been designated as "Sulfur Emission Control Areas" (SECAs) by the International Maritime Organization (IMO). For instance, the IMO designated the Baltic Sea, the North Sea, and the English Channel as SECAs in 2005 (IMO, 2016). In addition, the United States (U.S.) - Canadian coastal zone was designated as an "Emissions Control Area" (ECA) in 2012, where the restrictions were imposed on sulfur oxide (SO_x), nitrogen oxide (NO_x), and particulate matter (PM) emissions. The vessels, sailing through the ECAs, are not allowed to burn fuel with the sulfur content of more than 0.10% m/m after 1 January 2015 (IMO, 2016). In the event of a disruption in the planned operations of the vessels, sailing through ECAs, liner shipping companies must comply with the IMO regulations while trying to recover the vessel schedules, improve environmental sustainability and energy efficiency. The term "energy efficiency" can be defined as the efficient utilization of fuel (i.e., cost effective utilization of fuel). Since the vessels, sailing through ECAs, can use only expensive low-sulfur fuel, energy efficiency becomes a critical factor in selecting the appropriate vessel schedule recovery strategy.

Several factors, such as the impacts of disruptions on the planned vessel schedules, the demand for efficient fuel utilization in liner shipping, and the existing environmental regulations guiding vessel emissions, emphasize the need for the development of effective green vessel schedule recovery methods, which can be used by liner shipping companies in practice. A few studies have discussed the vessel schedule recovery in liner shipping and proposed a set mathematical models for the vessel schedule recovery problem (Brouer et al., 2013; Li et al., 2015, 2016; Cheraghchi et al., 2018). However, none of the existing studies, which focused on vessel schedule recovery, have taken into account the liner shipping routes, which pass via ECAs and where additional regulations are imposed by IMO that may affect the disruption recovery action. This chapter of the dissertation presents a novel mixed-integer nonlinear programming model for the green vessel schedule recovery problem for the liner shipping route, which passes via ECAs. The model considers the existing environmental regulations, enforced by IMO, and proposes two vessel schedule recovery strategies. The proposed nonlinear mathematical model is linearized and solved to optimality using CPLEX.

Furthermore, a set of numerical experiments are conducted for the Asia-North Europe LL5 route, which is served by OOCL liner shipping company and passes via ECAs with the SO_x emission control. Important managerial insights, which would be of interest to liner shipping companies, are revealed using the proposed mathematical model and the developed solution approach. The methodology, presented in this chapter, will assist liner shipping companies with efficient vessel schedule recovery, minimizing monetary losses endured as a result of disruptions in vessel schedules, improving energy efficiency and environmental sustainability throughout the transportation process. The latter aspects are considered as important in liner shipping and supply chain management (Centobelli et al., 2018; Kim and Lee, 2018; Sun et al., 2018; Sakalis, et al., 2019).

3.2. Problem Description

This section of the dissertation chapter presents a detailed description of the vessel schedule recovery problem for the liner shipping route, which passes via the areas designated by the IMO as ECAs, and the major modeling assumptions.

3.2.1. Liner Shipping Route Description

A liner shipping route, connecting multiple ports of call, is typically served either by a single liner shipping company or multiple liner shipping companies that form an alliance. However, the present study will consider the liner shipping route, served by a single liner shipping company. Let $P = \{1, \dots, m^1\}$ denote the set of ports that will be visited by the vessels, dispatched for service of the liner shipping route by the liner shipping company.

The dispatched vessels, sail from port p to $p+1$ along voyage leg p. Throughout this study, it is assumed that the order of port visits at the liner shipping route is known. Usually, a vessel visits each port of the liner shipping route once. However, in some instances, a port could be called multiple times during the voyage. Generally, the order of port visits (otherwise referred to as "port rotation" or "port network" in the state-of-the-art and the state-of-practice) and the port service frequency are decided by the liner shipping companies at the strategic and tactical levels, respectively (Meng et al., 2014). Figure 10 presents an example of the liner shipping route, where vessels serve 5 ports, namely: (1) the Port of Genoa (Italy); (2) the Port of Barcelona (Spain); (3) the Port of Jeddah (Saudi Arabia); (4) the Port of Shanghai (China); and (5) the Port of Pusan (South Korea).

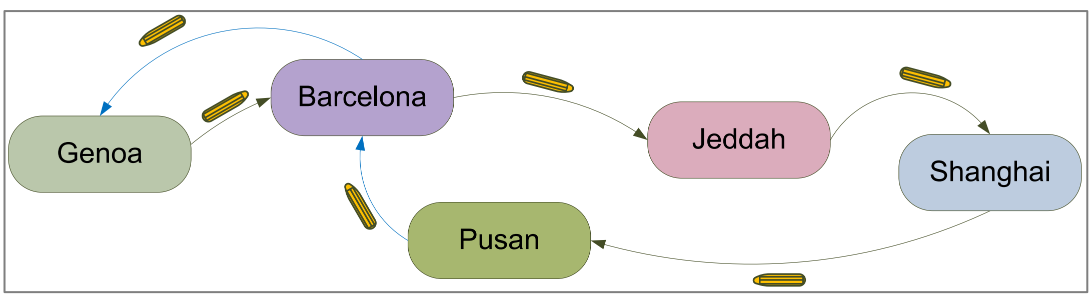


Figure 10 A liner shipping route example

Figure 11 The port rotation graph example

The Ports of Jeddah, Shanghai, and Pusan are visited once, while the Ports of Barcelona and Genoa are visited twice. Figure 11 illustrates the port rotation graph that is used for modeling of the liner shipping route, presented in Figure 10. The port rotation graph contains a total of two dummy nodes, which are used to model a second visit to the same port of call at the liner shipping route. The dummy nodes "Barcelona*"and "Genoa*" are added and placed after the node for the Port of Pusan to model an additional visit to the Ports of Barcelona and Genoa, respectively. Therefore, the total number of ports visits for the considered example becomes $|P| = 5 + 2 = 7$.

3.2.2. Vessel Service at Ports

The liner shipping operator typically plans the arrival time of vessels at each port along the liner shipping route at the tactical level. Let $\tau_p^{arr}, p \in P$ (hours) represent the planned arrival time of vessels at port p. The vessel arrival time at each port of call at the liner shipping route is jointly planned by the marine container terminal (MCT) operator and the liner shipping company. The liner shipping company ensures that the planned arrival time at each port is within the time window (TW) agreed between both parties (i.e., the MCT operator and the liner shipping company). The duration of the arrival TW at port p is established considering the start of TW at port p, which is denoted by $\tau_p^{st}, p \in P$ (hours), and the end of TW at port p, represented by $\tau_p^{ft}, p \in P$ (hours). Several factors may affect the planned arrival TW duration at each port of call, some of which include the availability of handling equipment, the availability of MCT berthing positions, the vessel arrival frequency, and others (Dulebenets and Ozguven, 2017; Dulebenets, 2018a-d; OOCL, 2019).

If a vessel arrives at a port of call before the start of negotiated arrival TW, the vessel is moored to a dedicated waiting area before service. The planned waiting time of vessels at port $p+1$ ($\tau_{p+1}^{wait}, p \in P$ – hours) can be estimated based on the following: (i) the start of TW at port $p+1$; (ii) the planned vessel departure time from port p ($\tau_p^{dep}, p \in P$ – hours); and (iii) the planned sailing time between ports p and $p+1$ ($\tau_p^{sail}, p \in P$ – hours). The planned waiting time of vessels at port $p+1$ can be estimated using the following relationships:

$$\tau_{p+1}^{wait} = \tau_{p+1}^{st} - \left(\tau_p^{dep} + \tau_p^{sail}\right) \forall p \in P, p < |P| \tag{1}$$

$$\tau_1^{wait} = \tau_1^{st} - \left(\tau_p^{dep} + \tau_p^{sail}\right) + \varphi \cdot V \ \forall p \in P, p = |P| \tag{2}$$

Furthermore, the product of the agreed port service frequency (φ – hours) and the total number of vessels deployed for service of ports along the liner shipping route (V – vessels) is required to calculate the vessel waiting time at the first port of call (i.e., τ_1^{wait}). The latter estimation represents the planned total turnaround time of vessels at the given liner shipping route (see section 3.2.4 for more details). Note that the planned total turnaround time of vessels in the estimation captures a round voyage of vessels as well as the return of vessels at the first port of call (Dulebenets, 2018a-d).

Throughout the vessel schedule design at the tactical level, the liner shipping company and the MCT operator agree to the vessel handling rate at each port of call of the considered liner shipping route. It is presumed in this study that the MCT operator at port p is able to offer a set of handling rates $H_p = \left\{1, \dots, m_p^2\right\}, p \in P$ to the liner shipping company for service of the arriving vessels. Also, the MCT operator provides a unique handling productivity ($pr_{ph}, p \in P, h \in H_p$, measured in twenty-foot equivalent units per hour – TEUs/hour) for each handling rate offered to the liner shipping company. It is assumed that the container demand ($d_p^{port}, p \in P$ – TEUs) is known. The planned handling time of vessels at port p ($\tau_p^{hand}, p \in P$ – hours) can be estimated using the container demand at that port and the requested handling productivity as follows:

$$\tau_p^{hand} = \sum_{h \in H_p} \left(\frac{d_p^{port}}{pr_{ph}} \right) x_{ph} \; \forall p \in P \tag{3}$$

where:

$x_{ph}, p \in P, h \in H_p$ – is the handling rate selection parameter (=1 if handling rate h is requested at port p; =0 otherwise).

A liner shipping company will be required to pay a handling cost ($c_{ph}^{port}, p \in P, h \in H_p$ – USD/TEU) if a handling rate h is requested at port p for service of vessels. Moreover, several types of disruptions at MCTs, including disruptions due to labor strikes, port congestion, natural disasters resulting in port infrastructure damages, and others, may further cause an increment in the planned waiting and handling times of vessels. The actual waiting and handling times of vessels at port p will be denoted as $\overline{\boldsymbol{\tau}_p^{wait}}, p \in P$ (hours) and $\overline{\boldsymbol{\tau}_p^{hand}}, p \in P$ (hours), respectively.

Furthermore, if a disruption occurs at preceding ports of call, the planned arrival time of vessels at a given port of call may be affected. The actual vessel arrival time will be expressed as $\overline{\boldsymbol{\tau}_p^{arr}}, p \in P$ (hours). A detailed explanation of the vessel schedule recovery strategies considered in this study, which can be used to mitigate the impact of the delays caused by disruptions at ports of call, will be discussed in section 3.2.8 of this chapter. The vessel arrival delay ($\overline{\boldsymbol{\tau}_p^{del}}, p \in P$) at port p can be estimated using the actual and planned vessel arrival times as follows:

$$\overline{\boldsymbol{\tau}_p^{del}} \geq \overline{\boldsymbol{\tau}_p^{arr}} - \tau_p^{arr} \; \forall p \in P \tag{4}$$

Delays caused by disruptions in the planned arrival time of vessels at ports of call may negatively impact both liner shipping and MCT operations. Thus, a delayed vessel arrival time cost ($c_p^{del}, p \in P$ – USD/hour) will be imposed to the liner shipping company if the planned arrival time of vessels is violated at the port of call.

3.2.3. Fuel Consumption

In the vessel schedule design at the tactical level, it is a usually assumed that the vessel fleet, which is deployed to serve the ports of the given liner shipping route, is of homogeneous nature (Wang et al., 2014; Dulebenets et al., 2015, Dulebenets, 2018a-d). The key technical specifications of homogenous vessels, such as the capacity of the main and auxiliary vessel engines, structure of the main and auxiliary vessel engines, and maximum possible sailing speed, are the same. However, the assumption that vessels are homogeneous may not be totally correct in actual liner shipping operations for certain routes. This is because identical vessels may differ in their technical characteristics due to previous history of vessel repairs, age, utilization, and other factors. The planned fuel consumption per nautical mile (nmi) at voyage leg p ($f_p, p \in P$ – tons/nmi) is calculated in this study based on the available liner shipping literature (Wang and Meng, 2012c) as follows:

$$f_p = \frac{\gamma(s_p)^{(\alpha-1)}}{24} \; \forall p \in P \tag{5}$$

where:

α, γ – are the fuel consumption function coefficients;

$s_p, p \in P$ – is the planned sailing speed adopted for vessels at voyage leg p (knots).

The fuel consumption coefficients (α, γ) in equation (5) are usually estimated based on the historical data, which contain the information regarding the fuel consumption and sailing speed for a vessel fleet, serving a given liner shipping route. The planned sailing time at voyage leg p can be estimated using on the length of that voyage leg ($d_p^{leg}, p \in P$ – nmi) and the planned sailing speed as follows:

$$\tau_p^{sail} = \frac{d_p^{leg}}{s_p} \; \forall p \in P \tag{6}$$

Various forms of disruptions in sea, such as mechanical failure of vessel engines, inclement weather, inexperience/errors of the vessel crew, etc., may further lead to a reduction in the planned sailing speed of vessels. Therefore, the actual sailing speed at the voyage leg that experienced a disruptive event ($\overline{\boldsymbol{s}_p}, p \in P$ – knots) would be lower than the planned sailing speed: $\overline{\boldsymbol{s}_p} < s_p, p \in P$. A reduction of the vessel sailing speed will lead to a decrease the fuel consumption and the associated fuel consumption costs.

On the other hand, a reduction in the vessel sailing speed will lead to an increment in the actual sailing time at a given voyage leg ($\overline{\boldsymbol{\tau}_p^{sail}}, p \in P$ – hours), thus, causing a delayed arrival at the next port of call. A detailed explanation of the various vessel schedule recovery strategies that can be implemented to compensate for the delays, incurred as a result of disruptions in sea, will be discussed in section 3.2.8.

3.2.4. Port Service Frequency

The liner shipping company needs to make sure that the agreed port service frequency is met at the ports of the liner shipping route during the vessel schedule design at the tactical level. The latter can be accomplished based on the following relationship (Wang et al., 2014; Alhrabi et al., 2015; Dulebenets, 2018a-d):

$$\varphi \cdot V = \sum_{p \in P} \tau_p^{sail} + \sum_{p \in P} \tau_p^{wait} + \sum_{p \in P} \tau_p^{hand} \tag{7}$$

The planned total vessel turnaround time at the liner shipping route, which is defined as the time taken by a vessel to sail from the port of origin, call other ports of the liner shipping route, and return to the port of origin is calculated using the right-hand side of equation (7). The components of equation (7), which are used to compute the planned total vessel turnaround time, include: (a) the planned total vessel sailing time; (b) the planned total waiting time of vessels at ports of call; and (c) the planned total port handling time. Note that disruptions at ports and in sea, may result in a deviation of the actual total vessel turnaround time ($\overline{\boldsymbol{VTT}}$ – hours) from the planned total vessel turnaround time (VTT – hours). The actual total vessel turnaround time can be estimated as follows:

$$\overline{\boldsymbol{VTT}} = \sum_{p \in P} \overline{\boldsymbol{\tau}_p^{sail}} + \sum_{p \in P} \overline{\boldsymbol{\tau}_p^{wait}} + \sum_{p \in P} \overline{\boldsymbol{\tau}_p^{hand}} \tag{8}$$

If the total vessel turnaround time is increased due to disruptions in the planned schedule ($\overline{\boldsymbol{VTT}} > VTT$), the liner shipping company will not be able to maintain the agreed service frequency at ports of call. This may cause a disturbance in the liner shipping operations. Thus, liner shipping companies seek to avoid any deviations from the planned total vessel turnaround time. Moreover, if certain vessel schedule recovery strategies are efficiently implemented in the event of a disruption, the liner shipping company may be able to reduce (or even eliminate) deviations from the planned total vessel turnaround time.

3.2.5. Vessel Sailing Speed Selection

At the vessel scheduling stage (tactical level), the planned vessel sailing speed ($s_p, p \in P$ – knots) is decided by the liner shipping company at each voyage leg of a given liner shipping route (Wang et al., 2013; Wang et al., 2014). A wide range of factors may affect the planned sailing speed of vessels at each voyage leg along the liner shipping route. Wang et al. (2013) highlighted that liner shipping companies set a lower bound on the vessel sailing speed (s^{min} – knots) to minimize the wear on the vessel's engine. On the other hand, the upper bound on the vessel sailing speed (s^{max} – knots) is primarily determined by the vessel's engine capacity (Psaraftis and Kontovas, 2013).

As mentioned earlier, disruptive events in sea may substantially impact the planned vessel sailing speed. The latter may lead to fluctuations of the fuel consumption of vessels and result in late vessel arrivals at the consecutive ports of call. Nevertheless, the vessel sailing speed adjustment strategy may be implemented to recover the vessel schedules from disruptive events (more details will be provided in section 3.2.8).

3.2.6. Container Inventory Cost

This study assumes that during the vessel schedule design the liner shipping company has information regarding the total number of containers (i.e., TEUs) to be shipped at each voyage leg of the liner shipping route. Based on the information retrieved from the liner shipping literature, the container inventory cost can be estimated using the unit inventory cost of shipping a TEU (c^{inv} – USD/TEU/hour), the total number of TEUs transported at voyage legs ($d_p^{sea}, p \in P$ – TEUs), and planned total vessel sailing time at voyage legs of the liner shipping route (Wang et al., 2014; Dulebenets, 2018a-d) as follows:

$$CIC = \sum_{p \in P} c^{inv}\, d_p^{sea} \tau_p^{sail} \tag{9}$$

As previously mentioned, the planned vessel sailing speed at voyage legs will be affected by disruptions in sea and/or at ports. Note that at certain voyage legs where disruptive events occur, the reduction in sailing speed ($\overline{\boldsymbol{s}_p} < s_p, p \in P$) will lead to an increment in the planned vessel sailing time. The delay in the vessel schedule, caused by disruptions, can be recovered by increasing the vessel sailing speed at the subsequent voyage legs. The latter action will lead to a reduction in the planned sailing time. In order to estimate the actual container inventory cost ($\overline{\boldsymbol{CIC}}$– USD), the planned vessel sailing time in equation (9) is replaced with the actual sailing time of vessels at voyage legs ($\overline{\boldsymbol{\tau}_p^{sail}}, p \in P$ – hours) as follows:

$$\overline{\boldsymbol{CI}} = \sum_{p \in P} c^{inv}\, d_p^{sea} \overline{\boldsymbol{\tau}_p^{sail}} \tag{10}$$

3.2.7. Existing International Maritime Organization regulations on emissions

The existing environmental guidelines put in place by the IMO under "*Sulphur oxides (SO_x) and Particulate Matter (PM) – Regulation 14*", which imposes restrictions on the emissions of SO_x and PM produced by vessels in the areas that are designated as ECAs, are considered in this study (IMO, 2016). The latter consideration will improve efficient utilization of fuel (i.e., energy efficiency) and environmental sustainability of liner shipping. Specifically, regulation 14 requires that the vessels that sail through ECAs must use fuels with sulfur content not exceeding 0.10% m/m (IMO, 2016). In order to adhere to the existing IMO regulations, this study proposes that the vessels deployed by the liner shipping company will use two types of fuel (namely, Marine Gas Oil [MGO] and Heavy Fuel Oil [HFO]) throughout the voyage.

This study assumes that the liner shipping company will select a more costly MGO with the sulfur content of 0.10% when sailing through the areas designated as ECAs ($SC_p = 0.1\% \ \forall p \in P^*$, where P^* – is a set of voyage legs, which pass via ECAs; $SC_p, p \in P$ – is the sulfur content of fuel used at voyage leg p), while HFO with the sulfur content of 3.5% will be selected at the voyage legs of the liner shipping route that are outside ECAs ($SC_p = 3.5\% \ \forall p \in P^0$, where P^0 – is a set of voyage legs passing outside ECAs).

Furthermore, there exists some IMO regulations on nitrogen oxide (NO_x) pollutants, generated by vessels in some ECAs (the North American area and the United States Caribbean Sea). In order to comply with the latter regulations, it is assumed that the diesel engines of vessels, deployed by the liner shipping company, satisfy the Tier III limits. The latter assumption does not apply to the liner shipping routes, which pass via ECAs in the Baltic Sea and the North Sea (where restrictions are imposed on SO_x emission only).

3.2.8. Vessel Schedule Disruptions and Recovery

Disruptive events may occur in sea and/or at ports of call. Disruptive events at ports may be as a result of labor strikes, natural disasters that lead to the destruction of port infrastructure, port congestion, and others. Also, disruptions in sea may be as a result of inexperience/errors of the vessel crew, inclement weather, mechanical failure of vessel engines, and others. Let $y_p^{port} = 1, p \in P$ if a disruptive event takes place at port p (=0 otherwise). Let $y_p^{sea} = 1, p \in P$ if a disruptive event takes place at voyage leg p (=0 otherwise). Note that both $y_p^{port}, p \in P$ and $y_p^{sea}, p \in P$ are considered as parameters in this study based on the fact that the vessel schedule recovery problem for the liner shipping route, which passes via ECAs, is an operational-level decision problem in liner shipping.

At the operational-level decision making, the liner shipping company have a knowledge of where disruption(s) occurred. Also, the liner shipping company has a knowledge of the length of time a disruptive event is expected to last. The expected time period of a disruptive event at ports will be further referred to as $\delta_p^{port}, p \in P$ (hours), while the expected reduction in the vessel sailing speed due to disruptions is sea will be represented as $\delta_p^{sea}, p \in P$ (knots). The vessel schedule recovery strategies that could assist the liner shipping company with the recovery of the vessel schedule after disruptive events at the liner shipping route, which passes via ECAs, are as follows: (a) vessel sailing speed adjustment; and (b) port skipping.

The liner shipping company may resolve the vessel schedule recovery problem by selecting a higher vessel sailing speed at voyage legs of the liner shipping route to effectively recover the vessel schedule and recover the delays, suffered due to disruptive events in sea and/or at ports of call. Let $\Delta_p^{sea}, p \in P$ (knots) represent the vessel sailing speed adjustment at voyage leg p of the liner shipping route. Note that an increase in the vessel sailing speed at voyage legs will lead to an increase in the fuel consumption by the vessels, deployed for service of the given liner shipping route, which will increase the actual total fuel cost incurred by the liner shipping company. This study assumes that the liner shipping company will not be able to alter the vessel sailing speed at the voyage leg of the liner shipping route that undergoes a disruptive event. If the delay, caused by a disruptive event, significantly impacts the liner shipping operations at a specific voyage leg of the liner shipping route, the liner shipping company may not be able to completely recover the vessel schedule even after selecting the maximum vessel sailing speed at the consecutive voyage legs.

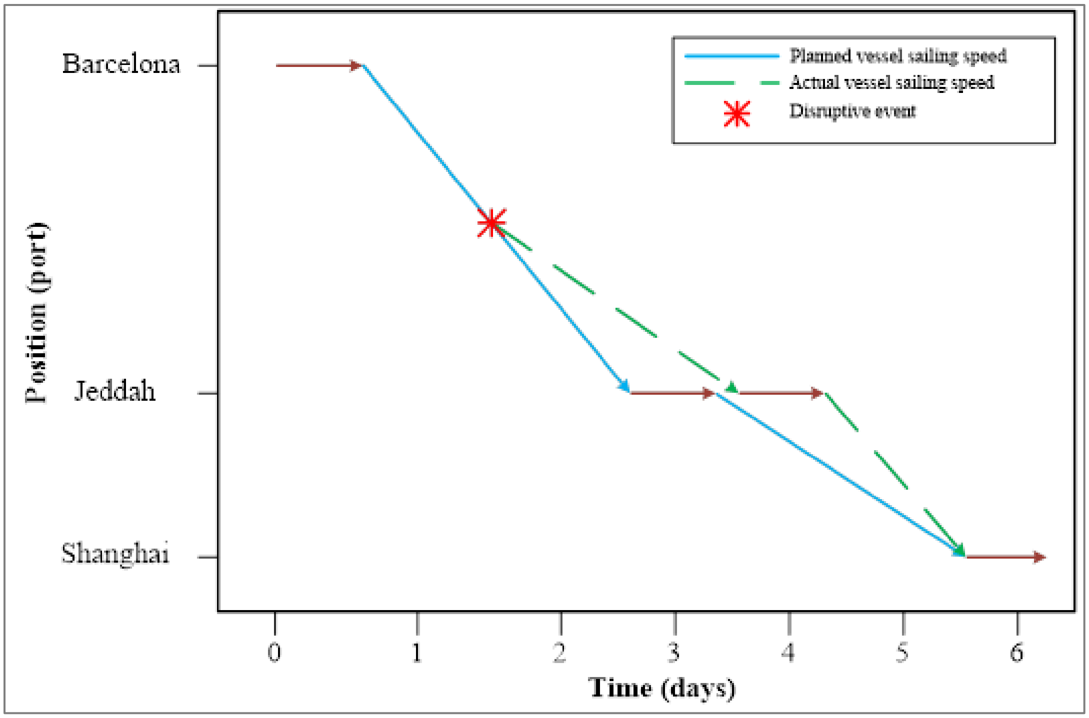


Figure 12 An example of the vessel sailing speed adjustment

An example of the vessel schedule recovery strategy, which is based on the vessel sailing speed adjustment, is illustrated in Figure 12. The horizontal and vertical axes of the time-space network, which is presented in Figure 12, depict the time within the planning horizon (in days) and the port position, respectively. A vessel dispatched by a liner shipping company, which is scheduled to visit three ports, namely the Ports of Barcelona, Jeddah, and Shanghai, experienced a disruption after leaving the Port of Barcelona. The latter disruption caused a late arrival at the Port of Jeddah. In order to fully recover the schedule and retain the planned arrival time at the Port of Shanghai, the liner shipping company increased the vessel sailing speed at the voyage leg between the Ports of Jeddah and Shanghai.

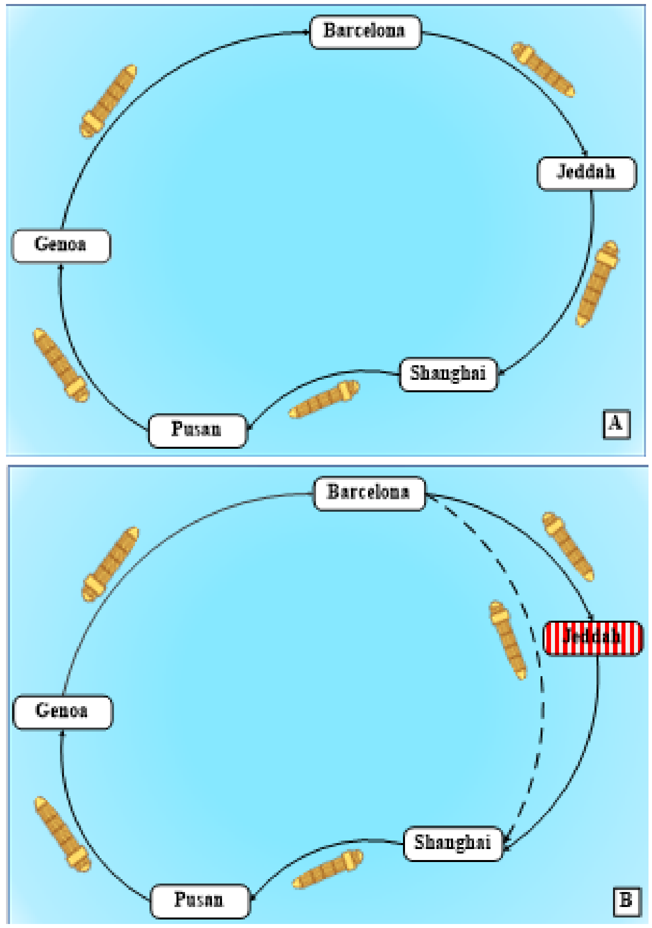


Figure 13 An example of port skipping: A-port rotation before schedule recovery; B-port rotation after schedule recovery

Furthermore, the liner shipping company may decide not to skip port p and withstand the delay. Let $\boldsymbol{x}_p^{skip}, p \in P$ denote the port skipping decision variable (=1 if port p is skipped; =0 otherwise). However, if the duration of a disruptive event at a given port of call of the liner shipping route is anticipated to be significant, the liner shipping company will have to skip that port to minimize other additional liner shipping route service costs that may be incurred because of the disruptive event. An example of port skipping due to a disruptive event is shown in Figure 13. In the presented example of port skipping, a vessel, which is scheduled to visit the Port of Genoa, the Port of Barcelona, the Port of Jeddah, the Port of Shanghai, and the Port of Pusan, respectively, skips the Port of Jeddah because of disruptive events at the port and visits only the Port of Genoa, the Port of Barcelona, the Port of Shanghai, and the Port of Pusan. Note that the decision of the liner shipping company to skip a port of call in the port rotation because of a disruptive event at the port does not alter the sequence of visits to the consecutive ports (i.e., it is assumed that the port rotation remains unchanged even if the liner shipping company skips a port).

Also, if a port is skipped by the liner shipping company due to a disruptive event at that port of call, it will not be able to deliver the import containers and pick up the export containers at the port. In this study, a port skipping cost ($c_p^{skip}, p \in P$ – USD) is forced on the liner shipping company if it decides to skip a port due to a disruptive event. The port skipping penalty may be forced for every single port skipping decision or over a defined time period (such as quarterly or annually). Generally, the terms and conditions of settling the port skipping penalty are negotiated between the MCT operators and the liner shipping company in a contractual agreement between both players. The port skipping cost is usually introduced by the MCT operator to reimburse the MCT operator for the unmet demand, reserved handling equipment, and reserved yard storage space for containers.

The vessel schedule recovery strategies examined in this study (i.e., vessel sailing speed adjustment and port skipping) can be administered by the liner shipping company to recover the vessel schedule due to disruptive events in sea and/or at ports of call. Based on the extent of a disruptive event, the liner shipping company may be willing to implement both recovery strategies (if the additional liner shipping route service costs due to that disruptive event can be minimized). Notwithstanding, if the cost of administering the aforementioned vessel schedule recovery strategies is significantly high, the liner shipping company may decide to suffer the impacts of a disruptive event and not apply any of the proposed vessel schedule recovery strategies.

3.2.9. Decisions

The decision problem, which is investigated in this study, can be described as the operational-level problem in liner shipping and will be called as the green vessel schedule recovery problem. The major decisions, required to be addressed in the green vessel schedule recovery problem by the liner shipping company, are as follows:

A) Determine the voyage legs of the liner shipping route, where the vessel sailing speed adjustment recovery strategy will be a favorable alternative to mitigate the impact of the delays, caused by a disruptive event;

B) Decide if energy efficient vessel schedules would be a favorable alternative to compensate for the delays, caused by a disruptive event (i.e., a small increase in the vessel sailing speed will not substantially increase the actual fuel consumption and the associated cost, but may not be sufficient to recover the delays);

C) Determine whether the vessel sailing speed adjustment recovery strategy would be an efficient alternative at the voyage legs, which pass via ECAs;

D) Skip a port of call where a disruptive event occurs or wait until the port recovers from that disruption and is able to provide service of vessels;

E) Select effective vessel schedule recovery strategies with the aim of reducing the vessel arrival delays at ports of call throughout the voyage.

The decisions, which must be made by the liner shipping company to recover the vessel schedule for the liner shipping route, which passes via ECAs, are interconnected in their nature. The liner shipping company may have to increase the sailing speed of vessels at voyage legs of the liner shipping route to compensate for the delays, caused by disruptive events in sea and/or at ports of call, taking into account the limits on the vessel sailing speed ($s^{min} \leq \overline{\boldsymbol{s}_p} \leq s^{max}\ \forall p \in P$). The latter decision will allow reducing the vessel arrival delays and the associated late arrival cost, but may substantially increase the actual total fuel cost, especially when sailing via ECAs (since the liner shipping company is required to use expensive low-sulfur MGO). If the delay due to a disruptive event is too large, the liner shipping company may decide to skip the affected port of call, which will incur the port skipping cost. The port skipping option may allow the liner shipping company selecting the lower vessel sailing speed, when compared to the planned sailing speed (due to the time savings from port skipping), and consequently decrease the actual fuel consumption at other voyage legs.

If a disruptive event causes significant delays in sea and/or at ports of call, the actual total vessel turnaround time may substantially increase, and the liner shipping company will not be able to maintain the agreed service frequency at ports of call. Failure to provide the agreed service frequency at ports of call will negatively affect the liner shipping operations. However, an efficient implementation of the proposed vessel schedule recovery strategies (i.e., vessel sailing speed adjustment and port skipping) will allow the liner shipping company reducing or even eliminating deviations from the planned total vessel turnaround time. The objective of the liner shipping company is to effectively recover the vessel schedule and minimize the total profit loss as a result of disruptions in sea and/or at ports of call.

3.3. Mathematical Model

This section of the dissertation presents a mixed-integer nonlinear programming model for the green vessel schedule recovery problem (the model will be referred to as **GVSRP**), which takes into account the existing IMO regulations at the voyage legs that pass via ECAs. The **GVSRP** ensures that the low-sulfur fuel is used by vessels when sailing via voyage legs with ECAs. The nomenclature, which will be adopted throughout the remaining part of this chapter, is presented next.

