Optimization Applications in Maritime Logistics and Operations

WANG KAI

PhD

The Hong Kong Polytechnic University

2019

The Hong Kong Polytechnic University

Department of Logistics and Maritime Studies

Optimization Applications in Maritime Logistics and Operations

Wang Kai

A thesis submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy

July 2019

Certificate of Originality

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgment has been made in the text.

__________________________ (Signed)

29/07/2019 (Name of student)

Abstract

This thesis investigates four optimization problems in maritime logistics and operations, where the first two problems are related to container ships that transport cargo and the other two problems are related to cruise ships that transport passengers. The first problem concerns the container ship type decision. It aims to determine the ship types deployed on shipping routes while taking the possible empty container repositioning and the usage of novel foldable containers into account. The second problem addresses the optimal reefer slot conversion for container freight transportation. It optimizes the number of reefer slots in a fleet of container ships deployed on a shipping route and re-optimizes the sequence of these ships to maximize the revenue. The third problem investigates the cruise itinerary schedule design for a cruise ship. It determines the visiting sequence of several ports of call and the corresponding arrival and departure times at the ports, so as to maximize the monetary value of cruise passengers' utility minus operations costs. The fourth problem focuses on cruise service planning. It proposes a solution approach to schedule available cruise services for a cruise ship over a planning horizon while considering berth availability at ports of call and decreasing marginal profit for each cruise service. To solve the four problems, different operations research methods are proposed, such as network flow modeling, mixed integer linear programming, simulation algorithms, dynamic programming, model linearization techniques, and heuristic algorithms. By referring to real-world data, extensive numerical experiments are conducted to validate the effectiveness of the proposed methods. Some potential managerial insights behind the problems are also revealed.

Acknowledgments

I would like to thank my supervisor Dr Shuaian Wang for his full support all the time and thank my thesis board members, Professor Miao Song, Professor Xiangtong Qi, Professor Yanzhi Li, and Dr Shuaian Wang for their time and valuable feedback. I would also like to thank the financial support from the Hong Kong Ph.D. Fellowship Scheme 2016/2017 and thank the research funding support from the Department of Logistics and Maritime Studies, The Hong Kong Polytechnic University.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

- Twenty-foot equivalent units (TEUs)
- Origin-destination (O–D)
- Network flow (NF)
- Mathematical programming (MP)
- Mixed integer linear programming (MILP)
- Cruise itinerary schedule design (CISD)
- Revenue management (RM)
- Vehicle routing problems with time windows (VRPTW)
- Dynamic programming (DP)
- Cruise service planning (CSP)

Chapter 1: Introduction

This thesis includes four essays with a focus on maritime logistics and operations. It studies four optimization application problems in the field, where the first two problems are related to container ships that transport cargo and the other two problems are related to cruise ships that ship cruise passengers. Different operations research methods are adapted to provide effective solution approaches for optimization problems. Extensive experiments are conducted to draw managerial insights on the problems.

1.1 BACKGROUND

In the container shipping industry, container ships are used to transport cargo among seaports in the world, which contributes to the majority of shipping volume in the global trade. The cost-effectiveness of sea transportation is the major competitiveness compared with other transportation modes, such as road and air transportation. Thus, shipping companies endeavor to optimize their operations such that they can reduce their operations costs. This is especially important now since the industry is experiencing a transformation to an environmentally friendly industry (Xia et al., 2019), which request more investments from the shipping companies.

In the cruise shipping industry, cruise ships serve the purposes of providing pleasure voyages. Once cruise passengers are on aboard, the voyages and the activities by the cruise ships bring utility experience to the passengers, for which the cruise ships earn profits. The transportation is not the major purpose of the cruise shipping since the cruise passengers normally will return to the same port where they embark. The cruise industry is a very promising industry and it keeps booming in recent years, especially for the Asia market (Wang et al., 2016; Wang et al., 2017). However, the studies on this industry are rare in the literature, but the operations of the industry are very urgent to be investigated.

The container shipping industry and the cruise shipping industry share many similarities since they all belong to the maritime logistics and operations. They all follow some pre-determined schedules to traverse a set of fixed ports of call, and they need to dwell at berths of ports to conduct some on-shore activities. The major operational cost of the container and cruise ships is the fuel consumption cost. However, they have several remarkable differences. For instance, the container shipping aims to transport the cargo from its origin port to its destination port, but the cruise shipping aims to provide voyage service for the cruise passengers on aboard.

In this thesis, four operation optimization problems will be addressed and solved for the container shipping and the cruise shipping, from which some similarities and differences between the two industries can be sensed. The first two problems aim to optimize the operations for container ships such that the operational costs can be reduced. The other two problems aim to improve the operations for cruise ships such that the operating profits can be increased. Different operations research methods are adopted to solve the problems, and extensive numerical experiments are conducted to explore the hidden insights behind the problems.

1.2 THESIS OUTLINE

The remainder of this thesis is organized as follows. Chapter 2 and 3 are related to the operations of container ships, and Chapter 4 and 5 are related to the operations of cruise ships. In specific, Chapter 2 presents a study of ship type decision considering empty container repositioning and foldable containers. Chapter 3 studies the optimal reefer slot conversion for container freight transportation. Chapter 4 considers the problem of cruise itinerary schedule design for a cruise ship. Chapter 5 addresses the cruise service planning considering berth availability and decreasing marginal profit. Chapter 6 concludes the thesis.

Chapter 2: Container Ship Type Decision

This chapter addresses a ship fleet type decision problem with considering empty container repositioning and foldable containers. This decision problem determines the capacity of container ships deployed in a given shipping route. In reality, the ship fleet deployment decision is usually made empirically according to laden container transportation and does not consider the possible empty container repositioning. Meanwhile, a novel mode ‘foldable container’ has shown its economic and logistical viability in recent years. This study hence also considers the use of foldable containers and aims to find under what conditions, a shipping liner needs to use the foldable containers in its liner shipping services. To solve the problem, we formulate a network flow model with a revised network simplex algorithm, based on which an exact solution approach is designed to determine the optimal ship type. A mixed-integer programming model is also formulated for the problem. Numerical experiments based on real-world voyages are conducted to find some managerial implications on the ship fleet deployment and the foldable container usage.

2.1 INTRODUCTION

A shipping liner normally operates weekly-serviced ship routes with fixed schedules to transport containers. Given a shipping route, a shipping liner deploys a fleet of container ships for the operation over a planning horizon, e.g., six months. One of the critical decisions for the shipping liner on the fleet is ship type decision, which determines the capacity of container ships of the fleet deployed on the shipping route. Empirically, the shipping liner deploys a suitable fleet type of ships on each route based on the laden container transportation over the planning horizon, which guarantees that the deployed ships have the capacity to accommodate all the laden containers in all the voyages. Under this circumstance, the shipping liner would not deploy a ship fleet with a larger capacity as it increases the fixed operating cost for maintaining the fleet. It is reasonable for the shipping liner to make such decision only considering the laden container transportation. However, if we further consider the empty container repositioning on the route, the ship type decision can be more complicated.

The empty container repositioning originates from the imbalance of container flow between different regions in liner shipping routes. Take the trans-Pacific trade lane for example: according to UNCTAD (2016), in 2015, the annual container flow from Asia to North America (i.e., the eastbound) was around 15.8 million twenty-foot equivalent units (TEUs), and the container flow in the opposite westbound direction was 7.4 million TEUs, which generated the imbalance of container flow for 8.4 million TEUs. This imbalance contributes to tremendous empty container accumulation in import-dominant areas (North America) and the serious empty container shortage in export-dominant areas (Asia). This leads to a critical problem on the empty container availability for the laden container transportation consignment in those export-dominant areas or ports. In those export-dominant ports, the arriving laden containers from incoming ships become empty and are stored in depots after devanning, which can only fulfill part of the empty container requirement for the sake of their export-dominant characters. As a result, the empty container repositioning from the surplus ports (i.e., import-dominant ports) to the deficit ports (i.e., export-dominant ports) becomes necessary. However, the empty containers repositioned between the ports occupy the capacity of the container ships traversing the corresponding voyages in the shipping route. Henceforth, the ship type decision is no longer straightforward when considering the empty container repositioning.

Figure 2.1: Four foldable containers and a standard container (Shintani et al., 2010)

Storing empty containers in the depots and repositioning empty containers among the ports inevitably incur storage cost and repositioning cost for the shipping liner, respectively (Lee and Yu, 2012). To reduce costs, the usage of foldable containers is an effective method. The idea of foldable containers is not so new, and several container companies have developed foldable containers, such as Fallpac AB and Holland Container Innovation. Those foldable containers have equivalent storage capacity and size as standard containers and a foldable container only occupies one-quarter storage space of a standard container in folded status, as shown in Figure 2.1 (See Appendix A for the specification comparison between a standard container and a foldable container). After becoming empty, the foldable containers will be in folded status for the storage in the depots or for the repositioning to other ports. As four foldable empty containers in the folded status equal one standard empty container, it saves 75% storage space by using foldable containers, which leads to significant decrease in the repositioning cost and the storage cost. However, using the foldable containers could incur additional costs for the shipping liner. Firstly, the purchasing fee or long-term leasing cost of the foldable containers is higher than that of the standard containers. Secondly, folding and unfolding processes involve labor cost in the ports for the empty container repositioning. Therefore, there is a trade-off by using foldable containers between reducing the storage cost and the repositioning cost and incurring the additional costs.

Currently, foldable containers are not widely used in the liner shipping industry and stakeholders of the industry are trying to make the foldable containers prevalent. Here, we summary two practical concerns that may impede the usage of foldable containers at present. Firstly, maintaining a foldable container fleet needs a considerable investment at the first phrase, as the building cost of a foldable container is double as that of a standard container (Goh et al., 2016). Considering the shipping market is experiencing a depression (UNCTAD, 2016), the majority of shipping lines may not have enough funding to replace the standard containers in their container fleet with foldable containers. Secondly, folding and unfolding activities in container terminals incur additional labor operations. Henceforth, container terminals and shipping lines need to negotiate a comprehensive agreement on maintaining the operations and training technicians, which may not be achieved at the moment. Although these concerns can exist in practices, the usage of foldable containers is still promising in the near future. We take Holland Container Innovations (HCI), the manufacturer of the 4FOLD foldable container, as a typical example to illustrate industry trends of using foldable containers. Holland Container Innovations (2017a) reported that some major shipping lines (e.g., APL, Samudera Indonesia and Seatrade) have used 4FOLD foldable containers in their shipping routes, and an increasing number of shipping lines have signed the contracts with HCI to promote the usage of the foldable containers, such as Emirates Shipping Line (Word Cargo News, 2017). Meanwhile, HCI is providing the folding training programs for some container terminals around the world in the preparation for using foldable containers, such as Tetris Container Terminal in Moscow, Ljubljana Container Terminal in Slovenia and Qingdao Shitengkeyun Depot.

Motivated by the above problem justifications and industry trends, our study aims to solve a problem of ship type decision considering the empty container repositioning and foldable containers, in order to minimize the total cost that occurs in a given planning horizon for the shipping route. The problem focuses on related decisions in both tactical and operational levels. In the tactical level, it first determines the ship type of the container ship fleet (denoted as ship type decision), which decides the capacity (in TEUs) of container ships deployed in the shipping route. Then, the problem determines the number of foldable and standard containers leased (or kept) in the ports initially for the usage of the planning horizon, which is a container fleet sizing in essential (denoted as long-term container leasing). In the operational level, upon each weekly service, if there are empty containers surplus in some ports, the problem decides the number of empty containers that the visiting ship should reposition to other deficit ports. In case of the empty container deficit, the shipping liner can lease empty containers in origin ports and return them in destination ports (denoted as short-term container leasing) to fulfill the transportation consignments. Here, we summarize the empty container repositioning and the container fleet sizing as the empty container allocation.

If the empty container repositioning is not involved, the ship type decision is to guarantee that the deployed ships have the capacity to accommodate all the laden container transportation and a ship fleet with a larger capacity will not be an option. However, involving empty container repositioning complicates the ship fleet deployment. The empty container repositioning provides the shipping liner with the motivation to deploy a ship fleet with a larger capacity. Although it will raise the fixed operation cost, it gives the shipping liner more flexibility and capacity to reposition empty containers among ports. Meanwhile, the container fleet sizing intertwines with the ship fleet deployment and the empty container repositioning. The container fleet sizing determines the total number of containers flowing in the planning horizon. As those containers would be either in the depots or on the ships, the effects on the ship type decision are inescapable. Normally, the larger the container fleet, the more the empty containers repositioned.

Based on the above analysis, this paper presents an explorative study on the problem of ship type decision considering the empty container repositioning and foldable containers. In the study, we find that given the ship type with a specific capacity, the problem transfers to a nonstandard minimum cost flow problem, which solves the container fleet sizing and the empty container repositioning. For the nonstandard minimum cost flow problem, we build a network flow model by constructing a network for the flow of empty containers. Due to the usage of standard and foldable containers, the network inevitably has some parallel arcs sharing the same capacity restriction such that one cannot apply some standard network algorithms (e.g., the network simplex algorithm (Ahuja et al., 1993)) to solve it. To tackle the above issue, we propose a revised network simplex algorithm (an exact algorithm) by introducing dynamic capacity restrictions and revising the pivot operation of the standard algorithm. Based on the reduced costs derived from the revised network simplex algorithm, we propose a solution approach to determine the optimal ship type. By applying the solution approach, we conduct extensive experiments to find insights on the ship type decision and the foldable container usage.

The remainder of this chapter is as follows: Section 2.2 reviews some related works. Section 2.3 elaborates the background information and decisions on the problem. Section 2.4 presents a network flow model given the capacity of a ship. Section 2.5 elaborates the developed solution approach that embeds a revised network simplex algorithm. Section 2.6 shows some experiments for finding insights on the ship type decision and the foldable container usage. The last section presents some conclusions.

2.2 LITERATURE REVIEW

There have been numerous studies related to the ship fleet deployment and empty container repositioning problems. For the ship fleet deployment, to the best of our knowledge, Perakis and Jaramillo (1991) was the first study to address it, in which they built integer linear programming models for the problem. Thereafter, there were generally two types of studies on the problem. One type assumes that the container shipment demand is deterministic (Gelareh and Meng, 2010; Brouer et al., 2013; Plum et al., 2013). For instance, Gelareh and Meng (2010) developed a mixed integer nonlinear programming model for a short-term fleet deployment problem, in which the optimal vessel speeds for different vessel types on different routes are considered. The other type of studies relaxed the deterministic demand assumption and treated the container shipment demand in a stochastic manner (Meng and Wang, 2012; Ng, 2014; Ng, 2015). Meng and Wang (2012) addressed a practical ship fleet problem under the background of week-dependent container shipment demand. Their study generated practical container routes considering transit time constraints by using space-time network approach. For more works on the ship fleet deployment, one can refer to Ng (2016), in which it elaborated a class of fleet deployment models.

For the empty container repositioning or empty container allocation, Crainic et al. (1993) introduced two dynamic formulations for empty container allocation in single and multi-commodity cases, which provided a general framework to formulate this class of problems. Cheung and Chen (1998) considered a dynamic empty container allocation problem, which helped to determine the number of containers leased to fulfill the demands of customers over time. The management of importing and exporting empty containers in a port was analyzed by Li et al. (2004) based on the multi-stage inventory theory, and Markov decision processes were proposed for the problem. Li et al. (2007) extended the previous study to a multi-port application with a proposed heuristic algorithm for the problem. The empty container repositioning problem for general shipping service routes was formulated by Song and Dong

(2010) based on container flow balancing mechanism. Menh and Wang (2011) embedded the empty container repositioning into the liner shipping service network design. They verified that the network considering empty container could cut down the network cost significantly. Song and Dong (2011) combined the laden container routing problem and empty container repositioning problem. With fixed vessel schedules and shipping service network, their study attempted to minimize the sum of all container related costs in routing and repositioning processes.

However, the majority of these related works treated the ship fleet deployment and the empty container repositioning as individual parts, i.e. they did not consider the two decisions in their studies simultaneously. As it shows in the introduction that the two decisions interact with each other in real-world operations, one may obtain a local optimum rather than the global optimum for the shipping service only considering a single part of the two decisions.

On the other hand, few kinds of literature have studied the empty container repositioning considering the usage of foldable containers. Konings (2005) has addressed the economic and logistical viability of using foldable containers, which enhanced the confidence to use foldable containers in sea transport. Shintani et al. (2010) investigated the impact of using foldable containers in hinterland transport, which showed that the foldable containers substantially save on the repositioning cost compared to the standard containers. Moon et al. (2013) was almost the first to model the usage of standard containers and foldable containers in empty container repositioning and proposed a heuristic algorithm to solve their problem. Based on Moon et al. (2013), Myung and Moon (2014) found that the previous problem transfers to a minimum cost flow if they do not consider the capacity restrictions when repositioning empty containers. In our study, we recognize the trouble that when considering standard containers and foldable containers, after involving the capacity restrictions (which is compulsory, as our problem needs to determine the ship capacity), we will obtain a nonstandard minimum cost flow. Fortunately, we design a revised network simplex algorithm that can easily tackle the trouble.