Nomenclature

Sets

$P = \{1, \ldots, m^1\}$	set of ports to be visited (ports)
$H_p = \{1, \ldots, m_p^2\}, p \in P$	set of available handling rates at port p (handling rates)

Decision Variables

$\Delta_p^{sea} \in \mathbb{R}\ \forall p \in P$	vessel sailing speed adjustment at voyage leg p (knots)
$\boldsymbol{x}_p^{skip} \in \mathbb{B}\ \forall p \in P$	=1 if port p is skipped (=0 otherwise)

Auxiliary Variables

$\overline{\boldsymbol{s}_p} \in \mathbb{R}^+\ \forall p \in P$	actual sailing speed of vessels at voyage leg p (knots)

$\overline{\boldsymbol{\tau}_p^{arr}} \in \mathbb{R}^+ \; \forall p \in P$	actual arrival time of vessels at port p (hours)
$\overline{\boldsymbol{\tau}_p^{wait}} \in \mathbb{R}^+ \; \forall p \in P$	actual waiting time of vessels at port p (hours)
$\overline{\boldsymbol{\tau}_p^{hand}} \in \mathbb{R}^+ \; \forall p \in P$	actual handling time of vessels at port p (hours)
$\overline{\boldsymbol{\tau}_p^{dep}} \in \mathbb{R}^+ \; \forall p \in P$	actual departure time of vessels from port p (hours)
$\overline{\boldsymbol{\tau}_p^{sail}} \in \mathbb{R}^+ \; \forall p \in P$	actual sailing time of vessels at voyage leg p that connects ports p and $p+1$ (hours)
$\overline{\boldsymbol{f}_p} \in \mathbb{R}^+ \; \forall p \in P$	actual fuel consumption at voyage leg p (tons)
$\overline{\boldsymbol{\tau}_p^{del}} \in \mathbb{R}^+ \; \forall p \in P$	vessel arrival delay at port p (hours)
$\overline{\boldsymbol{VTT}} \in \mathbb{R}^+$	actual total vessel turnaround time (hours)
$\overline{\boldsymbol{REV}} \in \mathbb{R}^+$	actual total revenue to be generated by the liner shipping company (USD)
$\overline{\boldsymbol{PHC}} \in \mathbb{R}^+$	actual total port handling cost (USD)
$\overline{\boldsymbol{LAC}} \in \mathbb{R}^+$	actual total late vessel arrival cost (USD)
$\overline{\boldsymbol{FCC}} \in \mathbb{R}^+$	actual total fuel cost (USD)
$\overline{\boldsymbol{CIC}} \in \mathbb{R}^+$	actual total container inventory cost (USD)
$\overline{\boldsymbol{TP}} \in \mathbb{R}^+$	actual total profit to be generated by the liner shipping company (USD)

Parameters

$m^1 \in \mathbb{N}$	number of ports to be visited (ports)
$m_p^2 \in \mathbb{N} \; \forall p \in P$	number of available handling rates at port p (handling rates)

$\tau_p^{arr} \in \mathbb{R}^+ \ \forall p \in P$	planned arrival time of vessels at port p (hours)
$\tau_p^{st} \in \mathbb{R}^+ \ \forall p \in P$	start of TW at port p (hours)
$\tau_p^{ft} \in \mathbb{R}^+ \ \forall p \in P$	end of TW at port p (hours)
$\varphi \in \mathbb{N}$	agreed port service frequency (hours)
$V \in \mathbb{N}$	total number of vessels deployed for service of ports along the liner shipping route (vessels)
$d_p^{port} \in \mathbb{R}^+ \ \forall p \in P$	container demand at port p (TEUs)
$pr_{ph} \in \mathbb{R}^+ \ \forall p \in P,$ $h \in H_p$	handling productivity at port p under handling rate h (TEUs/hour)
$x_{ph} \in \mathbb{B} \ \forall p \in P,$ $h \in H_p$	=1 if handling rate h is requested at port p (=0 otherwise)
$d_p^{leg} \in \mathbb{R}^+ \ \forall p \in P$	length of voyage leg p (nmi)
$\alpha, \gamma \in \mathbb{R}^+$	fuel consumption coefficients
$s_p \in \mathbb{R}^+ \ \forall p \in P$	planned vessel sailing speed at port p (knots)
$s^{min} \in \mathbb{R}^+$	minimum vessel sailing speed (knots)
$s^{max} \in \mathbb{R}^+$	maximum vessel sailing speed (knots)
$d_p^{sea} \in \mathbb{R}^+ \ \forall \ p \in P$	number of containers transported at voyage leg p (TEUs)
$y_p^{port} \in \mathbb{B} \ \forall p \in P$	=1 if a disruptive event occurred at port p (=0 otherwise)
$y_p^{sea} \in \mathbb{B} \ \forall p \in P$	=1 if a disruptive event occurred at voyage leg p (=0 otherwise)
$\delta_p^{port} \in \mathbb{R}^+ \ \forall p \in$	expected duration of a disruptive event at port p (hours)

$\delta_p^{sea} \in \mathbb{R}\ \forall p \in P$	expected vessel sailing speed change due to a disruptive event at voyage leg p (knots)
$c_p^{cargo} \in \mathbb{R}^+\ \forall p \in P$	freight rate for shipping a TEU from port p to port $p+1$ (USD/TEU)
$c_{ph}^{port} \in \mathbb{R}^+\ \forall p \in P,$ $h \in H_p$	handling cost at port p under handling rate h (USD/TEU)
$c_p^{del} \in \mathbb{R}^+\ \forall p \in P$	delayed vessel arrival cost at port p (USD/hour)
$c_p^f \in \mathbb{R}^+\ \forall p \in P$	unit fuel cost when sailing at voyage leg p (USD/ton)
$c^{oper} \in \mathbb{R}^+$	vessel operational cost (USD/hour)
$c^{inv} \in \mathbb{R}^+$	unit container inventory cost (USD/TEU/hour)
$c_p^{skip} \in \mathbb{R}^+\ \forall p \in P$	cost for skipping port p due to a disruptive event (USD)
$VOC \in \mathbb{R}^+$	planned total vessel operational cost (USD)
$TP \in \mathbb{R}^+$	planned total profit to be generated by the liner shipping company (USD)

Green Vessel Schedule Recovery Problem (**GVSRP**):

$$min\ [TP - \overline{\boldsymbol{TP}}] \tag{11}$$

Subject to:

$$\overline{\boldsymbol{s}_p} \leq s_p + \delta_p^{sea} y_p^{sea} + \Delta_p^{sea}(1 - y_p^{sea})\ \forall p \in P \tag{12}$$

$$\overline{\boldsymbol{s}_p} \leq s^{max}\ \forall p \in P \tag{13}$$

$$\overline{\boldsymbol{s}_p} \geq s^{min} + \delta_p^{sea} y_p^{sea}\ \forall p \in P \tag{14}$$

$$\overline{\boldsymbol{\tau}_p^{sail}} = \frac{d_p^{leg}}{\overline{\boldsymbol{s}_p}} \ \forall p \in P \tag{15}$$

$$\overline{\boldsymbol{f}_p} = \frac{\gamma(\overline{\boldsymbol{s}_p})^{(\alpha-1)}}{24} \ \forall p \in P \tag{16}$$

$$\overline{\boldsymbol{\tau}_{p+1}^{arr}} = \overline{\boldsymbol{\tau}_p^{dep}} + \overline{\boldsymbol{\tau}_p^{sail}} \ \forall p \in P, p < m^1 \tag{17}$$

$$\overline{\boldsymbol{\tau}_1^{arr}} = \overline{\boldsymbol{\tau}_p^{dep}} + \overline{\boldsymbol{\tau}_p^{sail}} - \overline{\boldsymbol{VTT}} \ \forall p \in P, p = m^1 \tag{18}$$

$$\overline{\boldsymbol{\tau}_p^{hand}} = (\sum_{h \in H_p} \left(\frac{d_p^{port}}{pr_{ph}}\right) x_{ph} + \delta_p^{port} y_p^{port})\left(1 - \boldsymbol{x}_p^{skip}\right) \ \forall p \in P \tag{19}$$

$$\overline{\boldsymbol{\tau}_{p+1}^{wait}} \geq \tau_{p+1}^{st} - \left(\overline{\boldsymbol{\tau}_p^{dep}} + \overline{\boldsymbol{\tau}_p^{sail}}\right) \forall p \in P, p < m^1 \tag{20}$$

$$\overline{\boldsymbol{\tau}_1^{wait}} \geq \tau_1^{st} - \left(\overline{\boldsymbol{\tau}_p^{dep}} + \overline{\boldsymbol{\tau}_p^{sail}}\right) + \overline{\boldsymbol{VTT}} \ \forall p \in P, p = m^1 \tag{21}$$

$$\overline{\boldsymbol{\tau}_p^{del}} \geq \overline{\boldsymbol{\tau}_p^{arr}} - \tau_p^{arr} \ \forall p \in P \tag{22}$$

$$\overline{\boldsymbol{\tau}_p^{dep}} = \overline{\boldsymbol{\tau}_p^{arr}} + \overline{\boldsymbol{\tau}_p^{wait}} + \overline{\boldsymbol{\tau}_p^{hand}} \ \forall p \in P \tag{23}$$

$$\boldsymbol{x}_p^{skip} \leq y_p^{port} \ \forall p \in P \tag{24}$$

$$\overline{\boldsymbol{VTT}} = \sum_{p \in P} \overline{\boldsymbol{\tau}_p^{sail}} + \sum_{p \in P} \overline{\boldsymbol{\tau}_p^{wait}} + \sum_{p \in P} \overline{\boldsymbol{\tau}_p^{hand}} \tag{25}$$

$$\overline{\boldsymbol{REV}} = \sum_{p \in P} c_p^{cargo} d_p^{port} \left(1 - \boldsymbol{x}_p^{skip}\right) \tag{26}$$

$$\overline{\boldsymbol{PHC}} = \sum_{p \in P} \sum_{h \in H_p} c_{ph}^{port} d_p^{port} + \sum_{p \in P} c_p^{skip} \boldsymbol{x}_p^{skip} \tag{27}$$

$$\overline{\boldsymbol{LAC}} = \sum_{p \in P} c_p^{del} \overline{\boldsymbol{\tau}_p^{del}} \tag{28}$$

$$\overline{\boldsymbol{FCC}} = \sum_{p \in P} c_p^f d_p^{leg} \overline{\boldsymbol{f}_p} \tag{29}$$

$$\overline{\boldsymbol{CIC}} = \sum_{p \in P} c^{inv} d_p^{sea} \overline{\boldsymbol{\tau}_p^{sail}} \tag{30}$$

$$VOC = c^{oper} \phi V \tag{31}$$

$$\overline{\boldsymbol{TP}} = [\overline{\boldsymbol{REV}} - (\overline{\boldsymbol{PHC}} + \overline{\boldsymbol{LAC}} + \overline{\boldsymbol{FCC}} + \overline{\boldsymbol{CIC}} + VOC)] \tag{32}$$

The objective function (11) in the **GVSRP** mathematical model aims to minimize the total profit loss suffered throughout liner shipping due to disruptions in sea and/or at ports of call for the liner shipping route, which passes via ECAs. Constraint set (12) calculates the vessel sailing speed for the recovered vessel schedule at each voyage leg of the given liner shipping route, which passes via ECAs. The proposed model assumes that the sailing speed adjustment recovery option cannot be selected for the vessel schedule recovery by the liner shipping company at the voyage legs, where a disruptive event occurs in sea (i.e., the liner shipping company cannot increase the vessel sailing speed at the voyage leg that is experiencing disruptions). Constraint sets (13) and (14) establish the limits (maximum and minimum values) of the vessel sailing speed at each voyage leg of the liner shipping route, which passes via ECAs. Constraint set (15) computes the vessel sailing time at each voyage leg of the given liner shipping route, which passes via ECAs, based on the recovered vessel schedule. Constraint set (16) calculates the fuel consumption at each voyage leg of the given liner shipping route, which passes via ECAs, based on the recovered vessel schedule.

Constraint sets (17)-(23) compute a number of important components for the recovered vessel schedule, including: (i) the vessel arrival time; (ii) the vessel handling time; (iii) the vessel waiting time; (iv) the vessel arrival delay; and (v) the vessel departure time. Constraint set (24) ensures that a port of the given liner shipping route, which passes via ECAs, can be skipped only if a disruptive event occurs at the port. Constraint set (25) estimates the actual total turnaround time of the vessel. Constraint sets (26)-(32) estimate all the cost components of the objective function (11) for the **GVSRP** mathematical model. The cost components include: (i) the actual total revenue; (ii) the actual total port handling cost; (iii) the actual total late vessel arrival cost; (iv) the actual total fuel cost; (v) the actual total container inventory cost; (vi) the total vessel operational cost; and (vii) the actual total profit for the recovered vessel schedule. As discussed earlier, the unit fuel cost $c_p^f, p \in P$ (USD/ton) changes when the vessel is sailing at voyage legs within and outside ECAs. In order to comply with the existing IMO regulations, the liner shipping company must use a more expensive low-sulfur fuel when sailing through ECAs ($c_p^f = c^{MGO}\ \forall p \in P^*$, where c^{MGO} – is the unit cost of MGO). However, the liner shipping company will change the fuel selection to cheaper HFO fuel at the voyage legs outside ECAs ($c_p^f = c^{HFO}\ \forall p \in P^0$, where c_p^{HFO} – is the unit cost of HFO).

3.4. Solution Methodology

The **GVSRP** mathematical model, which is proposed in this study, is nonlinear due to constraint set (15), which computes the actual vessel sailing time at each voyage leg, and constraint set (16), which calculates the actual fuel consumption at each voyage leg of the liner shipping route, which passes via ECAs. To linearize constraint set (15), the reciprocal of the actual vessel sailing speed $\boldsymbol{v}_p = \frac{1}{\overline{s_p}}\ \forall p \in P$ will be used to substitute the actual vessel sailing speed $\overline{\boldsymbol{s}_p}, p \in P$ in the model. Also, the planned sailing speed

$s_p, p \in P$ will be substituted with its reciprocal $\dot{v}_p = \frac{1}{s_p}$ $\forall p \in P$. Moreover, there is the need to adjust the expected vessel sailing speed reduction due to a disruptive event at a certain voyage leg ($\delta_p^{sea}, p \in P$ – measured in knots).

Let $\delta_p^{\dot{s}ea}, p \in P$ represent the expected vessel sailing speed change due to a disruptive event at a certain voyage leg, measured in knots^{-1} (note that the parameter is altered to the reciprocal of the vessel sailing speed change for consistency). Also, let $\Delta_p^{\dot{s}ea}, p \in P$ represent the vessel sailing speed adjustment at a given voyage, measured in knots^{-1}. The fuel consumption function, which is estimated using the reciprocal of the vessel sailing speed $\boldsymbol{v}_p, p \in P$, is denoted by $\boldsymbol{FC}_p, p \in P$ (tons). The piecewise linear static secant approximation will be adopted throughout this study to linearize the **GVSRP** mathematical model. Based on liner shipping literature, the number of secant lines is predefined for static piecewise linear secant approximations (Dulebenets, 2015a).

The piecewise function $\overline{\boldsymbol{FC}}_{pr}, p \in P, r \in K$ estimates the nonlinear function $\boldsymbol{FC}_p, p \in P$ for a given number of linear segments; here, $K = \{1, \dots, r\}$ represents a set of linear segments in the piecewise function. Also, let $\boldsymbol{b}_{pk} = 1$ if segment k is selected to approximate the fuel consumption function at voyage leg p of the liner shipping route (=0 otherwise). Let $st_k, k \in K$ represent the vessel speed reciprocal value at the start of linear segment k. Denote ed_k, $k \in K$ as the vessel speed reciprocal value at the end of linear segment k. Let $SL_k, k \in K$ represent the slope of linear segment k. Denote $IN_k, k \in K$ as the intercept of linear segment k. Let M_1 and M_2 be sufficiently large positive numbers. The mixed-integer nonlinear **GVSRP** mathematical model can be further reformulated as a mixed-integer linear mathematical model. The model, which will be referred to as **GVSRPL**, is presented as follows.

Linearized Green Vessel Schedule Recovery Problem (**GVSRPL**):

$$min\ [TP - \overline{\boldsymbol{TP}}] \tag{33}$$

Subject to:

Constraint sets (17)-(28), (30)-(32)

$$\boldsymbol{v}_p \geq \dot{v}_p + \delta_p^{\dot{s}ea} y_p^{sea} + \Delta_p^{\dot{s}ea}(1 - y_p^{sea})\ \forall p \in P \tag{34}$$

$$\boldsymbol{v}_p \geq \frac{1}{s^{max}}\ \forall p \in P \tag{35}$$

$$\boldsymbol{v}_p \leq \frac{1}{s^{min}} + \delta_p^{\dot{s}ea} y_p^{sea}\ \forall p \in P \tag{36}$$

$$\overline{\boldsymbol{\tau}_p^{sail}} = d_p^{leg}\ \boldsymbol{v}_p\ \forall p \in P \tag{37}$$

$$\sum_{k \in K} \boldsymbol{b}_{pk} = 1\ \forall p \in P \tag{38}$$

$$st_k \boldsymbol{b}_{pk} \leq \boldsymbol{v}_p\ \forall p \in P, k \in K \tag{39}$$

$$ed_k + M_1(1 - \boldsymbol{b}_{pk}) \geq \boldsymbol{v}_p\ \forall p \in P, k \in K \tag{40}$$

$$\overline{\boldsymbol{FC}}_{pk} \geq SL_k \boldsymbol{v}_p + IN_k - M_2(1 - \boldsymbol{b}_{pk})\ \forall p \in P, k \in K \tag{41}$$

$$\overline{\boldsymbol{FCC}} = \sum_{p \in P} \sum_{k \in K} c_p^f d_p^{leg} \overline{\boldsymbol{FC}}_{pk} \tag{42}$$

The objective function (33) in the proposed **GVSRPL** mathematical model aims to minimize the total profit loss suffered throughout liner shipping due to disruptions in sea and/or at ports of call for the liner shipping route, which passes via ECAs. Constraint set (34) calculates the reciprocal of the vessel sailing speed at the voyage legs of the given liner shipping route, which passes via ECAs, based on the recovered vessel schedule. Constraint sets (35) and (36) establish the limits for the reciprocal of the vessel sailing speed at the voyage legs of the given liner shipping route, which passes via ECAs. Constraint set (37) computes the vessel sailing time using the reciprocal of the vessel sailing speed at the voyage legs of the given liner shipping route, which passes via ECAs, based on the recovered vessel schedule. Constraint set (38) guarantees that only one linear segment will be selected to approximate the fuel consumption function at the voyage legs of the given liner shipping route, which passes via ECAs, based on the recovered vessel schedule.

Constraint sets (39) and (40) establish the bounds for the reciprocal of the vessel sailing speed, when a given linear segment k is selected to approximate the fuel consumption function, at the voyage legs of the given liner shipping route, which passes via ECAs. Constraint set (41) computes the fuel consumption based on the reciprocal of the vessel sailing speed at the voyage legs of the given liner shipping route, which passes via ECAs, based on the recovered vessel schedule. Constraint set (42) calculates the actual total fuel cost that will be endured by the liner shipping company.

Some preliminary numerical experiments were performed, and the results indicated that the **GVSRPL** mathematical model can be solved to the global optimality using CPLEX for the realistic-size liner shipping routes and within an acceptable computational time. Hence, there is no need to develop other approximate solution approaches for the **GVSRPL** mathematical model. CPLEX will be adopted in this study as the solution approach. Generally, an increase in the number of linear segments in the piecewise approximation for the fuel consumption function enhances its accuracy.

However, this may result in an increase in the computational time required to solve the **GVSRPL** mathematical model (because of increasing number of variables in the **GVSRPL** mathematical model). Additional computational experiments were conducted in this study to examine the effects of increasing number of linear segments in the piecewise approximation on the accuracy of the fuel consumption function and computational time (see section 3.5.2 for more details).

3.5. Computational Experiments

This section of the dissertation chapter presents the numerical experiments that were conducted to showcase how the proposed **GVSRPL** mathematical model could be used for decision making by liner shipping companies faced with disruptive events at the liner shipping routes, which pass via ECAs. A Dell Inspiron AMD FX-9800P Processor with 16 GB of RAM was used in conducting all the numerical experiments in this study. Moreover, the procedure for generating the piecewise secant approximations, which were further applied to linearize the fuel consumption function, was developed using MATLAB 2016a software (MathWorks, 2019).

The **GVSRPL** mathematical model was encoded in the General Algebraic Modeling System (GAMS, 2019) and solved to the global optimality using CPLEX. The next section of the manuscript presents the following: (1) input data generation; (2) development of the piecewise approximation for the fuel consumption function; and (3) managerial insights.

3.5.1. Input Data Generation

The Asia-North Europe LL5 liner shipping route, which passes via ECAs is considered in this study. The liner shipping route, used as a case study (see Figure 14), is served by OOCL liner shipping company (OOCL, 2019). Note that the information provided in Figure 14 was extracted from the data, provided by OOCL (2019). The considered liner shipping route connects Asia, Arabian Sea, Red Sea, North Africa, Malta, and North Europe. It can be observed in Figure 14 that the Asia-North Europe LL5 liner shipping route passes via the North Sea and the English Channel, where the IMO has imposed SO_x emission restrictions (and designated these areas as ECAs). A total of 14 ports of call are included in the port rotation for the Asia-North Europe LL5 liner shipping route, where the Port of Le Havre (France) is visited twice. Every week, each port of the liner shipping route is visited once. Using the world seaports catalogue (Ports.com), the distances between the consecutive ports of the liner shipping route in nautical miles were estimated and are presented in parenthesis:

1. Port of Le Havre, France (335) → 2. Port of Rotterdam, Netherlands (341) → 3. Port of Hamburg, Germany (426) → 4. Port of Antwerp, Belgium (244) → 5. Le Port of Le Havre, France (2538) → 6. Port of Marsaxlokk, Malta (1917) → 7. Port of Jeddah, Saudi Arabia (6470) → 8. Port of Nansha, China (1400) → 9. Port of Qingdao, China (439) → 10. Port of Ningbo, China (87) → 11. Port of Shanghai, China (968) → 12. Port of Yantian, China (1114) → 13. Port of Cai Mep, Vietnam (775) → 14. Port of Singapore, Singapore (9087) → 1. Port of Le Havre, France.

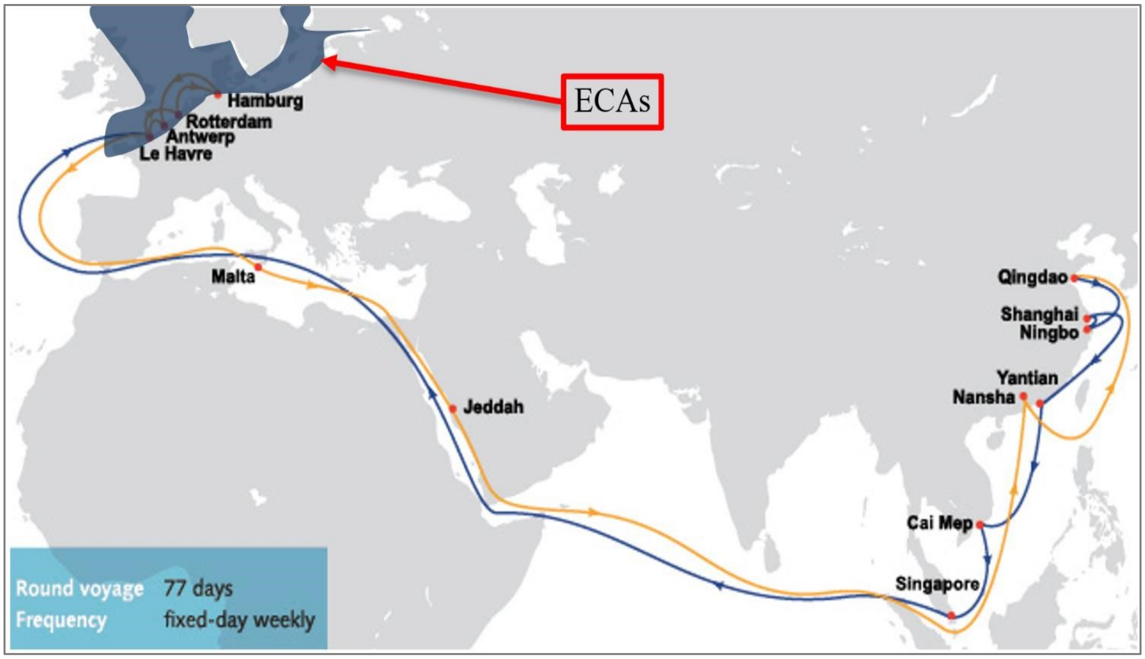


Figure 14 The Asia-North Europe LL5 route

To perform the numerical experiments for this study, the data, which has been widely adopted in the liner shipping literature and the MCT operations literature (Wang and Meng, 2012a-c; Wang et al., 2014; Zampelli et al., 2014; Dulebenets, 2016a-b; Dulebenets, 2018a-f; Dulebenets et al., 2018a-b; Dulebenets, 2019a-c; Abioye et al., 2019; World Shipping Council, 2019; OOCL, 2019, etc.), was adopted in generating the parameter values for the **GVSRPL** mathematical model. The parameter values, used in the computational experiments, are presented in Table 3.

At each port of the port network, the end of TW was computed based on a mathematical relationship that exists between the following components: (1) the end of TW at the preceding port; (2) both the upper and lower limits of the vessel sailing speed; and (3) the length of voyage leg between the consecutive ports in the port rotation. The relationship is defined as follows: $\tau_{p+1}^{ft} = \tau_p^{ft} + \frac{d_p^{leg}}{U[s^{min}; s^{max}]}$ $\forall p \in P$ (hours). Throughout this study, the notation U will be used for the values that are selected from a set of uniformly distributed pseudorandom numbers within a defined interval. The values of the vessel sailing speed were assumed to range from $s^{min} = 15$ knots to $s^{max} = 25$ knots (Wang and Meng 2012a-c).

Table 3 The parameter values used for the numerical experiments

Parameter	Value	Source(s)
Number of ports to be visited: m^1 (ports)	14	OOCL (2019)
Number of available handling rates at ports: m^2 (handling rates)	4	N/A
Agreed port service frequency: φ (hours)	168	OOCL (2019)
Total number of vessels deployed: V (vessels)	15	N/A
Container demand at ports: $d_p^{port}, p \in P$ (TEUs)	$U[200; 2{,}000]$	Dulebenets (2016a, 2018a-d)
Handling productivity at ports: $pr_{ph}, p \in P, h \in H_p$ (TEUs/hour)	$U[50; 125]$	Dulebenets (2016a, 2018a-d)
Fuel consumption coefficients: α, γ	$\alpha = 3.0, \gamma = 0.012$	Wang and Meng (2012b); Psaraftis and Kontovas (2013)
Planned vessel sailing speed: $s_p, p \in P$ (knots)	$U[17; 25]$	N/A
Minimum vessel sailing speed: s^{min} (knots)	15	Wang and Meng (2012a-c)

Table 3 The parameter values used for the numerical experiments – continued

Parameter	Value	Source(s)
Maximum vessel sailing speed: s^{max} (knots)	25	Wang and Meng (2012a-c)
Number of containers transported at voyage legs: $d_p^{sea}, p \in P$ (TEUs)	$U[5{,}000; 8{,}000]$	Dulebenets (2016a, 2018a-d)
Disruption occurrence at ports: $y_p^{port}, p \in P$	Varies depending on the case for disruption occurrence	
Disruption occurrence in sea: $y_p^{sea}, p \in P$	Varies depending on the case for disruption occurrence	
Expected duration of disruptive events at ports: $\delta_p^{port}, p \in P$ (hours)	$U[10; 100]$	N/A
Expected vessel sailing speed change due to disruptive events at voyage legs: $\delta_p^{sea}, p \in P$ (knots)	$-U[0.1; 5.0]$	N/A
Freight rate for shipping a TEU from port p to port $p+1$: $c_p^{cargo}, p \in P$ (USD/TEU)	$U[4{,}000; 6{,}000]$	N/A
Average handling cost at ports: hc^{av} (USD/TEU)	$U[200; 500]$	Dulebenets (2018a-d)
Handling cost at ports: $c_{ph}^{port}, p \in P, h \in H_p$ (USD/TEU)	$c_{ph}^{hand} = hc^{av} \pm U[0; 50]$ $\forall p \in P, h \in H_p$	Dulebenets (2018a-d)
Delayed vessel arrival cost at ports: $c_p^{del}, p \in P$ (USD/hour)	$U[5{,}000; 8{,}000]$	Zampelli et al. (2014); Dulebenets (2018a-d)
Unit HFO cost: c^{HFO} (USD/ton)	200	Wang and Meng (2012a-c)
Unit MGO cost: c^{MGO} (USD/ton)	500	Wang and Meng (2012a-c)
Vessel operational cost: c^{oper} (USD/hour)	1,785.71	Wang and Meng (2012a-c)
Unit container inventory cost: c^{inv} (USD/TEU/hour)	0.50	Wang et al. (2014)
Port skipping inconvenience coefficient: μ	1.10	N/A

Table 3 The parameter values used for the numerical experiments – continued

Parameter	Value	Source(s)
Port skipping cost: $c_p^{skip}, p \in P$ (USD)	$c_p^{skip} = \mu \cdot hc^{av} \cdot d_p^{port}$ $\forall p \in P$	N/A
Planned total profit: TP (USD)	60,000,000	N/A

The expected vessel sailing speed reduction at voyage legs, caused by disruptive events, was assumed to vary between 0.1 knots and 5.0 knots: $\delta_p^{sea} = -U[0.1; 5.0]\ \forall p \in P$ (knots). The expected duration of disruptive events at ports of call was assumed to range between 10 hours and 100 hours: $\delta_p^{port} = U[10; 100]\ \forall p \in P$ (hours). Various scenarios of disruption occurrence in sea and at ports of call will be evaluated throughout the numerical experiments for the considered liner shipping route using the proposed solution methodology (see section 3.5.3 for more details). The weekly container demand at ports of call was assumed to vary between 200 TEUs and 2,000 TEUs: $d_p^{port} = U[200; 2{,}000]\ \forall p \in P$ (TEUs). The number of containers to be transported at voyage legs was assumed to differ between 5,000 TEUs and 8,000 TEUs: $d_p^{sea} = U[5{,}000; 8{,}000]\ \forall p \in P$ (TEUs). It was assumed that the MCT operator at each port could offer four handling rates, from which the liner shipping company could request only one.

The handling productivities for the respective handling rates were assumed to vary between 50 TEUs/hour and 125 TEUs/hour from one port to another. Variations in the handling productivities from one port to another can be explained by the fact that the MCT operators at certain ports may have more handling equipment available for service of the arriving vessels and, therefore, are able to offer the handling rates with higher handling productivities to the liner shipping company as compared to the MCT operators with less handling equipment available. The planned handling time of vessels at port p was estimated using the following relationship: $\tau_p^{hand} = \sum_{h \in H_p} \left(\frac{d_p^{port}}{pr_{ph}} \right) x_{ph} \; \forall p \in P$ (hours). The negotiated handling rate (i.e., the value of parameter $x_{ph}, p \in P, h \in H_p$) was chosen in a random manner from the set of available handling rates at each port of call.

The planned vessel sailing speed was as assigned as follows: $s_p = U[17; 25] \; \forall p \in P$ (knots). The planned arrival time of vessels at port $p + 1$ was estimated as follows: $\tau_{p+1}^{arr} = \tau_p^{arr} + \tau_p^{hand} + \frac{d_p^{leg}}{s_p} \; \forall p \in P$ (hours). As discussed earlier, the port service frequency for the Asia-North Europe LL5 liner shipping route is one week (OOCL, 2019) – $\varphi = 168$ hours. The total number of vessels, deployed for service of ports, was set to $V = 15$ vessels. The vessel handling cost per TEU at port p (which is not skipped) under handling rate h was computed as follows: $c_{ph}^{hand} = hc^{av} \pm U[0; 50] \; \forall p \in P, h \in H_p$ (USD/TEU), where hc^{av} denotes the average handling cost.

The average handling cost was assumed to range between 200 USD/TEU and 500 USD/TEU: $hc^{av} = U[200; 500] \; \forall p \in P$ (USD/TEU). Note that higher average handling costs were imposed by the MCT operator for the handling rates with higher handling productivities. The freight rate for shipping a TEU from port p to $p + 1$ was assumed to vary between 4,000 USD/TEU and 6,000 USD/TEU: $c_p^{cargo} = U[4{,}000; 6{,}000] \; \forall p \in P$

(USD/TEU). The values, adopted for the delayed vessel arrival cost, varied between 5,000 USD/hour and 8,000 USD/hour: $c_p^{del} = U[5{,}000; 8{,}000]\ \forall p \in P$ (USD/hour) (Zampelli et al., 2014; Dulebenets, 2018a-d).

In this study, the unit cost of HFO fuel was set to $c^{HFO} = 200$ USD/ton, while the unit cost of MGO fuel was assumed to be $c^{MGO} = 500$ USD/ton. As a part of the numerical experiments, an additional sensitivity analysis will be performed to investigate the sensitivity of the change in unit cost of HFO and the unit cost of MGO (see section 3.5.3.1 for more details). The unit container inventory cost was set to $c^{inv} = 0.50$ USD/TEU/hour (Wang et al. 2014, Dulebenets, 2018a-d). The vessel weekly operational cost was set to $c^{oper} = 300{,}000$ USD/week (or $c^{oper} = 1{,}785.71$ USD/hour), while the planned total profit to be generated by the liner shipping company was assumed to be $TP = 60{,}000{,}000$ USD.

The cost of skipping port p was computed based on the container demand at that port and the average port handling cost at that port as follows: $c_p^{skip} = \mu \cdot hc^{av} \cdot d_p^{port}$ (USD), where μ – is the port skipping inconvenience coefficient. Initially, the port skipping inconvenience coefficient was assumed to be $\mu = 1.10$. As a part of the numerical experiments, an additional sensitivity analysis will be performed to investigate the impact of varying the unit port skipping inconvenience coefficient on the **GVSRPL** mathematical model (see section 3.5.3.2 for more details).

Table 4 The piecewise approximation analysis results

Scenario ID	Segments, $\lvert K \rvert$	$\boldsymbol{Z}$, 10^6 USD	$\boldsymbol{Z}^*$, 10^6 USD	$\boldsymbol{\nabla}$, %	CPU time, sec
1	2	1.6392	1.6407	0.092	0.7
2	3	1.6393	1.6401	0.048	0.6
3	4	1.6397	1.6401	0.028	0.7
4	5	1.6400	1.6403	0.018	0.7
5	6	1.6402	1.6404	0.011	0.7
6	7	1.6401	1.6402	0.008	0.7
7	8	1.6402	1.6403	0.007	0.8
8	9	1.6402	1.6403	0.006	0.8
9	10	1.6403	1.6403	0.004	0.8
10	15	1.6404	1.6404	0.002	0.8
11	20	1.6404	1.6404	0.001	0.9
12	30	1.6405	1.6405	0.001	0.9
13	40	1.6401	1.6401	0.000	2.3
14	50	1.6404	1.6404	0.000	2.7
15	60	1.6404	1.6404	0.000	3.3
16	70	1.6402	1.6403	0.000	3.6
17	80	1.6403	1.6403	0.000	3.8
18	90	1.6403	1.6403	0.000	14.9
19	100	1.6402	1.6402	0.000	17.2

3.5.2. Development of the Piecewise Approximation for the Fuel Consumption Function

A set of numerical experiments were performed to examine the interrelation between the following: (1) the number of linear segments in the piecewise function; (ii) the accuracy of the fuel consumption function approximation; and (iii) the computational time that is needed to solve the **GVSRPL** mathematical model. In total, 19 scenarios were generated by changing the number of linear segments in the piecewise function from 2 to 100 as presented in Table 4. Also, Figure 15 illustrates the examples of piecewise approximations of the nonlinear fuel consumption function $FC(v) = \frac{0.012(v)^{-2}}{24}$ for the scenarios with 1 linear segment, 2 linear segments, 5 linear segments, and 10 linear segments. From Figure 15, it can be observed that an increase in the number of linear segments led to an increase in the accuracy of approximation for $FC(\boldsymbol{v})$.