Compared with the above literature, our study incorporates the empty container allocation (including the container fleet sizing and the empty container repositioning) into the ship type decision in order to obtain the global optimal solution for a shipping route over a planning horizon. It further considers the usage of foldable containers, which aims to see whether the shipping liner should apply the foldable containers in the shipping service. Given a ship type for considering capacity restrictions, it overcomes the trouble faced by Myung and Moon (2014) by designing a revised network simplex algorithm. In all, we can tackle all the above decisions by an integrated solution approach.

2.3 PROBLEM DESCRIPTION

Our problem focuses on ship type decision considering the empty container repositioning and foldable containers for a given shipping service route. A fleet of container ships with certain capacity is to be determined for weekly serving the ports along the shipping route. The incoming container ship transports weekly laden containers originating from the ports to destination ports. In each port, the empty container availability is critical for the shipping liner to meet the laden container transportation. Generally, there are three empty container supplies to fulfill laden container transportation. The economic supply is the arriving containers with fully loaded goods from the incoming ship. Once these fully loaded containers arrive at the ports and are delivered to consignees for unloading, the containers become empty and are stored in depots for the laden consignment. The second supply is to reposition the empty containers from surplus ports to deficit ports along the shipping route, which occupy the capacity of the container ships among voyage legs. However, if the stored and repositioned empty containers cannot meet the weekly laden container transportation, the shipping liner must lease empty containers from container companies by short-term container leasing, which is the third supply for the empty containers. The short-term container leasing is on an O-D pair basis (See Section 2.3.2), which is different from the long-term container leasing that is on a planning horizon basis (See Section 2.3.1).

Figure 2.2: A transpacific shipping service route operated by CMA CGM (CMA CGM, 2017)

In this study, the given shipping route has a fixed port rotation, shown by an illustrative example in Figure 2.2. The itinerary of this route forms a loop: we can arbitrarily deem that this itinerary starts at Shanghai and ends at Shanghai. Let $p \in P$ represent the index of the ports on a round trip for the route. Then, for this route, we can define Shanghai as Port 1, Ningbo as Port 2, Pusan as Port 3, Los Angeles as Port 4 and Oakland as Port 5. Based on the given route, the shipping liner has a set of O–D (Origin-Destination) port pairs D. The laden container transportation arises on those pairs in each week. We represent (o, d) as the index for O–D port pairs, where $o \in P, d \in P$. Note that we study the shipping routes that have no butterfly ports in the routes, i.e., the route can visit each port at most once.

For the given shipping service route, the shipping liner normally offers services for the ports on a weekly basis. In other words, there is a week interval for each port to be visited by one round trip and its next round trip. Let e represent the index of round trips, and E as the set of round trips for one planning horizon. The weekly laden container transportation consignments for each port accumulate between the visiting times of two adjacent round trips and are fulfilled by the latter round trip. Here, we denote $d_{od,e}$ as the number of laden containers accumulated in Port o between the time that the port is visited by the $(e-1)^{st}$ round trip and the time that the port is visited by the e^{th} round trip, and will be transported to Port d by the e^{th} round trip. Here, note that we use the number of round trips rather than the number of weeks to represent the planning horizon, and the time interval between two round trips for a port is one week.

The number of ships deployed in the route is pre-determined. The number of ships corresponds to the number of weeks needed for the round trip in the weekly shipping service, i.e., if a round trip for the route needs N weeks, there must be N ships deployed in the route such that the weekly shipping services can be guaranteed. Here notice that the n^{th} ship ($n \in \{1,2,\ldots,N\}$) is assigned for the $\{n^{th}, (n+N)^{th}, (n+2N)^{th}, (n+3N)^{th}, \ldots\}$ round trips.

2.3.1 Tactical level planning

In the tactical level, the problem involves two decisions. The first one is the ship type decision. The ship type decision is mainly on choosing the ship type to deploy with a certain capacity, measured by TEUs. Fulfilling the laden container transportation on the shipping service route is the basic criteria for the deployment, which means the deployed ship type must have the capacity to carry all the laden containers from origin ports to destination ports. However, there is a trade-off on whether to deploy the ships with a larger capacity or not. If the deployed ship type has a larger capacity, the fixed operating cost for the ship fleet is higher, but the larger capacity means more empty containers can be repositioned from surplus ports to deficit ports, which could save the high cost spent on short-term container leasing in those deficit ports.

The second decision at the tactical level is the container fleet sizing (or we say the long-term container leasing), which aims to determine the number of foldable empty containers and standard empty containers that are leased in the ports along the shipping route initially. All those leased empty containers construct a container fleet for the usage of the planning horizon to serve the laden container demands. Both foldable containers and standard containers are available for long-term leasing.

2.3.2 Operational level planning

Once a port is visited by a round trip, the shipping liner should make some operational level decisions. To fulfill the weekly laden container transportations, the numbers of foldable containers and standard containers in the depot need to be allocated for the laden container transportation. However, if the stored empty containers are insufficient for the transportation consignment, the shipping liner must lease empty containers from container leasing companies by short-term leasing. The leased containers return to the container leasing companies at destination ports, and the repositioning of the containers, as well as container repairs and maintenance, are the duties of the container leasing companies. The short-term leasing follows the so-called Master Lease Agreement for shipping containers (Wolff et al., 2007; Container Auction, 2017). If there are empty containers surplus after fulfilling the transportation consignment, the shipping liner needs to decide on whether to reposition those empty containers to other deficit ports and how many empty containers to be repositioned by considering the remaining capacity of the ship when visiting the port by the round trip.

In summary, our problem aims to solve the ship type decision and the container fleet sizing at the tactical level and allocate the empty containers among ports at the operational level. In the tactical level, the ship type decision determines the capacity (in TEUs) of the container ships deployed for the fleet. The container fleet sizing determines the number of long-term leasing foldable containers and the number of long-term leasing standard containers in each port. In the operation level, foldable empty containers and standard empty containers are allocated in each port to fulfill the laden container transportation consignment, the short-term leasing containers are involved if there is empty container deficit, and the empty container repositioning is to be determined if there is empty container surplus.

2.3.3 Assumptions

Before addressing the model for our problem, we clarify some underlying assumptions:

(i) In the beginning, all the ships depart from the first port in the shipping route, and they depart one by one with one-week interval (i.e., the first ship departs in the first week; the second ship departs in the second week, and so on).

Assumption (i) indicates that when a shipping liner starts to operate a weekly shipping service, it will mass a ship fleet at a homeport (i.e., the first port), and dispatch ships with a one-week interval to form the weekly service pattern.

(ii) For each port, the weekly laden container transportation consignments that accumulate between two adjacent round trips must be fulfilled by the latter round trip, i.e., those laden containers must be loaded into the incoming ship by the latter round trip.

Under assumption (ii), the accumulated consignments must be transported to destination ports by the incoming ship; otherwise, they will not arrive at customers on time.

(iii) When laden containers arrive at destination ports, it will take several weeks for devanning (i.e., the process that the containers are delivered to consignees for unpacking and returned to the ports). After the container devanning process, the laden containers become empty containers for the next transportation consignments.

Assumption (iii) shows when laden containers arrive at destination ports, the containers cannot be used immediately for next consignments, as they carry cargo inside. It takes time for delivering the laden containers to customers and unloading the cargo. It is worthwhile to mention that shipping liner companies normally would pose a required time for the devanning process, upon which the consignees should return empty containers (Hanh, 2003; Shipping and Freight Resource, 2017). The required time for returning empty containers (i.e., the devanning process) vary among shipping liner companies, such as COSCO requires ten days for returning (COSCO, 2017), OOCL allows five days for returning (OOCL, 2017). Supposing a shipping liner company sets two weeks for the required time, in reality, it may happen that consignees return empty containers earlier than two weeks (e.g., five days or ten days) in a stochastic manner. Here, to facilitate the exposition of our study, we assume all those empty containers are available for next transportation consignments after the required time for the devanning process (e.g., two weeks in the above case), even though some empty containers may be returned earlier.

The objective of our problem is to minimize the total cost over one planning horizon, including the fixed operation cost, the long-term container leasing cost, the short-term container leasing cost, the repositioning cost, and the storage cost.

2.4 MODEL FORMULATION

In essence, our problem has a latent network structure when the capacity of the ship fleet is determined. Given the ship capacity, we can transfer the problem to *a nonstandard minimum cost flow problem* by formulating a network flow (NF) model, rather than a mathematical programming (MP) model. An MP model normally needs some commercial solvers to optimize, such as CPLEX and Gurobi, which are not desirable for many shipping liner companies. However, several network algorithms can easily solve an NF model to optimality, for example, the *network simplex algorithm*. Therefore, in this section, we construct an NF model by building a network for the problem given the ship capacity. In the next section, we will design a solution approach with a revised network simplex algorithm to solve the NF model and optimize the ship capacity.

In the section, we first introduce some notations for sets and input parameters. Then, to avoid confusion, we will build a sub-network for the problem when only considering using standard containers, which leads to a preliminary NF model (denoted as $\boldsymbol{PNF}$). In the next, we further build a sub-network for foldable containers. By incorporating it to the sub-network for standard containers, we obtain a whole network for the NF model (denoted as $\boldsymbol{TNF}$) that solves the problem given a ship capacity. However, the incorporation would impose a trouble that two parallel arcs share a specific capacity restriction, simultaneously. We will tackle this trouble when designing the revised network simplex algorithm in the next section.

2.4.1 Notations

Indices and sets:

p: Index of ports,

P: Set of all the ports in the shipping service route,

(o, d): Index of O–D port pairs, where $o \in P, d \in P$,

D: Set of O–D port pairs and $D \coloneqq \{(o, d) \in P \times P | o \neq d\}$,

v: Index of ship types,

V: Set of ship types for the shipping service route,

e: Index of round trips,

E: Set of all the round trips in the planning horizon,

Input parameters:

N: Number of ships deployed in the shipping service route,

M: Number of foldable containers that can be folded into one standard container,

C^v: Fixed operation cost in the planning horizon when the ships in Type v are deployed in the shipping service route, $v \in V$,

K^v: Container capacity of the ships in Type v with the unit of TEUs, $v \in V$,

w_p: Number of weeks that are needed for the devanning process in Port p, $p \in P$,

$d_{od,e}$: Number of laden container transportation consignments from Port o to Port d that should be transported by the e^{th} round trip, $(o, d) \in D, e \in E$,

s_p^S: Unit weekly storage cost of a standard container in Port p, $p \in P$,

s_p^F: Unit weekly storage cost of a foldable container in Port p, $p \in P$,

r_{od}^{S}: Unit repositioning cost of a standard container from Port o to Port d, including container loading cost (a_o^S) and unloading cost (b_d^S), $(o, d) \in D$,

r_{od}^{F}: Unit repositioning cost of a foldable container from Port o to Port d, including container loading cost (a_o^F) and unloading cost (b_d^F), folding cost (A_o) and unfolding cost (B_d), $(o, d) \in D$,

l_{od}: Unit short-term leasing cost of a standard container from Port o to Port d, $(o, d) \in D$,

L_p^S: Long-term leasing cost of a standard container for the planning horizon usage in Port p, $p \in P$,

L_p^F: Long-term leasing cost of a foldable container for the planning horizon usage in Port p, $p \in P$.

Here, notice that "from Port o to Port d by the e^{th} round trip" means that the containers are loaded from Port o to the ship when the port is visited by the e^{th} round trip, and those containers will be transported to Port d. If $o < d$, the containers will arrive at Port d by the e^{th} round trip; If $o > d$, the containers will arrive at Port d by the $(e + N)^{th}$ round trip, as the ship would return to Port 1 and restart a new round trip.

2.4.2 A preliminary NF model for standard containers

Given the type of ships deployed has the capacity in K TEUs, we only allow using standard containers to transport goods in this subsection. The sub-network built for standard containers will firstly embed the decisions on the container fleet sizing (i.e., the long-term container leasing) and the empty container repositioning, as the decisions are also the same for foldable containers. Then, we extend the sub-network to consider the short-term container leasing, which only involves the standard containers.

Long-term containers leasing and empty container repositioning

Before constructing the sub-network for standard containers, we divide r_{od}^{S} (i.e., unit repositioning cost of a standard container from Port o to Port d) into two parts, i.e., the loading cost in Port o (denoted as a_o^S) and the unloading cost in Port d (denoted as b_d^S), where $r_{od}^{S} = a_o^S + b_d^S$ as suggested in the parameter definition.

Notice that the imbalance of laden container flow leads to the empty container repositioning among the ports. As all laden container transportation consignments (i.e., $d_{od,e}$) have to be fulfilled by the e^{th} round trip, we could analyze the empty containers deficit or surplus in each port on each round trip caused by the imbalance of laden container flow. Here, we denote $Q_{p,e}$ as the number of empty containers deficit or surplus in Port p when visited by the e^{th} round trip, calculated by Eq. (2.1) and Eq. (2.2).

$$Q_{p,e} = -\sum_{o=p,(o,d)\in D} d_{od,e} \qquad \forall p \in P, e = 1, \tag{2.1}$$

$$Q_{p,e} = \sum_{d=p,o<d,(o,d)\in D} d_{od,e-w_p} + \sum_{d=p,o>d,(o,d)\in D} d_{od,e-N-w_p} - \sum_{o=p,(o,d)\in D} d_{od,e}$$
$$\forall p \in P, e \in E/\{1\}, \tag{2.2}$$

If $Q_{p,e} > 0$ ($Q_{p,e} \leq 0$), it indicates that there are $Q_{p,e}$ ($-Q_{p,e}$) number of empty containers surplus (deficit) in Port p when visited by the e^{th} round trip. The long-term containers leasing generates empty containers, and the empty container repositioning induces the empty container flow between the deficit ports (i.e., the demand ports) and the surplus ports (i.e., the supply ports). Henceforth, we can construct a flow network for the empty containers.

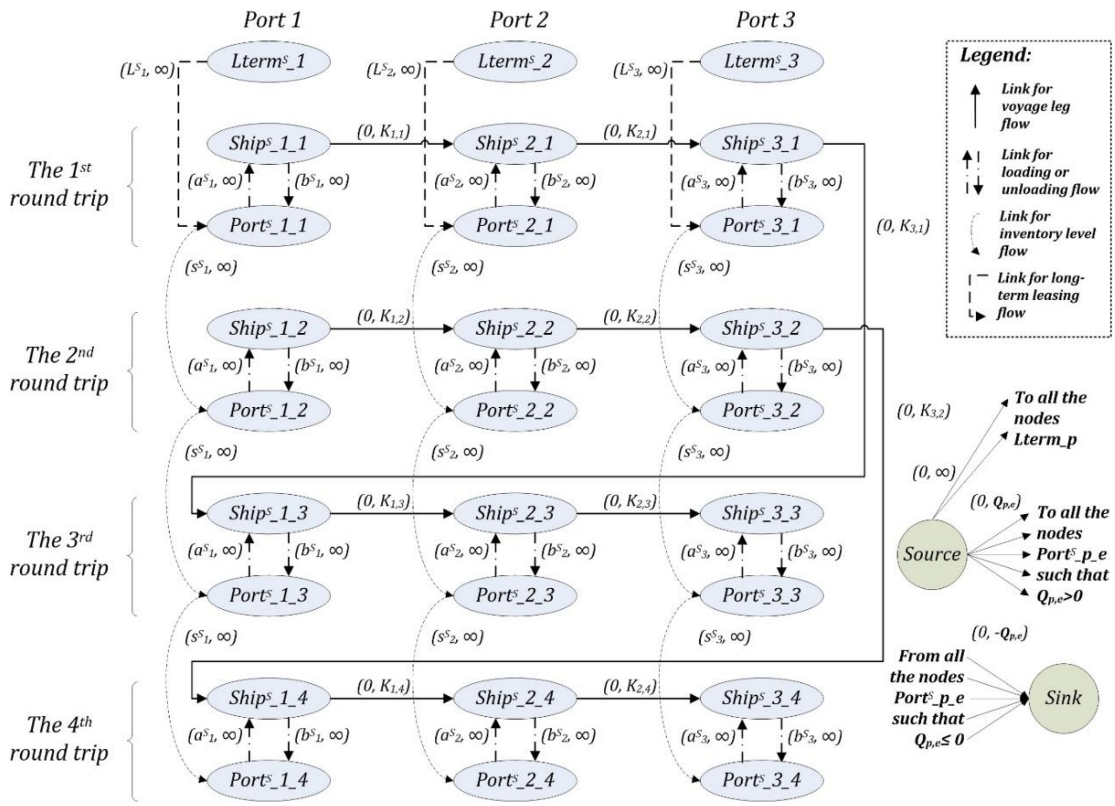


Figure 2.3: A sub-network for standard containers without considering the short-term container leasing

The sub-network contains $|P| + 2 \cdot |E| \cdot |P| + 2$ nodes. Among them, the $|P|$ nodes define the flow conversion for the long-term container leasing in Port p at the beginning of the planning horizon, labelled as $Lterm^S\_p$. The $2 \cdot |E| \cdot |P|$ nodes are categorized into $|E| \cdot |P|$ groups of two kinds of nodes. One kind of nodes in a group denotes the flow conservation in the ship for the e^{th} round trip after visiting Port p, labeled as $Ship^S\_p\_e$. The other kind of nodes denotes the flow conservation in Port p after visited by the e^{th} round trip, labeled as $Port^S\_p\_e$. Two additional dummy nodes represent the source node (labelled as $Source$) and the sink node (labelled as $Sink$) respectively. To facilitate the understanding of the sub-network construction, we give a shipping service route for the example through this section. The route is: Singapore (1) → Hong Kong (2) → Xiamen (3) → Singapore. A round trip for the route needs two weeks, which means two liner ships are deployed with the capacity as K. A planning horizon includes four round trips. Then, Figure 2.3 illustrates an example for the sub-network construction.

In the sub-network network for standard containers, the arcs between nodes correspond to the decision variables of the problem.

- The arc from $Lterm^S\_p$ to $Port^S\_p\_1$ represents the long-term container leasing activity in Port p. The amount of flow on the arc denotes the number of empty containers leased for the planning horizon usage. The cost for the arc is L_p^S. The capacity on the arc is ∞.
- The arc from Node $Ship^S\_p\_e$ to $Ship^S\_(p+1)\_e$ represents the voyage leg from Port p to Port $p+1$ by the ship for the e^{th} round trip. The amount of the flow on the arc denotes the number of empty containers carried on the ship in the voyage leg. Here note that: (i) The voyage leg from Port $|P|$ to Port 1 by the same ship for the e^{th} round trip is the arc from Node $Ship\_|P|\_e$ to $Ship\_1\_(e+N)$. (ii) The cost for the arc is zero, as we have decomposed the repositioning cost. (iii) As the flows of laden containers are pre-determined, the remaining capacity in each voyage leg (on each arc) is confirmed, denoted as $K_{p,e}$ (the remaining capacity in the voyage leg from Port p to Port $p+1$ by the ship for the e^{th} round trip), which can be calculated as follows.

$$K_{p,e} = K - \sum_{o\leq p, d>p, (o,d)\in D} d_{od,e} - \sum_{d\geq p+1, o>d, (o,d)\in D} d_{od,e-N} \quad \forall p \in P, e \in E, \tag{2.3}$$

- The arc from Node $Port^S\_p\_e$ to $Ship^S\_\_p\_e$ (resp., Node $Ship^S\_p\_e$ to $Port^S\_p\_e$) represents the empty container loading process from Port p to the ship (resp., unloading process from the ship to Port p) for the e^{th} round trip. The amount of the flow on the arc denotes the number of empty containers loaded to the ship (resp., unloaded to the port), and the cost for the arc is a_p^S (resp., b_p^S), i.e., the container loading cost at Port p (resp., the container unloading cost at Port p). The capacity on the arc is ∞.
- The arc from Node $Port^S\_p\_e$ to $Port^S\_p\_(e+1)$ represents the empty container inventory (i.e., the empty containers left) in Port p after visited by the e^{th} round trip. The amount of the flow on the arc denotes the number of empty containers left in the port after visited by the e^{th} round trip (i.e., the inventory level $\delta_{p,e}^S$). The cost for the arc is s_p. The capacity on the arc is ∞.

With the two additional dummy nodes, i.e., Node $Source$ and Node $Sink$, we firstly construct the dummy arcs from Node $Source$ to all the nodes $Lterm^S\_p$ with zero cost coefficient and infinity capacity. Then, we build the dummy arcs from Node $Source$ to all the nodes $Port^S\_p\_e$ such that $Q_{p,e} > 0$ (resp., from all the nodes $Port\_p\_e$ such that $Q_{p,e} \leq 0$ to Node $Sink$). The costs for all the arcs are zero. The capacity on the arc from Node $Source$ to Node $Port^S\_p\_e$ is $Q_{p,e}$ (resp., from Node $Port^S\_p\_e$ to $Sink$ is $-Q_{p,e}$).

Short-term container leasing

We extend the previous sub-network to consider short-term container leasing. Referring to the concept of short-term container leasing in Section 2.3, if empty containers in origin ports are scarce, the shipping liner has to lease empty containers in the ports for laden container transportation consignments and return those containers at destination ports after unpacking the containers. In essence, the short-term container leasing has no effects on laden containers, as all transportation consignments must be fulfilled. However, it affects the empty container demand in the origin ports and the empty container supply in the destination ports. Specifically, assuming that when Port o is visited by the e^{th} round trip, due to the dearth of empty containers in the port, the shipping liner has to lease some empty containers (say $\gamma_{od,e}$) to transport the goods in laden containers to Port d. The short-term container leasing fulfills $\gamma_{od,e}$ empty container demand in Port o, but $\gamma_{od,e}$ empty containers are excluded in the empty container supply in Port d as those leased empty containers have to be returned to container leasing companies. Therefore, the empty container demand in Port o by the e^{th} round trip decreases by $\gamma_{od,e}$, and the empty container supply in Port d by the $(e + w_d)^{th}$ (if $d > o$) or $(e + N + w_d)^{th}$ (if $d < o$) round trip decreases by $\gamma_{od,e}$, virtually.

Based on the above analysis, if we further consider the short-term container leasing, the previous sub-network without considering the short-term container leasing (i.e., Figure 2.3) should be modified as follows (see Figure 2.4 for the following modifications): (i) We add a pairwise node for each node $Port^S\_p\_e$, denoted as $BPort^S\_p\_e$. Here, Node $BPort^S\_p\_e$ (resp., Node $Port^S\_p\_e$) shows the empty container flow before (resp., after) using the short-term container leasing. (ii) We disconnect the dummy arcs from Node $Source$ to all the nodes $Port^S\_p\_e$ and from all the nodes $Port^S\_p\_e$ to Node $Sink$. (iii) We construct the dummy arcs from Node $Source$ to all the nodes $BPort^S\_p\_e$ such that $Q_{p,e} > 0$ (resp., from all the nodes $BPort^S\_p\_e$ to Node $Sink$ such that $Q_{p,e} \leq 0$). The costs for all the arcs are zero. The capacity on the arc from Node $Source$ to $BPort^S\_p\_e$ is $Q_{p,e}$ (resp., from Node $BPort^S\_p\_e$ to $Sink$ is $-Q_{p,e}$). (iv) If $Q_{p,e} > 0$ ($Q_{p,e} \leq 0$), we construct the dummy arc from Node $BPort^S\_p\_e$ to $Port^S\_p\_e$ (resp., from Node $Port^S\_p\_e$ to $BPort^S\_p\_e$) with arc capacity as ∞ and arc cost as zero. (v) For two nodes $BPort^S\_p\_e$, there exist an origin node $BPort^S\_o\_e$

and a destination node $BPort^S\_d\_e^1$ (if $d > o$, $e^1 = e + w_d$; if $d < o$, $e^1 = e + N + w_d$). When there is empty container deficit in Node $BPort^S\_o\_e$ (i.e., $Q_{o,e} \leq 0$), the short-term container leasing is possible in the node, and the arc from Node $BPort^S\_d\_e^1$ to $BPort^S\_o\_e$ for the short-term container leasing is constructed. Notice that for the voyage direction, the laden containers flow from Node $BPort^S\_o\_e$ to $BPort^S\_d\_e^1$, but here, the empty containers flow in the opposite direction. The capacity for the arc is $d_{od,e}$ as the maximum empty container demand from Port o to d is the laden container demand $d_{od,e}$. The cost on the arc is l_{od} (i.e., the short-term leasing cost).

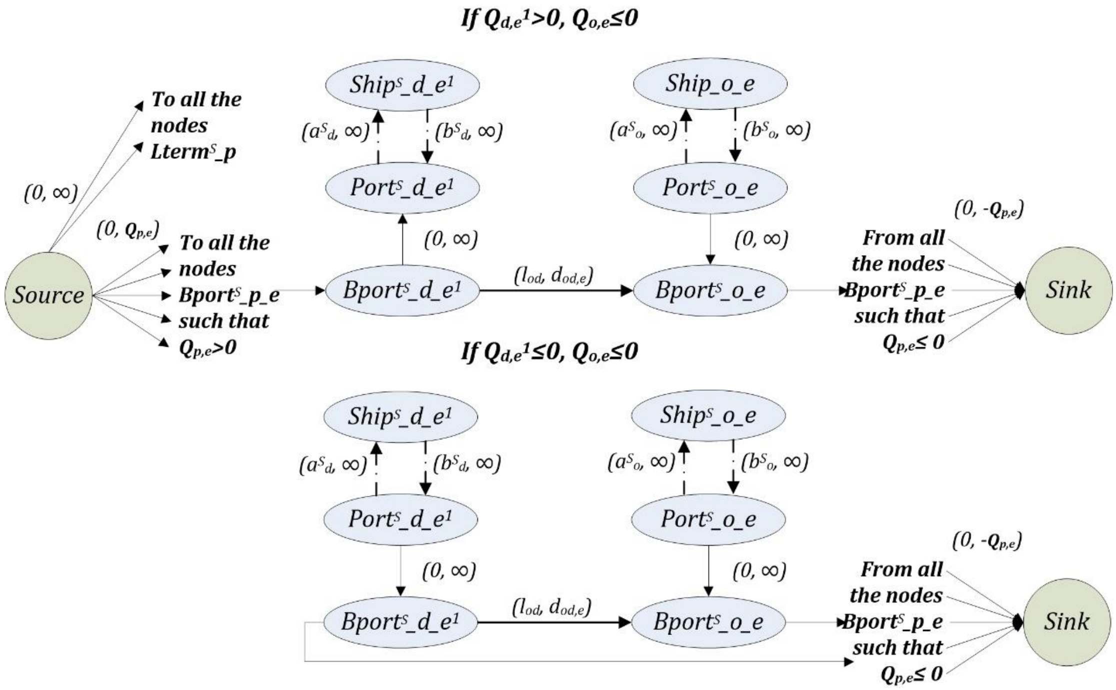


Figure 2.4: The sub-network defined for the preliminary NF model

It is worthwhile to mention that in this subsection, we refer the short-term container leasing to the Master Lease Agreement mentioned in Section 2.3.2, in which empty containers are leased and the cost is charged on an O-D port pair basis. In real-world operations, the shipping liner company and container leasing company could have a lease agreement that is on a round trip basis. Under the agreement, the shipping liner company can lease a certain number of empty containers at Port p, and this number of empty containers must be returned at Port p after several weeks (or round trips). If this is the agreement applied between some shipping liner companies and container leasing containers, we can make the following modifications to the network. Firstly, we define g_p as the number of weeks that the shipping liner company needs to return leased empty containers at Port p, and define q_p as the unit cost of leasing empty containers for g_p weeks at Port p. Then, for modifying the network, we connect the arcs from $Port^S\_p\_(e+q_p)$ to $Port^S\_p\_e$ with arc capacity as ∞ and arc cost as g_p. Note that although some empty containers (say ξ empty containers) are leased by the e^{th} round trip and are returned by the $(e+q_p)^{th}$ round trip at Port p, the empty container flow in the network is in the opposite direction. This is due to that the empty container supply by the $(e+q_p)^{th}$ round trip (resp., the e^{th} round trip) at Port p will decrease by (resp., increase by) ξ empty containers for the returning process (resp., the leasing process).

Until now, we have constructed a whole sub-network for the problem when only considering using standard containers, which leads to the preliminary NF model ($\boldsymbol{PNF}$ model). For $\boldsymbol{PNF}$ model, we need to fulfill Node $Sink$ with total empty container demand $\sum_{p\in P,e\in E}(-Q_{p,e})^+$ by originating from Node $Source$. The goal is to minimize the total cost through the sub-network, which is a standard minimum cost flow problem.

2.4.3 The NF model for both standard containers and foldable containers

In this subsection, we incorporate the foldable containers into $\boldsymbol{PNF}$ model for the NF model that solves our problem given the ship capacity K ($\boldsymbol{TNF}$ model). Firstly, we construct a sub-network for foldable containers. Except from the short-term container leasing, the foldable containers also have the long-term container leasing and the empty container repositioning. Henceforth, the sub-network for foldable containers is similar to the sub-network shown for the standard containers in Figure 2.3. Figure 2.5 shows an example for the sub-network for foldable containers, in which the nodes $Ship^F\_p\_e$, $Port^F\_p\_e$ and $Lterm^F\_p$ correspond to the nodes $Ship^S\_p\_e$, $Port^S\_p\_e$ and $Lterm^S\_p$ in Figure 2.3, respectively. Note that the costs on the arcs from Node $Port^F\_p\_e$ to $Ship^F\_\_p\_e$ and from Node $Ship^F\_p\_e$ to $Port^F\_p\_e$ are slightly different from that of standard containers, as there are additional folding and unfolding costs (A_o and B_d) for foldable containers.

To embed the sub-network for the foldable containers into $\boldsymbol{PNF}$ model defined in Section 2.4.2, we need to build some connections as shown in Figure 2.6: (i) we add a pairwise dummy node for nodes $BPort^S\_p\_e$ and $Port^F\_p\_e$, denoted as $TPort\_p\_e$. Here, Node $TPort\_p\_e$ accumulates the empty container surplus or deficit for standard containers and foldable containers; (ii) we disconnect all dummy arcs from Node $Source$ to all other nodes or from all other nodes to Node $Sink$; (iii) we construct the dummy arcs from Node $Source$ to all the nodes $TPort\_p\_e$ such that $Q_{p,e}>0$ (resp., from all the nodes $TPort\_p\_e$ to Node $Sink$ such that $Q_{p,e}\le 0$). The costs for all the arcs are zero. The capacity on the arc from Node $Source$ to $TPort\_p\_e$ is $Q_{p,e}$ (resp., from Node $BPort^S\_p\_e$ to $Sink$ is $-Q_{p,e}$); (iv) if $Q_{p,e}>0$, we construct the dummy arcs from Node $TPort\_p\_e$ to $BPort^S\_p\_e$ and Node $TPort\_p\_e$ to

$Port^F\_p\_e$, to split empty container flow to the sub-network of standard containers and foldable containers, respectively. (v) if $Q_{p,e} < 0$, we construct the dummy arcs from Node $BPort^S\_p\_e$ to $TPort\_p\_e$ and Node $Port^F\_p\_e$ to $TPort\_p\_e$ to accumulate empty container flow from the sub-network of standard containers and foldable containers, respectively. Note that $TPort\_p\_e$ serve as the node to allocate the empty container demand to standard containers by node $BPort^S\_p\_e$ and foldable containers by node $Port^F\_p\_e$.

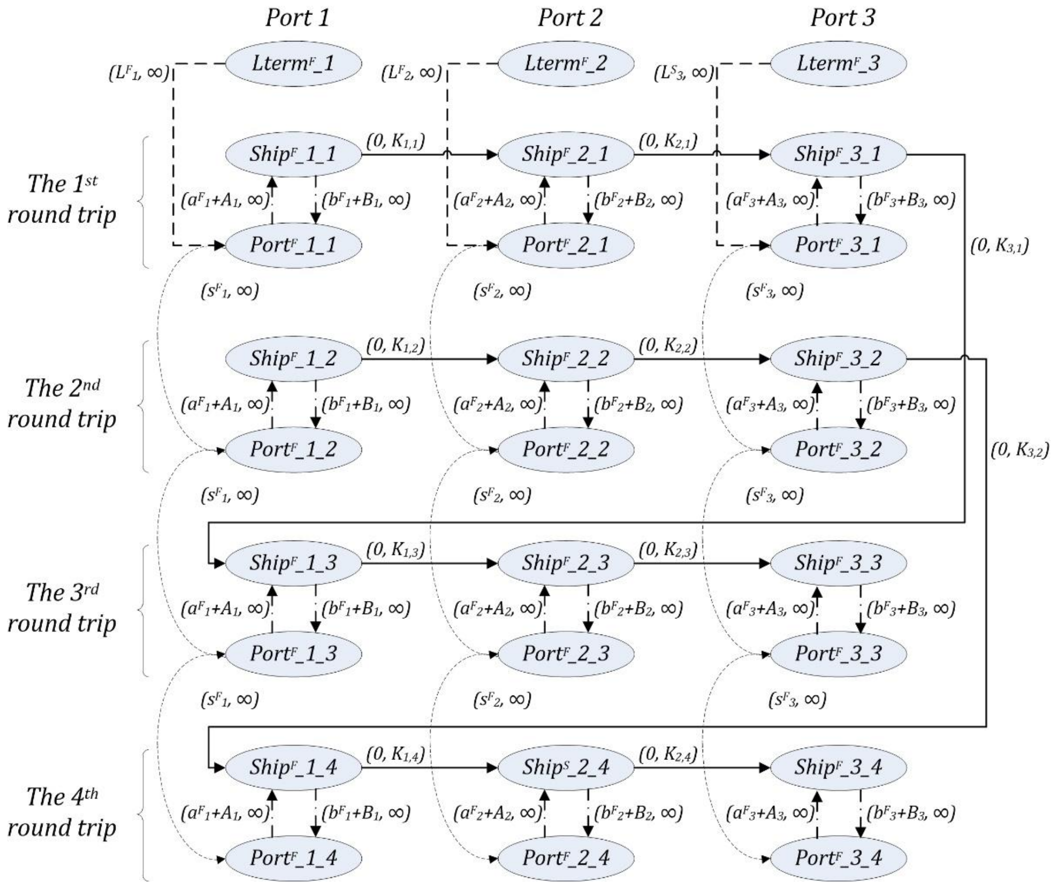


Figure 2.5: A sub-network for foldable containers

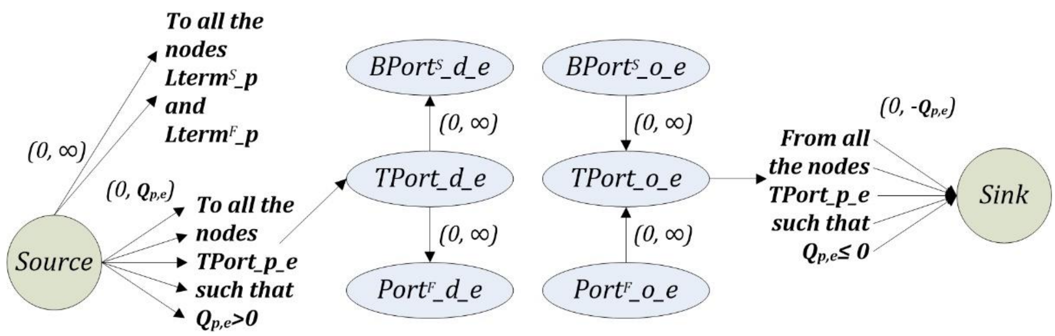


Figure 2.6: Connections between standard containers and foldable containers in TNF model

As we have constructed the whole flow network for our problem, it is worthwhile to show the total number of nodes involved in the network by referring Figure 2.3 to Figure 2.6. Figure

2.3 defines the subnetwork for standard containers and it contains $|P| + 2|P||E|$ nodes; Figure 2.4 introduces $BPort^S\_p\_e$ nodes for considering the short-term container leasing and it adds $|P||E|$ nodes to the network; Figure 2.5 defines the subnetwork for foldable containers and it adds $|P| + 2|P||E|$ nodes to the network; Figure 2.6 introduces $TPort\_p\_e$ nodes for combining two subnetworks and it adds $|P||E|$ nodes to the network. In all, the network has $|P| + 6|P||E| + 2$ after adding the dummy $Source$ and $Sink$ nodes, which is a polynomial function to the input parameters $|P|$ and $|E|$.