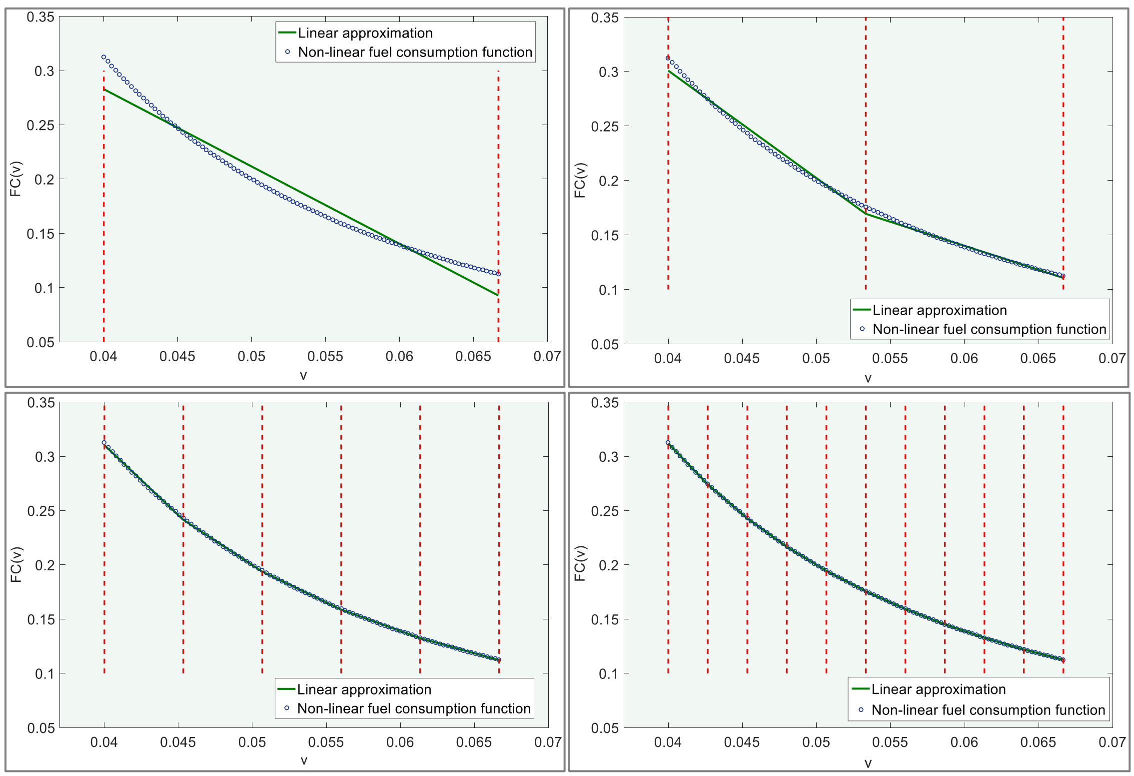


Figure 15 The examples of fuel consumption function linear approximations

Furthermore, the **GVSRPL** mathematical model was solved for each scenario presented in Table 4, using a defined number of linear segments. Throughout this phase of the computational experiments, it was assumed that there are no disruptions in sea and/or at ports of call. The results, which were extracted from the numerical experiments are presented in Table 4. The information presented include: (i) the scenario ID; (ii) the number of linear segments – $|K|$; (iii) the **GVSRPL** objective function value – $\boldsymbol{Z}$; (iv) the value of nonlinear objective function at the solution, which was provided by **GVSRPL** – $\boldsymbol{Z}^*$; (v) the objective gap $\boldsymbol{\nabla} = \left|\frac{\boldsymbol{Z}^*-\boldsymbol{Z}}{\boldsymbol{Z}^*}\right|$; and (vi) the average value of CPU time over a total of 10 replications. Based on the results, a significant increase in computational time of the **GVSRPL** was observed when the values for the number of linear segments were higher than 30. However, there was no substantial change in the objective gap. Thus, for the approximation of the fuel consumption function, a piecewise function with 30 linear segments will be used throughout the numerical experiments. A piecewise function with 30 linear segments will also be used in the analysis of the managerial insights.

Table 5 The considered unit fuel cost values for the generated problem instances

Instance	Unit HFO cost (USD/ton)	Unit MGO cost (USD/ton)
1	200	500
2	250	550
3	300	600
4	350	650
5	400	700
6	450	750
7	500	800
8	550	850
9	600	900
10	650	950

3.5.3. Managerial Insights

Using the numerical data generated, a total of 10 problem instances were created by varying the unit cost of both HFO and the unit cost of MGO with an addition of 50 USD/ton. The problem instances that were developed are presented in Table 5. The solution methodology, presented in this study, was applied to solve the **GVSRPL** mathematical model for all the problem instances considered. In addition, a total of three hypothetical cases of disruptions were evaluated for each problem instance. The cases of disruption considered include:

1) Case 1: No Disruptions in Sea and at Ports

   First, an ideal condition was considered, in which there are no disruptions in sea that may substantially impact the planned vessel sailing speed at voyage legs of the liner shipping route examined in this study. Moreover, disruptions at ports of call that may result in significant delays in vessel service were not considered in this case. The vessels visit all the ports of call in the port rotation.

2) Case 2: Disruptions in Sea and at Ports within ECAs

   The second case models disruptions in sea at certain voyage legs and at specific ports of call within ECAs. This case models a strike at the Port of Antwerp (Belgium) with an expected duration of $\delta_4^{port} = 50$ hours. Moreover, there is a disruption in sea due to poor weather conditions at voyage leg "4", which links the Port of Antwerp (Belgium) and the Port of Le Havre (France). The latter disruptive event is expected to reduce the planned vessel sailing speed at voyage leg "4" by $\delta_4^{sea} = -4.0$ knots. Note that for the considered liner shipping route, the Port of Antwerp (Belgium) and the Port of Le Havre (France) are both situated inside ECAs, where the liner shipping company can only use low-sulfur MGO fuel.

3) Case 3: Disruptions in Sea and at Ports within and outside ECAs

The third case models disruptions in sea at certain voyage legs and at specific ports of call within and outside ECAs. In this case, there is a strike at the Port of Antwerp (Belgium), which is expected to last for $\delta_4^{port} = 50$ hours. Also, some handling equipment units are reported to malfunction at the Port of Le Havre (France), which resulted in a disruption in vessel service at the port with an expected duration of $\delta_5^{port} = 85$ hours. In addition, the Port of Marsaxlokk (Malta) experiences a bottleneck, which caused a disruption that is expected to last for $\delta_6^{port} = 15$ hours. In addition, disruptions in sea, caused by poor weather conditions are reported at voyage leg "3", which links the Port of Hamburg (Germany) and the Port of Antwerp (Belgium), voyage leg "4", which links the Port of Antwerp (Belgium) and the Port of Le Havre (France), and voyage leg "5", which links the Port of Le Havre (France) and the Port of Marsaxlokk (Malta). The disruptions reported at the voyage legs are expected to decrease the planned vessel sailing speed by $\delta_3^{sea} = -3.8$ knots, $\delta_4^{sea} = -4.0$ knots, and $\delta_5^{sea} = -0.8$ knots, respectively. Note that for the considered liner shipping route, the ports that are linked by voyage legs "1" to "4" are within the areas that are designated as ECAs, while the other ports are outside the ECAs.

Furthermore, as a part of the numerical experiments, the sensitivity of the **GVSRPL** mathematical model to variation in the unit costs of HFO and MGO fuels and the port skipping cost will be analyzed sections 3.5.3.1 and 3.5.3.2 of the dissertation, respectively.

3.5.3.1. Sensitivity of the recovered vessel schedules to the unit fuel costs

This section discusses the effects of changing unit fuel costs (both HFO and MGO) on the recovered vessel schedules with a primary emphasis on the following three aspects: (a) port skipping decisions; (b) vessel sailing speed and sailing time; and (c) total profit loss and its components.

(a) Port skipping decisions

Throughout the numerical experiments, the port skipping decisions made from using the **GVSRPL** mathematical model were identified for all the problem instances and each one of the three disruption cases considered. Results from the computational experiments revealed that changes in the unit cost of HFO and MGO did not impact the port skipping decisions. Moreover, the disruption type was found to be the major factor, which influenced the port skipping decisions. Figure 16 presents the port skipping decisions, retrieved from the **GVSRPL** mathematical model for the disruption cases considered.

For disruption case 1 (where there were no disruptions in sea and at ports within and outside ECAs), it was found that the vessels did not skip any port of call – see Figure 16(a). Therefore, the liner shipping company was inclined to maintain the planned vessel schedule despite increasing the unit cost of HFO and MGO. However, for disruption case 2 (where there were disruptions in sea and at ports within ECAs), the liner shipping company decided that skipping the Port of Antwerp (Belgium) (located within an ECA) was the most favorable decision in order to effectively recover the vessel schedule after the disruptive events - Figure 16(b).

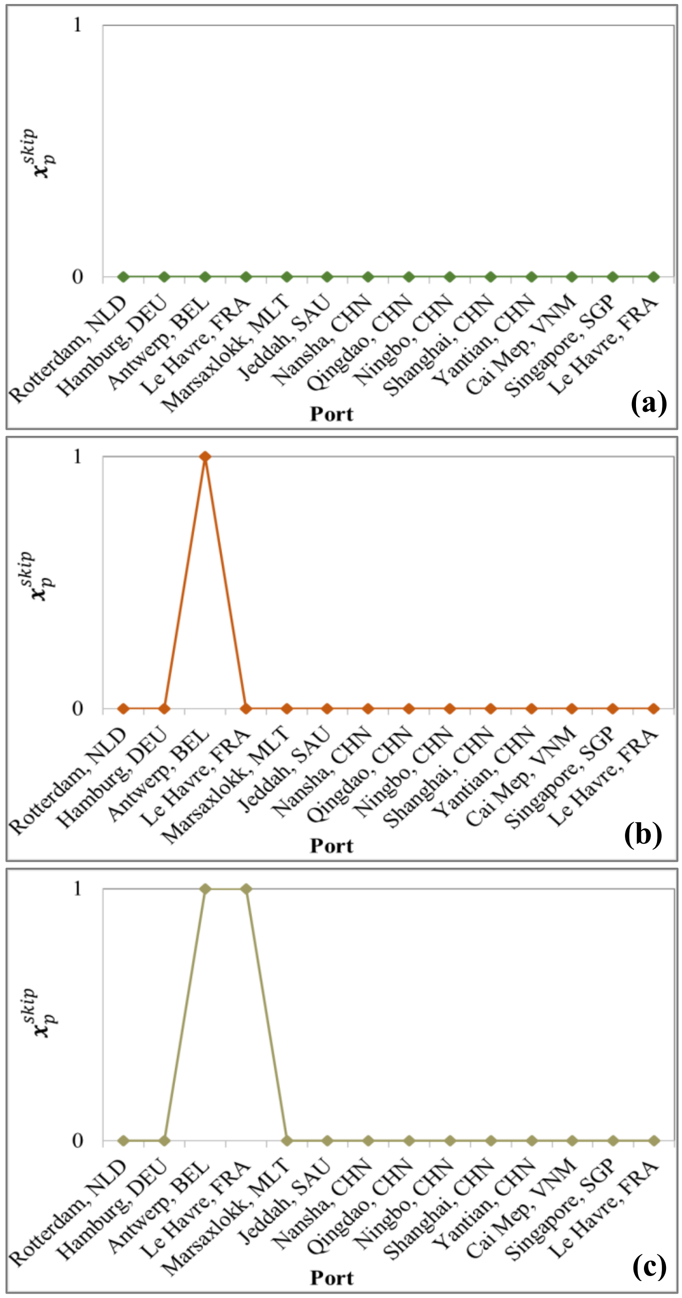


Figure 16 The port skipping decisions for the considered disruption cases: (a) disruption case 1; (b) disruption case 2; and (c) disruption case 3

On the other hand, for disruption case 3 (where there were disruptions in sea and at ports within and outside ECAs), the liner shipping company decided that skipping the

Port of Antwerp (Belgium) and the Port of Le Havre (France) was the most favorable decision in order to efficiently recover the vessel schedule after the disruptive events - Figure 16(c). Hence, based on the results from conducted numerical experiments, it was found that as the number of disruptive events increased along the given liner shipping route, there were significant changes in the vessel schedule that mandated the liner shipping company to execute recovery strategies that can be considered as more radical (i.e., port skipping instead of vessel sailing speed adjustment).

Furthermore, an increase in the unit fuel cost further restricts the implementation of the vessel sailing speed adjustment strategy by the liner shipping company. The latter can be explained by the fact that an increase in the unit fuel cost as well as increasing vessel sailing speed are likely to substantially increase the actual total fuel cost. Note that an increase in the actual total fuel cost will lead to a reduction in the actual total profit to be generated by the liner shipping company.

(b) Vessel sailing speed and sailing time

Throughout the numerical experiments, the average value of the vessel sailing speed adjustment at voyage legs, suggested by the **GVSRPL** mathematical model was estimated for all the generated problem instances as well as disruption cases 2 and 3. Figure 17 presents the average vessel sailing speed adjustment for the considered problem instances and disruption cases 2 and 3. In addition, the average vessel sailing speed obtained from using the **GVSRPL** mathematical model was calculated for all the considered problem instances as well as disruption cases 1, 2, and 3. Figure 18 presents the average vessel sailing speed for the considered problem instances. In this study, the vessel sailing speed adjustment was not estimated for disruption case 1 because there were no disruptions in sea and/or at ports considered in this case.

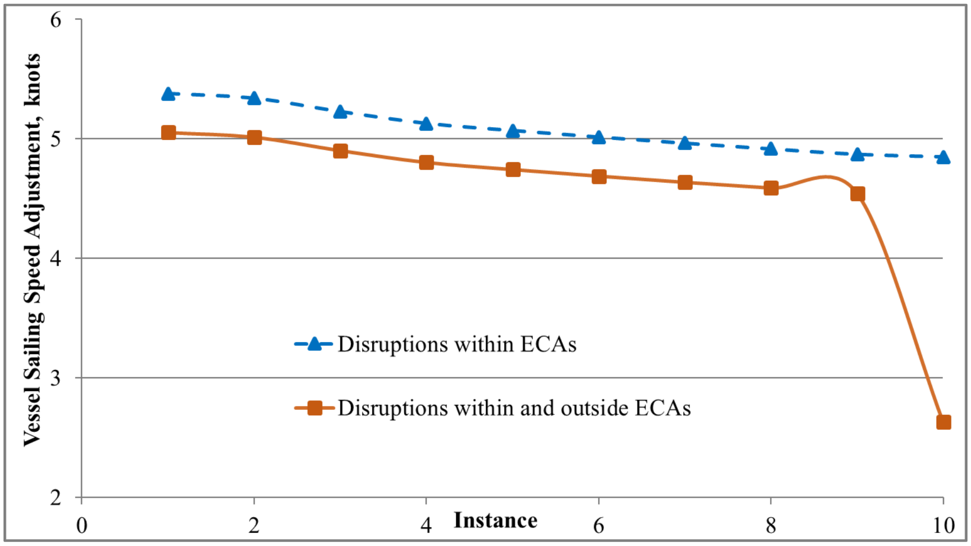


Figure 17 The average vessel sailing speed adjustment for the considered problem instances

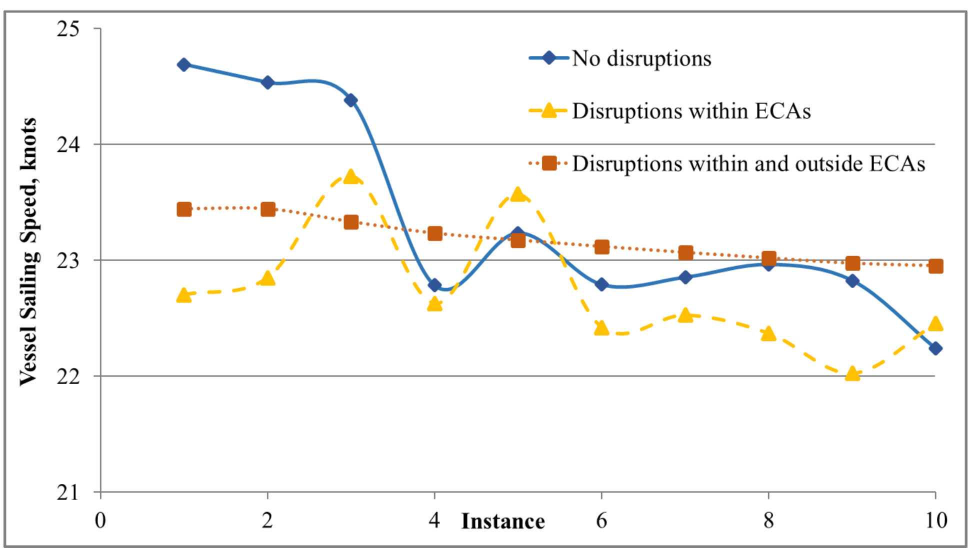


Figure 18 The average vessel sailing speed for the considered problem instances

From the results presented in Figure 18, a number of changes in the average vessel sailing speed were noticed as the unit cost of HFO and MGO increases even for disruption case 1. However, the vessel sailing speed adjustment was not selected by the liner shipping company as the vessel schedule recovery strategy. Throughout the numerical experiments, in addition to the average vessel sailing speed adjustment and the average vessel sailing speed, the total vessel sailing time was calculated for all the generated problem instances as well as disruption cases 1, 2, and 3 using the **GVSRPL** mathematical model. Figure 19 presents the total vessel sailing time for the considered problem instances.

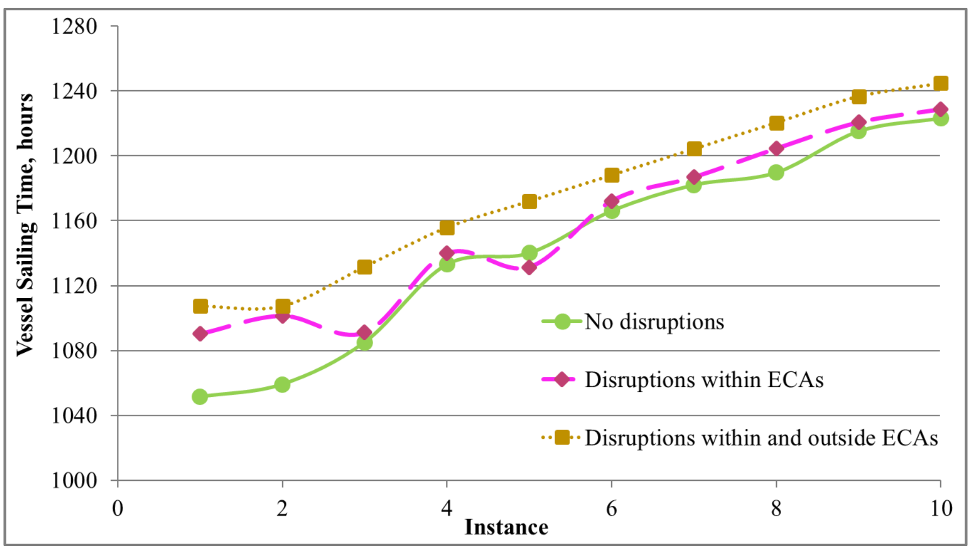


Figure 19 The total vessel sailing time for the considered problem instances

Results from the numerical experiments reveal that the average vessel sailing speed was lower for disruption cases 2 and 3 when compared to disruption case 1, which led to an increase in the total vessel sailing time. The latter pattern can be justified by the fact that certain disruptive events at some voyage legs resulted in a significant reduction in the planned vessel sailing speed (i.e., the vessel sailing speed values selected under disruption cases 2 and 3). Moreover, the liner shipping company could not sail at the planned vessel sailing speed for disruption cases 2 and 3 (i.e., achieve the vessel sailing speed values used under disruption case 1) despite the application of the vessel sailing speed adjustment strategy.

Furthermore, increasing the unit cost of HFO and MGO generally led to a reduction in the average vessel sailing speed for each one of the considered disruption cases. The reduction in the average vessel sailing speed can be supported by the fact that the liner shipping company aimed to reduce the actual fuel consumption as well as the corresponding cost. Also, increasing the unit cost of HFO and MGO led to a reduction in the average vessel sailing speed adjustment for the recovered vessel schedules for both disruption cases 2 and 3.

Additionally, some variations in the average vessel sailing speed can be observed from one problem instance to another. The latter can be justified by the fact that the arithmetic average vessel sailing speed does not take into account the length of voyage legs. However, more logical orders were observed for the total vessel sailing time, due to the fact that it does not only account for the vessel sailing speed but also for the length of voyage legs: $\overline{\boldsymbol{\tau}_p^{sail}} = \frac{d_p^{leg}}{\overline{s_p}}\ \forall p \in P$ (hours). Generally, higher total vessel sailing time values were recorded when disruptions occur in sea and at ports within and outside ECAs (i.e., disruption case 3), as compared to when disruptions occur in sea and at ports within ECAs only (i.e., disruption case 2). Thus, it can be concluded that an increase in the number of disruptive events along the considered liner shipping route resulted in major changes in the planned vessel schedule and consequently increased the total vessel sailing time.

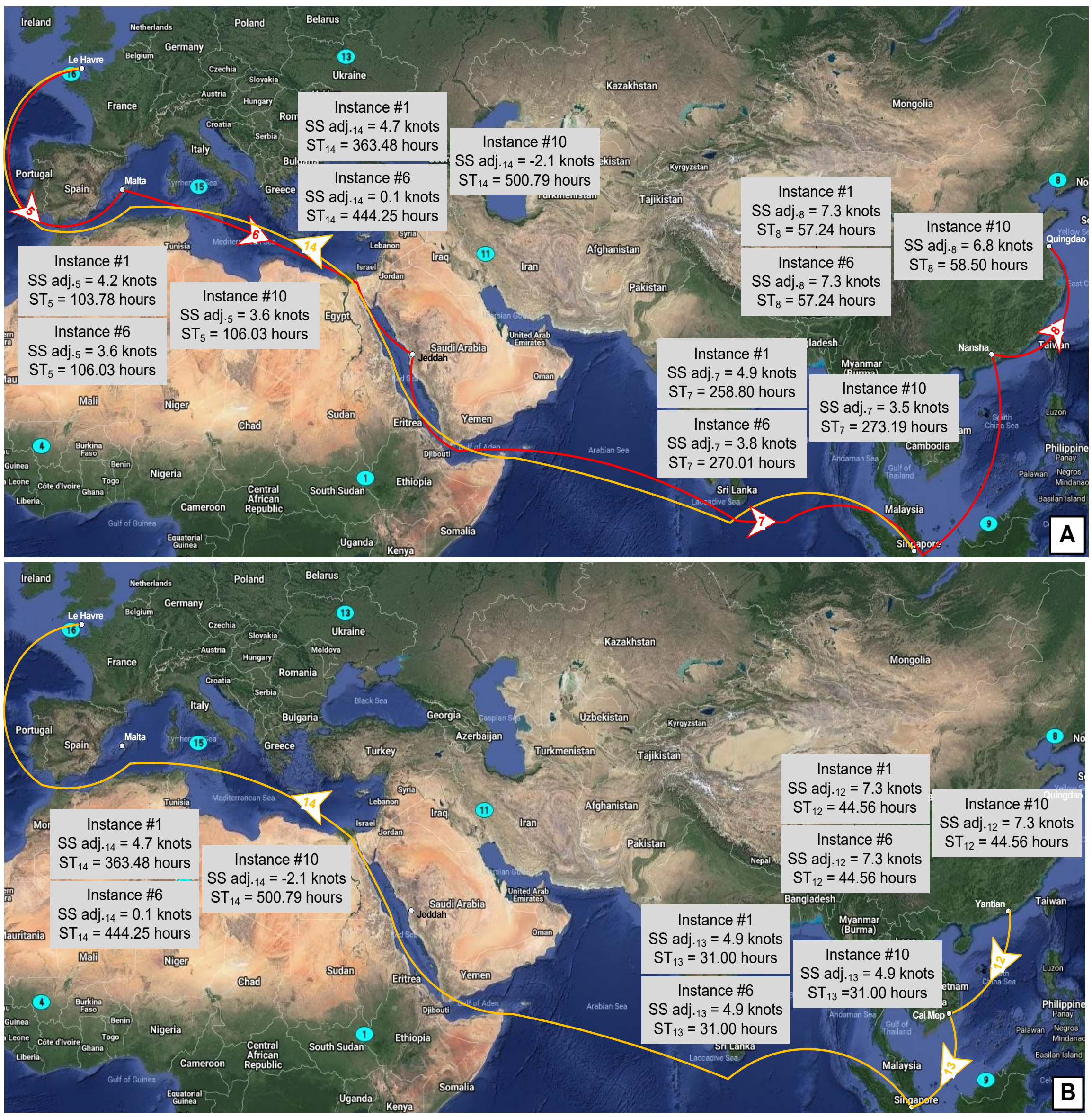


Figure 20 The vessel sailing speed adjustment and the total vessel sailing time outside ECAs for: (A) disruption case 2; and (B) disruption case 3

The scope of numerical experiments conducted in this study also included a detailed evaluation of changes in the vessel sailing speed adjustment and the total sailing time at each voyage leg of the given liner shipping route due to increasing unit cost of HFO and MGO for disruption cases 2 and 3. The vessel sailing speed adjustment and the total sailing time at some of the voyage legs, passing outside ECAs, are presented in Figure 20 for problem instances 1, 6 and 10 and disruption cases 2 and 3.

Note that increasing unit cost of HFO and MGO did not substantially affect the vessel sailing speed adjustment and the total sailing time at the voyage legs, passing within ECAs. Based on the results, retrieved from the **GVSRPL** mathematical model, it can be observed that increasing unit cost of HFO and MGO generally decreased the vessel sailing speed adjustment but increased the total sailing time for disruption case 2. Similar effects of the unit fuel cost on the vessel sailing speed adjustment and the total sailing time were recorded for disruption case 3 as well.

(c) Total profit loss and its components

The objective function of the **GVSRPL** mathematical model and its components were retrieved for all the generated problem instances and disruption cases (see Figure 21). The cost components that were estimated include: (1) the total profit loss endured by the liner shipping company – $\boldsymbol{Z}$; (2) the actual total profit – $\overline{\boldsymbol{TP}}$; (3) the actual total revenue – $\overline{\boldsymbol{REV}}$; (4) the actual total port handling cost – $\overline{\boldsymbol{PHC}}$; (5) the actual total late vessel arrival cost – $\overline{\boldsymbol{LAC}}$; (6) the actual total fuel cost – $\overline{\boldsymbol{FCC}}$; and (7) the actual total container inventory cost – $\overline{\boldsymbol{CIC}}$.

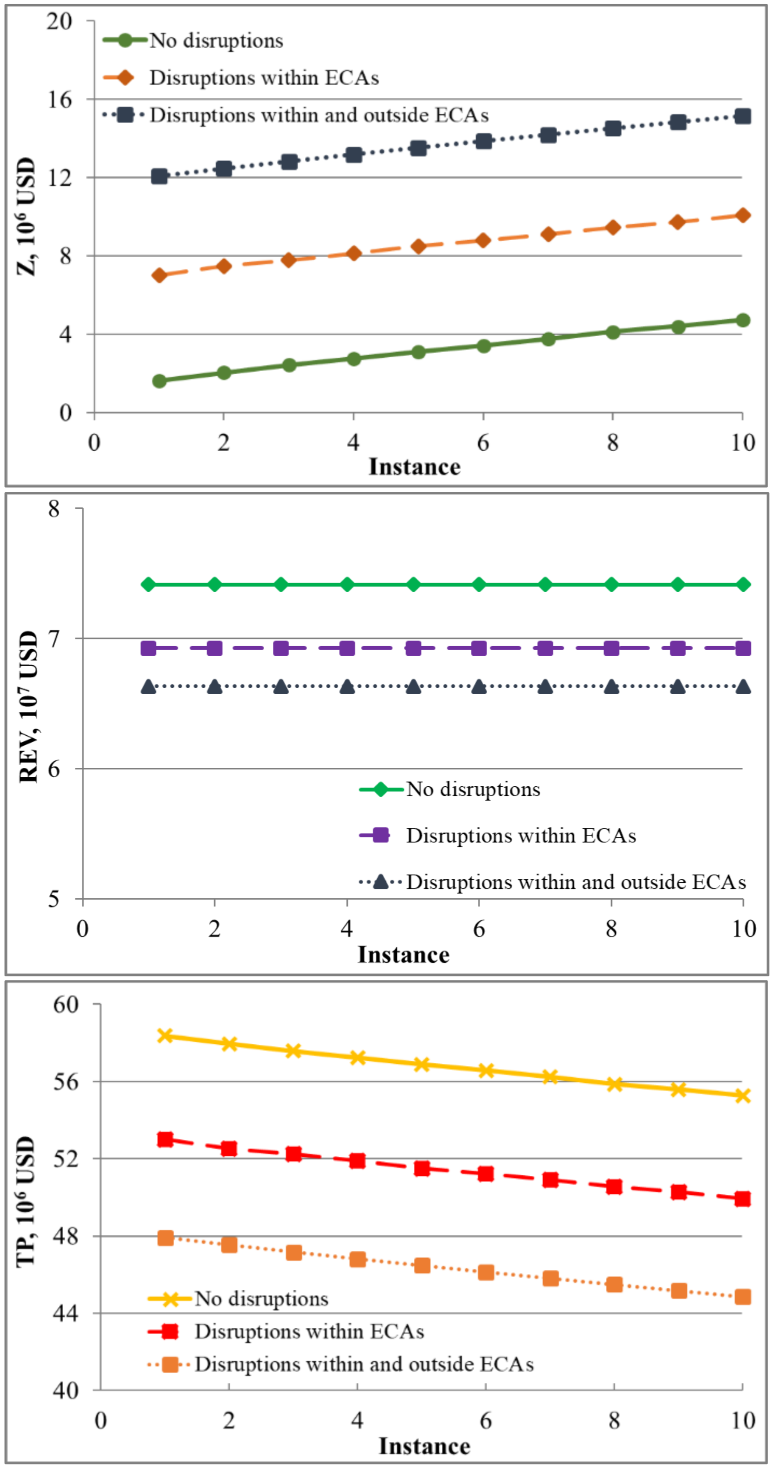


Figure 21 The objective function and its components

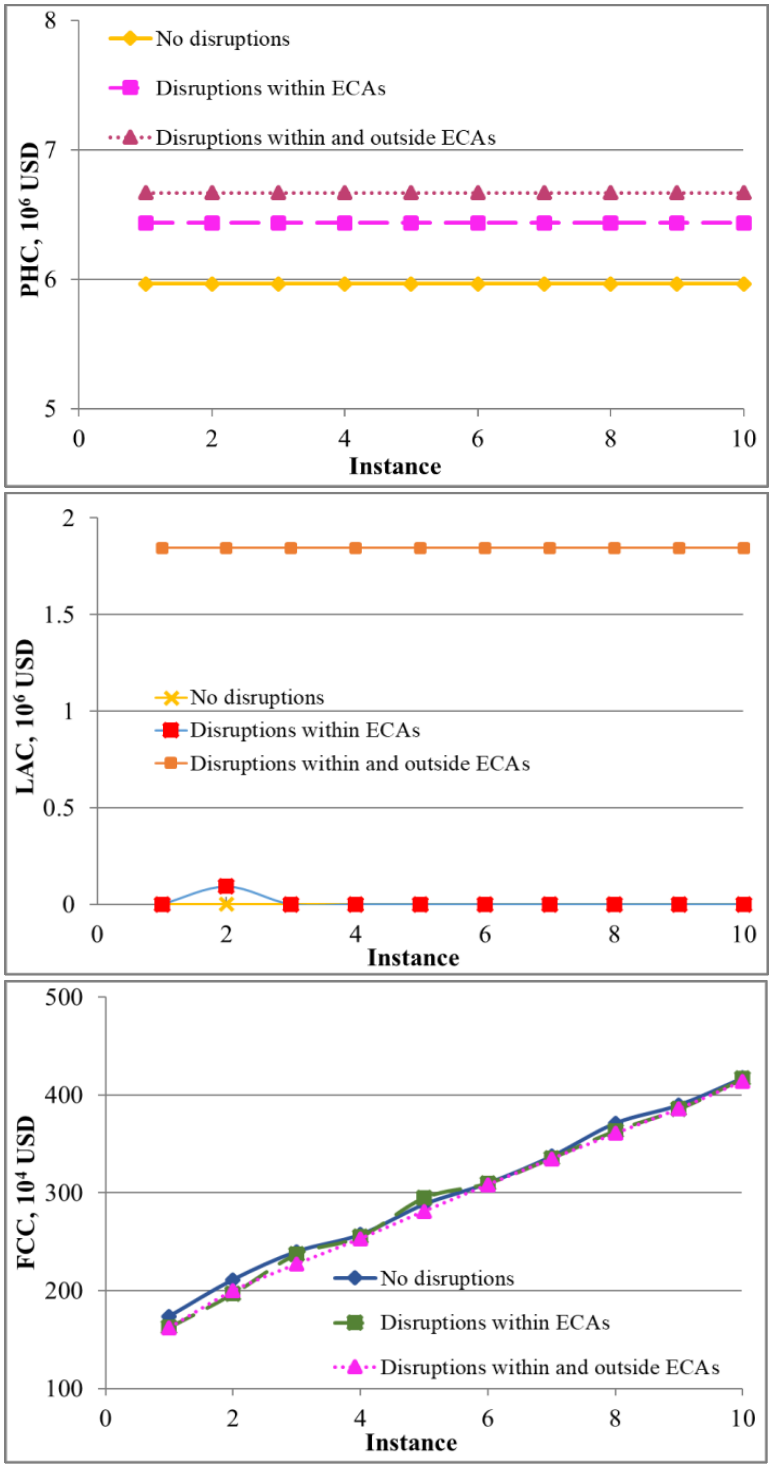


Figure 21 The objective function and its components – continued

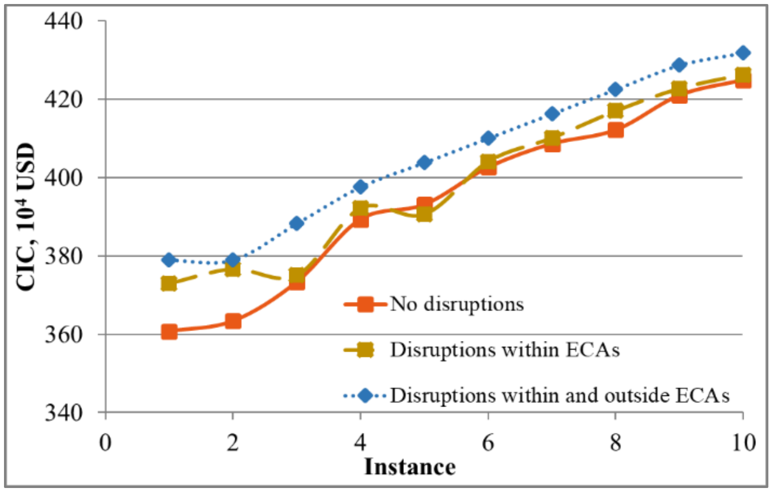


Figure 21 The objective function and its components – continued

Based on the conducted numerical experiments, it was found that the actual total revenue, generated by the liner shipping company was lower for disruption cases 2 and 3 as compared to disruption case 1. The latter can be explained by the fact that the liner shipping company had to skip certain ports of call and was not able to generate any revenue from serving these ports. Specifically, in disruption case 2 (disruptions occur in sea and at ports within ECAs), the liner shipping company had to skip the Port of Antwerp (Belgium). On the other hand, in disruption case 3 (disruptions occur in sea and at ports within and outside ECAs), the liner shipping company was required to skip the Port of Antwerp (Belgium) and the Port of Le Havre (France) in order to effectively recover the vessel schedule.

Furthermore, the actual total port handling cost was higher for disruption cases 2 and 3 as compared to disruption case 1, since the liner shipping company endured the additional port skipping costs. The actual total fuel cost increased with increasing unit cost of HFO and MGO from one problem instance to another for all the considered disruption cases. Also, an increase in the unit cost of HFO and MGO generally decreased the average vessel sailing speed for all the considered disruption cases, which further increased the sailing time at the voyage legs of the given liner shipping route and the actual total container inventory cost. Higher container inventory costs were typically recorded for disruption cases 2 and 3 as compared to disruption case 1 due to the additional delays that were caused by disruptions in sea and at ports within and outside ECAs. Moreover, as a result of disruptions, the vessels were not able to arrive within the agreed port arrival TWs, which further increased the actual total late vessel arrival cost.

Throughout the numerical experiments, it was found the actual total profit, generated by the liner shipping company, decreased with increasing unit cost of HFO and MGO from one problem instance to another for all the considered disruption cases. The latter increased the total profit loss endured by the liner shipping company. The least actual total profit and the highest total profit loss were recorded for the case, when disruptions occur in sea and at ports within and outside ECAs (i.e., disruption case 3). However, without application of the appropriate vessel schedule recovery strategies (e.g., vessel sailing speed adjustment and port skipping) the total profit loss is expected to significantly increase.

3.5.3.2. Sensitivity of the recovered vessel schedules to the port skipping cost

This section of the dissertation analyzes the impacts of varying the port skipping cost endured by the liner shipping company on the recovered vessel schedules. As a part of the numerical experiments, the port skipping inconvenience coefficient (μ) value was varied from $\mu = [1.00]$ to $\mu = [10.00]$ with an addition of $[1.00]$. Using the problem instances generated for the disruption cases 2 and 3, the **GVSRPL** mathematical model was solved. The results retrieved from the numerical experiments are presented next for disruption cases 2 and 3.

- Case 2 – Disruptions at voyage leg “4”, which joins the Port of Antwerp (Belgium) and the Port of Le Havre (France), and the Port of Antwerp (Belgium)

Figure 22 presents the results of the port skipping decisions retrieved for all the generated problem instances of disruption case 2 and the Port of Antwerp (Belgium). From Figure 22, it was found that the liner shipping company skipped the Port of Antwerp (Belgium) for all the problem instances considered, when the port skipping inconvenience coefficient was fixed as $\mu = [1.00]$ – see Figure 22(a). The latter finding can be explained by the fact that skipping the Port of Antwerp (Belgium) was the most effective strategy for the liner shipping company to recover the disrupted vessel schedule (i.e., the port skipping cost in this case was lower as compared to the other supplemental route service costs that could be endured by the liner shipping company due to disruptions). However, increasing the port skipping inconvenience coefficient to $\mu = [2.00]$ may substantially increase the port skipping cost to be suffered by the liner shipping company. Thus, the Port of Antwerp (Belgium) was not skipped by the liner shipping company for most of the problem instances analyzed and the port skipping inconvenience coefficient of $\mu = [2.00]$ – see Figure 22(b).

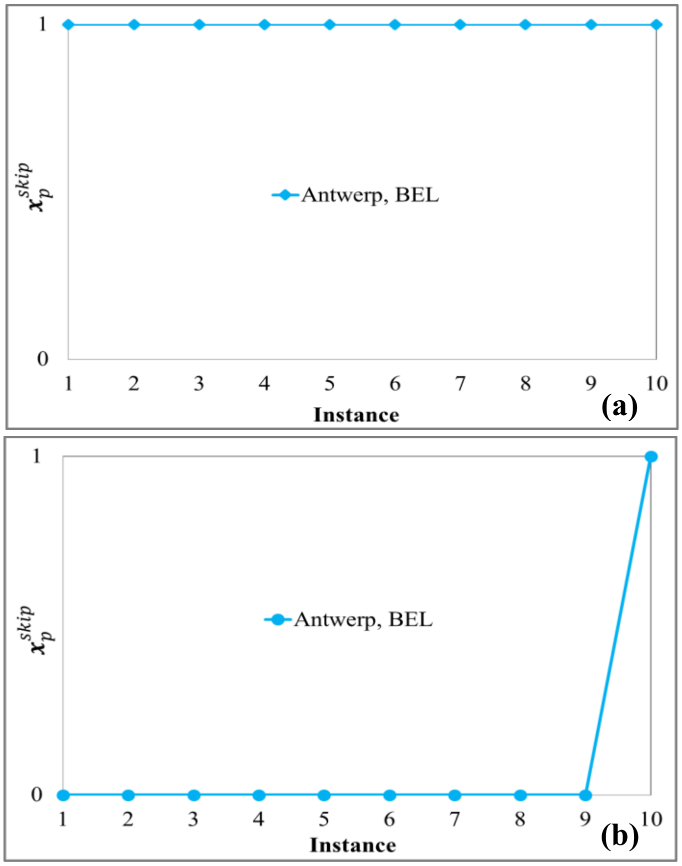


Figure 22 The port skipping decisions for disruption case 2: (a) $\mu = [1.0]$; and (b) $\mu = [2.0]$

It can be observed that the liner shipping company skipped the Port of Antwerp (Belgium) only for problem instance 10, which has the highest unit cost of HFO and MGO. The latter finding can be supported by the fact that the liner shipping company could only make limited changes to the vessel sailing speed because of increasing unit cost of HFO and MGO; thus, skipping the Port of Antwerp (Belgium) was the most favorable vessel schedule recovery option for problem instance 10. Findings from the computational experiments suggest that the port skipping decisions could be substantially impacted with the port skipping cost for various cases of disruptions in sea and at ports within ECAs.

- Case 3 – Disruptions at voyage leg "3", which joins the Port of Hamburg (Germany) and the Port of Antwerp (Belgium), voyage leg "4", which joins the Port of Antwerp (Belgium) and the Port of Le Havre (France), voyage leg "5", which joins the Port of Le Havre (France) and the Port of Marsaxlokk (Malta), and disruptions at the Port of Antwerp (Belgium), the Port of Le Havre (France), and the Port of Marsaxlokk (Malta)

Figure 23 presents the port skipping decisions retrieved for all the generated problem instances of disruption case 3 for the following ports: (a) the Port of Antwerp (Belgium); (b) the Port of Le Havre (France); and (c) the Port of Marsaxlokk (Malta). The results demonstrated that the liner shipping company skipped the Port of Antwerp (Belgium) and the Port of Le Havre (France), which are both located inside the areas designated as ECAs, for all the considered problem instances, when the port skipping inconvenience coefficient was assigned as $\mu = [1.0] \div [7.0]$ – see Figure 23(a). The latter finding can be explained by the fact that skipping the Port of Antwerp (Belgium) and the Port of Le Havre (France) was the most beneficial decision for the liner shipping company in order to effectively recover the vessel schedule (i.e., the port skipping costs were generally lower when compared to the other supplemental route service costs, which could be endured by the liner shipping company as a result of disruptions).

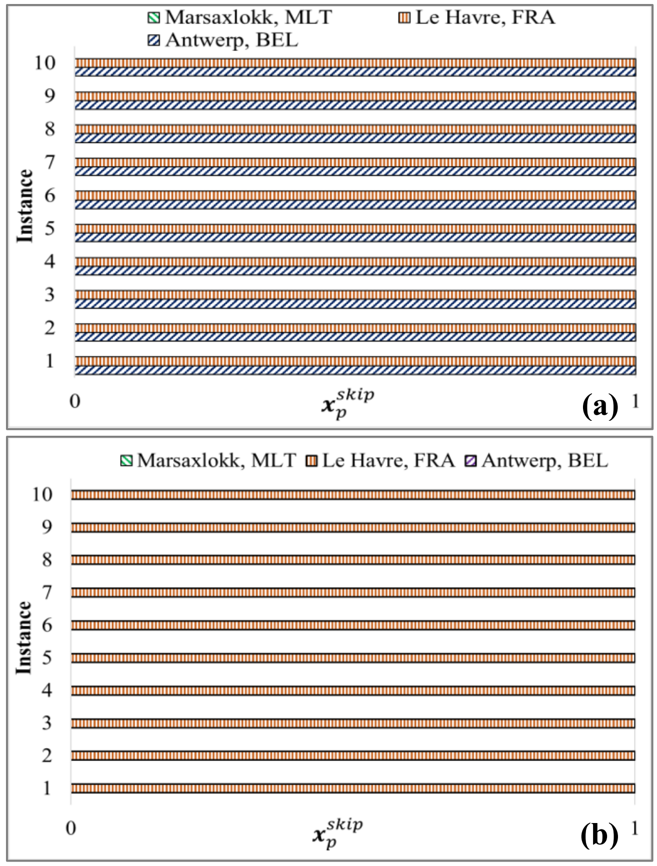


Figure 23 The port skipping decisions for disruption case 3: (a) $\mu = [1.0] \div [7.0]$; and (b) $\mu = [8.0] \div [10.0]$

Furthermore, increasing the port skipping inconvenience coefficient to $\mu = [8.0] \div [10.0]$ might substantially increase the port skipping cost to be suffered by the liner shipping company. In this case, the liner shipping company decided not to skip the Port of Antwerp (Belgium) for all the problem instances considered and when the port skipping inconvenience coefficient was set at $\mu = [8.0] \div [10.0]$ – see Figure 23(b). The results revealed that varying the unit cost of HFO and MGO from one problem instance to another did not affect the port skipping decisions made by the liner shipping company. However, the liner shipping company skipped the Port of Le Havre (France) despite an increment in the port skipping inconvenience coefficient up to $\mu = [8.0] \div [10.0]$ in order to effectively recover the vessel schedule. The latter finding can be explained by the fact that the expected disruption duration of the disruptive event at the Port of Le Havre (France) is higher as compared to the Port of Antwerp (Belgium). Specifically, the disruption at the Port of Le Havre (France) is expected to last for $\delta_5^{port} = 85$ hours, while the disruptive event at the Port of Antwerp (Belgium) is expected to last for $\delta_4^{port} = 50$ hours.

From the computational experiments, it can be deduced that the port skipping decisions might be substantially impacted with the port skipping cost for various cases of disruptions, when disruptive events occur in sea and at ports within and outside ECAs.

3.6. Conclusions

This chapter of the dissertation presented a novel mixed-integer nonlinear mathematical model for the green vessel schedule recovery problem for the liner shipping route, which passes via ECAs. The IMO enforces certain regulations on the sulfur content of fuels used by vessels within ECAs. The mathematical model proposed in this chapter aimed to minimize the total profit loss, suffered by a given liner shipping company because of disruptions in the planned operations. A total of two vessel recovery strategies, which have been widely used in the state-of-the-art and state-of-practice were considered. The latter recovery strategies include: (1) vessel sailing speed adjustment; and (2) port skipping. The nonlinear model was linearized using the static secant approximation method and solved to the global optimality using CPLEX.

A number of numerical experiments were performed for the Asia-North Europe LL5 liner shipping route, which is served by OOCL liner shipping company and passes via ECAs. The results from the numerical experiments demonstrated that an increase in the number of disruptive events in sea and at ports along the given liner shipping route generally yielded substantial changes in the vessel schedule and mandated the liner shipping company to carry out more drastic recovery strategies (i.e., port skipping became favorable as compared to vessel sailing speed adjustment). Furthermore, an increase in the unit fuel cost restricted the execution of the vessel sailing speed adjustment strategy. Note that an increase in the unit cost of fuel and an increase in the vessel sailing speed might significantly increase the actual total fuel cost. The findings from the computational experiments also suggest that the port skipping decisions could be substantially impacted by the port skipping cost for the cases, when disruptive events occur in sea and at ports within and outside ECAs.

The computational experiments demonstrate that the mathematical model proposed in this chapter and the developed solution approach can help liner shipping companies with efficient vessel schedule recovery in the event of disruptions, minimize the monetary losses due to disruptions in vessel schedules, and improve energy efficiency as well as environmental sustainability.

CHAPTER 4

VESSEL SCHEDULE RECOVERY PROBLEM IN LINER SHIPPING: EVALUATION OF VARIOUS RECOVERY OPTIONS

4.1. Background

The major components of vessel operations in liner shipping, such as vessel sailing speed, vessel sailing time between ports of call, arrival time, departure time, and waiting time of vessels at ports, are planned at the tactical level. However, several factors, including natural hazards, adverse weather conditions, port congestion, piracy attacks, labor strikes, and others, may interrupt the planned schedule of vessels and cause a delay throughout the voyage. For example, in the year of 2013, there was a labor strike at the Kwai Tsing container terminal in Hong Kong, which resulted in significant delays in the delivery of cargo and caused liner shipping companies to suffer enormous monetary losses (TradeWinds, 2013). In case of disruptions at a port of call, the liner shipping company may choose to divert the cargo. For instance, the ports on the West Coast of the United States (U.S.) were affected by a labor strike in the year of 2015. Several liner shipping companies were forced to divert some cargo to the Ports of Vancouver and Prince Rupert in Canada, and rail was used for the cargo delivery to the end customers in the U.S. (Purolator, 2016).

Usually, disruptions in liner shipping operations negatively impact schedule adherence as well as the reliability of service. In order to reduce the impacts of disruptions on the planned operations of vessels throughout the voyage, liner shipping companies seek the most efficient schedule recovery strategies that can be adopted in real-time to mitigate delays. The vessel schedule recovery problem in categorized as an operational-level decision problem in liner shipping. Disruption and uncertainty in liner shipping are closely related phenomena (Lee and Song, 2017). Lee and Song (2017) categorized uncertainties into two groups, namely: (1) regular uncertainties (probabilistic events in liner shipping operations that happen repeatedly); and (2) disruption events (infrequent events that occur in shipping operations).

Although liner shipping companies do not plan for disruption events, there is a need to give a dynamic response whenever they occur during a voyage. If a liner shipping company can adequately mitigate the impact of disruptive events on the planned operations with minimal additional cost, it may have a competitive advantage over others. The latter reemphasizes the need for efficient disruption management in liner shipping. The vessel schedule recovery problem in liner shipping has been addressed by a number of researchers. Moreover, various vessel schedule recovery strategies have been suggested in the literature, including vessel sailing speed adjustment, port skipping, and port swapping (Brouer et al., 2013; Li et al., 2015, 2016; Cheraghchi et al., 2018, Abioye et al., 2019).

This chapter of the dissertation presents a novel mixed-integer nonlinear programming model for the vessel schedule recovery problem. The proposed model considers four major vessel schedule recovery strategies, which include: (1) vessel sailing speed adjustment; (2) handling rate adjustment; (3) port skipping; and (4) port skipping with cargo diversion. Despite the fact that some researchers have considered the vessel sailing speed adjustment and the port skipping strategies, none of the studies published on vessel schedule recovery in liner shipping to date have applied handling rate adjustment and port skipping with cargo diversion recovery strategies. The nonlinear mathematical model proposed herein is solved using BARON. A set of numerical experiments are performed for the Middle East-West Mediterranean route, which is served by OOCL liner shipping company. A number of important managerial insights, revealed from using the proposed solution methodology, are presented in this chapter.

4.2. Problem Description

This section of the dissertation presents a description of the vessel schedule recovery problem and the major modeling assumptions.

4.2.1. Liner Shipping Route Description and Vessel Service at Ports

This study considers a liner shipping route, where vessels are required to visit a set of ports $P = \{1, \dots, m^1\}$. It is expected that the port rotation is known, and every port is called once. Note that in some cases, a port could be called more than once during the voyage. Usually, liner shipping companies determine the port rotation and port service frequency at the strategic and tactical levels of decision making, respectively (Meng et al., 2014). Figure 24 presents an example of the liner shipping route, where vessels are expected to serve a total of 7 ports, including the Port of Amsterdam (Netherlands), the Port of Le Havre (France), the Port of Barcelona (Spain), the Port of Radès (Tunisia), the Port of Hangzhou (China), the Port of Ningbo (China), and the Port of Shanghai (China). The vessels deployed for the service of the liner shipping route visit the Ports of Le Havre, Radès, Hangzhou, Ningbo, and Shanghai once, while the Ports of Barcelona and Amsterdam are visited twice.

Figure 25 shows a port rotation graph for the considered liner shipping route. The additional dummy nodes, included in the port rotation graph after a visit to the Port of

Shanghai, are used to illustrate another visit to the Ports of Barcelona and Amsterdam; thus, the total number of ports to be visited becomes $|P| = 7 + 2 = 9$.

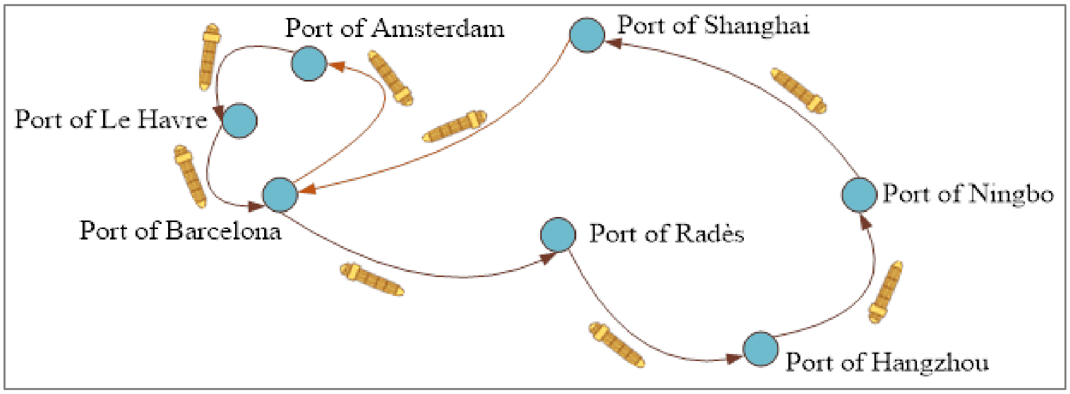


Figure 24 A liner shipping route example

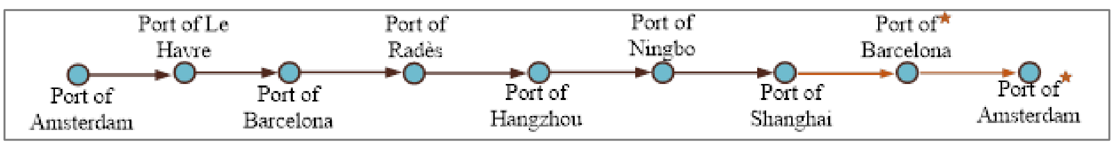


Figure 25 The port rotation graph for the liner shipping route

Usually, the arrival time of vessels at each port of call is planned by the liner shipping companies at the tactical level. Denote $\tau_p^{arr}, p \in P$ (hours) as the planned arrival time of vessels at port p. The liner shipping company and the marine container terminal (MCT) operator at every port of call decide and establish the suitable arrival window (TW). Let $\tau_p^{st}, p \in P$ (hours) represent the start of a TW at port p and $\tau_p^{ft}, p \in P$ (hours) represent the end of a TW at port p. If a vessel arrives at a port of call before the planned arrival TW, the vessel will be moored to a dedicated waiting area at the port and anchored before the start of service. The planned vessel waiting time at port $p + 1$

($\tau_{p+1}^{wait}, p \in P$ – hours) can be estimated based on the beginning of TW at port $p+1$, the planned sailing time between ports p and $p+1$ ($\tau_p^{sail}, p \in P$ – hours), as well as the planned departure time of vessels from port p ($\tau_p^{dep}, p \in P$ – hours), using the following relationship:

$$\tau_{p+1}^{wait} = \tau_{p+1}^{st} - \left(\tau_p^{dep} + \tau_p^{sail}\right) \forall p \in P, p < |P| \tag{43}$$

$$\tau_1^{wait} = \tau_1^{st} - \left(\tau_p^{dep} + \tau_p^{sail}\right) + \varphi \cdot V \, \forall p \in P, p = |P| \tag{44}$$

To calculate the waiting time of vessels at the first port of call (i.e., τ_1^{wait}), there is the need to consider the planned total turnaround time of vessels that are sent off for service of the liner shipping route. The product of the agreed port service frequency (φ – hours) and the total number of vessels dispatched for service of the liner shipping route (V – vessels) yields the planned total turnaround time of vessels (Dulebenets, 2015a, 2018 a-d). In addition, the MCT operator at each port of call offers a set of handling rates $H_p = \{1, \dots, m_p^2\}, p \in P$ to the liner shipping company for the service of vessels at the port. The planned vessel handling time at port p ($\tau_p^{hand}, p \in P$ – hours) can be estimated using the following relationship:

$$\tau_p^{hand} = \sum_{h \in H_p} \left(\frac{d_p^{port}}{pr_{ph}}\right) x_{ph} \, \forall p \in P \tag{45}$$

where:

$d_p^{port}, p \in P$ – weekly container demand at port p (twenty-foot equivalent units – TEUs);

$pr_{ph}, p \in P, h \in H_p$ – handling productivity at port p under handling rate h (TEUs/hour);

$x_{ph}, p \in P, h \in H_p$ – is the handling rate selection parameter (=1 if handling rate h is requested at port p; =0 otherwise).

If the liner shipping company requests handling rate h from the MCT operator at port p for the service of a vessel, the corresponding handling cost ($c_{ph}^{port}, p \in P, h \in H_p$ – USD/TEU) will be charged. Usually, the higher the handling rate, the higher the handling cost. Various types of disruptive events at MCTs (such as port congestion, port infrastructure damages due to natural disasters, vessel service delays due to labor strikes) may lead to an increase in the planned waiting time and handling time of vessels. Let $\overline{\boldsymbol{\tau}_p^{wait}}, p \in P$ (hours) and $\overline{\boldsymbol{\tau}_p^{hand}}, p \in P$ (hours) represent the actual waiting time and handling time of vessels, respectively. Also, if there are disruptions in sea and at ports of call early in voyage, the delay may propagate throughout the voyage and affect the arrival times of vessels at the succeeding ports. In this study, the actual arrival time of vessels at port p will be denoted as $\overline{\boldsymbol{\tau}_p^{arr}}, p \in P$ (hours). The vessel arrival delay at port p ($\overline{\boldsymbol{\tau}_p^{del}}, p \in P$ – hours) can be computed using the following relationship:

$$\overline{\boldsymbol{\tau}_p^{del}} \geq \overline{\boldsymbol{\tau}_p^{arr}} - \tau_p^{arr} \; \forall p \in P \tag{46}$$

A violation of the planned arrival time of vessels at ports is often caused by disruptions in the planned operations at MCTs. If there are any changes in the planned arrival time of vessels at ports of call, a delayed vessel arrival time cost ($c_p^{del}, p \in P$ – USD/hour) will be imposed to the liner shipping company by the MCT operator.

4.2.2. Port Service Frequency

In real life, every liner shipping company is required to provide the negotiated service frequency at each port of the given liner shipping route. Using the following relationship, liner shipping companies can ensure that the agreed port service frequency is met (Wang et al., 2014; Alhrabi et al., 2015; Dulebenets, 2018b-e):

$$\varphi \cdot V = \sum_{p \in P} \tau_p^{sail} + \sum_{p \in P} \tau_p^{wait} + \sum_{p \in P} \tau_p^{hand} \tag{47}$$

Additionally, the planned total vessel turnaround time, which is estimated from the right-hand side of equation (47), may be significantly affected by disruptions in sea and/or at ports. The actual total vessel turnaround time ($\overline{\boldsymbol{VTT}}$ – hours) can be estimated as follows:

$$\overline{\boldsymbol{VTT}} = \sum_{p \in P} \overline{\boldsymbol{\tau}_p^{sail}} + \sum_{p \in P} \overline{\boldsymbol{\tau}_p^{wait}} + \sum_{p \in P} \overline{\boldsymbol{\tau}_p^{hand}} \tag{48}$$

An increase in the actual total vessel turnaround time due to disruptions ($\overline{\boldsymbol{VTT}} > VTT$) may cause the liner shipping company to violate the agreed port service frequency. The latter has negative implications for liner shipping operations and service reliability. However, if the liner shipping company can efficiently implement some vessel schedule recovery actions, any potential deviations from the agreed service frequency caused by disruptions can be prevented.

4.2.3. Fuel Consumption Modeling and Vessel Sailing Speed Selection

Throughout this study, it is assumed that the liner shipping company possesses a homogenous fleet of vessels, which are dispatched for the service of the liner shipping route (Wang et al., 2014; Dulebenets et al., 2015, Dulebenets, 2018b-e). The main technical specifications of homogeneous vessels, including the structure of the main and auxiliary vessel engines, the capacity of the main and auxiliary vessel engines, the maximum vessel sailing speed, and others, are alike. It is important to note that in reality, several factors, such as history of vessel repairs, age of vessels, vessel use, etc., may cause certain changes in the technical characteristics of identical vessels. The latter may affect the accuracy of the assumption of homogeneity.

The planned fuel consumption per nautical mile (nmi) at voyage leg p ($f_p, p \in P$ – tons/nmi) for the vessels dispatched for the service of the liner shipping route can be estimated using the following relationship, which has been used quite often in the available liner shipping literature (Wang and Meng, 2012c):

$$f_p = \frac{\gamma (s_p)^{(\alpha-1)}}{24} \; \forall p \in P \tag{49}$$

where:

α, γ – are the fuel consumption function coefficients;

$s_p, p \in P$ – is the planned sailing speed adopted for vessels at voyage leg p (knots).

Generally, the liner shipping company plans the sailing speed of vessels ($s_p, p \in P$ – knots) at each voyage leg of the liner shipping route at the tactical level of liner shipping planning (Wang et al., 2013a; Wang et al., 2014). The planned sailing time of vessels at voyage leg p can be estimated using the length of voyage leg p ($d_p^{leg}, p \in P$ – nmi) and the planned sailing speed as follows:

$$\tau_p^{sail} = \frac{d_p^{leg}}{s_p} \; \forall p \in P \tag{50}$$

Note that disruptive events in sea (e.g., vessel crew errors, inclement weather) may cause a reduction in the planned sailing speed of vessels at certain voyage legs. In case of the latter, the actual sailing speed at a given voyage leg ($\overline{\boldsymbol{s}_p}, p \in P$ – knots) will be reduced as compared to the planned sailing speed: $\overline{\boldsymbol{s}_p} < s_p, p \in P$. Moreover, a decrease in the planned sailing speed of vessels due to disruptions will result in a decrease in the fuel consumption and the actual fuel consumption cost. On the other hand, a reduction in the planned sailing speed of vessels will cause an increase in the actual sailing time at a given voyage leg ($\overline{\boldsymbol{\tau}_p^{sail}}, p \in P$ – hours). The latter may cause significant delays the planned schedule. A number of factors may influence the sailing speed of vessels that is adopted by the liner shipping company at each voyage leg of the liner shipping route.

Generally, the lower bound on the vessel sailing speed (s^{min} – knots) is imposed to minimize the wear on the vessel's main engine (Wang and Meng, 2012c), while the upper bound on the vessel sailing speed (s^{max} – knots) is determined by the power of the vessel's main engine (Psaraftis and Kontovas, 2013). The total fuel cost (FCC) throughout the voyage can be estimated based on the unit cost of fuel (c^f – USD/ton), the length of voyage leg p ($d_p^{leg}, p \in P$ – nmi), and the planned fuel consumption per nautical mile at voyage leg p ($f_p, p \in P$ – tons/nmi) for the vessels as follows:

$$FCC = c^f \sum_{p \in P} d_p^{leg} f_p \tag{51}$$

4.2.4. Vessel Schedule Disruptions and Recovery

Vessel schedule disruptions may occur as a result of disruptive events in sea and/or at ports. In this study, a total of four major strategies that can be implemented by liner shipping companies to recover the vessel schedule after disruptive events were considered. The proposed recovery strategies include: (1) adjustment of vessel sailing speeds at certain voyage legs of the liner shipping route; (2) adjustment of vessel handling rates at ports of call; (3) port skipping without cargo diversion; and (4) port skipping with cargo diversion. During the voyage, the liner shipping company may decide to endure the delay created by disruptive events. However, if the disruptive event is expected to last for a long time at a certain port of call, the liner shipping company will have to skip the port. The latter action will reduce added liner shipping route service costs that will be incurred as a result of the disruptive event.

If the liner shipping company decides to skip a port because of a disruption, the liner shipping company will be mandated to pay a port skipping cost ($c_p^{skip}, p \in P$ – USD) in order to recompense the MCT operator for the reserved yard storage space, reserved handling equipment, as well as unmet demand. If the liner shipping company skips a port due to a disruptive event, the vessels will not be able to deliver the import containers and pick up the export containers at the skipped port. However, the unmet demand may be diverted from the skipped port to other ports of call. In case of the latter, the liner shipping company will be required to pay an additional cost to ensure that the cargo will be delivered to the designated destinations. Figure 26 shows an example of the port skipping recovery option. The presented example shows a vessel, which was originally scheduled to visit ports "1", "2", "3", "4", and "5", respectively. However, because of a disruptive event that occurred at port "5", the vessel visited only ports "1", "2", "3", and "4", respectively, and skipped port "5".

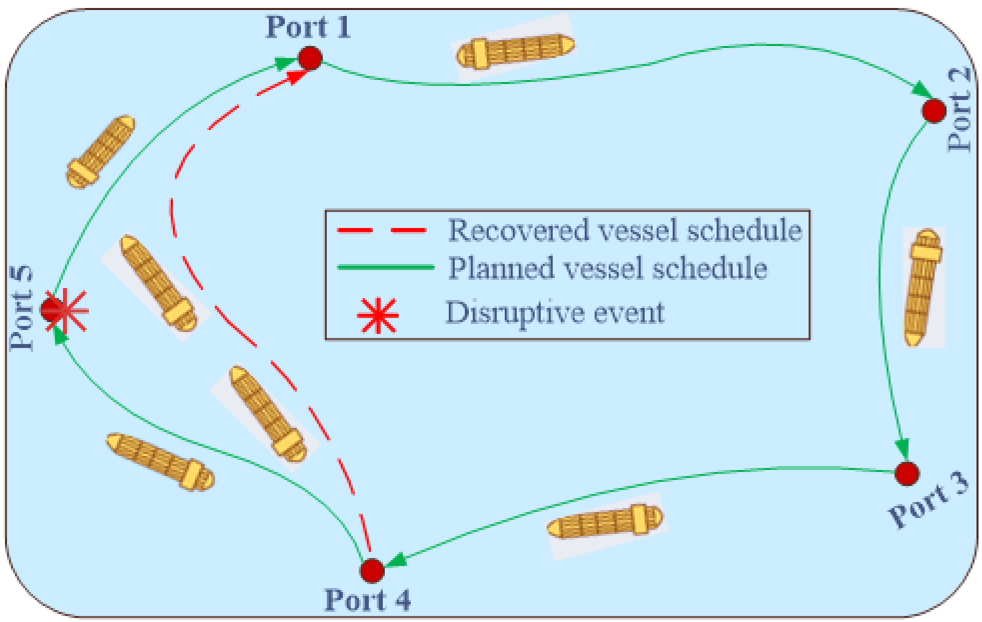


Figure 26 An example of port skipping recovery option

Another strategy that can be used by liner shipping companies to recover the vessel schedule due to disruptions is the vessel sailing speed adjustment. If there is a delay, the liner shipping company may increase the sailing speed at voyage legs. The latter may allow the liner shipping company to recover the schedule and keep the planned arrival time at subsequent ports. This study assumes that a liner shipping company cannot adjust the vessel sailing speed at voyage legs where a disruptive event occurs. An example of the vessel sailing speed adjustment recovery strategy is illustrated in Figure 27. As shown in Figure 27, the vessel that was originally scheduled to visit ports “1”, “2”, “3”, “4”, and “5”, respectively, encountered a disruptive event in sea at voyage leg “2”. To recover the delay caused by the disruption, the liner shipping company increased the planned vessel sailing speed at voyage legs “3” and “4”.