Capacity restriction sharing

The above incorporation process of the two sub-networks for $\boldsymbol{TNF}$ model induces a trouble that makes our problem a nonstandard minimum cost flow problem. That is two parallel arcs sharing a specific capacity restriction, simultaneously. In Figure 2.3, the arc from Node $Ship^S\_p\_e$ to $Ship^S\_(p+1)\_e$ carries the flow of standard empty containers on the voyage leg from Port p to Port $p+1$ by the ship for the e^{th} round trip. In Figure 2.5, the arc from Node $Ship^F\_p\_e$ to $Ship^F\_(p+1)\_e$ carries the flow of foldable empty containers on the same voyage leg. Henceforth, the two parallel arcs share the same capacity restriction $K_{p,e}$, as they require repositioning empty containers on the same ship at the same voyage. More importantly, the flows on the parallel arcs occupy different units of the capacity, due to the feature of foldable containers. By supposing $x^S_{p,e}$ and $x^F_{p,e}$ are the flow on the two parallel arcs, we need to enforce that:

$$0 \leq x^S_{p,e} + \frac{x^F_{p,e}}{M} \leq K_{p,e} \qquad \forall p \in P, e \in E, \tag{2.4}$$

for the capacity restriction sharing. This characteristic leads to the trouble that we cannot directly transfer our problem given the ship capacity to a standard minimum cost flow problem. Alternatively, to avoid the trouble, we introduce two dynamic capacity restrictions for the two parallel arcs, denoted as $\mu^S_{p,e}$ and $\mu^F_{p,e}$, respectively. Based on $\mu^S_{p,e}$ and $\mu^F_{p,e}$, we separate the sharing capacity restriction $K_{p,e}$ to two individual ones such that:

$$0 \leq x^S_{p,e} \leq \mu^S_{p,e} \qquad \forall p \in P, e \in E, \tag{2.5}$$

$$0 \leq x^F_{p,e} \leq \mu^F_{p,e} \qquad \forall p \in P, e \in E. \tag{2.6}$$

Meanwhile, the two individual capacity restrictions must hold that:

$$\mu^S_{p,e} + \frac{\mu^F_{p,e}}{M} = K_{p,e} \qquad \forall p \in P, e \in E. \tag{2.7}$$

Note $\mu^S_{p,e}$ and $\mu^F_{p,e}$ keep dynamically changed in the algorithm developed in the next section, so long as Eq. (2.7) holds. Here, we can initialize any values for $\mu^S_{p,e}$ and $\mu^F_{p,e}$ without considering that the values will lead to no feasible solutions for the $\boldsymbol{TNF}$ model. This is due to that the short-term container leasing of standard containers can always treat the empty container imbalance between deficit nodes and surplus nodes. With the separated capacity restrictions, we can solve the $\boldsymbol{TNF}$ model by several network algorithms.

2.5 SOLUTION APPROACH

The solution approach for our problem is an iterative procedure. In this section, we firstly design a revised network simplex algorithm to solve the $\boldsymbol{TNF}$ model given a ship capacity. Then, for the solution approach, we initialize at $K = K^1$ that is the capacity of Type 1 ship (assuming to be the smallest ship type) for running the algorithm. Based on the information from the previous running of the algorithm, we select another ship capacity K^v, given which it again invokes the algorithm to derive the minimum flow cost for empty containers, denoted as σ^v. The summation of the fixed operation cost C^v and σ^v is the total minimum cost when using ships in Type v for the fleet. By comparing those costs, we can obtain the optimal solution for our problem as well as the total optimal cost. In this section, we also formulate a mixed-integer linear programming model (MILP) for the problem, which can be solved directly by CPLEX solver for verifying the optimality of the proposed solution approach.

2.5.1 A revised network simplex algorithm

The network simplex algorithm is perhaps the most powerful algorithm to solve the minimum cost flow problem. The *Cycle Free Property*, *Spanning Tree Property* and *Minimum Cost Flow Optimality Conditions* are the major principles supporting the algorithm. One can refer to Chapter 11 of the book by Ahuja et al. (1993) for detailed descriptions of those properties and the algorithm. Here, we will briefly introduce the properties and the algorithm, and propose a revised network simplex algorithm for solving our $\boldsymbol{TNF}$ model. Note that to present the algorithm in a general way and avoid confusions, we use the set $\mathcal{A}$ to denote the set of all arcs in the network constructed in Section 2.4. Arc $(i, j) \in \mathcal{A}$ denotes a specific arc from node i to node j in the network with a cost coefficient c_{ij} and a capacity restriction μ_{ij}.

(i) *Spanning Tree Property*: If a minimum cost flow problem is bounded from below by a feasible region, the problem will always have an optimal spanning tree solution. A spanning tree solution splits the arc set $\mathcal{A}$ of the network into three parts. (a) $\boldsymbol{T}$, the spanning tree arc set, in which the flow on the arcs are unbounding. (b) $\boldsymbol{L}$, a non-tree arc set, in which the flow on the arcs equals zero. (c) $\boldsymbol{U}$, a non-tree arc set, in which the flow on the arcs equals the capacity restrictions. The triple $(\boldsymbol{T}, \boldsymbol{L}, \boldsymbol{U})$ is the so-called spanning tree structure.

(ii) *Minimum Cost Flow Optimality Conditions*: A feasible spanning tree $(\boldsymbol{T}, \boldsymbol{L}, \boldsymbol{U})$ is the optimal solution if the *arc reduced costs* c_{ij}^{π} satisfy the following conditions. (a) For all $(i, j) \in \boldsymbol{T}$, $c_{ij}^{\pi} = 0$; (b) For all $(i, j) \in \boldsymbol{L}$, $c_{ij}^{\pi} \geq 0$; (c) For all $(i, j) \in \boldsymbol{U}$, $c_{ij}^{\pi} \leq 0$. Given a spanning tree structure, c_{ij}^{π} is derived by using the cost coefficients on arcs and defined node potentials for nodes: it first assigns a node potential $\pi(1) = 0$ for the root node 1. Then by holding,

$$c_{ij}^{\pi} = c_{ij} - \pi(i) + \pi(j) = 0 \qquad \forall (i,j) \in \boldsymbol{T}, \tag{2.8}$$

it obtains all the nodes potentials $\pi(i)$ in the network, based on which c_{ij}^{π} of the non-tree arcs is derived by $c_{ij}^{\pi} = c_{ij} - \pi(i) + \pi(j), \forall (i,j) \in \boldsymbol{L}, (i,j) \in \boldsymbol{U}$. Note that c_{ij}^{π} has a similar meaning with the reduced cost in the *primal simplex algorithm* for the *linear programming problem*, which indicates the cost changed in the objective if we increase one more unit flow on the arc (i,j).

(iii) The network simplex algorithm generally maintains a feasible spanning tree structure in each iteration and moves from one structure to another one until reaching the optimality. (a) Given a $(\boldsymbol{T}, \boldsymbol{L}, \boldsymbol{U})$, the algorithm checks the optimality conditions. If all the conditions are satisfied, the algorithm stops, otherwise selects the most violation arc (by finding the maximum $|c_{ij}^{\pi}|$) from the arc set $\mathcal{V} = \{(i,j) \in \boldsymbol{L} \cup \boldsymbol{U}: if\ (i,j) \in \boldsymbol{L}, c_{ij}^{\pi} < 0;\ if\ (i,j) \in \boldsymbol{U}, c_{ij}^{\pi} > 0\}$. (b) It adds the violation arc (called the *entering arc*) into the current spanning tree structure, by which it obtains a negative cost cycle. That means increasing the flow on the forward direction of the cycle will decrease the current objective of the total flow cost. (c) It augments the maximum possible flow on the negative cost cycle until the flow of one arc in the cycle reaches zero or its capacity restriction (called the *leaving arc*). (d) It replaces the *leaving arc* with the *entering arc* for a new feasible spanning tree structure $(\boldsymbol{T}', \boldsymbol{L}', \boldsymbol{U}')$. The algorithm repeats the above procedure (a)-(d) until finding the optimal spanning tree structure $(\boldsymbol{T}^*, \boldsymbol{L}^*, \boldsymbol{U}^*)$.

Revisions in the pivot operation

The Part (c) in the above procedures of the network simplex algorithm is the *pivot operation*. Considering that our network constructed in Section 2.4 has dynamic capacity restrictions on parallel arcs, we revise the pivot operation of the standard network simplex algorithm for a revised network simplex algorithm to solve our $\boldsymbol{TNF}$ model. Here, we will firstly elaborate the standard pivot operation and then propose our revisions.

Supposing that the entering arc is (k,l), the combination of (k,l) and the spanning tree $\boldsymbol{T}$ forms a negative cost cycle $\boldsymbol{W}$, known as the *pivot cycle*. The cycle $\boldsymbol{W}$ has a direction that is the same as (k,l) if $(k,l) \in \boldsymbol{L}$, and is opposite to (k,l) if $(k,l) \in \boldsymbol{U}$. For all arcs in the cycle, the arcs following the cycle direction belong to a *forward arc* set $\overline{\boldsymbol{W}}$, and the arcs following the opposite cycle direction belong to a *backward arc* set $\underline{\boldsymbol{W}}$. Figure 2.7 shows an example for the cycle, in which arc $(3,4)$ is the entering arc, arcs $(5,0)$, $(0,1)$, $(2,3)$ belong to the set $\overline{\boldsymbol{W}}$, and arcs $(5,4)$, $(2,1)$ belong to the set $\underline{\boldsymbol{W}}$.

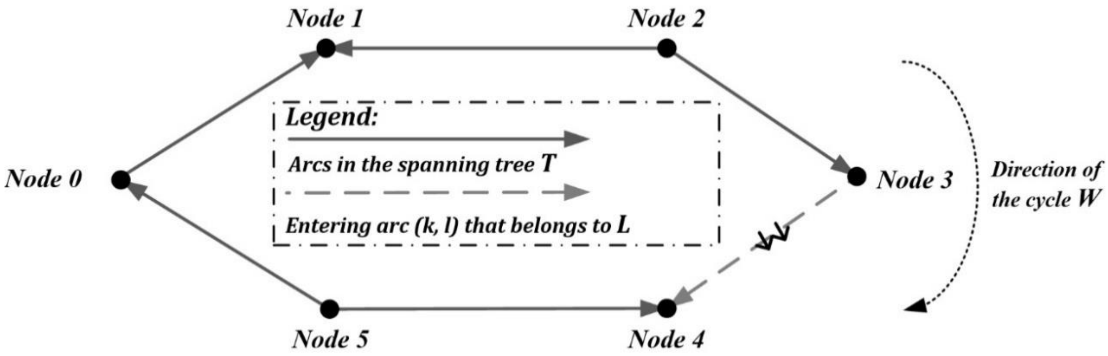


Figure 2.7: An example of the pivot cycle W

Supposing that x_{ij} is the existing flow on arc (i,j), the maximum flow change on each arc in the cycle is denoted by δ_{ij}, calculated by:

$$\delta_{ij} = \begin{cases} \mu_{ij} - x_{ij}, if\ (i,j) \in \overline{\boldsymbol{W}} \\ x_{ij} \qquad\quad , if\ (i,j) \in \underline{\boldsymbol{W}} \end{cases} \tag{2.9}$$

In the standard pivot operation, it will augment $\delta^* = \min\{\delta_{ij}: (i,j) \in \boldsymbol{W}\}$ amount of flow to guarantee the feasibility. Here, we start to revise the pivot operation to capture the dynamic capacity restrictions under two principles: (i) we need to make δ^* as large as possible. This is due to $\boldsymbol{W}$ is a negative cost cycle such that the more flow augmented on the cycle, the larger decreasing on the total flow cost. (ii) We must guarantee the feasibility when augmenting flow.

To facilitate our description of revisions for the pivot operation, we define $\epsilon_{p,e}^S$ and $\epsilon_{p,e}^F$ as the indices for two parallel arcs mentioned in Section 2.4.3 rather than still use (i,j) to denote the arcs. Then, we have two parallel arc sets $\mathcal{G}^S$ and $\mathcal{G}^F$, where $\epsilon_{p,e}^S \in \mathcal{G}^S \subset \mathcal{A}$ and $\epsilon_{p,e}^F \in \mathcal{G}^F \subset \mathcal{A}$. Supposing that the current allocated capacity for two parallel arcs are $\mu_{p,e}^S$ and $\mu_{p,e}^F$ satisfying Eq. (2.5)-(2.7), we will dynamically change the capacity allocation in the revised pivot operation to reach the optimality and guarantee the feasibility. Here, we suppose that $x_{p,e}^S$ and $x_{p,e}^F$ are existing flow on the two parallel arcs.

In the revised pivot operation, we need to check each pair of parallel arcs on the cycle $\boldsymbol{W}$. Basically, we need to distinguish three situations for one of two parallel arcs, i.e., (i) the arc belongs to the forward arc set $\overline{\boldsymbol{W}}$; (ii) the arc belongs to the backward arc set $\underline{\boldsymbol{W}}$; (iii) the arc does not belong to the cycle $\boldsymbol{W}$. Then, for an integration of two parallel arcs, there are nine scenarios, for each of which we have different ways to change the capacity restrictions for the parallel arcs.

Scenario 1: if $\epsilon_{p,e}^S \in \overline{\boldsymbol{W}}$ and $\epsilon_{p,e}^F \in \overline{\boldsymbol{W}}$, this is the scenario that needs the most attention, as we need to care about their capacity restrictions simultaneously based on Eq. (2.8). To make

δ^* larger, we need to change the capacity restrictions by solving the following optimization problem, where $\mu_{p,e}^S$ and $\mu_{p,e}^F$ are decision variables.

$$[\boldsymbol{M1}] \ \max\{\min\{\mu_{p,e}^S - x_{p,e}^S, \mu_{p,e}^F - x_{p,e}^F\}\} \tag{2.10}$$

subject to:

$$\mu_{p,e}^S + \frac{\mu_{p,e}^F}{M} = K_{p,e} \tag{2.11}$$

$$\mu_{p,e}^S \geq x_{p,e}^S \tag{2.12}$$

$$\mu_{p,e}^F \geq x_{p,e}^F \tag{2.13}$$

where objective (2.10) is equivalent to $\max\{(\mu_{p,e}^S - x_{p,e}^S) \times (\mu_{p,e}^F - x_{p,e}^F)\}$ holding constraints (2.12) and (2.13). Then, we can easily obtain closed-form solutions for the $\boldsymbol{M1}$ such that ${\mu_{p,e}^S}^* = \frac{MK_{p,e}+Mx_{p,e}^S-x_{p,e}^F}{2M}$ and ${\mu_{p,e}^F}^* = \frac{MK_{p,e}-Mx_{p,e}^S+x_{p,e}^F}{2}$.

Scenario 2: if $\epsilon_{p,e}^S \in \overline{\boldsymbol{W}}$ and $\epsilon_{p,e}^F \in \underline{\boldsymbol{W}}$, as the capacity restriction is not important for arc $\epsilon_{p,e}^F$ based on Eq. (2.9), we adjust ${\mu_{p,e}^F}^* = x_{p,e}^F$ and ${\mu_{p,e}^S}^* = K_{p,e} - \frac{{\mu_{p,e}^F}^*}{M} = K_{p,e} - \frac{x_{p,e}^F}{M}$ such that the capacity restriction on arc $\epsilon_{p,e}^S$ is maximum. Note that in this scenario, we need to pay more attention on the flow after the revised pivot operation. Supposing that we argument δ^* on the cycle, and $\epsilon_{p,e}^S$ is the leaving arc such that ${\mu_{p,e}^S}^* - x_{p,e}^S - \delta^* = 0$, we can further argument more flow after the revised pivot operation. This is due to the flow on arc $\epsilon_{p,e}^F$ will decrease by δ^*, under which condition we can further decrease its capacity to ${\mu_{p,e}^F}^* = x_{p,e}^F - \delta^*$ and increase the capacity of arc $\epsilon_{p,e}^S$ to ${\mu_{p,e}^S}^* = K_{p,e} - \frac{{\mu_{p,e}^F}^*}{M} = K_{p,e} - \frac{x_{p,e}^F-\delta^*}{M}$. We repeat the above process until $\epsilon_{p,e}^S$ is not the leaving arc. This leads to the following proposition:

Proposition 2.1: *if $\epsilon_{p,e}^S \in \overline{\boldsymbol{W}}$ and $\epsilon_{p,e}^F \in \underline{\boldsymbol{W}}$, the arc $\epsilon_{p,e}^S$ cannot be the leaving arc*.

Scenario 3: if $\epsilon_{p,e}^S \in \overline{\boldsymbol{W}}$ and $\epsilon_{p,e}^F \notin \boldsymbol{W}$, as the arc $\epsilon_{p,e}^F$ is not in the cycle, its flow will not change during the revised pivot operation. Then, we adjust ${\mu_{p,e}^F}^* = x_{p,e}^F$ and ${\mu_{p,e}^S}^* = K_{p,e} - \frac{{\mu_{p,e}^F}^*}{M} = K_{p,e} - \frac{x_{p,e}^F}{M}$ such that the capacity restriction on arc $\epsilon_{p,e}^S$ is maximum.

Scenario 4: if $\epsilon_{p,e}^S \in \underline{\boldsymbol{W}}$ and $\epsilon_{p,e}^F \in \overline{\boldsymbol{W}}$, the operation is similar to **Scenario 2**, which is not repeated here. We can also obtain a proposition that is similar to Proposition 2.1:

Proposition 2.2: *if $\epsilon_{p,e}^S \in \underline{\boldsymbol{W}}$ and $\epsilon_{p,e}^F \in \overline{\boldsymbol{W}}$, the arc $\epsilon_{p,e}^F$ cannot be the leaving arc*.

Scenario 5: if $\epsilon_{p,e}^S \in \underline{\boldsymbol{W}}$ and $\epsilon_{p,e}^F \in \underline{\boldsymbol{W}}$, we do not change the capacity restrictions.

Scenario 6: if $\epsilon_{p,e}^S \in \underline{\boldsymbol{W}}$ and $\epsilon_{p,e}^F \notin \boldsymbol{W}$, we do not change the capacity restrictions.

Scenario 7: if $\epsilon_{p,e}^{S} \notin \boldsymbol{W}$ and $\epsilon_{p,e}^{F} \in \overline{\boldsymbol{W}}$, the operation is similar to **Scenario 3**, which is not repeated here.

Scenario 8: if $\epsilon_{p,e}^{S} \notin \boldsymbol{W}$ and $\epsilon_{p,e}^{F} \in \underline{\boldsymbol{W}}$, we do not change the capacity restrictions.

Scenario 9: if $\epsilon_{p,e}^{S} \notin \boldsymbol{W}$ and $\epsilon_{p,e}^{F} \notin \boldsymbol{W}$, we do not change the capacity restrictions.

Until now, we obtain a revised network simplex algorithm, which embeds the above-revised pivot operation. The intuition behind the revised network simplex algorithm is that the capacity restrictions are only involved in the pivot operation when determining a leaving arc. Thus, we can dynamically change the capacity allocation for two parallel arcs in the pivot operation, by holding $\mu_{p,e}^{S} + \frac{\mu_{p,e}^{F}}{M} = K_{p,e}$ to guarantee the feasibility and by maximizing δ^{*} to reach the optimality. Note that the revised network simplex algorithm is applicable to any minimum cost flow problems with sharing a capacity restriction among arcs.

A further revision of the network

In the network constructed in Section 2.4, there are some pairs of nodes having two arcs in the opposite directions, such as the two opposite arcs between node $Ship^{S}\_p\_e$ and $Port^{S}\_p\_e$ shown in Figure 2.3. When applying the revised network simplex algorithm, it may cause trouble in the revised pivot operation on increasing/decreasing flow between two nodes. To avoid the trouble, we introduce some dummy nodes to ensure that between any two nodes, there is at most one connected arc. Figure 2.8 shows an example when there are two opposite arcs between node i and node j. By adding two dummy node i^{1} and node j^{1} and reconnecting arcs, we can deal with the above trouble.

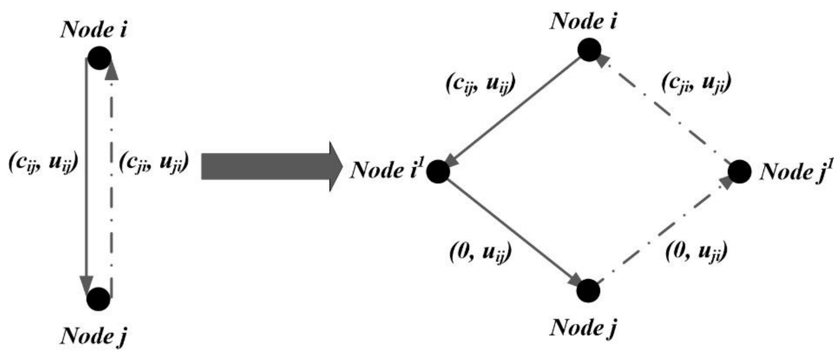


Figure 2.8: Adding dummy nodes to the network

2.5.2 Ship type decision by reduced costs

Given a ship type v with the capacity K^{v} and fixed operation cost C^{v}, we can invoke the above revised network simplex algorithm to derive the minimum flow cost σ^{v} for the empty containers. A straightforward way to find the optimal ship type is to invoke the algorithm to derive σ^{v} for all $v \in V$. Then, we can get the optimal ship type by $\min\{C^{v} + \sigma^{v}: \forall v \in V\}$.

This way is applicable to the practice, as the candidate set V for ship types is normally limited (in computational experiments, there are four ship types for selection). However, in this subsection, we introduce a reduced cost based bound to exclude some ship types from the optimal one.

We rank the set of ship types with an increasing container capacity order such that $K^1 < K^2 < \cdots < K^{|V|}$ and $C^1 < C^2 < \cdots < C^{|V|}$. Here, K^1 is the smallest capacity that should be able to carry all laden containers. We initialize the ship capacity at $K = K^1$ and run the revised network simplex algorithm. Supposing that it obtains the optimal spanning tree solution $(\boldsymbol{T^1}, \boldsymbol{L^1}, \boldsymbol{U^1})$, the solution has reduced costs c_{ij}^{π} satisfying the Minimum Cost Flow Optimality Conditions. Starting from the ship capacity K^1, if we increase the ship capacity to K^2, the fixed operation cost increases by $C^2 - C^1$. However, the minimum flow cost may decrease as we relax the ship capacity from K^1 to K^2. Therefore, when increasing ship capacity, there is a trade-off between the increasing of fixed operation cost and the decreasing of minimum flow cost. As the increasing of the fixed operation cost is pre-determined ($C^2 - C^1$), we need to judge whether the decreasing of minimum flow cost can compensate for the increasing operation cost $C^2 - C^1$.

For notational convenience, we denote $\Delta_{1,2} = \sigma^1 - \sigma^2$ as the decreasing of minimum flow cost by changing Type 1 ship to Type 2 ship. Here, we can use the reduced costs c_{ij}^{π} at ship capacity $K = K^1$ to derive an upper bound for $\Delta_{1,2}$. Recall that $c_{ij}^{\pi} \leq 0, \forall (i,j) \in \boldsymbol{U}$ actually means if the capacity of arc (i,j) increases by one unit, the minimum flow cost has the potential to decrease by $|c_{ij}^{\pi}|$. Considering a minimum cost flow problem is equivalent to $\min\{\sum_{(i,j)\in \boldsymbol{L}} c_{ij}^{\pi} x_{ij} - \sum_{(i,j)\in \boldsymbol{U}} |c_{ij}^{\pi}| x_{ij}\}$ (Ahuja et al., 1993), $\Delta_{1,2}$ has the upper bound $\sum_{(i,j)\in \boldsymbol{U}} \left|c_{ij}^{\pi}\right| (K^2 - K^1)$ if we do not have the parallel arcs and all arcs $(i,j) \in \boldsymbol{U}$ are restricted by the ship capacity. However, under the situation that our problem has parallel arcs that sharing capacity restrictions, the increased ship capacity $K^2 - K^1$ may be used by repositioning standard containers or foldable containers. Thus, we propose Procedure 2.1 to derive the upper bound for $\Delta_{1,2}$ (denoted by $\Delta_{1,2}^U$), in which $c_{\epsilon_{p,e}^S}^{\pi}$ and $c_{\epsilon_{p,e}^F}^{\pi}$ denote the reduced costs for the parallel arcs. Note that if we increase one unit ship capacity, the capacity on the parallel arcs for foldable containers can increase by M units. After obtaining the upper bound $\Delta_{1,2}^U$, we can compare it with $C^2 - C^1$. If $\Delta_{1,2}^U \leq C^2 - C^1$, it is unnecessary to further invoke the revised network simplex algorithm to derive σ^2 for Type 2 ship, as the $\Delta_{1,2}$ is impossible to compensate $C^2 - C^1$. We will repeat the Procedure 1 by increasing ship capacity to K^v until we find a ship type v such that $\Delta_{1,v}^U \geq C^v - C^1$, and then invoke the revised network simplex to derive the optimal spanning tree solution $(\boldsymbol{T^v}, \boldsymbol{L^v}, \boldsymbol{U^v})$. Starting from the ship capacity K^v, we also use the above method to exclude some ship types, until exploring the ship capacity $K^{|V|}$.

Procedure 2.1. *Deriving the upper bound for* $\Delta_{1,2}$

Input: *The reduced cost* c_{ij}^{π} *for the spanning tree* (T^1, L^1, U^1)
Output: *The upper bound* $\Delta_{1,2}^{U}$
Initialize $\Delta_{1,2}^{U} \leftarrow 0$
for all parallel arc $\epsilon_{p,e}^{S} \in \mathcal{G}^{S}$ **and** $\epsilon_{p,e}^{F} \in \mathcal{G}^{F}$ **do**
  if $\epsilon_{p,e}^{S} \in \boldsymbol{U}$ **and** $\epsilon_{p,e}^{F} \notin \boldsymbol{U}$ **then**
  $\Delta_{1,2}^{U} \leftarrow \Delta_{1,2}^{U} + (K^2 - K^1)|c_{\epsilon_{p,e}^{S}}^{\pi}|$
  else if $\epsilon_{p,e}^{S} \notin \boldsymbol{U}$ **and** $\epsilon_{p,e}^{F} \in \boldsymbol{U}$ **then**
  $\Delta_{1,2}^{U} \leftarrow \Delta_{1,2}^{U} + (K^2 - K^1)M|c_{\epsilon_{p,e}^{F}}^{\pi}|$
  else if $\epsilon_{p,e}^{S} \in \boldsymbol{U}$ **and** $\epsilon_{p,e}^{F} \in \boldsymbol{U}$ **then**
  $\Delta_{1,2}^{U} \leftarrow \Delta_{1,2}^{U} + (K^2 - K^1)\max\{|c_{\epsilon_{p,e}^{S}}^{\pi}|, M|c_{\epsilon_{p,e}^{F}}^{\pi}|\}$
  end if
end for

To facilitate the understanding, we show an example to exclude ship types. Supposing that we have invoked the algorithm to derive the reduced costs for the ship capacity at $K = K^1$, we derive $\Delta_{1,2}^{U} = 120$ by Procedure 2.1. Then, if $C^2 - C^1 = 200 \geq \Delta_{1,2}^{U}$, it is unnecessary to invoke the algorithm for the ship capacity at $K = K^2$. In the next, we replace K^2 with K^3 in Procedure 2.1. If we have $\Delta_{1,3}^{U} = 300$ and $C^3 - C^1 = 250$, we need to invoke the algorithm for the ship capacity at $K = K^3$.

Based on the upper bound derived by reduced costs, we can skip some ship types when invoking the revised network simplex algorithm. In the end, we compare the total costs of all those ship types explored by the algorithm for finding the optimal ship type.

In summary for the proposed solution approach, we have made the following improvements compared with the traditional network simplex algorithm. (i) Our network flow model has some parallel arcs sharing the same capacity restrictions, which are inevitable due to the co-existence of foldable and standard containers in the network (cf. Section 2.4.3). As the capacity restrictions tackled in the traditional network simplex algorithm must be unchanged with given values, we propose a tailored (or revised) network simplex algorithm for the problem. In the revised one, we introduce dynamic capacity restrictions for the parallel arcs and revise the pivot operations to guarantee the optimality (cf. Section 2.5.1). (ii) Our problem needs to determine the ship capacity, which further decides capacity restrictions on the arcs of the network. To achieve the goal, we use the reduced costs from our tailored algorithm to make the ship type decision (cf. Section 2.5.2). (iii) Using a network simplex algorithm to solve a minimum cost flow problem requires the construction of a network flow model as the prior task. Our solution approach elaborates a procedure to construct a flow network (cf. Section 2.4) for the empty container allocation.

2.5.3 A MILP model

The proposed solution approach is built on the network flow model constructed in Section 2.4. In this subsection, we formulate a MILP model for our research problem that can be solved by CPLEX solver directly. In the computational experiment section, we will use the results of the MILP model to verify the optimality of the proposed solution approach. Here, we first introduce some decision variables and then provide the model formulation.

Decision variables:

ε_v: binary, set to one if the ships in Type v are deployed, otherwise zero, $v \in V$;

ζ_p^S: integer, number of long-term leasing standard containers in Port $p, p \in P$;

ζ_p^F: integer, number of long-term leasing foldable containers in Port $p, p \in P$;

$\alpha_{od,e}^S$: integer, number of empty standard containers used to satisfy the laden container transportation consignments from Port o to Port d by the e^{th} round trip, $(o,d) \in D, e \in E$;

$\alpha_{od,e}^F$: integer, number of empty foldable containers used to satisfy the laden container transportation consignments from Port o to Port d by the e^{th} round trip, $(o,d) \in D, e \in E$;

$\beta_{od,e}^S$: integer, number of empty standard containers repositioned from Port o to Port d by the e^{th} round trip, $(o,d) \in D, e \in E$;

$\beta_{od,e}^F$: integer, number of empty foldable containers repositioned from Port o to Port d by the e^{th} round trip, $(o,d) \in D, e \in E$;

$\gamma_{od,e}$: integer, number of short-term empty containers leased in Port o for the e^{th} round trip and will returned in Port d, $(o,d) \in D, e \in E$;

$\delta_{p,e}^S$: integer, inventory level of empty standard containers (i.e., the empty standard containers left) at Port p after visited by the e^{th} round trip, $p \in P, e \in E$;

$\delta_{p,e}^F$: integer, inventory level of empty foldable containers (i.e., the empty foldable containers left) at Port p after visited by the e^{th} round trip, $p \in P, e \in E$;

$\eta_{p,e}$: integer, number of containers carried on the container ship of the e^{th} round trip after it visits Port p, $p \in P, e \in E$;