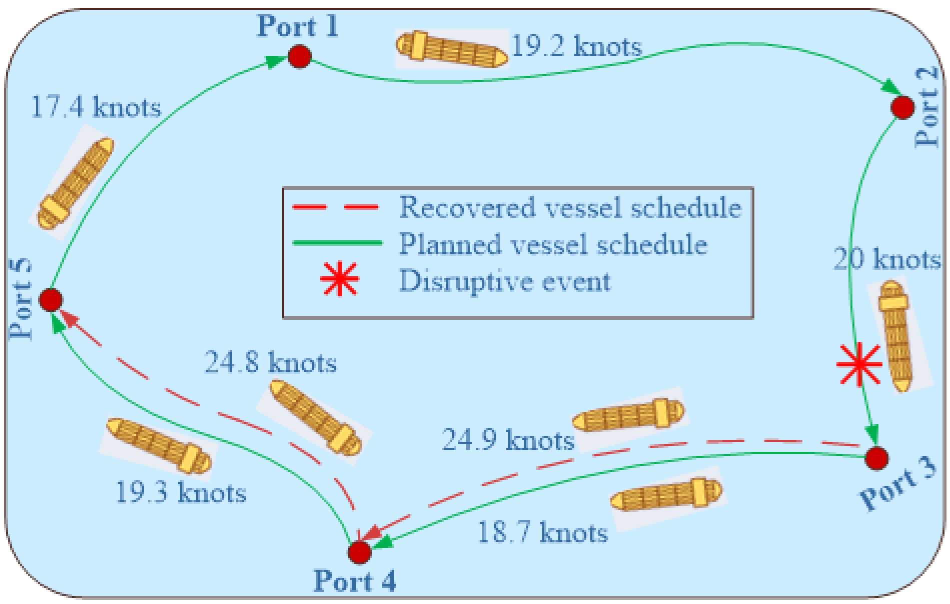


Figure 27 An example of the vessel sailing speed adjustment

Another vessel schedule recovery alternative that can be used to recover the vessel schedule consists in the fact that the liner shipping company is able to request for handling rates with higher handling productivities from the MCT operators at some ports of call (i.e., request handling rates that have higher handling productivities as compared to the originally requested handling rates before a disruptive event occurs). Let $\overline{x_{ph}}, p \in P, h \in H$ be the actual handling rate decision variable (=1 if handling rate h is requested at port p; =0 otherwise). It is assumed that no additional port handling costs ($c_{ph}^{port}, p \in P, h \in H_p$ – USD/TEU) will be imposed to the liner shipping company for the originally negotiated handling rate (i.e., $\overline{\boldsymbol{x}_{ph}} = x_{ph}\ \forall p \in P, h \in H$). Note that if the liner shipping company requests a handling rate with higher handling productivity from the MCT operator at a given port in order to offset the delays caused by a disruption, the MCT operator will levy extra port handling costs that commensurate to the requested handling productivity.

The availability of the port handling rate alternatives may vary from port to port depending on a number of factors (e.g., availability of MCT berthing positions, availability of handling equipment, vessel arrival frequency, disruptions that previously occurred at the MCT). The actual vessel handling time at port p can be calculated using the following relationship:

$$\overline{\boldsymbol{\tau}_p^{hand}} = \sum_{h \in H_p} \left(\frac{d_p^{port}}{pr_{ph}} \right) \overline{\boldsymbol{x}_{ph}}\ \forall p \in P \tag{52}$$

An example of a vessel schedule recovery strategy based on the vessel handling rate adjustment is presented in Figure 28. The horizontal and vertical axes of the time-space network represent the time within the planning horizon (in days) and position of ports, respectively. A vessel, scheduled to visit three ports (ports “1”, “2”, and “3”, respectively), experienced a disruption after departure from port “1”, which resulted in a late arrival at port “2”. In order to recover the schedule and maintain the planned departure from port “2”, the liner shipping company was able to request a handling rate with a handling productivity from the MCT operator at that port. The latter strategy allowed the liner shipping company maintaining a timely arrival to port “2” without increasing the vessel sailing speed.

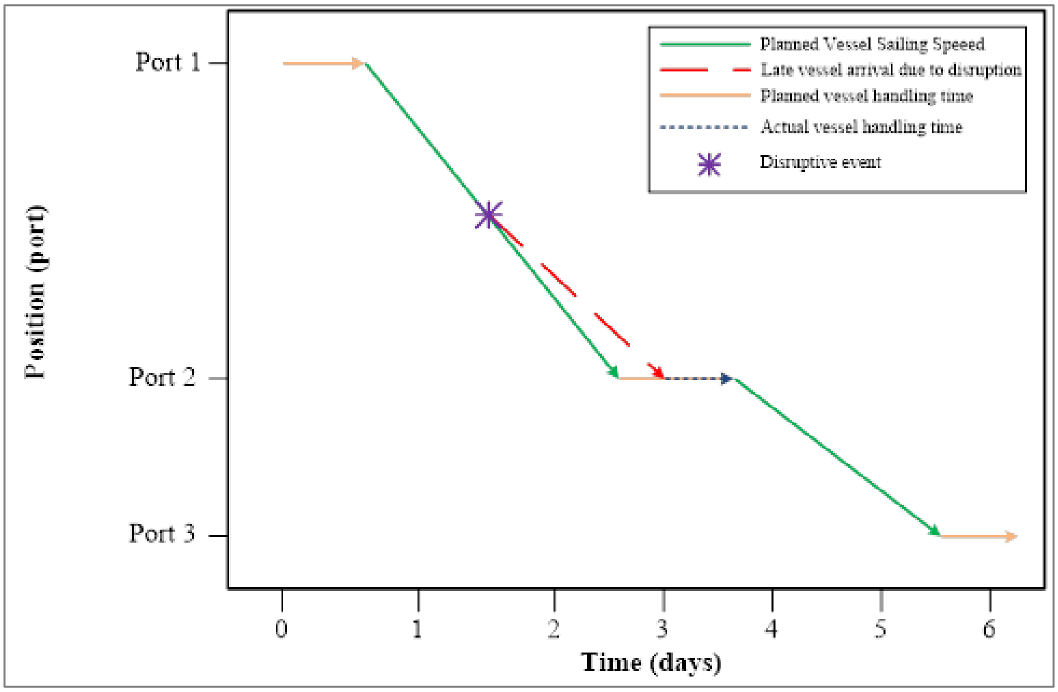


Figure 28 An example of a vessel handling rate adjustment

All the considered vessel schedule recovery strategies (i.e., port skipping with cargo diversion, port skipping without cargo diversion, vessel sailing speed adjustment, and vessel handling rate adjustment) can be implemented by the liner shipping company to recover the vessel schedule from disruptions in sea and/or at ports of call. Depending on the effects of a disruptive event, the liner shipping company may be willing to use several strategies (if they allow reducing additional liner shipping route service costs due to that disruptive event). However, if the cost of implementing the aforementioned vessel schedule recovery strategies is substantial, the liner shipping company may decide to endure the effects of a disruptive event and do not take any additional actions.

4.2.5. Diversion of Cargo from Skipped Ports

If a vessel skips a port, the vessel will not be able to deliver the import containers and pick the export containers at that particular port. The latter will consequently result in cargo misconnection and negatively impact the liner shipping operations. In this study, it is assumed that the container demand at a port that is skipped due to disruptions can be diverted to the subsequent ports of the port rotation. Denote $\boldsymbol{x}_{pp^*}^{div}, p, p^* \in P, p \neq p^*$ as the container diversion decision variable (=1 if containers should be diverted from a port p that experienced a disruption to alternative port p^*; =0 otherwise). Also, it is assumed that the liner shipping company can negotiate service of the diverted demand with the MCT operators and the inland operators at subsequent ports. Note that an additional cost will be charged to the liner shipping company by the MCT operator at port p^* for handling the cargo diverted from port p ($c_{pp^*}^{d-port}, p^* \in P$ – USD/TEU). Moreover, the liner shipping company will be required to reimburse the inland operators for delivery of the diverted cargo from port p^* to the appropriate destinations.

The cost, charged by inland operators for the inland transport of the cargo diverted from port p at port p^*, will be represented as $c_{pp^*}^{d-land}, p, p^* \in P$ (USD/TEU). An example of port skipping with cargo diversion recovery action is illustrated in Figure 29. In Figure 29, the vessel that was scheduled to visit ports “1”, “2”, “3”, “4”, and “5”, respectively, skips port “5” due to a disruption at port “5”. A total of 350 TEUs are diverted from the skipped port (port "5") to port "1", and the diverted demand is delivered to the end customers via intermodal connections of port "1".

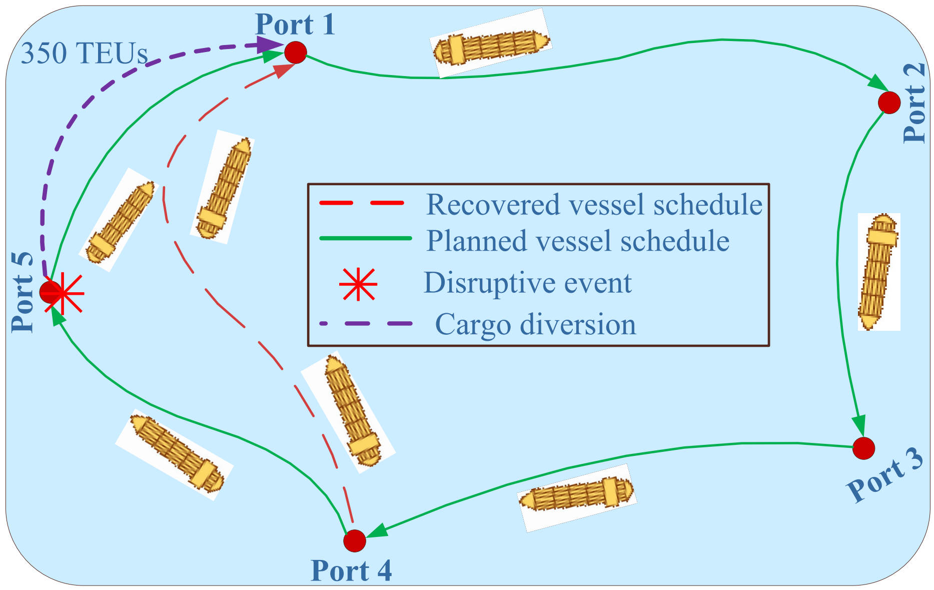


Figure 29 An example of port skipping with cargo diversion

Note that if the MCT operator at port p^* lacks the capacity to handle the diverted demand and/or the inland operators do not have the required resources to transport the diverted cargo from port p^* to the appropriate destinations, the liner shipping company cannot redirect cargo from port p to alternative port p^*. The MCT capacity that can be used for serving the diverted demand at port p will be further referred to as $C_p^{port}, p \in P$ (TEUs), while the inland transport capacity that can be used for delivery of the diverted cargo from port p to the assigned destinations will be denoted as $C_p^{land}, p \in P$ (TEUs). Let $y_{pp^*}, p, p^* \in P, p \neq p^*$ =1 if containers can be diverted from disrupted port p to alternative port p^* (=0 otherwise). Also, if a monetary penalty imposed on the liner shipping company because of misconnected cargo at port p (which will be referred to as $c_p^{mis}, p \in P$ – USD/TEU) as well as the port skipping cost ($c_p^{skip}, p \in P$ – USD) are not as significant as the extra costs that are incurred as a result of the service of the diverted demand at port p^*, the cargo diversion will not be a beneficial alternative.

In addition to the handling and intermodal capacities at the alternative ports, the decision to divert cargo is directly impacted by port location (e.g., the liner shipping company can divert cargo from the Port of Miami to the Port of New York but cannot divert cargo to the Port of Jeddah, as the Port of Miami and the Port of Jeddah are situated on separate continents and do not have any inland connection).

4.2.6. Major Decisions

The VSRP considered in this study can be classified as an operational-level problem in liner shipping operations. The major decisions to be addressed by the liner shipping company include the following:

(1) decide whether to skip the port of call that is affected by a disruptive event or wait until the port recovers from a disruption and can provide service for the arriving vessels;
(2) decide whether to divert the cargo (if a port is skipped) to other ports of call or suffer the cost incurred as a result of misconnected cargo and port skipping;
(3) identify other ports of call, where the cargo should be diverted if a port is skipped (if cargo diversion recovery option is found to be a beneficial alternative);

(4) decide whether to request the handling rates with higher handling productivities from MCT operators at certain ports of call in order to recover the delay caused by a disruptive event;

(5) identify the voyage legs of the liner shipping route, where the vessel sailing speed can be changed in order to minimize or completely remove the delays caused by a disruptive event;

(6) choose the vessel schedule recovery actions that would efficiently reduce vessel late arrivals at ports of the liner shipping route.

4.3. Mathematical Model

This section of the dissertation presents a mixed-integer nonlinear programming model for the vessel schedule recovery problem. The model to be proposed herein will be further referred to as **VSRP-1** throughout this manuscript. Moreover, the notations that will be used in this chapter of the dissertation are presented herein. Other notations will be defined throughout this chapter of the dissertation as required.

Nomenclature

Sets

$P = \{1, \dots, m^1\}$	set of ports to be visited (ports)
$H_p = \{1, \dots, m_p^2\}, p \in P$	set of available handling rates at port p (handling rates)

Decision Variables

$\boldsymbol{x}_p^{skip} \in \mathbb{B}\ \forall p \in P$	=1 if port p is skipped (=0 otherwise)
$\Delta_p^{sea} \in \mathbb{R}\ \forall p \in P$	vessel sailing speed adjustment at voyage leg p (knots)

$\overline{\boldsymbol{x}_{ph}} \in \mathbb{B}\ \forall p \in P, h \in H_p$	=1 if handling rate h is requested at port p (=0 otherwise)
$\boldsymbol{x}_{pp^*}^{div} \in \mathbb{B}\ \forall p, p^* \in P,$ $p \neq p^*$	=1 if containers are diverted from disrupted port p to alternative port p^* (=0 otherwise)

Auxiliary Variables

$\overline{\boldsymbol{s}_p} \in \mathbb{R}^+\ \forall p \in P$	actual sailing speed of vessels at voyage leg p (knots)
$\overline{\boldsymbol{\tau}_p^{arr}} \in \mathbb{R}^+\ \forall p \in P$	actual arrival time of vessels at port p (hours)
$\overline{\boldsymbol{\tau}_p^{wait}} \in \mathbb{R}^+\ \forall p \in P$	actual waiting time of vessels at port p (hours)
$\overline{\boldsymbol{\tau}_p^{hand}} \in \mathbb{R}^+\ \forall p \in P$	actual handling time of vessels at port p (hours)
$\overline{\boldsymbol{\tau}_p^{dep}} \in \mathbb{R}^+\ \forall p \in P$	actual departure time of vessels from port p (hours)
$\overline{\boldsymbol{\tau}_p^{sail}} \in \mathbb{R}^+\ \forall p \in P$	actual sailing time of vessels at voyage leg p that connects ports p and $p+1$ (hours)
$\overline{\boldsymbol{f}_p} \in \mathbb{R}^+\ \forall p \in P$	actual fuel consumption at voyage leg p (tons)
$\overline{\boldsymbol{\tau}_p^{del}} \in \mathbb{R}^+\ \forall p \in P$	vessel arrival delay at port p (hours)
$\boldsymbol{x}_p^{dd} \in \mathbb{B}\ \forall p \in P$	=1 if the diverted containers are handled at port p (=0 otherwise)
$\boldsymbol{d}_{pp^*}^{div} \in \mathbb{N}\ \forall p, p^* \in P,$ $p \neq p^*$	diverted demand from port p to alternative port p^* (TEUs)
$\overline{\boldsymbol{VTT}} \in \mathbb{R}^+$	actual vessel turnaround time (hours)
$\overline{\boldsymbol{REV}} \in \mathbb{R}^+$	actual total revenue to be generated by the liner shipping company (USD)

$\overline{\boldsymbol{PHC}} \in \mathbb{R}^{+}$	actual total port handling cost (USD)
$\overline{\boldsymbol{LAC}} \in \mathbb{R}^{+}$	actual total late vessel arrival cost (USD)
$\overline{\boldsymbol{FCC}} \in \mathbb{R}^{+}$	actual total fuel cost (USD)
$\overline{\boldsymbol{CDC}} \in \mathbb{R}^{+}$	actual total container diversion cost (USD)
$\overline{\boldsymbol{TP}} \in \mathbb{R}^{+}$	actual total profit to be generated by the liner shipping company (USD)

Parameters

$m^1 \in \mathbb{N}$	number of ports to be visited (ports)
$m^2 \in \mathbb{N}$	number of available handling rates at port p (handling rates)
$d_p^{port} \in \mathbb{R}^{+}\ \forall p \in P$	container demand at port p (TEUs)
$d_p^{leg} \in \mathbb{R}^{+}\ \forall p \in P$	length of voyage leg p (nmi)
$pr_{ph} \in \mathbb{R}^{+}\ \forall p \in P,$ $h \in H_p$	handling productivity at port p under handling rate h (TEUs/hour)
$\tau_p^{arr} \in \mathbb{R}^{+}\ \forall p \in P$	planned arrival time of vessels at port p (hours)
$\alpha, \gamma \in \mathbb{R}^{+}$	fuel consumption coefficients
$\varphi \in \mathbb{N}$	agreed port service frequency (hours)
$V \in \mathbb{N}$	number of vessels required for service of ports (vessels)
$s_p \in \mathbb{R}^{+}\ \forall p \in P$	planned vessel sailing speed at port p (knots)
$s^{min} \in \mathbb{R}^{+}$	minimum vessel sailing speed (knots)
$s^{max} \in \mathbb{R}^{+}$	maximum vessel sailing speed (knots)
$d_p^{sea} \in \mathbb{R}^{+}\ \forall p \in P$	number of containers transported at voyage leg p (TEUs)

$y_p^{port} \in \mathbb{B}\ \forall p \in P$	=1 if a disruption occurred at port p (=0 otherwise)
$y_p^{sea} \in \mathbb{B}\ \forall p \in P$	=1 if a disruption occurred at voyage leg p (=0 otherwise)
$\delta_p^{port} \in \mathbb{R}^+\ \forall p \in P$	expected duration of a disruptive event at port p (hours)
$\delta_p^{sea} \in \mathbb{R}\ \forall p \in P$	expected vessel sailing speed change due to a disruptive event at voyage leg p (knots)
$y_{pp^*} \in \mathbb{B}\ \forall p, p^* \in P$, $p \neq p^*$	=1 if containers can be diverted from disrupted port p to alternative port p^* (=0 otherwise)
$C_p^{port} \in \mathbb{R}^+\ \forall p \in P$	MCT capacity to serve the diverted demand at port p (TEUs)
$C_p^{land} \in \mathbb{R}^+\ \forall p \in P$	inland transport capacity for delivery of the diverted demand from port p to the assigned destinations (TEUs)
$\tau_p^{st} \in \mathbb{R}^+\ \forall p \in P$	start of TW at port p (hours)
$\tau_p^{ft} \in \mathbb{R}^+\ \forall p \in P$	end of TW at port p (hours)
$c^f \in \mathbb{R}^+$	unit fuel cost (USD/ton)
$c_p^{cargo} \in \mathbb{R}^+\ \forall p \in P$	freight rate for shipping a TEU from port p to port $p+1$ (USD)
$c_{ph}^{port} \in \mathbb{R}^+\ \forall p \in P$, $h \in H_p$	handling cost at port p under handling rate h (USD/TEU)
$c^{oper} \in \mathbb{R}^+$	vessel operational cost (USD/hour)
$c_p^{del} \in \mathbb{R}^+\ \forall p \in P$	delayed vessel arrival cost at port p (USD/hour)
$c_p^{skip} \in \mathbb{R}^+\ \forall p \in P$	cost for skipping port p due to a disruptive event (USD)

$c_p^{mis} \in \mathbb{R}^+ \ \forall p \in P$	penalty due to misconnected cargo at port p (USD/TEU)
$c_{pp^*}^{d-port} \in \mathbb{R}^+ \ \forall p, p^* \in P,$ $p \neq p^*$	additional cost for handling the cargo diverted from port p at port p^* (USD/TEU)
$c_{pp^*}^{d-land} \in \mathbb{R}^+ \ \forall p, p^* \in P,$ $p \neq p^*$	cost of inland transport of the cargo diverted from port p at port p^* (USD/TEU)
$VOC \in \mathbb{R}^+$	planned total vessel operational cost (USD)
$TP \in \mathbb{R}^+$	planned total profit to be generated by the liner shipping company (USD)

Vessel Schedule Recovery Problem (**VSRP-1**):

$$min\ [TP - \overline{\boldsymbol{TP}}] \tag{53}$$

Subject to:

$$\sum_{h \in H_p} \overline{\boldsymbol{x}_{ph}} = 1 \ \forall p \in P \tag{54}$$

$$\overline{\boldsymbol{s}_p} \leq s_p + \delta_p^{sea} y_p^{sea} + \Delta_p^{sea}(1 - y_p^{sea}) \ \forall p \in P \tag{55}$$

$$\overline{\boldsymbol{s}_p} \leq s^{max} \ \forall p \in P \tag{56}$$

$$\overline{\boldsymbol{s}_p} \geq s^{min} + \delta_p^{sea} y_p^{sea} \ \forall p \in P \tag{57}$$

$$\overline{\boldsymbol{\tau}_p^{sail}} = \frac{d_p^{leg}}{\overline{\boldsymbol{s}_p}} \ \forall p \in P \tag{58}$$

$$\overline{\boldsymbol{f}_p} = \frac{\gamma(\overline{\boldsymbol{s}_p})^{(\alpha-1)}}{24} \ \forall p \in P \tag{59}$$

$$\overline{\boldsymbol{\tau}_{p+1}^{arr}} = \overline{\boldsymbol{\tau}_p^{dep}} + \overline{\boldsymbol{\tau}_p^{sail}} \ \forall p \in P, p < m^1 \tag{60}$$

$$\overline{\boldsymbol{\tau}_1^{arr}} = \overline{\boldsymbol{\tau}_p^{dep}} + \overline{\boldsymbol{\tau}_p^{sail}} - \overline{\boldsymbol{VTT}} \ \forall p \in P, p = m^1 \tag{61}$$

$$\overline{\boldsymbol{\tau}_p^{del}} \geq \overline{\boldsymbol{\tau}_p^{arr}} - \tau_p^{arr} \ \forall p \in P \tag{62}$$

$$\boldsymbol{x}_p^{skip} \leq y_p^{port} \ \forall p \in P \tag{63}$$

$$\boldsymbol{x}_{pp^*}^{div} \leq \boldsymbol{x}_p^{skip} \ \forall p, p^* \in P, p \neq p^* \tag{64}$$

$$\boldsymbol{x}_{pp^*}^{div} \leq y_{pp^*} \ \forall p, p^* \in P, p \neq p^* \tag{65}$$

$$\boldsymbol{x}_{p^*}^{dd} \leq \sum_{p \in P: p \neq p^*} \boldsymbol{x}_{pp^*}^{div} \ \forall p^* \in P \tag{66}$$

$$\boldsymbol{d}_{pp^*}^{div} = d_p^{port} \boldsymbol{x}_{pp^*}^{div} \ \forall p, p^* \in P, p \neq p^* \tag{67}$$

$$\sum_{p \in P: p \neq p^*} \boldsymbol{d}_{pp^*}^{div} \leq C_{p^*}^{port} \boldsymbol{x}_{p^*}^{dd} \ \forall p^* \in P \tag{68}$$

$$\sum_{p \in P: p \neq p^*} \boldsymbol{d}_{pp^*}^{div} \leq C_{p^*}^{land} \boldsymbol{x}_{p^*}^{dd} \ \forall p^* \in P \tag{69}$$

$$\overline{\boldsymbol{\tau}_p^{hand}} = \left[\sum_{h \in H_p} \left(\frac{d_p^{port} + \sum_{p^* \in P: p^* \neq p} \boldsymbol{d}_{pp^*}^{div}}{pr_{ph}} \right) \overline{\boldsymbol{x}_{ph}} + \delta_p^{port} y_p^{port} \right] \left(1 - \boldsymbol{x}_p^{skip}\right) \tag{70}$$

$$\forall p \in P$$

$$\overline{\boldsymbol{\tau}_{p+1}^{wait}} \geq \tau_{p+1}^{st} - (\overline{\boldsymbol{\tau}_p^{dep}} + \overline{\boldsymbol{\tau}_p^{sail}}) \ \forall p \in P, p < m^1 \tag{71}$$

$$\overline{\boldsymbol{\tau}_1^{wait}} \geq \tau_1^{st} - (\overline{\boldsymbol{\tau}_p^{dep}} + \overline{\boldsymbol{\tau}_p^{sail}}) + \overline{\boldsymbol{VTT}} \ \forall p \in P, p = m^1 \tag{72}$$

$$\overline{\boldsymbol{\tau}_p^{dep}} = \overline{\boldsymbol{\tau}_p^{arr}} + \overline{\boldsymbol{\tau}_p^{wait}} + \overline{\boldsymbol{\tau}_p^{hand}} \ \forall p \in P \tag{73}$$

$$\overline{\boldsymbol{VTT}} = \sum_{p \in P} \overline{\boldsymbol{\tau}_p^{sail}} + \sum_{p \in P} \overline{\boldsymbol{\tau}_p^{wait}} + \sum_{p \in P} \overline{\boldsymbol{\tau}_p^{hand}} \tag{74}$$

$$\overline{\boldsymbol{REV}} = \sum_{p \in P} c_p^{cargo} d_p^{port} \left(1 - \boldsymbol{x}_p^{skip}\right) + \sum_{p \in} \sum_{p^* \in P} c_p^{cargo} \boldsymbol{d}_{pp^*}^{div} \tag{75}$$

$$\overline{\boldsymbol{PHC}} = \sum_{p \in P} \sum_{h \in H_p} c_{ph}^{port} d_p^{port} \overline{\boldsymbol{x}_{ph}} + \sum_{p \in P} (c_p^{skip} + c_p^{mis} d_p^{port}) \boldsymbol{x}_p^{skip} \tag{76}$$

$$\overline{\boldsymbol{LAC}} = \sum_{p \in P} c_p^{del} \overline{\boldsymbol{\tau}_p^{del}} \tag{77}$$

$$\overline{\boldsymbol{FCC}} = c^f \sum_{p \in P} d_p^{leg} \overline{\boldsymbol{f}_p} \tag{78}$$

$$\overline{\boldsymbol{CDC}} = \sum_{p \in P} \sum_{p^* \in P} (c_{pp^*}^{d-port} + c_{pp^*}^{d-land}) \boldsymbol{d}_{pp^*}^{div} \tag{79}$$

$$VOC = c^{oper} \phi V \tag{80}$$

$$\overline{\boldsymbol{TP}} = [\overline{\boldsymbol{REV}} - (\overline{\boldsymbol{PHC}} + \overline{\boldsymbol{LAC}} + \overline{\boldsymbol{FCC}} + \overline{\boldsymbol{CDC}} + VOC)] \tag{81}$$

In the **VSRP-1** mathematical model, the objective function (53) aims to minimize the total profit loss endured throughout liner shipping as a result of disruptive event(s) in sea and at ports during the voyage. Constraint set (54) guarantees that the liner shipping company chooses a single handling rate from the set of handling rates, provided by the MCT operator at each port of call of the given liner shipping route. Constraint set (55) estimates the actual sailing speed of vessels at each voyage leg, taking into account the possible occurrence of disruptions in sea and vessel sailing speed adjustments. As mentioned earlier in this chapter, it is assumed that the liner shipping company cannot change the sailing speed of vessels at the voyage leg, where a disruptive event occurs (which is accounted for by constraint set (55)). Constraint sets (56) and (57) establish the limits for the actual sailing speed of vessels depending on the recovered vessel schedule.

Constraint sets (58) and (59) estimate the actual sailing time and the actual fuel consumption of vessels, respectively, at each voyage leg of the liner shipping route based on the recovered vessel schedule. Constraint sets (60) and (61) compute the actual arrival time of vessels at each port of call considering the recovered vessel schedule. Constraint set (62) estimates the vessel arrival delays at ports of call of the liner shipping route depending on the recovered vessel schedule. Constraint set (63) guarantees that the vessel can only skip a port of call only if a disruptive event occurs at the port. Constraint set (64) stipulates that the liner shipping company can only divert cargo from a given port of call to the alternative port(s) only if that port is skipped. Constraint set (65) verifies the feasibility of cargo diversion from a given port to the alternative ports of call. Constraint set (66) identifies the ports of call that will handle the diverted demand from other ports that are faced with disruptive events.

Constraint set (67) calculates the diverted demand that will be served at some ports of call. Constraint set (68) guarantees that the MCT capacity will be adequate to serve the diverted demand at a given port of call of the liner shipping route. Constraint set (69) ensures that the inland transport operator at a given port of call will have enough capacity to deliver the diverted demand to the appropriate destinations. Constraint set (70) computes the actual handling time of vessels at each port of call using the recovered vessel schedule, taking into account potential port skipping and cargo diversion. Constraint sets (71)-(73) estimate the actual waiting time and departure time of vessels for each port of call of the liner shipping route using the recovered vessel schedule.

Constraint set (74) calculates the actual turnaround time of vessels based on the recovered vessel schedule. Constraint sets (75)-(79) compute the actual total revenue to be generated by the liner shipping company, the actual total port handling cost, the actual total late vessel arrival cost, the actual total fuel cost, and the actual total container diversion cost based on the recovered vessel schedule, respectively. Constraint set (80) estimates the planned total vessel operational cost. Constraint set (81) calculates the actual total profit to be generated by the liner shipping company based on the recovered vessel schedule.

4.4. Solution Methodology

The formulated **VSRP-1** mathematical model is nonlinear because of constraint sets (58), (59), and (70), which are used for computing the actual vessel sailing time, the actual fuel consumption at each voyage leg, and the actual port handling time, respectively. The nonlinearity of the **VSRP-1** can be reduced by revising the nonlinear constraint set (58). To achieve the latter, the actual vessel sailing speed $\overline{\boldsymbol{s}_p}, p \in P$ as well as the planned vessel sailing speed $s_p, p \in P$ can be replaced with their multiplicative inverse components $\boldsymbol{v}_p = \frac{1}{\overline{s_p}}\ \forall p \in P$ and $\dot{v}_p = \frac{1}{s_p}\ \forall p \in P$, respectively. Also, the anticipated difference in sailing speed ($\delta_p^{sea}, p \in P$ – knots) and the sailing speed adjustment ($\Delta_p^{sea}, p \in P$ – knots) will be revised accordingly for consistency. Let $\delta_p^{\dot{sea}}, p \in P$ (knots^{-1}) and $\Delta_p^{\dot{sea}}, p \in P$ (knots^{-1}) represent the anticipated sailing speed change and the sailing speed adjustment, respectively, at each voyage leg of the liner shipping route.

Various approaches have been used in the literature to address the nonlinearity of the fuel consumption function, including enumeration method (the vessel sailing speed is assumed to be constant at voyage legs), dynamic programming method (the problem is reduced to a shortest path problem), discretization method (the reciprocal values of the vessel sailing speed are discretized, and the fuel consumption function is estimated for each one of the discretized values), tailored method (approximating functions for the fuel consumption, such as a set of tangent or secant approximating lines, are used as a substitute for the nonlinear fuel consumption function), and second order cone programming method (the nonlinear model is reformulated as a mixed-integer second order cone programming model) (Wang et al., 2013b, Dulebenets, 2018a). The assumption of constant sailing speed is impractical as liner shipping companies usually select various sailing speeds at voyage legs; thus, the enumeration method is not accurate. A number of studies have reported that the tailored method performs better than the second order cone programming method (Wang et al. 2013b).

The accuracy of the dynamic programming and discretization methods in linearizing the fuel consumption function depends on the discretization level. Moreover, the accuracy of the tailored method in approximating the fuel consumption function depends on the number of segments considered. Certain studies have found that the selection of a high discretization level and number of segments in the fuel consumption function approximation may increase the computational time (Dulebenets, 2018a). Thus, there is the need to conduct further analysis to determine the suitable discretization level (for discretization methods) or number of segments (for tailored methods) to approximate the fuel consumption function.

This study will use the tailored method for linearizing the fuel consumption in the **VSRP-1** mathematical model. The static piecewise linear secant approximations will be used instead of tangent lines based on the fact that the tangent lines have been reported to underestimate fuel consumption, while secant lines may either underestimate or overestimate fuel consumption. A smaller number of secant liners is usually needed as compared to tangent lines and they are more accurate in estimating the fuel consumption.

In case of static piecewise linear secant approximations, the total number of linear secant segments is usually known (Dulebenets, 2015a). Here, the piecewise function $\overline{\boldsymbol{FC}}_{pr}, p \in P, r \in K$ estimates the nonlinear function $\boldsymbol{FC}_p, p \in P$ using a set of linear secant segments $K = \{1, \dots, r\}$. Let $\boldsymbol{b}_{pk} = 1$ if a linear secant segment k is set for approximation of the fuel consumption function at voyage leg p of the liner shipping route (=0 otherwise). Denote $st_k, k \in K$ and $ed_k, k \in K$ as the vessel sailing speed reciprocal values at the beginning of linear secant segment k and at the end of linear secant segment k, respectively. Denote $SL_k, k \in K$ and $IN_k, k \in K$ as the slope of linear secant segment k and the intercept of linear secant segment k, respectively. Let M_1 and M_2 be sufficiently large positive numbers. The mixed-integer nonlinear **VSRP-1** mathematical model, which has linearized vessel sailing time and fuel consumption constraints (**VSRP-2**), can be then expressed as follows:

Vessel Schedule Recovery Problem (**VSRP-2**):

$$min\ [TP - \overline{\boldsymbol{TP}}] \tag{82}$$

Subject to:

Constraint sets (54), (60)-(77), (79)-(81)

$$\boldsymbol{v}_p \geq \dot{v}_p + \delta_p^{\dot{sea}} y_p^{sea} + \Delta_p^{\dot{sea}}(1 - y_p^{sea})\ \forall p \in P \tag{83}$$

$$\boldsymbol{v}_p \geq \frac{1}{s^{max}}\ \forall p \in P \tag{84}$$

$$\boldsymbol{v}_p \leq \frac{1}{s^{min}} + \delta_p^{\dot{sea}} y_p^{sea}\ \forall p \in P \tag{85}$$

$$\overline{\boldsymbol{\tau}_p^{sail}} = d_p^{leg}\ \boldsymbol{v}_p\ \forall p \in P \tag{86}$$

$$\sum_{k\in K} \boldsymbol{b}_{pk} = 1 \ \forall p \in P \tag{87}$$

$$st_k \boldsymbol{b}_{pk} \le \boldsymbol{v}_p \ \forall p \in P, k \in K \tag{88}$$

$$ed_k + M_1(1 - \boldsymbol{b}_{pk}) \ge \boldsymbol{v}_p \ \forall p \in P, k \in K \tag{89}$$

$$\overline{\boldsymbol{FC}}_{pk} \ge SL_k \boldsymbol{v}_p + IN_k - M_2(1 - \boldsymbol{b}_{pk}) \ \forall p \in P, k \in K \tag{90}$$

$$\overline{\boldsymbol{FCC}} = c^f \sum_{p\in P} \sum_{k\in K} d_p^{leg} \overline{\boldsymbol{FC}}_{pk} \tag{91}$$

In the **VSRP-2** mathematical model, the objective function (82) aims to minimize the total profit loss endured throughout liner shipping as a result of disruptive event(s) in sea and at ports during the voyage. Constraint set (83) computes the multiplicative inverse of the recovered vessel sailing at each voyage leg of the liner shipping route. Constraint sets (84) and (85) define the bounds for the multiplicative inverse of the recovered sailing speed of vessels at the voyage legs of the liner shipping route. Constraint set (86) calculates the actual sailing time at the voyage legs of the liner shipping route using the multiplicative inverse of the recovered vessel sailing speed.