Mathematical model:

$$[\boldsymbol{M2}]\ \min \sum_{v\in V} C_v\varepsilon_v + \sum_{p\in P}(L_p^S\zeta_p^S + L_p^F\zeta_p^F) + \sum_{e\in E}\sum_{(o,d)\in D} l_{od}\gamma_{od,e} + \sum_{e\in E}\sum_{(o,d)\in D}(r_{od}^S\beta_{od,e}^S + r_{od}^F\beta_{od,e}^F) + \sum_{e\in E}\sum_{p\in P}(s_p^S\delta_{p,e}^S + s_p^F\delta_{p,e}^F) \quad (2.14)$$

subject to:

$$\sum_{v\in V}\varepsilon_v = 1 \tag{2.15}$$

$$\alpha^S_{od,e} + \alpha^F_{od,e} + \gamma_{od,e} = d_{od,e} \qquad \forall (o,d)\in D, e\in E, \tag{2.16}$$

$$\zeta^S_p + \sum_{d=p,o<d,(o,d)\in D}\beta^S_{od,e} = \sum_{o=p,(o,d)\in D}(\alpha^S_{od,e} + \beta^S_{od,e}) + \delta^S_{p,e} \qquad \forall p\in P, e=1, \tag{2.17}$$

$$\zeta^F_p + \sum_{d=p,o<d,(o,d)\in D}\beta^F_{od,e} = \sum_{o=p,(o,d)\in D}(\alpha^F_{od,e} + \beta^F_{od,e}) + \delta^F_{p,e} \qquad \forall p\in P, e=1, \tag{2.18}$$

$$\delta^S_{p,e-1} + \sum_{d=p,o<d,(o,d)\in D}\beta^S_{od,e} + \sum_{d=p,o>d,(o,d)\in D}\beta^S_{od,e-N} + \sum_{d=p,o<d,(o,d)\in D}\alpha^S_{od,e-w_p} + \sum_{d=p,o>d,(o,d)\in D}\alpha^S_{od,e-N-w_p} = \sum_{o=p,(o,d)\in D}(\alpha^S_{od,e} + \beta^S_{od,e}) + \delta^S_{p,e} \qquad \forall p\in P, e\in E\backslash\{1\}, \tag{2.19}$$

$$\delta^F_{p,e-1} + \sum_{d=p,o<d,(o,d)\in D}\beta^F_{od,e} + \sum_{d=p,o>d,(o,d)\in D}\beta^F_{od,e-N} + \sum_{d=p,o<d,(o,d)\in D}\alpha^F_{od,e-w_p} + \sum_{d=p,o>d,(o,d)\in D}\alpha^F_{od,e-N-w_p} = \sum_{o=p,(o,d)\in D}(\alpha^F_{od,e} + \beta^F_{od,e}) + \delta^F_{p,e} \qquad \forall p\in P, e\in E\backslash\{1\}, \tag{2.20}$$

$$\eta_{p,e} = \sum_{o\le p,d>p,(o,d)\in D}(d_{od,e} + \beta^S_{od,e} + \beta^F_{od,e}/M) + \sum_{d\ge p+1,o>d,(o,d)\in D}(d_{od,e-N} + \beta^S_{od,e-N} + \beta^F_{od,e-N}/M) \qquad \forall p\in P/\{P\}, e\in E, \tag{2.21}$$

$$\eta_{p,e} = \sum_{o>d,(o,d)\in D}(d_{od,e} + \beta^S_{od,e} + \beta^F_{od,e}/M) \qquad \forall p=|P|, e\in E \tag{2.22}$$

$$\eta_{p,e} \le \sum_{v\in V}K_v\varepsilon_v \qquad \forall p\in P, e\in E, \tag{2.23}$$

$$\varepsilon_v \in \{0,1\} \qquad \forall v\in V, \tag{2.24}$$

$$\zeta^S_p, \zeta^F_p \ge 0 \qquad \forall p\in P, \tag{2.25}$$

$$\alpha^S_{od,e}, \alpha^F_{od,e}, \beta^S_{od,e}, \beta^F_{od,e}, \gamma_{od,e} \ge 0 \qquad \forall (o,d)\in D, e\in E, \tag{2.26}$$

$$\delta^S_{p,e}, \delta^F_{p,e}, \eta_{p,e} \ge 0 \qquad \forall p\in P, e\in E. \tag{2.27}$$

Here, note that $\alpha^S_{od,e} := 0$, $\beta^S_{od,e} := 0$, $\alpha^F_{od,e} := 0$ and $\beta^F_{od,e} := 0$ when $e < 1$.

In the above model, Objective (2.14) minimizes the total cost, including the fixed operation cost, the long-term leasing cost, the short-term leasing cost, the repositioning cost, and the storage cost. Constraint (2.15) guarantees that only one type of ships can be selected. Constraints (2.16) enforce that the laden container transportation consignments in each port by each round trip must be fulfilled by using available empty standard containers, foldable containers or short-term leasing containers in the port. Constraints (2.17) provide the inventory equations for empty standard containers in each port after visited by the 1^{st} round trip. The left sides of the equations list the number of leased empty containers in each port at the beginning (i.e., ζ^S_p) and the empty containers arrived in each port by the 1^{st} round trip (i.e., $\sum_{d=p,o<d,(o,d)\in D}\beta^S_{od,e}$). The right sides of the equations show the inventory level of empty

containers in each port after the 1^{st} round trip (i.e., $\delta^S_{p,e}$) and the number of empty containers flowing out of the port by the 1^{st} round trip (i.e., $\sum_{o=p,(o,d)\in D}(\alpha^S_{od,e}+\beta^S_{od,e})$). Constraints (2.18) are similar as Constraints (2.17), which are the inventory equations for empty foldable containers by the 1^{st} round trip. Constraints (2.19) and Constraints (2.20) list the inventory equations in Port p after visited by the e^{th} round trip. The left-sides of the constraints also show the empty container supply, including the empty containers left in the port after visited by $(e-1)^{th}$ round trip (i.e., the inventory level in Port p after visited by $(e-1)^{th}$ round trip), the arrived repositioning empty containers, and the arrived devanning laden containers. Here, notice that: (i) if Port p is the destination port d, and the origin port $o<d$ (the origin port $o>d$), the containers transported from Port o to Port d by the e^{th} round trip will arrive at the Port d by the e^{th} round trip (the $(e+N)^{th}$ round trip). (ii) When laden containers arrive at the destination ports, it will take w_p weeks for the devanning of the containers and become available empty containers for the next consignment in the ports. The right sides of Constraints (2.19) and Constraints (2.20) are the same as that of Constraints (2.17) and Constraints (2.18) respectively. Constraints (2.21) and Constraints (2.22) calculate the number of containers carried in the deployed ship on the e^{th} round trip after visiting Port p. Constraints (2.23) enforce that the number of containers carried in the ships cannot exceed the capacity of the type of the deployed ships. Constraints (2.24-2.27) define the decision variables.

2.6 COMPUTATIONAL EXPERIMENT

In this section, based on three real-world shipping service routes, we conduct extensive computational experiments to find insights on the ship type decision and the foldable container usage by using our proposed solution approach. We run the experiments by a PC equipped with 3.30GHz of Intel Core i5 CPU and 16GB of RAM. For all the test instances in the experiments, the planning horizon is half a year, i.e., 26 weeks. As the shipping service is on a weekly basis, the total round trips are 26 (i.e., $|E|$=26).

2.6.1 Test instances on three real-world shipping service routes

To generate test instances for the experiments, we select three real-world shipping service routes operated by CMA CGM shipping liner, which is labeled as BOHAI, LIBERTY2, and AANAANLCMA. Figure 2.9 depicts the three real-world shipping service routes. (i) The port rotation of the route BOHAI is Lianyungang (1) → Shanghai (2) → Ningbo (3) → Los Angeles (4) → Oakland (5) → Lianyungang; the rotation time is 42 days, and 6 ships are deployed. (ii) The port rotation of the route LIBERTY2 is Antwerp (1) → Bremerhaven (2) → Rotterdam

(3) → Le Havre (4) → New York (5) → Norfolk (6) → Charleston (7) → Antwerp; the rotation time is 28 days, and 4 ships are deployed. (iii) The port rotation of the route AANAANLCMA is Yokohama (1) → Osaka (2) → Pusan (3) → Shanghai (4) → Ningbo (5) → Kaohsiung (6) → Melbourne (7) → Sydney (8) → Brisbane (9) → Yokohama; the rotation time is 42 days, and 6 ships are deployed. In fact, the three shipping service routes are the representatives of three trade routes: Asia-North America trade route, North Europe-North America trade route, and Australia-Far East trade route. The three routes have different degrees of the imbalance of laden container flow.

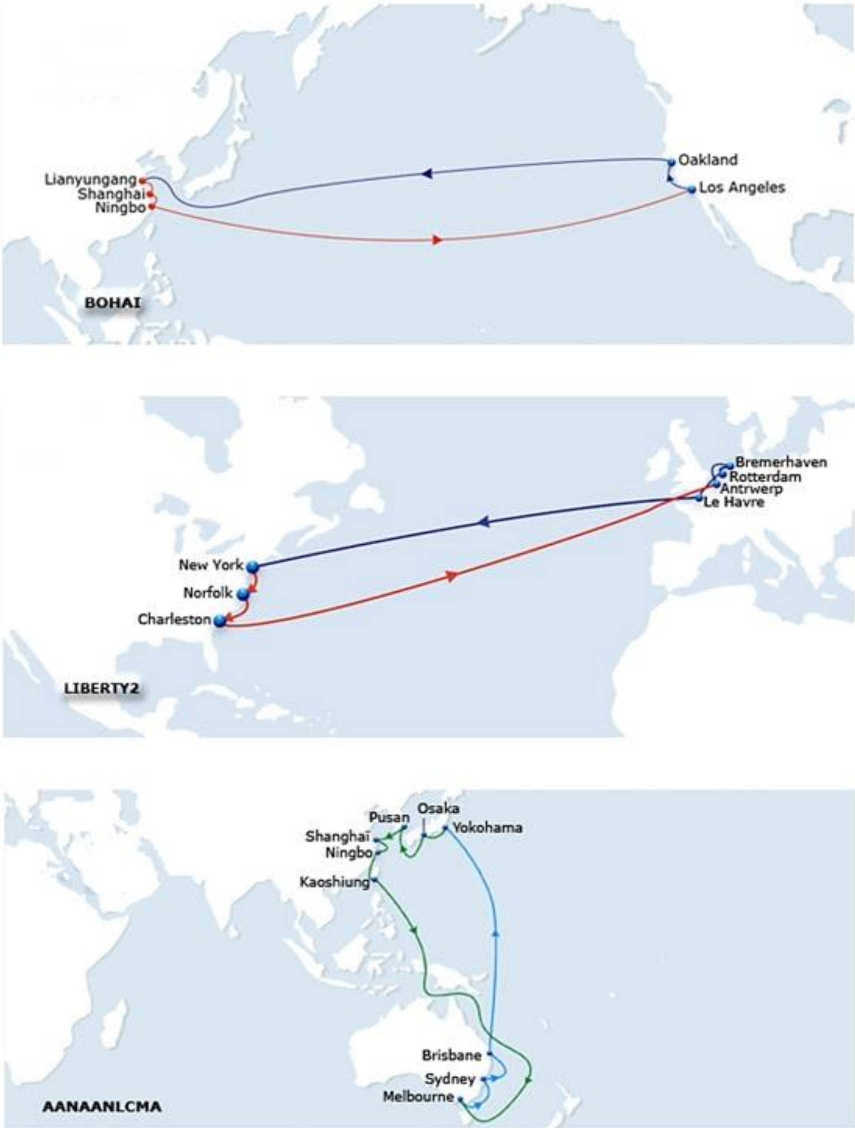


Figure 2.9: Three selected shipping services routes operated by CMA CGM (CMA CGM, 2017)

According to Word Shipping Council (2013), we estimate that the imbalance ratio of laden container flow for Asia-North America trade route is about 1.99 (i.e., Eastbound / Westbound), the imbalance ratio for North Europe-North America trade route is about 1.27 (i.e., Westbound / Eastbound), and the imbalance ratio for Australia-Far East trade route is about 1.73 (i.e., Southbound / Northbound). In fact, different imbalance ratios lead to different degrees of the necessity for the empty container repositioning. Based on the imbalance ratios, the weekly laden container transportation consignments are randomly generated for each selected shipping service route as follows: (i) For the route BOHAI, the transportation consignments from an Asian port to a North American port follow the uniform distribution $U(600, 800)$, and the transportation consignments from a North American port to an Asian port follow the uniform distribution $U(300, 400)$. (ii) For the route LIBERTY2, the transportation consignments from a North Europe port to a North American port follow the uniform distribution $U(400,500)$, and the transportation consignments from a North American port to a North Europe port follow the uniform distribution $U(300, 400)$. (iii) For the route AANAANLCMA, the transportation consignments from an Asian port to an Australian port follow the uniform distribution $U(500, 700)$, and the transportation consignments from an Australian port to an Asian port follow the uniform distribution $U(300, 400)$. For all the three routes, there are no transportation consignments within the same region.

Table 2.1: Data for relevant container costs

Relevant container costs	Per foldable container	Per standard container
Weekly storage cost	US$10	US$40
Loading or unloading cost	US$13	US$50
Long-term leasing cost	US$960	US$480
Folding and unfolding cost	US$20	

Table 2.2: Candidate ship type and fixed operation cost

Ship route	Ship type (TEUs) and fixed operating costs (million US$)								
	4,400	5,000	5,400	5,800	6,200	11,000	11,400	11,800	12,000
BOHAI	14.07	15.00	15.21	15.32					
LIBERTY2		8.62	9.53	10.20	10.48				
AANAANLCMA						22.23	23.00	23.44	23.52

By referring to Moon and Hong (2016), and Konings (2005), we set all the relevant costs for foldable and standard empty containers, which are shown in Table 2.1. Here, we assume that all the costs are the same for different ports, and four foldable containers can be folded as one standard container. The short-term leasing cost is charged based on the travel time between origin ports and destination ports. According to Moon and Hong (2016), the unit short-term leasing cost is set as US$170/week, for example, if the travel time between an origin port and a destination port is two weeks, the short-term leasing cost is US$340. For the three selected shipping service routes, the candidate ship types and the fixed operating cost for the whole planning horizon by each ship type are presented in Table 2.2 (Meng and Wang, 2012).

2.6.2 Optimality check for the proposed solution approach

In Section 2.5, we propose the solution approach and formulate the MILP model for the problem. Here, we apply the two methods to solve problem instances of three shipping routes. The test instances are randomly generated by using the parameter settings in Section 2.6.1. The results of using the proposed solution approach and using the MILP model by CPLEX solver are given in Table 2.3. As can be seen, both methods derive the same optimal solution for the problem, which verifies the optimality of the proposed solution approach. With respect to the computation time, both methods outperform each other in some instances and on average, using the proposed solution is slightly faster than using the MILP model by CPLEX solver. Since CPLEX solver is a commercial solver and does not outperform the proposed method, the proposed solution embedded with the revised network simplex algorithm is more desirable for shipping liner companies, as it does not invoke any MILP solvers.

Table 2.3: Comparing the proposed method with the MILP model by CPLEX solver

Instance		**The solution approach**		**The MILP model**		**Time ratio**
Shipping route	Instance ID	Z(million US$)	CPU time (seconds)	Z(million US$)	CPU time (seconds)	
BOHAI	B_3_1	36.32	3	36.32	3	1.00
	B_3_2	37.45	4	37.45	6	0.67
	B_3_3	38.64	2	38.64	3	0.67
	B_3_4	37.71	3	37.71	6	0.50
	B_3_5	38.06	3	38.06	3	1.00
LIBERTY2	L_3_6	33.78	11	33.78	15	0.72
	L_3_7	33.45	24	33.45	21	1.14
	L_3_8	32.97	12	32.97	15	0.77
	L_3_9	33.63	24	33.63	20	1.21
	L_3_10	33.85	21	33.85	17	1.24
AANAANLCMA	A_3_11	83.74	58	83.74	59	0.99
	A_3_12	82.67	55	82.67	53	1.04
	A_3_13	83.31	70	83.31	74	0.94
	A_3_14	82.78	97	82.78	83	1.16
	A_3_15	82.46	83	82.46	95	0.87
					Average:	0.93

Note*: (i) "Z(million US$)" represents the objective values derived by the two methods with the unit of million US$. (ii) "CPU time" shows the computation time with the unit of seconds. (iii) "Time ratio" is the CPU time of the solution approach divided by the CPU time of the MILP model by CPLEX solver.*

2.6.3 Comparing a model that only considers laden container transportation

One of the major motivations of this paper is to incorporate the empty container allocation into the ship type decision for the ship fleet deployment. Here, we conduct experiments to compare our proposed model with the model that does not consider the empty containers on the problem. For the traditional model, we decide the ship type by only considering the laden containers, by which we can calculate the container flows for all the voyages. Then, the ship type that has the minimum capacity to accommodate all the container flows is determined as the selected ship type. Assuming that the capacity and the fixed operating cost for the selected ship type is K^1 and C^1, we run the revised network simplex algorithm only to find the minimum flow cost for empty containers, which determines the total cost $C^1 + \sigma^1$ for the traditional model.

Table 2.4: Comparing the proposed model and the traditional model without empty container allocation

Instance		The proposed model		The traditional model		Gap
Shipping route	Instance ID	$Z1$(million US$)	Ship fleet	$Z2$(million US$)	Ship fleet	
BOHAI	B_4_1	38.13	5,400	38.39	5,000	0.68%
	B_4_2	37.68	5,000	38.00	4,400	0.86%
	B_4_3	37.10	5,000	37.37	4,400	0.74%
	B_4_4	37.72	5,400	37.72	5,400	0.00%
	B_4_5	38.38	5,800	38.74	5,400	0.93%
Imbalance ratio of laden container flow: 1.99; # of ports: 5					Average:	0.64%
LIBERTY2	L_4_6	33.13	5,800	33.28	5,400	0.46%
	L_4_7	34.04	6,200	34.21	5,800	0.51%
	L_4_8	33.61	5,800	33.77	5,400	0.49%
	L_4_9	33.26	5,400	33.26	5,400	0.00%
	L_4_10	33.13	5,400	33.13	5,400	0.00%
Imbalance ratio of laden container flow: 1.27; # of ports: 7					Average:	0.29%
AANAANLCMA	A_4_11	84.26	12,000	85.53	11,400	1.51%
	A_4_12	83.14	11,400	84.37	11,000	1.48%
	A_4_13	82.93	11,400	83.93	11,000	1.21%
	A_4_14	83.96	11,800	85.09	11,400	1.35%
	A_4_15	83.16	11,400	84.08	11,000	1.11%
Imbalance ratio of laden container flow: 1.73; # of ports: 9					Average:	1.33%

Note*: (i) $Z1$(million US$) and $Z2$(million US$) represent the objective values of the two models with the unit of million US$. (ii) "Ship fleet" shows the capacity (in TEUs) of the selected ship type. (iii) "Gap" shows the difference on the total costs by the two models, which is calculated by* $(Z2 - Z1)/Z1$.

The comparison between the proposed model and the traditional model is listed in Table 2.4, where "Ship fleet" shows the capacity of the selected ship fleet types by the two models, and "Gap" shows the difference in the total costs by the two models. In the majority of the instances in Table 2.4, the selected ship fleet types are different by the two models. More importantly, the ship fleet capacity selected by the proposed model is no less than the ship fleet capacity selected by the traditional model, which is consistent with our previous discussion, i.e., considering the empty containers gives the shipping liner motivation to deploy larger container ships. However, the impact of considering the empty container allocation varies among the three shipping routes. For the route AANAANLCMA, which does not consider the empty container allocation, the total cost rises by near 1.33% on average; but for the route LIBERTY2, the total cost rises by near 0.29% on average. Here, note that if the selected ship fleet types by the two models are the same, the total costs are the same, because we also optimize empty container related decisions in the traditional model.

The above-mentioned phenomenon attributes to the different trade routes that the three shipping routes belong. The route AANAANLCMA is one shipping route of Australia-Far East trade route, and the route LIBERTY2 is one shipping route of North Europe-North America trade route. As a result, the route AANAANLCMA has a higher imbalance ratio of laden container flow than the route LIBERTY2, which makes the empty container repositioning more necessary for the route AANAANLCMA. Thus, for the route AANAANLCMA, it is more important to consider empty containers in the ship type decision, which is verified by the high total cost gaps in "Gap". For the route BOHAI, although the imbalance of laden container flow for the route is significant, the total cost gap is not so obvious compared with the route AANAANLCMA, which is due to that only five ports of call are involved in the route BOHAI. Based on the above analysis, we can conclude that considering the empty container allocation is critical for the ship fleet deployment, especially for the shipping routes that have high imbalance ratios of laden container flow, and the shipping routes that traverse many ports of call.

2.6.4 Performance evaluation of using foldable containers

Although researchers have proved that the economic and logistical viability of using foldable container, the foldable containers still are not prevalent among the shipping services. In this section, we aim to investigate how much cost the shipping liner can save if the foldable containers are truly used in shipping services. In this subsection, we conduct some experiments on comparing the proposed model (i.e., $\boldsymbol{TNF}$ model and ship type decision) with the model that does not use the foldable containers (i.e., $\boldsymbol{PNF}$ model and ship type decision). Note that we still use the solution approach proposed in Section 2.5 to derive the optimal container flow and the optimal ship type for the two cases. The results are reported in Table 2.5, where "Container fleet" shows the total number of containers used for the complete planning horizon, and "Gap" shows the difference on the total costs by the two models.

Table 2.5: Comparison between the proposed model and the model that does not use the foldable containers

Instance		**With foldable containers**			**Without foldable containers**			**Gap**
Shipping route	Instance ID	Z(million US$)	Ship fleet	Container fleet	Z(million US$)	Ship fleet	Container fleet	
BOHAI	B_5_1	37.88	5,000	38,474	37.98	5,000	38,451	0.27%
	B_5_2	38.12	5,400	38,825	38.27	5,800	38,367	0.40%
	B_5_3	37.88	5,000	38,367	38.01	5,400	38,290	0.34%
	B_5_4	37.96	5,400	38,605	38.06	5,400	38,460	0.26%
	B_5_5	38.16	5,800	38,880	38.26	5,800	38,429	0.28%
							Average:	0.31%
LIBERTY2	L_5_6	33.13	5,400	42,492	33.15	5,400	42,485	0.05%
	L_5_7	33.23	5,800	42,555	33.25	5,800	42,555	0.03%
	L_5_8	33.24	5,800	42,494	33.25	5,800	42,494	0.04%
	L_5_9	33.22	5,800	42,621	33.25	5,800	42,603	0.08%
	L_5_10	33.05	5,400	42,348	33.06	5,400	42,348	0.04%
							Average:	0.05%
AANAANLCMA	A_5_11	82.84	11,400	99,516	83.30	11,800	99,316	0.56%
	A_5_12	83.12	11,800	100,110	83.63	12,000	100,013	0.62%
	A_5_13	82.80	11,400	99,597	83.27	11,400	99,325	0.56%
	A_5_14	82.71	11,000	99,548	83.23	11,400	99,361	0.63%
	A_5_15	83.25	11,800	99,733	83.69	12,000	99,645	0.53%
							Average:	0.58%

***Note**: (i) $Z1$(million US$) and $Z2$(million US$) represent the objective values with the unit of million US$. (ii) "Ship fleet" shows the capacity (in TEUs) of the selected ship type. (ii) "Container fleet" shows the total number of empty containers used for the whole planning horizon, including the total number of the empty containers owned initially and the long-term leasing empty containers. (iii) "Gap" shows the difference on the total costs by the two models, which is calculated by $(Z2 - Z1)/Z1$.*

In Table 2.5, the container fleet (i.e., the total number of containers) using foldable containers is no less than the container fleet that does not use foldable containers. This result suggests that using foldable containers motivates the shipping liner to enlarge its container fleet, which makes it more powerful to handle the laden container demands. Meanwhile, there is nearly no advantage on cost reduction for the route LIBERTY2 by using foldable containers as the total cost gaps are less than 0.10%, and using foldable containers has the biggest impact on the route AANAANLCMA among the three routes. The results are in line with the results of Table 2.4. However, the impacts of using foldable containers on the total cost for all the three routes are not so significant as all the total cost gaps are less than 0.70%, which implies that under the current cost settings, the shipping liner does not have a strong incentive on cost reduction to use the foldable containers. This may be the reason why the foldable containers are still not prevalent among the shipping services. To find strong incentives for using the foldable containers for the shipping liner, we will analyze the effects of cost settings on the foldable container usage in Section 2.6.5. Meanwhile, Table 2.5 shows the foldable container usage could affect the ship type decision. In two instances of the route BOHAI (Instance

B_6_2 and B_6_3) and all instances of the route AANAANLCMA except Instance A_6_13, after using foldable containers, it will choose a smaller ship fleet. It may attribute to that after using foldable containers the empty container repositioning will occupy less storage space on ships when repositioning foldable containers. Thus, a smaller ship fleet may be enough for carrying all laden and empty containers.

2.6.5 Effects of cost settings on the foldable container usage

In this section, our goal is to find under which conditions, the shipping liner would use foldable containers on large scale. Compared with standard containers, foldable containers have higher long-term leasing cost and extra folding and unfolding cost. Therefore, we test the effects of the long-term leasing cost and the folding and unfolding cost on the foldable container usage in the section. We define a ratio $\rho = \sum_{p \in P} \zeta_p^F / (\sum_{p \in P} \zeta_p^F + \sum_{p \in P} \zeta_p^S)$ to show the usage of foldable containers, where ζ_p^S and ζ_p^F are the number of standard containers and foldable containers used for the long-term container leasing. The bigger the ratio is the more foldable containers are leased for the usage of the planning horizon.

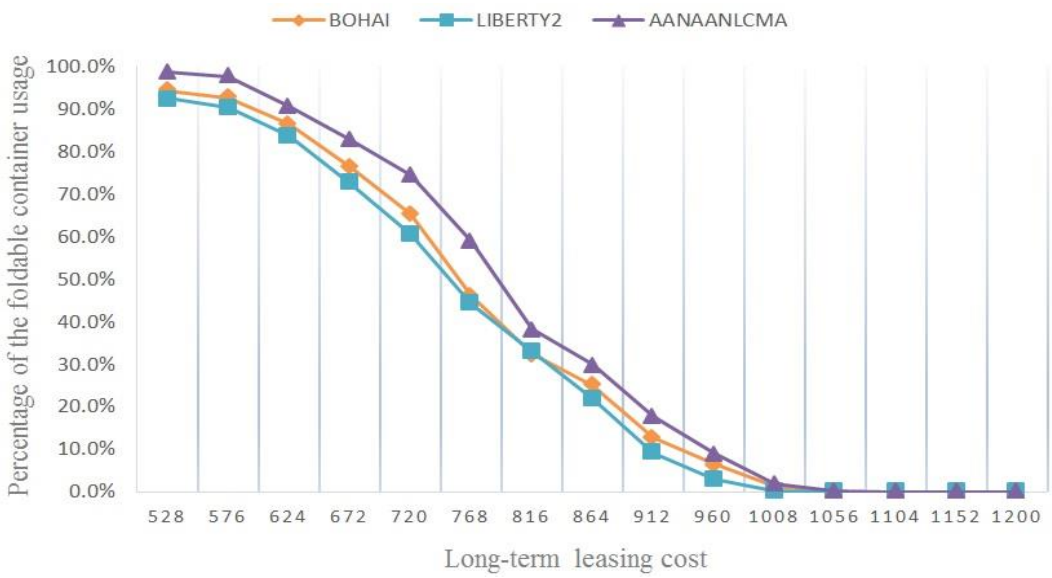


Figure 2.10: Effect of the long-term leasing cost on the foldable container usage

Figure 2.10 illustrates the effect of the long-term leasing cost on the foldable container usage, where the y-axis shows the ratio ρ, and x-axis indicates the long-term leasing cost of a foldable container. In Figure 2.10, we keep the long-term leasing cost of a standard container unchanged (i.e., US$480), and increase the long-term leasing cost of a foldable container from US528 to US$1200. As can be seen, all three curves for the three shipping routes descend fast when the long-term leasing cost increases, and a formal proof (See Appendix B) can verify the non-increasing trend of using foldable containers. Under the current cost setting, i.e., the long-term leasing cost of a foldable container is US$960, the foldable container usage is in low ratio. If the cost reduces to US$768, the shipping liner can have equal usage on both standard containers and foldable containers. However, if the cost is beyond US$1056, there is no need to consider the usage of foldable containers. Therefore, we can summarize that the foldable container usage is highly dependent on the long-term leasing cost, and reducing the long-term leasing cost could be an effective way to make the foldable containers become prevalent.

Under the different long-term leasing cost of foldable containers, we also compare the average total cost gap between the case with using foldable containers and the case without using foldable containers, the results of which are listed in Table 2.6. As can be seen, when the long-term leasing cost decreases, using foldable containers saves the total cost more significantly. If the long-term leasing cost drops to US$528, the total saving reaches 27.51%. However, if the long-term leasing cost is beyond US$1104, it makes no difference between the case by using foldable containers and the case without using foldable containers.

Table 2.6: Total cost saving after using foldable containers under different long-term leasing cost

long-term leasing cost	528	576	624	672	720	768	816
Total cost saving	27.51%	22.26%	17.04%	12.49%	8.56%	5.44%	3.19%
long-term leasing cost	864	912	960	1008	1056	1104	1152
Total cost saving	1.83%	0.86%	0.26%	0.11%	0.02%	0.00%	0.00%

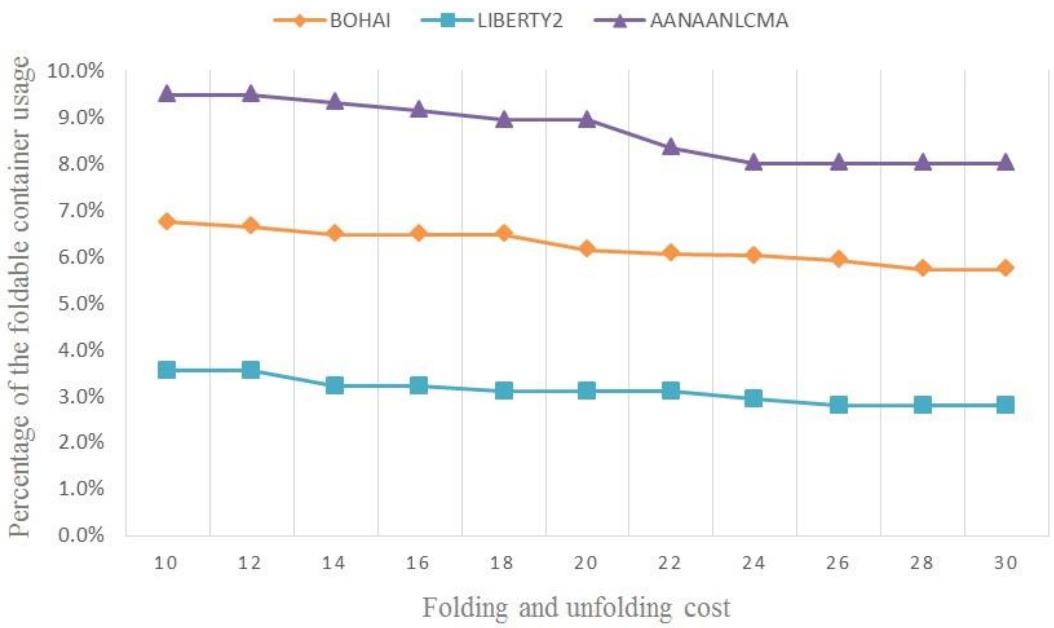


Figure 2.11: Effect of the folding and unfolding cost on foldable container usage

Figure 2.11 shows the effect of the folding and unfolding cost on the foldable container usage, where the y-axis shows the ratio ρ, and the x-axis indicates the folding and unfolding cost of a foldable container (US$20 in the current cost setting). Here, we increase the folding and unfolding cost of a foldable container from US10 to US$30. In the figure, the three curves of three shipping service routes are almost flat, and the foldable container usage maintains at around 8.5% for the route AANAANLCMA, around 6.4% of the route BOHAI, and around 3.0% for the route LIBERTY2. Thus, we can conclude that the foldable container usage is not sensitive to the folding and unfolding cost, and the reduction of the folding and unfolding cost will not spur the foldable container usage significantly.

In summary, the foldable container usage is highly dependent on the long-term leasing cost, but it is not sensitive to the folding and unfolding cost in the current cost settings. The reason why the usage of foldable containers shows an insensitive reaction to the folding and unfolding cost may attribute to the dominant role of the long-term leasing cost of using foldable containers. According to Figure 2.10, when the long-term leasing cost of foldable containers is US$960, the percentage of the foldable container usage is low for the three shipping routes (below 10%), indicating that using standard containers is much more cost-effective than using foldable containers. Under the case, the decreasing of the folding and unfolding cost may not be a comparatively strong incentive for the shipping lines to use foldable containers.

2.6.6 Analysis of cost-dependent sensitivity

The previous subsection shows that when the long-term leasing cost is high, the foldable container usage has a low sensitivity in response to the folding and unfolding cost. In this subsection, we aim to explore the relationship between the foldable container usage's sensitivity to the folding and unfolding cost and the long-term leasing cost. To investigate whether the long-term leasing cost affects the sensitivity to the folding and unfolding, we focus on the route AANAANLCMA and conduct sensitivity analysis for the folding and unfolding under different long-term leasing cost. Given a long-term leasing cost, in order to measure the sensitivity in the same metric, we define a sensitivity ratio $\sigma = \frac{\rho_1 - \rho_0}{\rho_0}$, where ρ_0 is the percentage of foldable containers used under US$20 folding and unfolding cost (the baseline setting), and ρ_1 is the percentage under other costs, such as US$10 and US$30. In the experiments, we set the long-term leasing cost to US$960, US$860, US$760, US$660 and US$560, under each of which, we change the folding and unfolding cost to detect the sensitivity.

Figure 2.12 shows the relationship between the sensitivity to the folding and unfolding cost and the long-term leasing cost, where the y-axis shows the sensitivity ratio σ, and x-axis indicates the folding and unfolding cost. See the highest "blue" point for an example to depict the figure, which shows that, given the long-term leasing cost as US$860, when the folding and unfolding cost decreases from US$20 to US$5, the percentage of foldable container usage will increase by 54%. Each line in the figure corresponds to the sensitivity under each long-term leasing cost, and a steeper line means the foldable container usage is more sensitive to the folding and unfolding cost. In general, Figure 2.12 illustrates that the sensitivity to the folding and unfolding cost depends on the long-term leasing cost. More specifically, when the long-term leasing cost decreases from US$960 to US$860 (resp. decreases from US$860 to US$560), the line becomes steeper (resp. smoother) such that the foldable container usage becomes more sensitive (resp. less sensitive) to the folding and unfolding cost.