Constraint set (87) ensures that not more than one linear secant segment will be selected for approximation of the fuel consumption function at each voyage leg of the liner shipping route for the recovered vessel schedule. Constraint sets (88) and (89) establish limits for the multiplicative inverse of the actual vessel sailing speed, when a given linear secant segment is selected for approximation of the fuel consumption function at a certain voyage leg. Constraint set (90) estimates the actual fuel consumption at each voyage leg of the liner shipping route considering the actual sailing speed of vessels. Constraint set (91) computes the actual total fuel cost.

Although the actual vessel sailing time and actual fuel consumption components of the **VSRP-2** mathematical model have been linearized, the model is still nonlinear because of the high nonlinearity of constraint set (70), which calculates the actual port handling time at each port of call for the recovered vessel schedule. In this study, a nonlinear optimization solver BARON will be applied to solve **VSRP-2** to the global optimality. Initial computational experiments showed that BARON could solve **VSRP-2** to global optimality within an acceptable computational time for the realistic-size liner shipping routes. Moreover, a set of computational experiments were conducted in this study to investigate the correspondence between the number of linear secant segments in the piecewise function and correctness of the fuel consumption function approximation.

The methodology for producing the piecewise secant approximations was established using MATLAB 2016a software (MathWorks, 2019). Based on the results retrieved from the numerical experiments, the **VSRP-2** computational time increased substantially when the total number of linear secant segments selected in the piecewise function was higher than 15 without significant approximation accuracy improvements. Considering the latter finding, a piecewise function with 15 linear secant segments will be used throughout the numerical experiments. The nonlinear fuel consumption function $FC(\boldsymbol{v}) = \frac{0.012(\boldsymbol{v})^{-2}}{24}$ and the linear approximation, represented as a piecewise function with 15 linear secant segments, are illustrated in Figure 30.

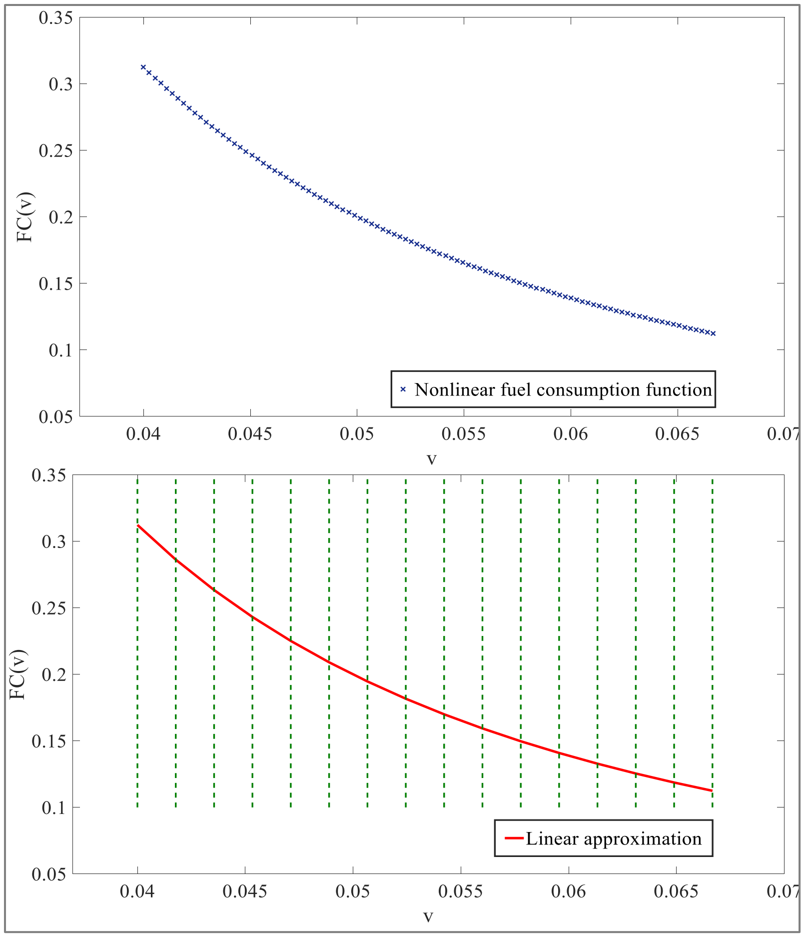


Figure 30 A nonlinear function and linearized approximation with 15 linear secant segments

4.5. Computational Experiments

This section of the dissertation presents the computational experiments that were conducted to exhibit the applicability of the **VSRP-2** mathematical model for decision making in case of disruptions in the planned operations of liner shipping companies. The computational experiments that were performed in this study, were carried out on a Dell Inspiron AMD FX-9800P Processor with 16 GB of RAM. The formulated **VSRP-2** mathematical model was encoded in the optimization software, called General Algebraic

Modeling System (GAMS, 2019), and solved to the global optimality using BARON. The upper limit of the computational time in BARON was set to 7,200 seconds, while the target optimality gap was fixed as 0.01%.

4.5.1. Input Data Generation

In this study, the Middle East-West Mediterranean WM3 Route (see Figure 31), which is served by the OOCL liner shipping company (OOCL, 2019), was considered to examine the performance of the **VSRP-2** mathematical model. Some of the major areas connected by the liner shipping route, include Mediterranean Sea, South Europe, Red Sea, North Africa, Arabian Sea, Middle East, and Asia. The port network for the Middle East-West Mediterranean WM3 Route has a total of 17 ports of call, where the Ports of Jeddah (Saudi Arabia), Marsaxlokk (Malta), and Genoa (Italy) are each visited twice, and other ports are visited no more than once. The port rotation can be exhibited as follows (the square brackets in the expression show the distances between the consecutive ports of call in nautical miles (Ports.com)):

1. Fos, France [226] → 2. Genoa, Italy [712] → 3. Marsaxlokk, Malta [1,113] → 4. Damietta, Egypt [430] → 5. Aqaba, Jordan [571] → 6. Jeddah, Saudi Arabia [2,172] → 7. Hamad, United Arab Emirates [199] → 8. Jebel Ali, United Arab Emirates [746] → 9. Karachi, Pakistan [589] → 10. Nhava Sheva, India [429] → 11. Mundra, India [2,496] → 12. Jeddah, Saudi Arabia [1,908] → 13. Marsaxlokk, Malta [673] → 14. La Spezia, Italy [38] → 15. Genoa, Italy [586] → 16. Valencia, Spain [203] → 17. Barcelona, Spain [237] → 1. Fos, France.

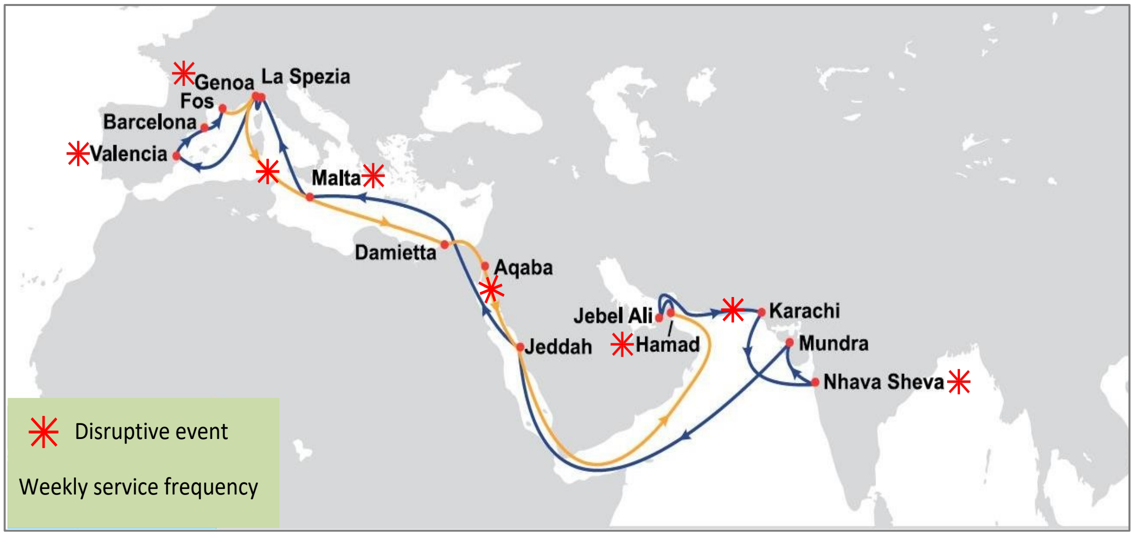


Figure 31 The Middle East-West Mediterranean WM3 route

The numerical data, needed to examine the **VSRP-2** mathematical model, were obtained using the data available in the liner shipping and marine container terminal literature (Wang and Meng, 2012a-c; Wang et al., 2014; Zampelli et al., 2014; Dulebenets, 2016a; Dulebenets, 2018a-e; Dulebenets et al., 2019; World Shipping Council, 2019; OOCL, 2019, Kavoosi, et. al., 2019, etc.). The parameter values, adopted in this study, are presented in Table 6.

Table 6 The parameter values used for the numerical experiments

Parameter	Value	Source(s)
Number of ports to be visited: m^1 (ports)	17	OOCL (2019)
Number of available handling rates at ports: m^2 (handling rates)	4	N/A
Container demand at ports: $d_p^{port}, p \in P$ (TEUs)	$U[200; 2{,}000]$	Dulebenets (2016a, 2018b-e)
Handling productivity at ports: $pr_{ph}, p \in P, h \in H_p$ (TEUs/hour)	$U[50; 125]$	Dulebenets (2016a, 2018b-e)

Table 6 The parameter values used for the numerical experiments – continued

Parameter	Value	Source(s)
Fuel consumption coefficients: α, γ	$\alpha = 3.0,\ \gamma = 0.012$	Wang and Meng (2012c); Psaraftis and Kontovas (2013)
Agreed port service frequency: φ (hours)	168	OOCL (2019)
Total number of vessels deployed: V (vessels)	15	N/A
Planned vessel sailing speed: $s_p, p \in P$ (knots)	$U[17; 25]$	N/A
Minimum vessel sailing speed: s^{min} (knots)	15	Wang and Meng (2012a-c)
Maximum vessel sailing speed: s^{max} (knots)	25	Wang and Meng (2012a-c)
Number of containers transported at voyage legs: $d_p^{sea}, p \in P$ (TEUs)	$U[5{,}000; 8{,}000]$	(Dulebenets (2016a, 2018b-e)
Disruption occurrence at ports: $y_p^{port}, p \in P$	Varies for each scenario of disruption occurrence	
Disruption occurrence in sea: $y_p^{sea}, p \in P$	Varies for each scenario of disruption occurrence	
Expected duration of disruptive events at ports: $\delta_p^{port}, p \in P$ (hours)	$U[10; 100]$	Abioye et al. (2019)
Expected vessel sailing speed change due to disruptive events at voyage legs: $\delta_p^{sea}, p \in P$ (knots)	$-U[0.1; 5.0]$	N/A
MCT capacity to serve the diverted demand at ports: $C_p^{port}, p \in P$ (TEUs)	$U[200; 500]$	N/A
Inland transport capacity for delivery of the diverted demand: $C_p^{land}, p \in P$ (TEUs)	$U[200; 500]$	N/A
Unit cost of fuel: c^f (USD/ton)	300	Fagerholt and Psaraftis (2015)
Freight rate for shipping a TEU from port p to port $p+1$: $c_p^{cargo}, p \in P$ (USD/TEU)	$U[4{,}000; 6{,}000]$	Abioye et al. (2019)
Average handling cost at ports: hc^{av} (USD/TEU)	$U[200; 500]$	Dulebenets (2016a, 2018a-d)
Handling cost at ports: $c_{ph}^{port}, p \in P, h \in H_p$ (USD/TEU)	$c_{ph}^{hand} = hc^a \pm U[0; 50]$ $\forall p \in P, h \in H_p$	Dulebenets (2016a, 2018b-e)

Table 6 The parameter values used for the numerical experiments – continued

Parameter	Value	Source(s)
Vessel operational cost: c^{oper} (USD/week)	300,000	Wang and Meng (2012a-c)
Delayed vessel arrival cost at ports: $c_p^{del}, p \in P$ (USD/hour)	$U[5{,}000; 8{,}000]$	Zampelli et al. (2014); Dulebenets (2018b-e)
Port skipping inconvenience coefficient: μ	1.10	(Abioye et al. (2019)
Port skipping cost: $c_p^{skip}, p \in P$ (USD)	$c_p^{skip} = \mu \cdot hc^{av} \cdot d_p^{port}$ $\forall p \in P$	Abioye et al. (2019)
Penalty due to misconnected cargo: $c_p^{mis}, p \in P$ (USD/TEU)	$U[300; 500]$	N/A
Cost of handling the diverted cargo: $c_{pp^*}^{d-port}, p, p^* \in P, p \neq p^*$ (USD/TEU)	$U[400; 600]$	N/A
Cost of inland transport of the diverted cargo: $c_{pp^*}^{d-land}, p, p^* \in P, p \neq p^*$ (USD/TEU)	$U[600; 800]$	N/A
Planned total profit: TP (USD)	60,000,000	Abioye et al. (2019)

To estimate the end of a TW at the ports of call of the port network, the length of the voyage leg between the consecutive ports, the end of a TW at the preceding port, as well as the upper/lower bounds of the vessel sailing speed were considered. The mathematical relationship between the three parameters can be expressed as follows: $\tau_{p+1}^{ft} = \tau_p^{ft} + \frac{d_p^{leg}}{U[s^{min}; s^{max}]}$ $\forall p \in P$ (hours). The notation U will be adopted throughout this study to denote a set of uniformly distributed pseudorandom values within a definite range, specified in square brackets. The planned arrival time of vessels at port $p + 1$ was calculated as follows: $\tau_{p+1}^{arr} = \tau_p^{arr} + \tau_p^{hand} + \frac{d_p^{leg}}{s_p}$ $\forall p \in P$ (hours).

The vessel sailing speed values at voyage legs were assumed to vary between $s^{min} = 15$ knots and $s^{max} = 25$ knots (Wang and Meng 2012a-c). It was assumed that the expected vessel sailing speed change at voyage legs due to events varied between 0.1 knots and 5.0 knots: $\delta_p^{sea} = -U[0.1; 5.0]\ \forall p \in P$ (knots). Also, the anticipated duration of disruptive events at ports of call was assigned as follows: $\delta_p^{port} = U[10; 100]\ \forall p \in P$ (hours). The weekly container demand at ports of call was generated as: $d_p^{port} = U[200; 2{,}000]\ \forall p \in P$ (TEUs). The number of containers to be transported at voyage legs was assigned as follows: $d_p^{sea} = U[5{,}000; 8{,}000]\ \forall p \in P$ (TEUs).

It was assumed that the liner shipping company could request four handling rates from the MCT operator at each port of call on the port rotation, from which one could be selected for service. The handling productivities, offered by the MCT operator at each port, ranged between 50 TEUs/hour and 125 TEUs/hour. If a disruptive event occurs during the voyage, the liner shipping company may select higher handling rate at ports to reduce the actual handling time and recover the schedule. The planned handling time of vessels at port p was computed using the following relationship: $\tau_p^{hand} = \sum_{h \in H_p} \left(\frac{d_p^{port}}{pr_{ph}} \right) x_{ph}\ \forall p \in P$ (hours). The negotiated handling rate (i.e., the value of parameter $x_{ph}, p \in P, h \in H_p$) at each port of call was randomly selected from a set of handling rates offered by the MCT operator at each port. The planned vessel sailing speed was as generated as follows: $s_p = U[17; 25]\ \forall p \in P$ (knots).

The OOCL liner shipping company offers a weekly port service frequency for the Middle East-West Mediterranean WM3 liner shipping route (OOCL, 2019) – $\varphi = 168$ hours. It was assumed that the liner shipping company deployed a total of $V = 15$ vessels for service of ports at the liner shipping route. If a port is not skipped, the vessel handling cost per TEU at the port p under handling rate h was calculated using the following relationship: $c_{ph}^{hand} = hc^{av} \pm U[0; 50]\ \forall p \in P, h \in H_p$ (USD/TEU). The symbol hc^{av} denotes the average handling cost. The average handling cost was generated as follows: $hc^{av} = U[200; 500]\ \forall p \in P$ (USD/TEU). If the liner shipping company selects a handling rate with higher handling productivity at ports, the MCT operator would impose a higher average handling cost. The freight rate for shipping a TEU from port p to $p+1$ was generated as: $c_p^{cargo} = U[4{,}000; 6{,}000]\ \forall p \in P$ (USD/TEU). The unit cost of fuel was assumed to be $c^f = 300$ USD/ton (Fagerholt and Psaraftis 2015). The effects of changing the unit fuel cost on **VSRP-2** will be examined in this study (see section 4.5.3.3).

The delayed vessel arrival cost was assigned as follows: $c_p^{del} = U[5{,}000; 8{,}000]\ \forall p \in P$ (USD/hour) (Zampelli et al., 2014; Dulebenets, 2018b-e). The MCT capacity to serve the diverted demand at port p was generated as: $C_p^{port} = U[200; 500]\ \forall p \in P$ (TEUs), while the inland transport capacity for delivery of the diverted demand from port p to the assigned destinations was assigned as: $C_p^{land} = U[200; 500]\ \forall p \in P$ (TEUs). The sensitivity of **VSRP-2** to changes in inland transport and port handling capacities will be evaluated throughout the numerical experiments (see section 4.5.3.2). The penalty due to misconnected cargo was generated as: $c_p^{mis} = U[300; 500]\ \forall p \in P$ (USD/TEU). The additional cost for handling the cargo diverted from port p at port p^* was assigned as follows: $c_{pp^*}^{d-port} = U[400; 600]\ \forall p, p^* \in P, p \neq p^*$ (USD/TEU). The cost of inland transport of the cargo diverted from port p at port p^*

was generated as: $c_{pp^*}^{d-land} = U[600; 800]\ \forall p, p^* \in P, p \neq p^*$ (USD/TEU). The vessel weekly operational cost was assumed to be $c^{oper} = 300{,}000$ USD/week (or $c^{oper} = 1{,}785.71$ USD/hour).

This study assumes that the liner shipping company planned to generate a total profit of $TP = 60{,}000{,}000$ USD (Abioye et al. 2019). The port skipping cost was calculated using the following relationship: $c_p^{skip} = \mu \cdot hc^{av} \cdot d_p^{port}$ (USD), where μ – is the port skipping inconvenience coefficient. The port skipping inconvenience coefficient was assumed to be $\mu = 1.10$. An additional analysis will be conducted in this study to investigate the effect of change in the unit port skipping cost on the **VSRP-2** mathematical model (see section 4.5.3.1).

4.5.2. Managerial Insights for Various Disruption Scenarios

This section of the dissertation presents the managerial insights revealed from applying the proposed solution methodology to solve the **VSRP-2** mathematical model using the numerical data generated. In this study, five hypothetical scenarios of disruptions in sea and/or at ports of call of the liner shipping route were used to examine the **VSRP-2** mathematical model. The scenarios of disruptions, as well as the schedule recovery decisions that were recommended by **VSRP-2**, are discussed next.

Scenario 1: No disruption in sea or at ports

This is an ideal situation. In this case, there are no disruptions in sea or at ports of call that affect the planned liner shipping operations. The vessels deployed by the liner shipping company for the service of ports actually visit all the ports of the port network and arrive at the ports within the planned arrival TWs. Moreover, there are no delays in vessel service at ports. In this scenario, the liner shipping company does not have to undertake any recovery strategies.

Scenario 2: A disruption at a port early in the voyage

In this scenario, the MCT operator at the Port of Marsaxlokk (Malta) reports handling equipment breakdowns with an expected duration of $\delta_3^{port} = 50$ hours, i.e. a disruption occurred at a port early in the voyage. The following recovery strategies are recommended by **VSRP-2**: (1) skip the Port of Marsaxlokk (Malta) without container diversion; (2) adjust the vessel sailing speed at voyage legs; and (3) select the highest handling rate (125 TEUs/hour) at the Port of Damietta (Egypt) and the Port of Barcelona (Spain). The port skipping decisions for all the considered scenarios are presented in Figure 32. Figure 33 illustrates the average vessel sailing speed, while Figure 34 shows the average vessel sailing speed adjustment for the scenarios where disruptions occur. Additionally, Figure 36 illustrates the selected vessel handling rate at each port for all the scenarios.

Scenario 3: A disruption at a port later in the voyage

A congestion, which resulted in delays in vessel service, is reported at the Port of Valencia (Spain). The latter disruption is expected to last for $\delta_{16}^{port} = 41$ hours. Scenario "3" emulates the case of a disruption at a port later in the voyage. The following recovery strategies are recommended by **VSRP-2**: (1) skip the Port of Valencia (Spain) without container diversion (see Figure 32); (2) adjust the vessel sailing speed at voyage legs (see Figure 33 and Figure 34); and (3) select the highest handling rate (125 TEUs/hour) at the Port of Barcelona (Spain) (see Figure 36).

Scenario 4: Disruptions in sea

For this scenario, a disruption occurs in sea due to a pirate attack at voyage leg “5”, which connects the Port of Aqaba (Jordan) and the Port of Jeddah (Saudi Arabia). Also, a second disruption occurs in sea due to inclement weather at voyage leg “8”, which connects the Port of Jebel Ali (United Arab Emirates) and the Port of Karachi (Pakistan). The disruptions are expected to lower the planned vessel sailing speed at voyage legs “5” and “8” of the liner shipping route by $\delta_5^{sea} = 3.3$ knots and $\delta_8^{sea} = 5.0$ knots, respectively. The following recovery strategies are recommended by **VSRP-2**: (1) adjust the vessel sailing speed at voyage legs (see Figure 33 and Figure 34); and (2) select the highest handling rate (125 TEUs/hour) at the Port of Barcelona (Spain) (see Figure 36).

Scenario 5: Disruptions in sea and at ports

A labor strike is reported at the Port of Hamad (United Arab Emirates), which is expected to last for $\delta_7^{port} = 29$ hours. The Port of Nhava Sheva (India) is undergoing maintenance after a natural hazard. The latter disruption is expected to last for $\delta_{10}^{port} = 63$ hours. Additionally, a disruption caused by inclement weather conditions occurs in sea at voyage leg “2”, which connects the Port of Genoa (Italy) and the Port of Marsaxlokk (Malta). The latter disruption is expected to reduce the planned vessel sailing speed by $\delta_2^{sea} = 3.3$ knots. The following recovery strategies are recommended by **VSRP-2**: (1) skip the Port of Hamad (United Arab Emirates) without container diversion (see Figure 32); (2) skip the Port of Nhava Sheva (India) and divert containers to the Port of Mundra (India) (374 TEUs) (see Figure 32); (3) adjust the vessel sailing speed at voyage legs (see Figure 33 and Figure 34); and (4) select the highest handling rate (125 TEUs/hour) at the

Port of Marsaxlokk (Malta), the Port of Jebel Ali (United Arab Emirates), the Port of Mundra (India), and the Port of Barcelona (Spain) (see Figure 36).

4.5.2.1. Port skipping decisions

The port skipping decision, suggested by the **VSRP-2** mathematical model, was retrieved for all the scenarios of disruptions considered in this study. The results from the computational experiments suggest that the port skipping decision was primarily determined by the type of disruption considered in each scenario.

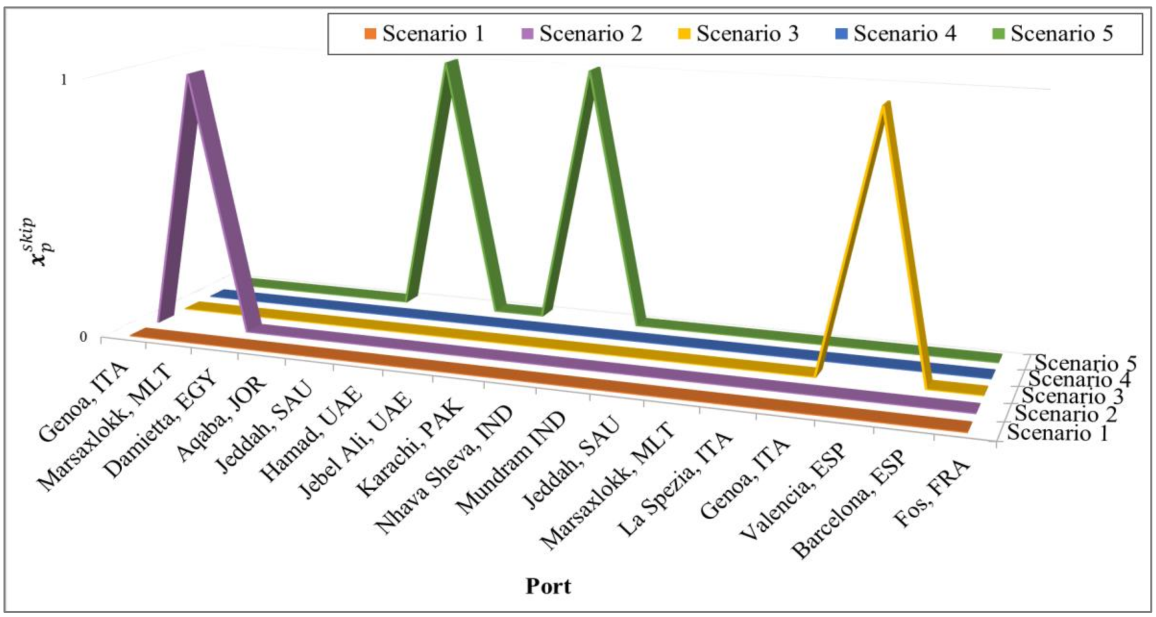


Figure 32 Port skipping decisions for the considered scenarios

When there are no disruptions in sea and at ports of call [scenario "1"], the vessels deployed for service did not skip any port at the liner shipping route; thus, the liner shipping company complied with the planned operations (see Figure 32). However, when a disruptive event occurs at a port early in the voyage [scenario "2"], skipping the Port of

Marsaxlokk (Malta), where the disruption occurred, without container diversion, was found to be the most beneficial recovery action that can be implemented by the liner shipping company in order to recover the vessel schedule (see Figure 32). Moreover, when a disruptive event occurs at a port later in the voyage [scenario “3”], skipping the Port of Valencia (Spain), where the disruption occurred, without container diversion, was found to be the most beneficial recovery strategy that can be implemented by the liner shipping company in order to recover the vessel schedule (see Figure 32).

Also, when disruptive events occur in sea [scenario “4”], the vessels did not skip any port of call (see Figure 32). Hence, the liner shipping company endured the delay and visited all the ports at the liner shipping route. In case of disruptive events in sea and at ports of call [scenario “5”], skipping the Port of Hamad (United Arab Emirates) without container diversion and skipping the Port of Nhava Sheva (India) with container diversion were found to be the most beneficial recovery actions that can be implemented by the liner shipping company in order to recover the vessel schedule (see Figure 32). The model suggested diverting 374 TEUs to the Port of Mundra (India). Note that the Port of Nhava Sheva (India) and the Port of Mundra (India) are in the same country and are connected by land. Furthermore, the vessels skip the ports where disruptions occurred.

The results from the numerical experiments indicated that an increase in the number of disruptive events at ports during a voyage significantly affected the vessel schedule, thus, the liner shipping company was required to implement more drastic recovery actions, such as port skipping with and/or without container diversion, instead of implementing the vessel sailing speed adjustment strategy and/or the handling rate adjustment strategy. Moreover, the option of port skipping is preferred when disruptive events occur at ports.

4.5.2.2. Vessel sailing speed adjustment decisions and sailing time

Throughout the numerical experiments, both the average vessel sailing speed and average vessel sailing speed adjustment were estimated for certain scenarios of disruptions [scenarios “2”, “3”, “4”, and “5”]. Note that the average vessel sailing speed and the average vessel sailing speed adjustment were not estimated when there were no disruptions in sea and at ports [scenario “1”], as the planned schedule was not affected. The results, retrieved from the computational experiments, revealed that the average vessel sailing speed adjustment and the average vessel sailing speed reduced when a disruptive event occurs at a port early in the voyage [scenario “2”] as compared to when a disruptive event occurs at a port towards the end of the voyage [scenario “3”] (see Figure 33 and Figure 34). Such finding can be justified by the fact that the liner shipping company has the ability to efficiently recover the vessel schedule if a disruptive event occurs at a port early in the voyage (for instance, vessel sailing speed can be increased at several voyage legs of the liner shipping route to eliminate the delays).

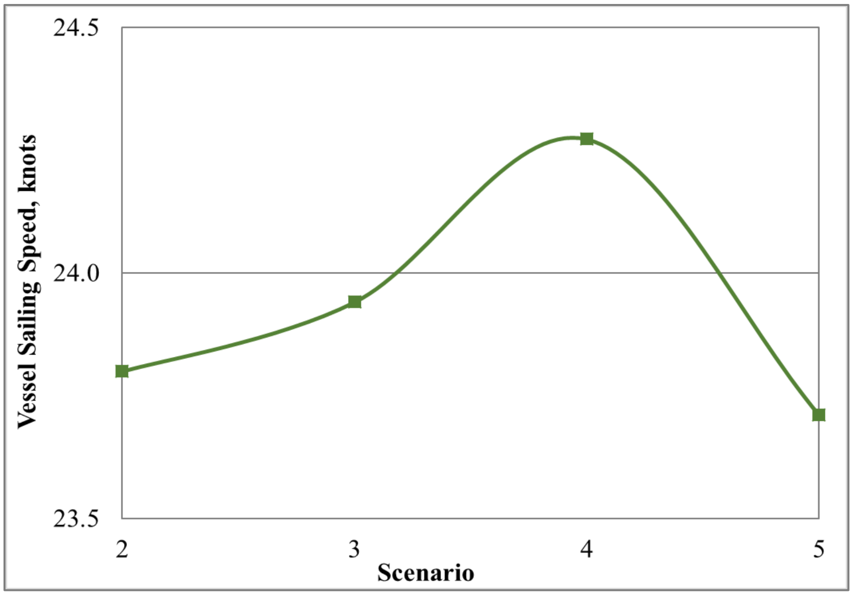


Figure 33 The average vessel sailing speed

However, vessel schedule recovery becomes more difficult when a disruptive event occurs at a port towards the end of the voyage (for example, the liner shipping company will have only a few voyage legs to adjust the vessel sailing speed, thus, a more substantial increase in the vessel sailing speed will be required). Furthermore, the results demonstrated that the vessel sailing speed adjustment recovery strategy was mainly used by the liner shipping company to recover the delays when disruptive events occurred in sea only [scenario “4”] – i.e., the port skipping recovery option was not selected for the vessel schedule recovery.

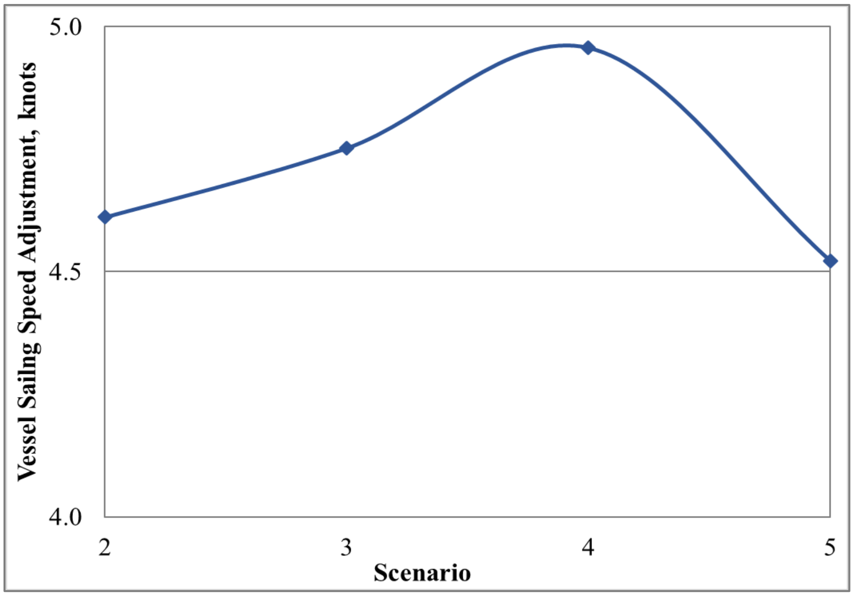


Figure 34 The average vessel sailing speed adjustment

The average vessel sailing speed, selected by the liner shipping company, was found to be lower when disruptions occurred in sea and at ports [scenario "5"]. The latter finding can be explained by the following: (1) the disruptive events in sea reduced the planned vessel sailing speed at voyage legs; and (2) due to several disruptive events at ports, the liner shipping company was required to skip certain ports in order to recover the schedule; therefore, the liner shipping company reduced the sailing speed at voyage legs after selecting the option of port skipping to reduce the actual fuel consumption and the associated cost. This finding indicates that when multiple disruptions occur in sea and at ports the use of the vessel sailing speed adjustment strategy was limited for the vessel schedule recovery.

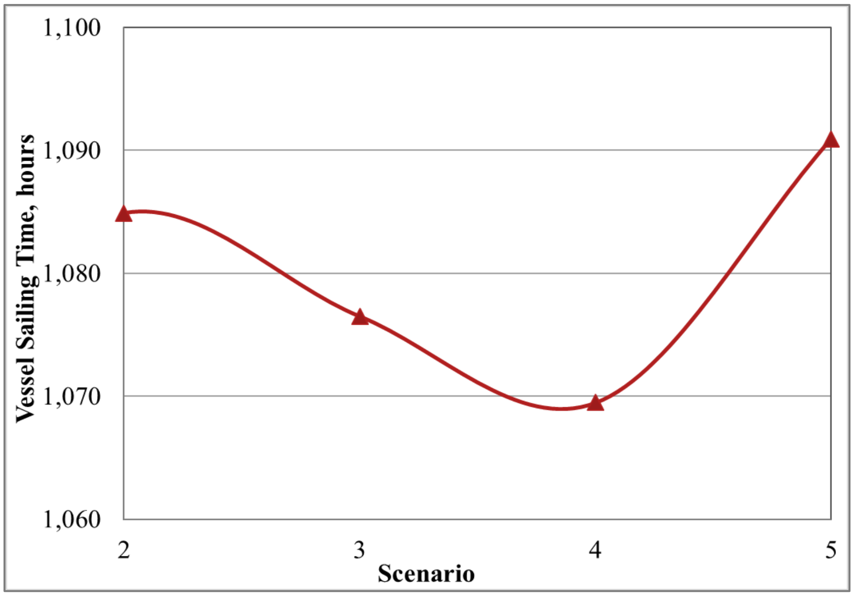


Figure 35 The total vessel sailing time for scenarios “2” – “5”

In addition to the average vessel sailing speed and the average vessel sailing speed adjustment, the total vessel sailing time for certain scenarios of disruptions [scenarios “2”, “3”, “4”, and “5”] was computed throughout the numerical experiments. Figure 35 presents the total vessel sailing time for scenarios “2”, “3”, “4”, and “5”. The results from the numerical experiments show that the total vessel sailing time was higher when a disruption occurs at a port early in the voyage [scenario “2”]. However, for the scenario where a disruption occurred at a port later in the voyage [scenario “3”], it can be observed that the average sailing speed adjustment increased and the total vessel sailing time decreased (see Figure 35). When disruptions occur in sea [scenario “4”], the total vessel sailing time decreased substantially due to an increase in the average vessel sailing speed and the average vessel sailing speed adjustment (the liner shipping company primarily adopted the vessel sailing speed adjustment strategy to recover the schedule).

Also, it can be observed that the total vessel sailing time was the highest when disruptions occurred in sea and at ports.

4.5.2.3. Vessel handling rate adjustment decisions

The vessel handling rate adjustment decision was retrieved from the **VSRP-2** mathematical model for each scenario of disruptions. For the scenarios with disruptions in sea and/or at ports [scenarios "2", "3", "4", and "5"], the selection of the highest handling rate (125 TEUs/hour) at the Port of Barcelona (Spain) (towards the end of the voyage) was found to be the most favorable decision for the liner shipping company in order to recover the vessel schedule (see Figure 36). Furthermore, the vessel handling rate adjustment recovery strategy was mainly beneficial when disruptions occur both in sea and at ports of call of the liner shipping route [scenario "5"]. In the latter scenario, the liner shipping company decided to select higher vessel handling rate at four ports of call to efficiently recover the vessel schedule. Implementation of the vessel sailing speed adjustment recovery strategy only was inadequate to recover the delays when the liner shipping company is faced with disruptive events both in sea and at ports.

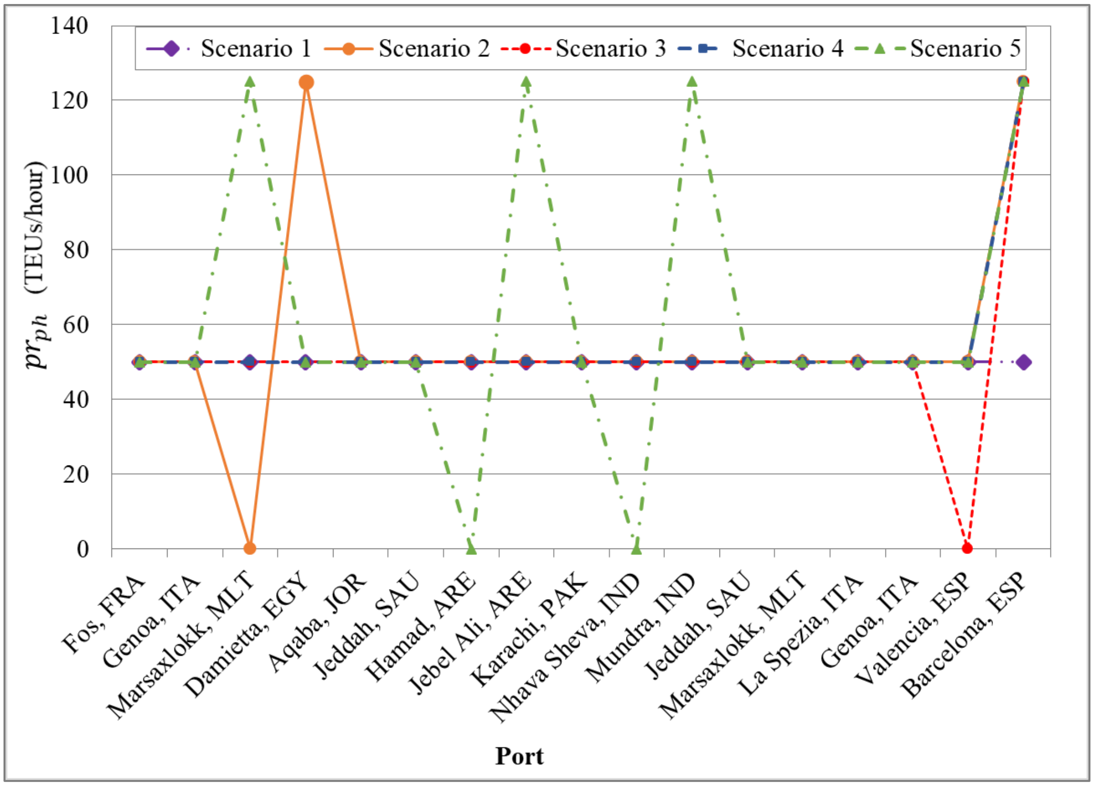


Figure 36 The vessel handling rate selection at ports for the considered scenarios

4.5.2.4. Total profit loss and its components

The objective function (i.e., the total profit loss, endured by the liner shipping company due to disruptive events in sea and at ports) of the **VSRP-2** mathematical model and its components were retrieved for each scenario (see Figure 37). The cost components that were retrieved include the following: (1) the total profit loss ($\boldsymbol{Z}$ – USD), which was endured by the liner shipping company due to disruptions; (2) the actual total profit ($\overline{\boldsymbol{TP}}$ – USD); (3) the actual total revenue ($\overline{\boldsymbol{REV}}$ – USD); (4) the actual total port handling cost ($\overline{\boldsymbol{PHC}}$ – USD); (5) the actual total late vessel arrival cost ($\overline{\boldsymbol{LAC}}$ – USD); (6) the actual total fuel cost ($\overline{\boldsymbol{FCC}}$ – USD); and (7) the actual container diversion cost ($\overline{\boldsymbol{CDC}}$ – USD).

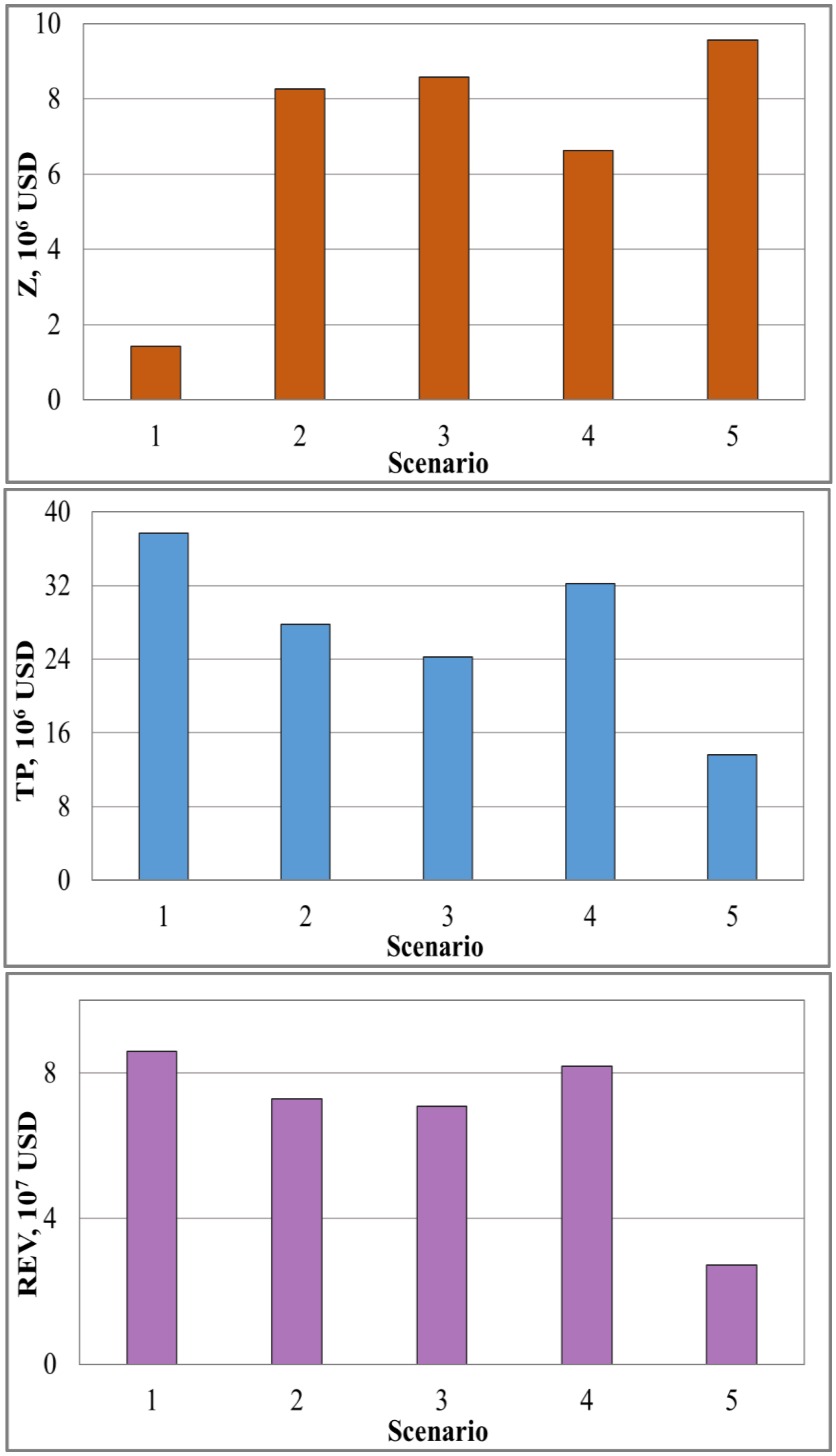


Figure 37 The total profit loss endured by the liner shipping company and other cost components

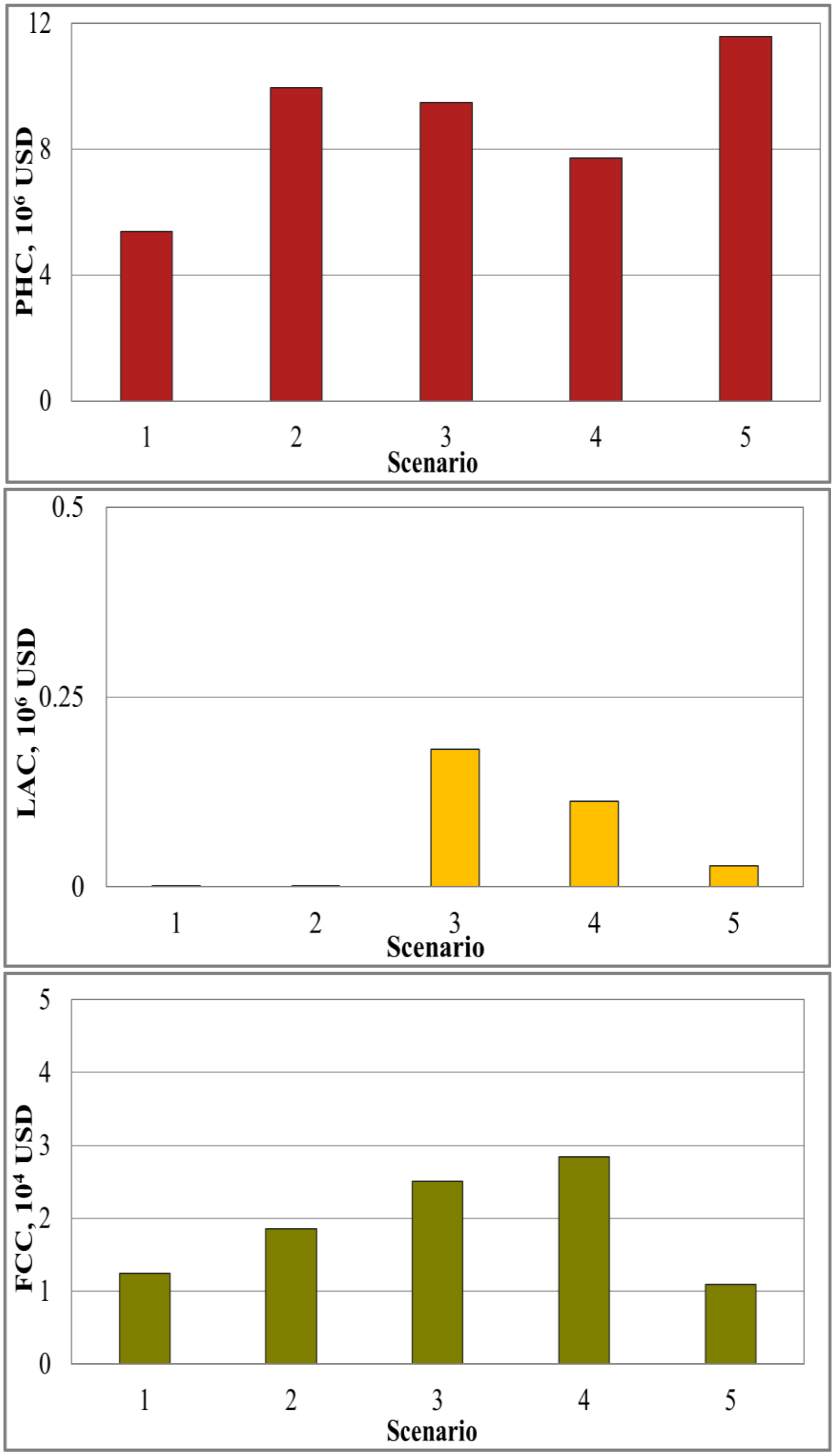


Figure 37 The total profit loss endured by the liner shipping company and other cost components – continued

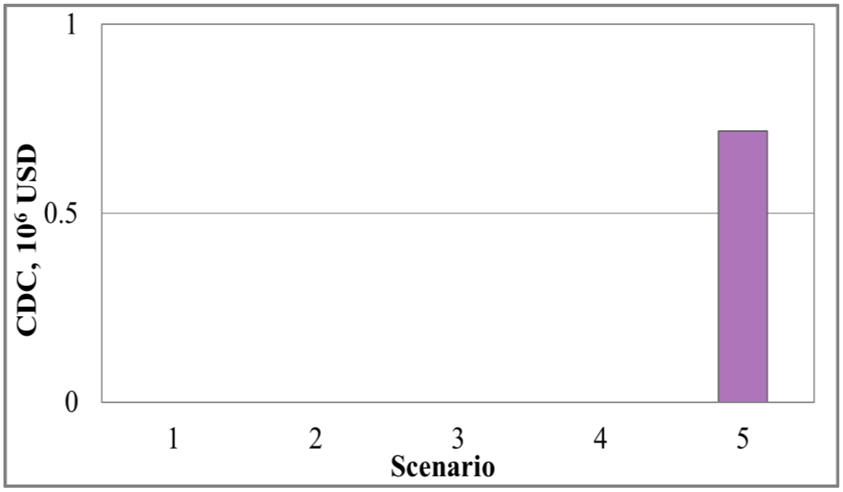


Figure 37 The total profit loss endured by the liner shipping company and other cost components – continued

From the numerical experiments conducted, the actual total revenue generated by the liner shipping company was lower when disruptive events occur during the voyage [scenarios "2", "3", and "5"] as compared to when there are no disruptive events in sea or at ports [scenario "1"]. The latter can be explained by the fact that the liner shipping company selected at least one recovery action (i.e., skipped certain ports with and/or without container diversion, adjusted the vessel sailing speed, adjusted the vessel handling rate) to recover the schedule, which increased the associated planned cost components for each scenario with disruptions. For instance, where the liner shipping company skipped a port without container diversion, no revenue was generated at the port, and a port skipping cost was imposed on the liner shipping company. Specifically, where a disruption occurred at a port earlier in the voyage, the liner shipping company had to skip the Port of Marsaxlokk (Malta) without container diversion. Similarly, where a disruption occurred later in the voyage, the liner shipping company skipped the Port of Valencia (Spain) without container diversion in order to recover the delay due to disruptions.

Throughout the numerical experiments, it was observed that the least actual total profit generated by the liner shipping company was recorded when there are more disruptions throughout the voyage [scenario "5"]. The actual total profit generated by the liner shipping company was the highest when there are no disruptive events in sea and/or at ports [scenario "1"]. Moreover, the actual total profit generated by the liner shipping company was higher when a disruptive event occurs early in the voyage [scenario "2"] as compared to when a disruptive event occurs later in the voyage [scenario "3"]. The latter can be explained by the fact that the liner shipping company had sufficient time to implement various recovery actions at lower costs in order to mitigate the impact of delays and recover the schedule when a disruption occurs early in the voyage [scenario "2"]. However, when a disruption occurs later in the voyage [scenario "3"], the liner shipping company had to implement more radical actions in order to effectively recover the schedule and incurred higher costs, which reduced the actual total profit.

Furthermore, when disruptions occur in sea and at ports [scenario "5"], the actual total port handling cost was higher, since the vessel handling rate adjustment was found to be a favorable strategy to recover the vessel schedule. Specifically, the maximum handling rate (125 TEUs/hour) was selected at a total of four ports, including the Port of Marsaxlokk (Malta), the Port of Jebel Ali (United Arab Emirates), the Port of Mundra (India), and the Port of Barcelona (Spain), in order to effectively recover the schedule. The latter increased the actual total port handling cost. Also, the liner shipping company endured the additional port skipping costs for the scenarios where disruptions occurred at ports, and certain ports were skipped without container diversion [scenarios “2”, “3”, and “5”], which increased the total port handling cost.

The actual total fuel cost was higher when disruptions occurred in sea [scenario “4”]. This can be justified by the fact that the liner shipping company primarily used the vessel sailing speed adjustment to effectively recover the schedule (i.e., the vessel sailing speed was increased at voyage legs). Lower actual total fuel consumption cost was recorded when several disruptive events occur both in sea and at ports [scenario “5”], since the liner shipping company skipped multiple ports and reduced the sailing speed at certain voyage legs to minimize the fuel consumption and its associated cost.

Based on the results, the actual total container diversion cost was recorded for the scenario when disruptions occur in sea and at ports [scenario “5”], since port skipping with cargo diversion was used as a recovery strategy. In addition, results from the conducted numerical experiments revealed that the total profit loss, suffered by the liner shipping company when disruptive events occur in sea and at ports [scenario “5”], is higher as compared to other scenarios of disruptions. The latter finding suggests that when disruptive events occur frequently during a voyage, profit losses may be unavoidable for liner shipping companies. However, the methodology presented in this study could be effectively used by liner shipping companies to reduce the total profit losses.

4.5.3. Sensitivity Analysis for the VSRP-2 Parameters

Throughout the numerical experiments, an additional analysis was conducted to investigate the effects of varying certain parameters of the **VSRP-2** mathematical model on the recovered vessel schedules. This section of the manuscript presents the managerial insights revealed from varying the following: (1) port skipping cost; and (2) inland and port handling capacities; and (3) unit fuel cost.

4.5.3.1. Analysis 1: sensitivity to the port skipping cost

A sensitivity analysis was conducted to investigate the effects of change in the unit port skipping cost on the recovered vessel schedule. Specifically, the port skipping inconvenience coefficient (μ) was changed from $\mu = [1.00]$ to $\mu = [40.00]$ with an increment of $[1.00]$. A total of three scenarios of disruptions [scenarios "2", "3", and "5"], where the vessel skipped certain ports, were considered. The **VSRP-2** mathematical model was solved for each scenario of disruptions with an increment in the port skipping cost.

Scenario 2: A disruption at a port early in the voyage

Figure 38 presents the port skipping decisions for disruption scenario "2", when the port skipping coefficient μ was changed as $[1.0] \div [40.0]$ by increasing the value by $[1.00]$. It was observed that the Port of Marsaxlokk (Malta) was skipped without container diversion by the liner shipping company when the port skipping inconvenience coefficient was set to $\mu = [1.0] \div [13.0]$ (see Figure 38a). The latter finding can be supported by the fact that skipping the Port of Marsaxlokk (Malta) without container diversion was the most beneficial decision for the liner shipping company in order to effectively recover the vessel schedule, when a disruption occurred at a port early in the voyage [scenario "2"]. The estimated port skipping cost for these port skipping inconvenience coefficient cases was lower as compared to the extra route costs that might be incurred by the liner shipping company without port skipping if a disruption occurs at a port early in the voyage.

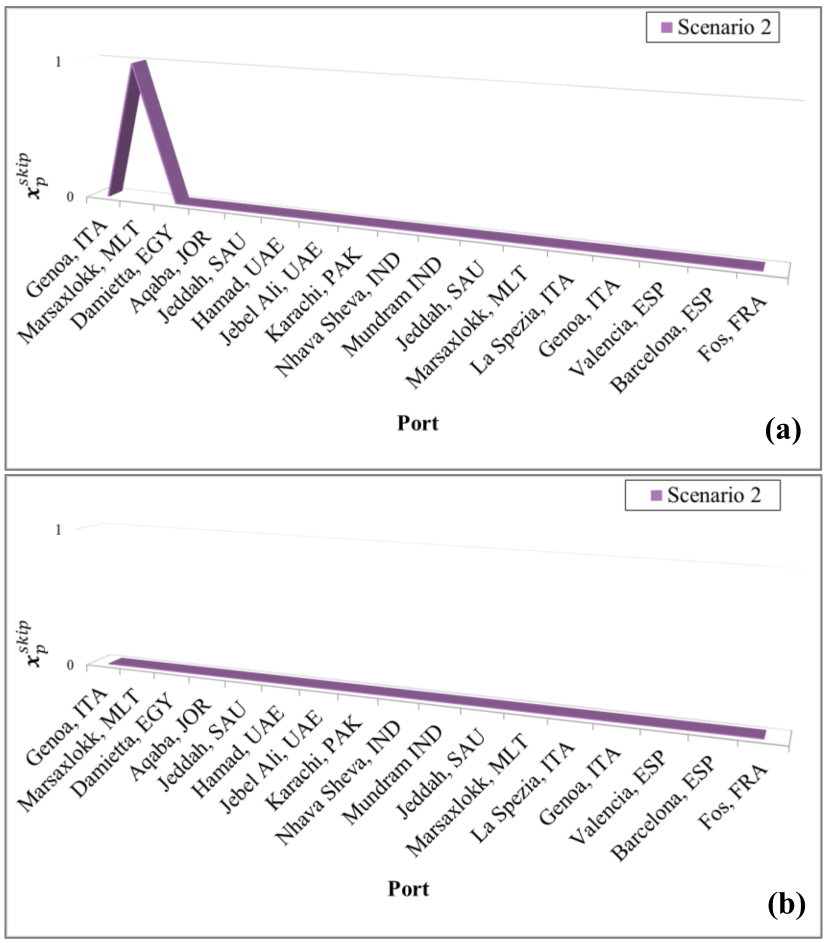


Figure 38 The port skipping decisions for disruption scenario 2: (a) $\mu = [1.0] \div [13.0]$; and (b) $\mu = [14.0] \div [40.0]$

Furthermore, when the port skipping inconvenience coefficient was increased to $\mu = [14.0] \div [40.0]$, it was observed that the liner shipping company did not skip the Port of Marsaxlokk (Malta) but endured the delay due to a disruption at the port (see Figure 38b). The latter finding can be explained by the fact that increasing the port skipping coefficient to $\mu = [14.0 \div 40.0]$ might cause a substantial increment in the port skipping cost to be endured by the liner shipping company. Hence, the liner shipping company did not skip the port when a disruption occurred early in the voyage [scenario "2"] and the port skipping inconvenience coefficient was increased to $\mu = [14.0] \div [40.0]$ in order to effectively recover the vessel schedule. The results from the numerical experiments demonstrated that the port skipping decisions when a disruption occurs at a port early in the voyage [scenario "2"] could be affected by the port skipping costs.

Scenario 3: A disruption at a port later in the voyage

The port skipping decisions for disruption scenario "3", when the port skipping coefficient μ was changed as $[1.0] \div [40.0]$ by increasing the value by $[1.00]$, is shown in Figure 39. It was observed that the Port of Valencia (Spain) was skipped without container diversion by the liner shipping company when the port skipping inconvenience coefficient was set to $\mu = [1.0] \div [36.0]$ (see Figure 39a). The latter finding can be supported by the fact that skipping the Port of Valencia (Spain) without container diversion was the most beneficial decision for the liner shipping company in order to effectively recover the vessel schedule when a disruption occurred at a port later in the voyage [scenario "3"]. The estimated port skipping cost for these port skipping inconvenience coefficient cases was lower as compared to the extra route costs that might be incurred by the liner shipping company without port skipping if a disruption occurs at a port later in the voyage.

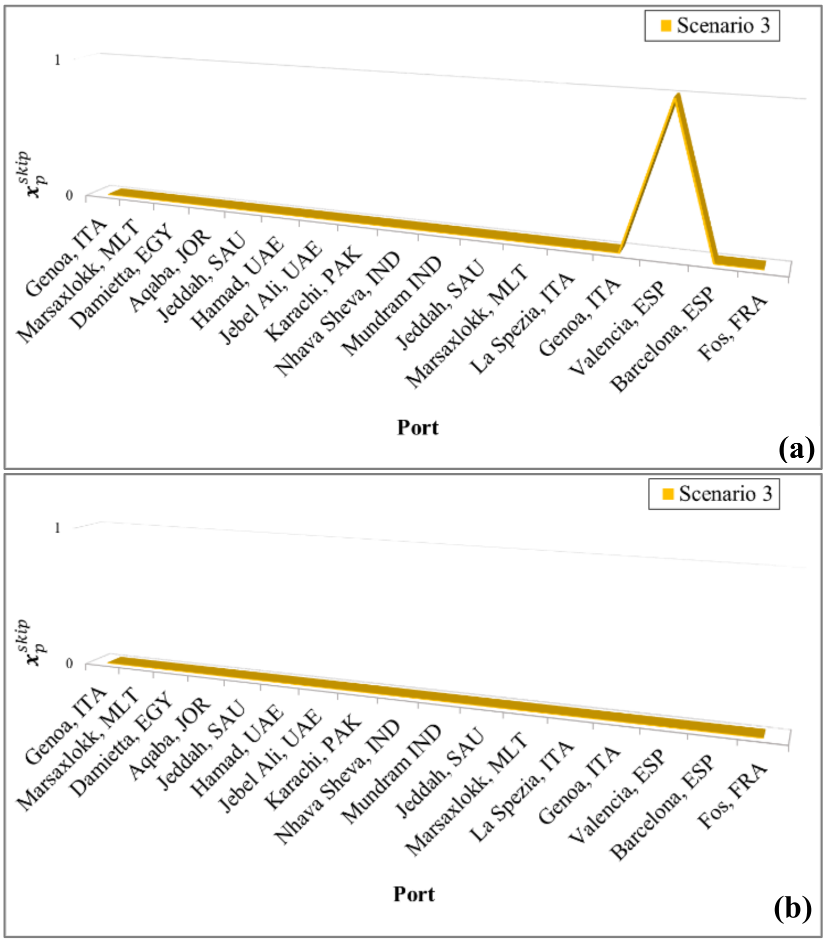


Figure 39 The port skipping decisions for disruption scenario 3: (a) $\mu = [1.0] \div [36.0]$; and (b) $\mu = [37.0] \div [40.0]$

However, when the port skipping inconvenience coefficient was increased to $\mu = [37.0] \div [40.0]$, it was observed that the liner shipping company did not skip the Port of Valencia (Spain) but endured the delay due to a disruption at the port (see Figure 39b). The latter finding can be supported by the fact that increasing the port skipping coefficient to $\mu = [37.0 \div 40.0]$ may cause a substantial increment in the port skipping cost to be endured by the liner shipping company. Thus, the liner shipping company did not skip the port when a disruption occurred later in the voyage [scenario "3"] and the port skipping inconvenience coefficient was increased to $\mu = [37.0] \div [40.0]$ in order to effectively recover the vessel schedule.

Note that when a disruption occurs at a port early in the voyage [scenario "2"], the liner shipping company decided to endure the delay after the port skipping coefficient was increased to $\mu = [14.0] \div [40.0]$, while the liner shipping company decided to endure the delay when a disruption occurs at a port later in the voyage [scenario "3"] after the port skipping coefficient was increased to $\mu = [37.0] \div [40.0]$. Such finding can be justified by the fact that the liner shipping has more flexibility to effectively recover the vessel schedule using other recovery options if a disruption occurs at a port early in the voyage [scenario "2"]; thus, lower port skipping cost can be endured. However, when a disruption occurs at a port later in the voyage, the liner shipping company has limited opportunities to effectively recover the vessel schedule and can endure a higher port skipping cost. The results from the numerical experiments suggested that the port skipping decisions when a disruption occurs at a port later in the voyage [scenario "3"] could be affected by the port skipping costs.

Scenario 5: Disruptions in sea and at ports

Figure 40 presents the port skipping decisions for disruption scenario "5", when the port skipping coefficient μ was changed as $[1.0] \div [40.0]$ by increasing the value by $[1.00]$. It was observed that the Port of Hamad (United Arab Emirates) was skipped without container diversion and the Port of Nhava Sheva (India) was skipped with 374 TEUs diverted to the Port of Mundra (India) by the liner shipping company when the port skipping inconvenience coefficient was set to $\mu = [1.0] \div [17.0]$ (see Figure 40a). Such finding can be supported by the fact that skipping the Port of Hamad (United Arab Emirates) without container diversion and the Port of Nhava Sheva (India) with container diversion (374 TEUs) to the Port of Mundra (India) was the most beneficial decision for the liner shipping company in order to successfully recover the vessel schedule when a disruption occurred in sea and at ports throughout the voyage [scenario "5"]. In this scenario, the estimated port skipping and container diversion costs were lower as compared to the extra route costs that might be incurred by the liner shipping company without port skipping if a disruption occurs in sea and at ports.

Furthermore, increasing the port skipping inconvenience coefficient to $\mu = [18.0] \div [40.0]$ might cause a substantial increase in the port skipping cost that will be incurred by the liner shipping company. It was observed that the liner shipping company did not skip the Port of Hamad (United Arab Emirates), but endured the delay due to a disruption at the port (see Figure 40b). Moreover, the liner shipping company still decided to skip the Port of Nhava Sheva (India) (see Figure 40b) with container diversion (374 TEUs) to the Port of Mundra (India) when the port skipping inconvenience coefficient was increased to $\mu = [18.0] \div [40.0]$ in order to successfully recover the schedule. Such finding can be explained by the fact that port skipping with cargo diversion was more cost-effective, as it allowed avoiding the additional costs due to misconnected cargo.

Therefore, the liner shipping company decided to endure the delay at the port of Port of Hamad (United Arab Emirates) but skipped the Port of Nhava Sheva (India) with container diversion to the Port of Mundra (India) in order to effectively recover the schedule. Based on the results from the numerical experiments, the port skipping decisions when disruptions occur in sea and at ports of call throughout the voyage [scenario "5"] could be affected by the port skipping costs.

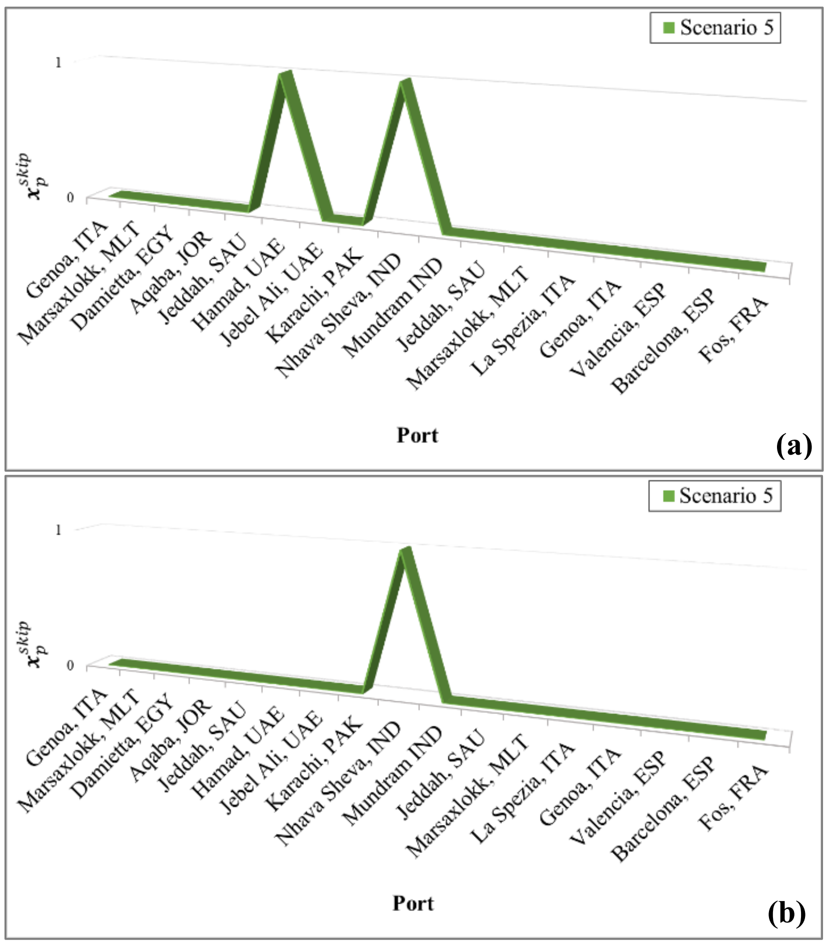


Figure 40 The port skipping decisions for disruption scenario 5: (a) $\mu = [1.0] \div [17.0]$; and (b) $\mu = [18.0] \div [40.0]$

4.5.3.2. Analysis 2: sensitivity to the inland transport and port handling capacities

This section discusses the effects of changing the inland and port handling capacities on the decision of the liner shipping company to divert cargo if a port is skipped due to a disruption. A total of five problem instances were generated by changing the inland transport and port handling capacities from 200 TEUs to 1000 TEUs with an increment of 200 TEUs. The developed problem instances are presented in Table 7.

Table 7 The considered inland transport and port handling capacities

Instance	MCT capacity to serve the diverted demand, C_p^{port} $\forall p \in P$ (TEUs)	Inland transport capacity for diverted demand, C_p^{land} $\forall p \in P$ (TEUs)
1	200	200
2	400	400
3	600	600
4	800	800
5	1000	1000

The **VSRP-2** mathematical model was solved for disruption scenarios “3” and “5” using the generated problem instances. Note that disruption scenarios “3” and “5” were considered because they were the only scenarios where a port can be skipped with container diversion by the liner shipping company based on the fact that some of the subsequent ports at the liner shipping route are in the same region. The results from the numerical experiments are presented next for disruption scenarios “3” and “5”.

Scenario 3: A disruption at a port later in the voyage

The port skipping decision with and without container diversion was retrieved from the **VSRP-2** mathematical model for each of the considered problem instances when a disruption occurs at a port later in the voyage [scenario “3”]. Table 8 presents the port skipping decisions with and without container diversion for scenario “3”. It was observed that when the inland transport and port handling capacities were each increased up to 600 TEUs, the liner shipping company decided to skip the Port of Valencia (Spain) without container diversion. However, when the inland transport and port handling capacities were increased up to 800 - 1000 TEUs, the Port of Valencia (Spain) was skipped, and 623 TEUs were diverted to the Port of Barcelona (Spain) by the liner shipping company. Such finding can be supported by the fact that skipping the Port of Valencia (Spain) and diverting 623 TEUs to the Port of Barcelona (Spain) was the most beneficial decision for the liner shipping company in order to recover the vessel schedule. Moreover, an increase in the inland transport and port handling capacities could allow the liner shipping company to deliver the diverted demand to the Port of Barcelona (Spain) and increase the revenue generated.

Table 8 Analysis results from scenario “3” for the considered problem instances

Instance	Port Skipping Decision	Container Diversion
1	Skip the Port of Valencia (Spain) without container diversion	N/A
2	Skip the Port of Valencia (Spain) without container diversion	N/A
3	Skip the Port of Valencia (Spain) without container diversion	N/A
4	Skip the Port of Valencia (Spain) with container diversion	Divert 623 TEUs to the Port of Barcelona (Spain)
5	Skip the Port of Valencia (Spain) with container diversion	Divert 623 TEUs to the Port of Barcelona (Spain)

Based on the results obtained from the computational experiments, it can be concluded that the port skipping decisions with container diversion and the number of containers diverted were significantly influenced by the MCT capacity to serve the diverted demand (TEUs) at ports and the capacity of the inland transport operator to deliver the diverted cargo to the end customers, when a disruption occurs at a port later in the voyage.

Scenario 5: Disruptions in sea and at ports

The port skipping decision with and without container diversion was retrieved from the **VSRP-2** mathematical model for each of the considered problem instances when disruptions occur in sea and at ports throughout the voyage [scenario “5”]. Table 9 presents the port skipping decisions with and without container diversion for scenario “5”. It was observed that when the inland transport and port handling capacities were each 200 TEUs, the liner shipping company skipped the Port of Hamad (United Arab Emirates) and the Port of Nhava Sheva (India) without container diversion. However, as the inland transport and port handling capacities increased from 200 to 800 TEUs (problem instances “2”, “3”, and “4”), the liner shipping company skipped the Port of Hamad (United Arab Emirates) without container diversion and skipped the Port of Nhava Sheva (India) with 374 TEUs diverted to the Port of Mundra (India). Such finding can be supported by the fact that skipping the Port of Hamad (United Arab Emirates) without container diversion and the Port of Nhava Sheva (India) with 374 TEUs diverted to the Port of Mundra (India) was the most beneficial decision for the liner shipping company in order to recover the vessel schedule.

Table 9 Analysis results from scenario "5" for the considered problem instances

Instance	Port Skipping Decision	Container Diversion
1	Skip the Port of Hamad (United Arab Emirates) without container diversion	N/A
	Skip the Port of Nhava Sheva (India) without container diversion	N/A
2	Skip the Port of Hamad (United Arab Emirates) without container diversion	N/A
	Skip the Port of Nhava Sheva (India) with container diversion	Divert 374 TEUs to the Port of Mundra (India)
3	Skip the Port of Hamad (United Arab Emirates) without container diversion	N/A
	Skip the Port of Nhava Sheva (India) with container diversion	Divert 374 TEUs to the Port of Mundra (India)
4	Skip the Port of Hamad (United Arab Emirates) without container diversion	N/A
	Skip the Port of Nhava Sheva (India) with container diversion	Divert 374 TEUs to the Port of Mundra (India)
5	Skip the Port of Hamad (United Arab Emirates) with container diversion	Divert 902 TEUs to the Port of Jebel Ali (United Arab Emirates)
	Skip the Port of Nhava Sheva (India) with container diversion	Divert 374 TEUs to the Port of Mundra (India)

On the other hand, when the inland transport and port handling capacities were increased up to 1000 TEUs, the liner shipping company skipped the Port of Hamad (United Arab Emirates) and diverted 902 TEUs to the Port of Jebel Ali (United Arab Emirates). Also, the Port of Nhava Sheva (India) was skipped with 374 TEUs diverted to the Port of Mundra (India) by the liner shipping company. The findings indicated that an increase in the inland transport and port handling capacities could allow the liner shipping company to deliver the diverted demand to the Ports of Jebel Ali (United Arab Emirates) and Mundra (India) and increase the revenue generated.

Based on the results obtained from the computational experiments, it can be concluded that the port skipping decisions with container diversion and the number of containers diverted were significantly influenced by the MCT capacity to serve the diverted demand (TEUs) at ports and the capacity of the inland transport operator to deliver the diverted cargo to the end customers, when disruptions occur in sea and at ports of call throughout the voyage.

4.5.3.3. Analysis 3: sensitivity to the unit fuel cost

An additional analysis was conducted to examine the effects of change in the unit fuel cost on the objective function (i.e., the total profit loss, endured by the liner shipping company due to disruptive events in sea and at ports) of the **VSRP-2** mathematical model and other cost components. A total of 12 problem instances were generated, by increasing the unit fuel cost from 250 to 800 USD/ton with an increment of 50 USD/ton. The developed problem instances are presented in Table 10. The proposed solution methodology was applied to solve the **VSRP-2** mathematical model for each of the generated problem instances and all scenarios of disruptions considered.

Table 10 The unit fuel cost values for the generated problem instances

Instance	Unit HFO cost (USD/ton)
1	250
2	300
3	350
4	400
5	450
6	500
7	550
8	600
9	650
10	700
11	750
12	800

The following cost components of the **VSRP-2** mathematical model were retrieved from the numerical experiments: (1) the total profit loss ($\boldsymbol{Z}$ – USD), which was endured by the liner shipping company due to disruptions; (2) the actual total profit ($\overline{\boldsymbol{TP}}$ – USD); (3) the actual total revenue ($\overline{\boldsymbol{REV}}$ – USD); (4) the actual total port handling cost ($\overline{\boldsymbol{PHC}}$ – USD); (5) the actual total late vessel arrival cost ($\overline{\boldsymbol{LAC}}$ – USD); (6) the actual total fuel cost ($\overline{\boldsymbol{FCC}}$ – USD); and (7) the actual container diversion cost ($\overline{\boldsymbol{CDC}}$ – USD). Figure 41 shows the objective function and other cost components of the **VSRP-2** mathematical model for the considered problem instances and disruption scenarios.

Results from the computational experiments revealed that the actual total revenue, which was generated by the liner shipping company, was higher when there were no disruptions in sea or at ports [scenario "1"] and lower when there were disruptions at certain voyage legs in sea and ports of call [scenario "5"] for the considered problem instances. The latter findings can be explained by the fact that the liner shipping company skipped certain ports in order to effectively recover the vessel schedule and was not able generate the expected revenue from those ports. However, where there were no disruptions in sea and at ports throughout the voyage, the liner shipping company was able to generate the expected revenue.

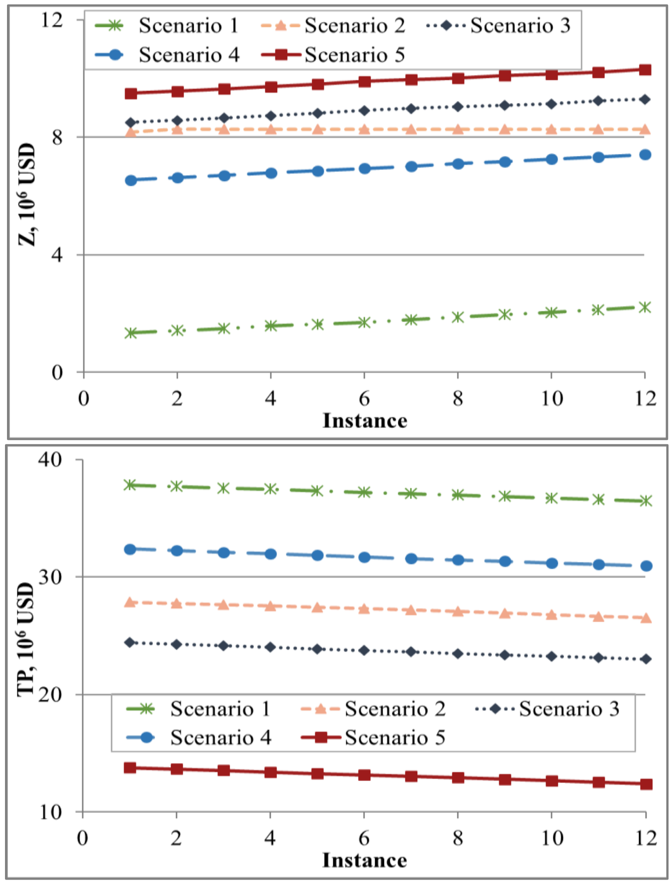


Figure 41 The objective function and its components for the considered problem instances

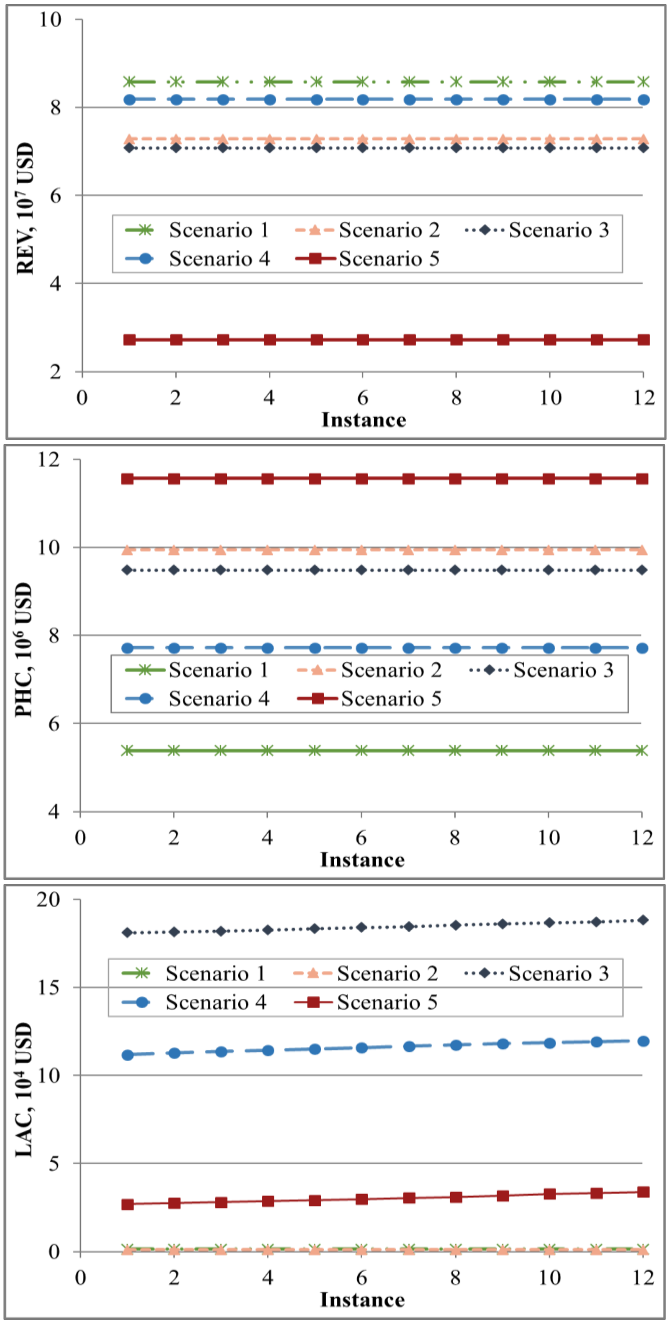


Figure 41 The objective function and its components for the considered problem instances – continued

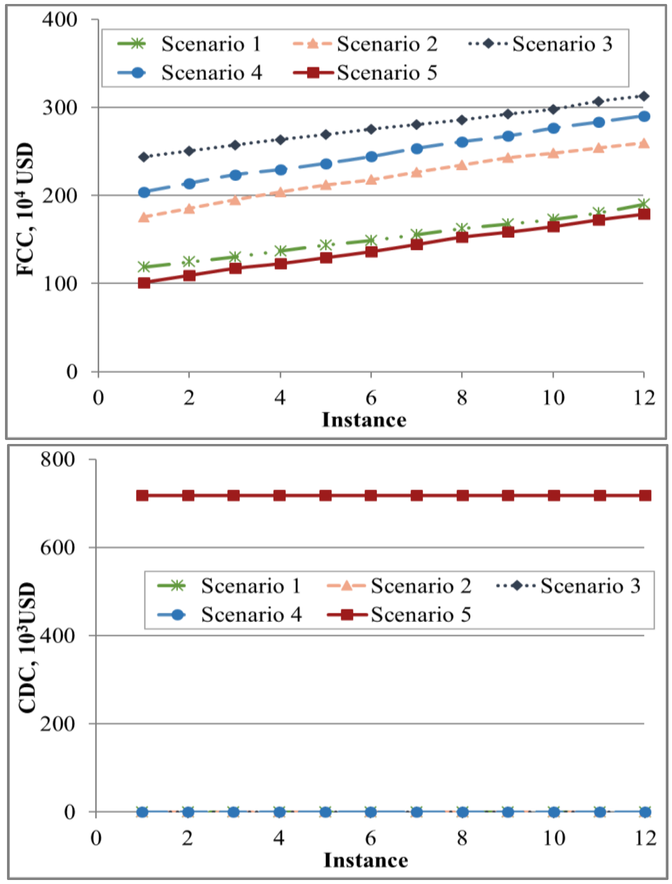


Figure 41 The objective function and its components for the considered problem instances – continued

Furthermore, an increase in the unit cost of fuel did not significantly affect the actual total revenue generated by the liner shipping company. Also, it was found that the actual total profit, generated by the liner shipping company decreased with an increasing unit cost of fuel for all the considered problem instances and scenarios of disruptions [scenarios "1", "2", "3", "4", and "5"]. Moreover, the actual total profit generated by the liner shipping company was higher when there were no disruptions in sea and at ports [scenario "1"] and lower where there were disruptions at certain voyage legs and ports of the liner shipping route [scenario "5"].

The actual total port handling cost was higher when there were disruptions at certain voyage legs and ports of the liner shipping route [scenario “5”] as compared to other scenarios of disruptions. The latter finding can be justified by the fact that the liner shipping company endured the additional port skipping costs and the cost of misconnected cargo at skipped ports, which significantly increased the actual total port handling cost. Also, the actual total fuel consumption cost increased with increasing unit fuel cost from one problem instance to another for all the considered scenarios of disruptions. Moreover, an increase in the unit cost of fuel for all the considered scenarios of disruptions generally resulted in a reduction in the average vessel sailing speed of vessels (as well as a reduction in the average vessel sailing speed adjustment), which resulted in an increase in the average sailing time of vessels at certain voyage legs of the liner shipping route. Figure 42, Figure 43, and Figure 44 present the average vessel sailing speed adjustment, average vessel sailing speed, and total vessel sailing time for disruption scenarios “3”, “4”, and “5”, respectively. The actual total late vessel arrival cost increased with an increasing unit cost of fuel from one problem instance to another for disruption scenarios “3”, “4”, and “5”.

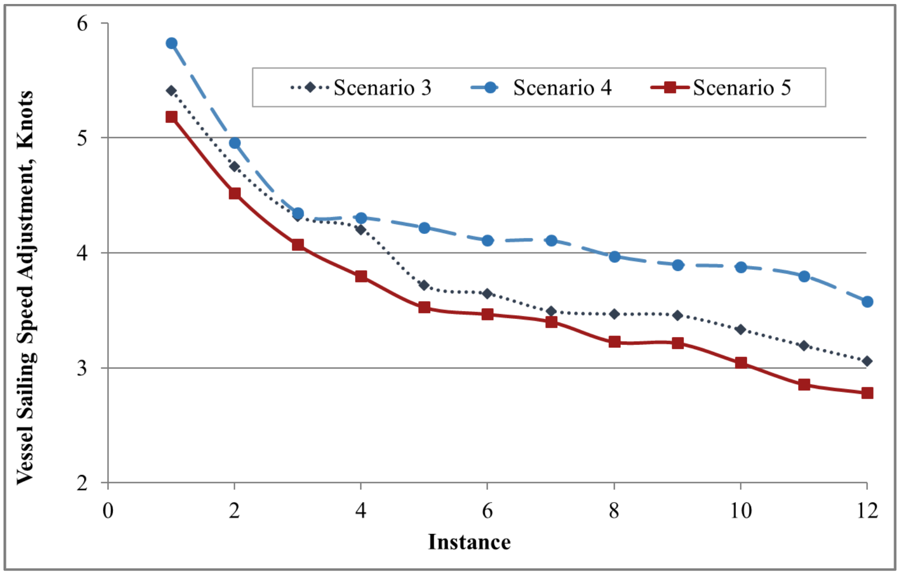


Figure 42 The average vessel sailing speed adjustment for the considered problem instances and for scenarios “3”, “4”, and “5”

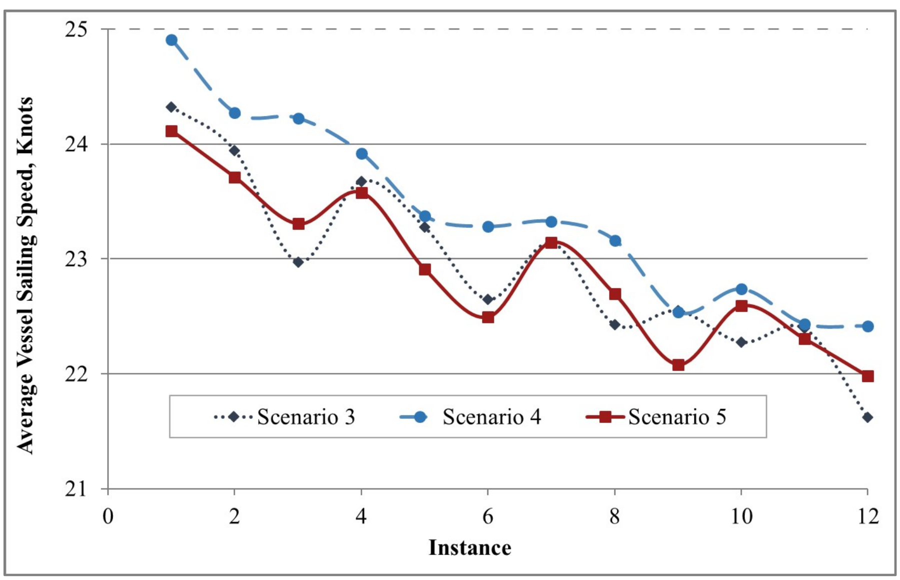


Figure 43 The average vessel sailing speed for the considered problem instances and for scenarios “3”, “4”, and “5”

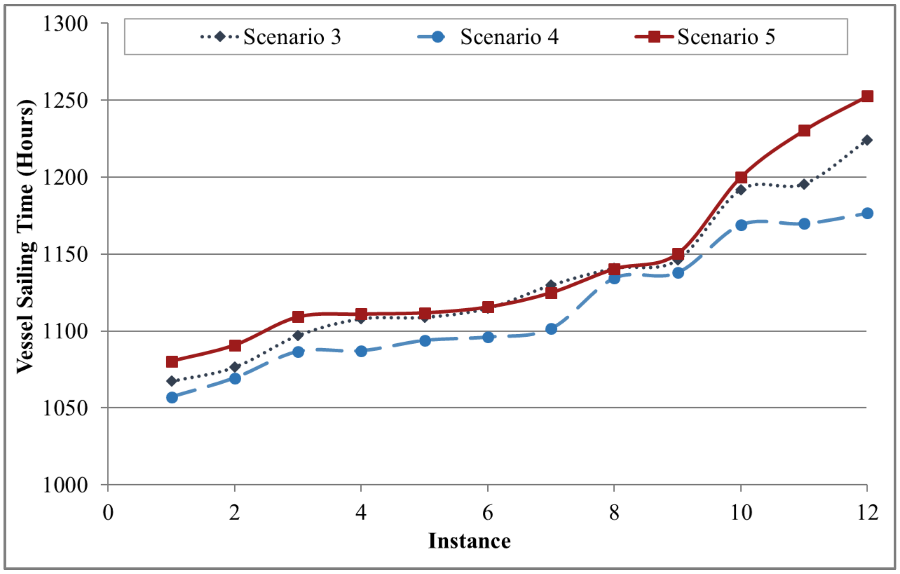


Figure 44 The total vessel sailing time for the considered problem instances and for scenarios “3”, “4”, and “5”

Based on the results from the numerical experiments, the container diversion cost was higher when there were disruptions in sea and at ports of call of the liner shipping route [scenario “5”], as compared to other disruption scenarios considered. Such finding can be explained by the fact that the liner shipping company decided to skip certain ports with container diversion when there were disruptions in sea and at ports [scenario “5”]. In addition, the total profit loss, endured by the liner shipping company, increased with an increase in the unit fuel cost from one problem instance to another for all the considered disruption scenarios. The least total profit loss was recorded when there were no disruptions in sea and at ports [scenario “1”], and the highest total profit loss was recorded when there were disruptions in sea and at ports of the liner shipping route [scenario “5”].

4.6. Conclusions

This chapter of the dissertation presented a novel mixed-integer nonlinear programming model for the vessel schedule recovery problem, aiming to minimize the total profit loss, endured by the liner shipping company as a result of disruptive event(s) in sea and at ports throughout the voyage. The proposed model considered four major vessel schedule recovery strategies, which included the following: (1) vessel sailing speed adjustment; (2) handling rate adjustment; (3) port skipping; and (4) port skipping with cargo diversion. The previous research efforts on vessel schedule recovery mostly considered the vessel sailing speed adjustment and the port skipping strategies. However, none of the studies published on vessel schedule recovery in liner shipping to date have considered handling rate adjustment and port skipping with cargo diversion recovery strategies, which could be applied simultaneously in order to effectively alleviate the effects of disruptions in liner shipping operations.

The nonlinear mathematical model, which was proposed in this chapter of the dissertation, was solved using BARON. A set of numerical experiments were performed for the Middle East-West Mediterranean route, which is served by OOCL liner shipping company. The results from computation experiments showed that an increase in the number of disruptive events at ports during a voyage significantly affected the vessel schedule. Therefore, the liner shipping company was required to implement more drastic recovery actions, such as port skipping with and/or without container diversion, instead of implementing the vessel sailing speed adjustment and/or handling rate adjustment. Moreover, the option of port skipping was found to be preferential when disruptive events occurred at ports. Implementation of the vessel sailing speed adjustment recovery strategy only was found to be inadequate to recover the delays when the liner shipping company was faced with disruptive events both in sea and at ports.

The results, retrieved from the computational experiments, revealed that the average vessel sailing speed adjustment and the average vessel sailing speed reduced when a disruptive event occurs at a port early in the voyage as compared to when a disruptive event occurs at a port towards the end of the voyage. The latter finding can be justified by the fact that the liner shipping company has the ability to efficiently recover the vessel schedule if a disruptive event occurs at a port early in the voyage (for instance, vessel sailing speed can be increased at several voyage legs of the liner shipping route to eliminate the delays). However, vessel schedule recovery becomes more difficult when a disruptive event occurs at a port towards the end of the voyage (for example, the liner shipping company will have only a few voyage legs to adjust the vessel sailing speed, thus, a more substantial increase in the vessel sailing speed will be required).

Based on the results, obtained from the computational experiments, it was observed that the port skipping decisions with container diversion and the number of containers diverted were significantly influenced by the marine container terminal capacity to serve the diverted demand at ports and the capacity of the inland transport operator to deliver the diverted cargo to the end customers when disruptions occur in sea and at ports of call throughout the voyage. The conducted experiments show that when disruptive events occur frequently during a voyage the profit losses may be unavoidable for the liner shipping companies. However, the methodology, presented in this chapter of the dissertation, could be effectively used by liner shipping companies to reduce the total profit losses.

CHAPTER 5

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

Liner shipping is an essential component of the global economy. Liner shipping involves the transport of containerized cargo from one port to another using container vessels. Over the last decades, the demand for liner shipping services has increased around the world, and continuous growth has been predicted. However, liner shipping companies face several challenges that affect liner shipping operations, some of which include: (1) bunker fuel consumption; (2) routing and scheduling; (3) speed optimization; (4) emissions; (5) uncertain port times; (6) network design; (7) schedule recovery; (8) alliance strategy, and others. Researchers have applied various strategies to solve the decision problems in liner shipping. Specifically, operations research methods have been widely adopted in addressing some of the major problems related to high fixed costs, high daily operational costs of container vessels, large fleet size, and alliances in liner shipping.

At the tactical level of decision making, the important components of liner shipping operations, including arrival, departure, and waiting times of vessels at ports, sailing speed of vessels, and port service frequency are planned by the liner shipping company. However, in reality, during a voyage, several types of disruptive events may take place in sea, such as inclement weather conditions, pirate attacks, crew strikes on vessels, mechanical faults from the vessel engine, etc. On the other hand, disruptive events at ports, including labor strikes at ports, congestion at ports, natural hazards, breakdown of handling equipment, and others, also affect the planned operations of liner shipping companies. Generally, disruptions in sea and or at ports cause delays that may last throughout the voyage. The disruptions in liner shipping operations adversely affect schedule adherence and the reliability of service of the liner shipping company. If disruptive events happen during a voyage, liner shipping companies actively seek the most efficient action that can be taken to recover the schedule. This dissertation addressed the disruptions in sea and at ports of call that may significantly impact the planned vessel schedule and cause significant monetary losses, among other negative externalities.

The review of the literature on vessel scheduling, which was conducted as a part of this work, revealed that the majority of studies published to date proposed the mathematical models, which aimed to minimize the total route service cost, minimize the total vessel weekly operational cost (TOC), minimize the total fuel consumption cost (TFC), minimize the total port handling cost (TPC), minimize the total service time window violation cost (TVC), minimize the total vessel emission cost (TEC), minimize the total container inventory cost (TIC), minimize the miscellaneous costs (MSC), and maximize the total revenue (REV) of the liner shipping companies. Researchers have proposed several types of mathematical formulations. Various optimization algorithms, including heuristic, metaheuristic, and exact optimization algorithms, have been used to solve the vessel scheduling problems in liner shipping. In addition, the reviewed studies, which addressed the vessel schedule recovery problem in liner shipping, mostly considered the vessel sailing speed adjustment and port skipping vessel schedule recovery strategies.

Several liner shipping routes pass via the areas that have been marked as Emission Control Areas (ECAs) by the International Maritime Organization (IMO), where restrictions are imposed on certain emissions produced by vessels, when sailing within the area. This dissertation presented a novel mixed-integer nonlinear mathematical model for the green vessel schedule recovery problem for the liner shipping route, which passes via ECAs. Specifically, certain regulations are imposed on the sulfur content of fuels used by vessels within ECAs. Here, liner shipping companies must consider energy efficiency and environmental sustainability in the vessel schedule recovery. The mathematical model, proposed for the problem, minimized the total profit loss, suffered by a given liner shipping company because of disruptions in the planned operations. The vessel sailing speed adjustment and port skipping strategies were proposed in the model. Moreover, the static secant approximation method was applied to linearize the nonlinear model, and the model was solved to the global optimality using CPLEX.

The Asia-North Europe LL5 liner shipping route, which is served by OOCL liner shipping company and passes via ECAs, was used to test the proposed model. A total of three cases of disruptions were considered (namely, no disruptions, disruptions within ECAs, and disruptions within and outside ECAs). The results from the numerical experiments showed that as the number of disruptive events in sea and at ports along the given liner shipping route increased, there were substantial changes in the vessel schedule, which forced the liner shipping company to skip certain ports of call. Furthermore, an increase in the unit fuel cost restricted the ability of the liner shipping company to apply the vessel sailing speed adjustment recovery strategy. It was also found that the decision of the liner shipping company to skip certain ports within and outside

ECAs, when disruptions occur, could be affected by the port skipping cost. The results retrieved from the numerical experiments showed that the developed solution approach could be applied by liner shipping companies when disruptions occur at the liner shipping route that passes via Emission Control Areas to efficiently recover the vessel schedule, minimize the monetary losses because of disruptions, and improve energy efficiency as well as environmental sustainability.

Furthermore, a nonlinear mathematical model was presented in this dissertation for the vessel schedule recovery problem in liner shipping, considering four major vessel schedule recovery strategies, namely: (1) vessel sailing speed adjustment; (2) handling rate adjustment; (3) port skipping; and (4) port skipping with cargo diversion. The handling rate adjustment and port skipping with cargo diversion recovery strategies, proposed in this dissertation, have not been considered in any of the existing studies that addressed the vessel schedule recovery problem in liner shipping. The proposed nonlinear mathematical model was solved using BARON. A set of computational experiments were conducted for the Middle East-West Mediterranean route, which is served by OOCL liner shipping company. A total of five disruption scenarios were considered to evaluate the proposed solution methodology. Specifically, the scenarios of disruptions were used to examine the cases of a disruption at a port early in the voyage, a disruption at a port later in the voyage, disruptions in sea, disruptions in sea and at ports of call. It was found that the liner shipping companies may have to implement multiple schedule recovery strategies when disruptive events occur in sea and at ports. The liner shipping company had to select the vessel handling rate adjustment strategy, along with the vessel sailing speed adjustment recovery strategy, to recover the vessel schedule effectively.

Also, the port skipping with container diversion recovery strategy may be beneficial for liner shipping to recover the schedule when disruptions occur in sea and at ports throughout the voyage. It is noteworthy, that container diversion between ports can be considered only if the ports are linked by intermodal transportation, which will allow for the delivery of the diverted cargo to the end customers. Moreover, the handling and intermodal capacities at the alternative ports must be enough to handle the diverted cargo. Furthermore, when a disruption occurs at a port, the liner shipping company may decide to endure the delay when the port skipping cost is high. The results from the numerical experiments also showed that when a disruption occurs at a port later in the voyage the port skipping decisions with container diversion and the number of containers diverted could be significantly influenced by the marine container terminal capacity to serve the diverted demand at ports and the capacity of the inland transport operator to deliver the diverted cargo to the end customers.

There are several extensions to the vessel schedule recovery problems that have been addressed in this dissertation, some of which include, but are not limited to, the following:

- The proposed **GVSRP** mathematical model can be applied for certain liner shipping routes that pass via ECAs and have restrictions imposed on SO_x, NO_x, and PM emissions;
- There are various types of emissions that could be accounted for, which include, but are not limited to, nitrogen oxide – NO_x, carbon monoxide – CO, non-methane volatile organic compounds – VOC, and others;

- Future studies may formulate mathematical models that consider stochastic disruptive events at voyage legs in sea and at ports of call of the liner shipping route, where the anticipated reduction in the vessel sailing speed in sea, as well as the anticipated disruption time period at ports, are uncertain;
- Other feasible vessel recovery strategies can be included in the mathematical models proposed in this study (e.g., port swapping);
- There is a need to consider various forms of uncertainty in the vessel schedule recovery model, such as uncertainty in fuel consumption and uncertainty in port handling time;
- Future studies may examine other strategies for linearizing the vessel schedule recovery mathematical models presented in this study, including discretization, outer approximations, second order cone programming, etc.;
- There is a need to conduct additional analyses to investigate the effects of increasing the additional cost of inland transport of the diverted cargo on the decision of liner shipping companies to skip certain ports with cargo diversion;
- Future studies need to take into account various berth scheduling concerns that may come up as a result of disruptions in the planned operations for ports of the liner shipping route that may or may not have soft time windows;
- A number of important objective components may be accounted for in future mathematical models, such as the actual total cost for the violation of arrival time windows, actual total emission cost, and others;
- Future research may consider developing mathematical models that account for the conflicting nature of some objectives in vessel schedule recovery (for instance

an increase in the vessel sailing speed in case of a disruptive event will reduce the total vessel sailing time but may increase the actual total profit loss, suffered by the liner shipping company).

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