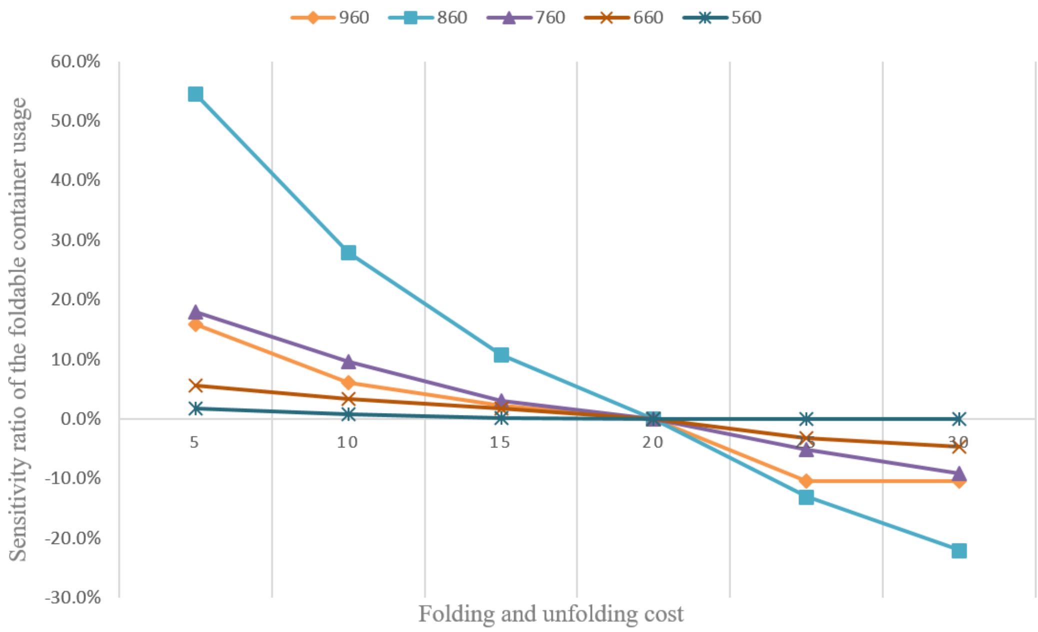


Figure 2.12: Long-term leasing cost dependent sensitivity to the folding and unfolding cost

An intuitive explanation for the phenomenon is that when the long-term leasing cost drops to a certain level (say US$860), using foldable containers becomes nearly the same cost-effective as using standard containers. At that level, the changes in the folding and unfolding cost may have evident effectiveness towards the foldable container usage. However, if the long-term leasing cost further reduces to a low level (say US$560), using foldable containers is much more cost-effective than using standard containers (cf. Figure 2.10, approximately 97.8% foldable container usage). Henceforth, decreasing the folding and unfolding cost may have a limited incentive to increase the foldable container usage. Based on the phenomenon, we can obtain some managerial insights for shipping lines when popularizing the usage of foldable containers. (i) If container leasing companies charge a high price for the long-term leasing of foldable containers, it may not be economic to use foldable containers considering some fixed operation costs incurred for using the foldable containers. (ii) If container leasing companies charge a moderate price, the shipping lines may make efforts to cut down the folding and unfolding cost by negotiating with port terminals, which can lead to a profitable result. (iii) If container leasing companies charge a low price, it is cost-effective to use foldable containers and the bargaining motivation of shipping lines on the folding and unfolding cost with port terminals might not be strong, as the cost reduction leads to a tiny benefit.

2.6.7 Sensitivity analysis on the number of weeks for the devanning process

In Section 2.4.1, there is an input parameter w_p showing the number of weeks allowed for the devanning process. As discussed in Section 2.3.3, this parameter indicates the required time for consignees to return empty containers. In essential, the parameter constructs a trade-off between shipping liner companies and customers (or consignees). If w_p becomes larger, the customers will have more flexibility to deal with the cargo carried in containers, but this would increase the opportunity cost for shipping liner companies, as they need empty containers as soon as possible to fulfill next transportation consignments. Here, to investigate the opportunity cost, we conduct a sensitivity analysis on the parameter w_p, the results of which are given in Table 2.7.

Table 2.7: Sensitivity analysis on the number of weeks allowed for returning empty containers

No. of weeks	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Total cost	70.93	75.53	85.48	96.13	107.35	118.80	129.98	140.81
Slope	4.60	9.95	10.65	11.22	11.45	11.18	10.83	NaN

Note: *(i) "Total cost" with a unit of million US\$ denotes the total cost on average of ten randomly generated instances. (ii) "Slope" shows the increasing rate at a specific number of weeks, for example, at "0" weeks, the rate is* $(75.53 - 70.93)/(1 - 0) = 4.60$. *(iii) "0" week for the devanning process is unrealistic in the real-world operations. The "0" week setting only serves as a benchmark in the sensitivity analysis.*

In the table, when the number of weeks allowed for the devanning process increases, the total cost grows significantly, which suggests the high opportunity cost for allowing more devanning time. Meanwhile, the slope of total cost increases before reaching "4" weeks and decreases after "4" weeks, which reveals that the total cost is increasing convex in the number of weeks first and then becomes increasing concave. More importantly, given "0" weeks as the benchmark, we can see that from "0" week to "1" week, the total cost increases by 4.60 million US\$, which is far less than other increasing rates (e.g., 9.95 million US\$ from "1" week to "2" weeks). Here, we can derive a managerial insight for shipping liner companies: Allowing one week for the devanning process is a better choice for shipping companies, which is the choice by OOCL (OOCL, 2017). Giving more weeks for the devanning process offers more flexibility for customers such that shipping liner companies may charge higher freight fee for compensating the opportunity cost. However, the loss may outweigh the benefit, as the total cost increases in a convex manner at the beginning based on the sensitivity analysis.

2.7 CONCLUSION

This paper makes an explorative study on the ship type decision considering the empty container repositioning and the foldable containers. Different from traditional research works on the ship fleet deployment, our study incorporates both the laden container transportation and the empty container repositioning into ship type decision in order to achieve the global optimum for a shipping service route over a whole planning horizon. Meanwhile, as researchers have shown the economic and logistical viability of foldable containers, the problem also considers the use of foldable containers, which aims to find under what conditions, the shipping liner needs to use the foldable containers in its liner shipping services.

In this study, we find that given the ship type with a certain capacity, the problem transfers to a nonstandard minimum cost flow. Henceforth, we build a network flow model for the problem by constructing a network. When considering standard containers and foldable containers, trouble arises in the network construction that is some parallel arcs share the same capacity restriction. To overcome this trouble, we design a revised network simplex algorithm that changes the standard pivot operation. The algorithm is applicable to any minimum cost flow problem with sharing capacity restrictions. Based on the algorithm, we develop a solution approach by using reduced costs for excluding some ship type, which can find the optimal ship type in the end. By using the solution approach, we conducted extensive numerical experiments to find some managerial implications on the ship fleet deployment and the foldable container usage.

Some useful managerial implications of this study are summarized from three perspectives. (i) *Ship type decision*: when deciding the ship type deployed in a ship fleet, only involving laden container transportation leads to sub-optimal solutions, as the possible empty container repositioning affects the decision. After including foldable containers, a smaller ship type can be expected to deploy, because foldable containers have the storage space advantage in the empty container repositioning. (ii) *Foldable container usage*: under the current cost setting, it is not cost-effective for shipping lines to use foldable containers, as the long-term leasing cost is high. However, if the long-term leasing cost cuts down, using foldable containers is encouraged, as foldable container usage is highly dependent on the long-term leasing cost. The foldable container usage's sensitivity to the folding and unfolding cost depends on the long-term leasing cost. With different long-term leasing costs, different efforts can be made to reduce the folding and unfolding cost. For example, if container leasing companies charge a moderate price for long-term leasing, the shipping lines may devote much efforts to cut down folding and unfolding cost, which can lead to a profitable result. (iii) *Container devanning time*: It is better to allow one-week time for the container devanning process. Although allowing more weeks for the devanning process brings more flexibility for customers such that shipping lines may obtain some benefits, the opportunity cost can outweigh the benefits, as the opportunity cost increases significantly after the one-week setting.

2.8 REFERENCES

Ahuja, R. K., Magnanti, T. L., Orlin, J. B., 1993. *Network Flows: Theory, Algorithms, and Applications*, New Jersey, USA.

APL, 2017. The perfect fit for all your different needs: your APL equipment guide, https://www.apl.com/wps/wcm/connect/659ca9b6-7eb3-4c16-82de-8de04abab7e9/Equipment+guide.pdf?MOD=AJPERES. Accessed on 10 August 2017.

Bell, M.G.H., Liu, X., Rioult, J., Angeloudis, P., 2013. A cost-based maritime container assignment model. *Transportation Research Part B* 58, 58–70.

Brouer, B.D., Alvarez, J.F., Plum, C.E., Pisinger, D., Sigurd, M.M., 2013. A base integer programming model and benchmark suite for liner-shipping network design. *Transportation Science* 48(2), 281–312.

Cheung, R.K., Chen, C.Y., 1998. A two-stage stochastic network model and solution methods for the dynamic empty container allocation problem. *Transportation Science* 32(2), 142–162.

Container Auction, 2017. Shipping container lease agreements. https://containerauction.com/read-news/shipping-container-lease-agreements. Accessed on 29 June 2016.

COSCO, 2017. Aust port charges: import container detention, http://www.fivestarshipping.com.au/australian-port-charges/container-detention/. Accessed on 12 August 2017.

CMA CGM, 2017. Lines and Services, https://www.cma-cgm.com/products-services/line-services. Accessed on 12 August 2017.

Crainic, T.G., Gendreau, M., Dejax, P., 1993. Dynamic and stochastic models for the allocation of empty containers. *Operations Research* 41, 102–126.

Gelareh, S., Meng, Q., 2010. A novel modeling approach for the fleet deployment problem within a short-term planning horizon. *Transportation Research Part E* 46(1), 76–89.

Goh, S. H., & Lee, J. L., 2016. Commercial viability of foldable ocean containers. *Proceedings - International Conference on Industrial Engineering and Operations Management*, Kuala Lumpur, Malaysia, March 8-10, 2016.

Hanh, L. D. 2003. The logistics of empty cargo containers in the Southern California region. *Final Report*, Long Beach, CA.

Holland Container Innovations, 2017a. 4FOLD customer cases. http://hcinnovations.nl/4fold-customer-cases/. Accessed on 10 August 2017.

Holland Container Innovations, 2017b. 4FOLD foldable container. http://hcinnovations.nl/4fold-foldable-container/. Accessed on 10 August 2017.

Konings, R., 2005. Foldable containers to reduce the costs of empty transport? A cost-benefit analysis from a chain and multi-actor perspective. *Maritime Economics and Logistics* 7(3), 223–249.

Lee, C.-Y., Yu, M.Z., 2012. Inbound container storage price competition between the container terminal and a remote container yard. *Flexible Services and Manufacturing* 24(3), 320–348.

Li, J.A., Liu, K., Leung, S.C.H., Lai, K.K., 2004. Empty container management in a port with long-run average criterion. *Mathematical and Computer Modelling* 40, 85–100.

Li, J.A., Leung, S.C.H., Wu, Y., Liu, K., 2007. Allocation of empty containers between multi-ports. *European Journal of Operational Research* 182, 400–412.

Meng, Q., Wang, T.S., Wang, S., 2012. Short-term liner ship fleet planning with container transshipment and uncertain container shipment demand. *European Journal of Operational Research* 223, 96–105.

Meng, Q., Wang, S., 2011. Liner shipping service network design with empty container repositioning. *Transportation Research Part E* 47(5), 695–708.

Meng, Q., Wang, S., 2012. Liner ship fleet deployment with week-dependent container shipment demand. *European Journal of Operational Research* 222, 241–252.

Moon, I. K., Do, Ngoc A. D., Konings, R., 2013. Foldable and standard containers in empty container repositioning. *Transportation Research Part E* 49, 107-124.

Moon, I. K., Hong, H., 2016. Repositioning of empty containers using both standard and foldable containers. *Maritime Economics & Logistics* 18, 61-77.

Myung, Y. S., Moon, I. K., 2014. A network flow model for the optimal allocation of both foldable and standard containers. *Operations Research Letters* 42(6-7), 484-488.

Ng, M.W., 2014. Distribution-free vessel deployment for liner shipping. *European Journal of Operational Research* 238(3), 858–862.

Ng, M.W., 2015. Container vessel fleet deployment for liner shipping with stochastic dependencies in shipping demand. *Transportation Research Part B* 74, 79–87.

Ng, M.W., 2016. Revisiting a class of liner fleet deployment models. *European Journal of Operational Research* 257(3), 773–776.

OOCL, 2017. Demurrage & detention free time and charges, http://www.oocl.com/hongkong/eng/localinformation/ddfreetime/Pages/default.aspx?site=hongkong&lang=eng. Accessed on 12 August 2017.

Perakis, A.N., Jaramillo, D.I., 1991. Fleet deployment optimization for liner shipping Part 1. Background, problem formulation and solution approaches. *Maritime Policy & Management* 18(3), 183–200.

Plum, C.E., Pisinger, D., Sigurd, M.M., 2013. A service flow model for the liner shipping network design problem. *European Journal of Operational Research* 235(2), 378–386.

Shintani, K., Konings, R., Imai, A., 2010. The impact of foldable containers on container fleet management costs in hinterland transport. *Transportation Research Part E* 46, 750–763.

Shipping and Freight Resource, 2017. Difference between demurrage and detention, https://shippingandfreightresource.com/difference-between-demurrage-and-detention/. Accessed on 12 August 2017.

Song, D.P., Dong, J.X., 2011. Flow balancing-based empty container repositioning in typical shipping service routes. *Maritime Economics and Logistics* 13(1), 61–77.

Song, D.P., Dong, J.X., 2012. Cargo routing and empty container repositioning in multiple shipping service routes. *Transportation Research Part B* 46(10), 1556–1575.

UNCTAD, 2016. Review of maritime transport. http://unctad.org/en/PublicationsLibrary/rmt2016_en.pdf. Accessed on 10 August 2017.

Wolff, J., Herz, N., & Flamig, H., 2007. Report on case study: Empty container logistics: Hamburg-Baltic Sea region. *Hamburg University of Technology, The Baltic Sea region programme*, 2013.

Word Shipping Council, 2013. About the industry: major trade routes in global trade. http://www.worldshipping.org/about-the-industry/global-trade/trade-routes. Accessed on 28 March 2016.

Word Cargo News, 2017. Container industry news: Folding boxes stack up. http://hcinnovations.nl/wp-content/uploads/2017/05/Press-20170401_World_Cargo_News.pdf. Accessed on 10 August 2017.

Chapter 3: Container Reefer Slot Conversion

This chapter addresses the reefer slot conversion problem for container freight transportation. Given a fleet of container ships of varying capacity, a cost-efficient approach for improving fleet utilization and reducing the number of delayed containers is to optimize the sequence of container ships in a given string, a problem which belongs to the ship-deployment class. A string sequence with 'uniformly' distributed ship capacity is more likely to accommodate a random container shipment demand. The number of one's total ship slots acts as a gauge of the capacity of the container ships. Meanwhile, in reality, there are actually two types of ship slots: dry slots and reefer slots. A dry slot only accommodates a dry container, while a reefer slot can accommodate either a dry or a reefer container. The numbers of dry and reefer slots for ships in a string are different. Therefore, in this study we propose a model that considers both dry and reefer slots and use it to elucidate the optimal ship-deployment sequence. The objective is to minimize the delay of dry and reefer containers when the demand is uncertain. Furthermore, based on the optimal sequence deduced, the study also investigates the need to convert some dry slots to reefer slots for the container ships.

3.1 INTRODUCTION

In a liner shipping network, the liner shipping company normally operates weekly-serviced ship routes with fixed schedules. That is, for a given shipping route, there is a fleet of container ships deployed such that the ports along the shipping route are visited on a weekly basis. In order to provide weekly services for all the ports, the number of ships deployed in the fleet should be the number of weeks needed to complete the shipping route (Bell et al., 2011; Meng and Wang, 2012; Lin and Tsai, 2014; Wang, 2017). For example, if traversing a route takes two weeks, the number of ships deployed should be two. When a container ship visits a port, the containers that have arrived at the port during the past week would then be loaded onto the ship to send them onwards to their destination ports. However, the ship's capacity, as measured by the number of 'twenty-foot equivalent units' (TEUs), is limited. Thus, some containers cannot be loaded onto the ship, and will therefore be delayed for one week.

In a container ship, ''slots'' are used to accommodate containers. The number of slots in a ship reflects the ship's capacity. Generally, there are two types of slots for a container ship, dry slots, and reefer slots. Reefer slots are equipped with an electrical outlet so that reefer containers can be accommodated which have an integrated cooling unit. Reefer containers cannot be placed in dry slots (due to lack of electricity supply) while dry containers can be placed on the reefer slots if there are any still available. For a ‘‘cold chain’’, these reefer containers and slots are critical in order to keep goods fresh (Cheaitou and Cariou, 2012; Rodrigue and Notteboom, 2015).

Among the world’s ship fleets, reefer container slots have been expected to rise 22% between 2013 and 2018 driven by the growth in demand for reefer cargo transportation (Sowinski, 2015). Nowadays, reefer slot capacity has already become a critical measure of the competitiveness between shipping liners. The largest-ever ships in the Hamburg Süd Group have more than 2,000 reefer slots on board and are the vessels with the largest reefer slot capacities in the world (Hamburg Süd, 2013). Hamburg Süd (2013) attributed the fact that they were performing well under difficult business conditions to their large reefer slot capacity. In comparison, Hanjin (which was the 7th largest shipping line in the world) only maintained several hundred reefer slots in their ships (Chen and Yahalom, 2013). Currently, Hanjin has already filed for bankruptcy due to a crisis in its financial affairs. Cool Logistics (2014) even ascribed the Hanjin crisis to their reefer cargo transportation arrangements. Empirically, in light of the underlying fierce competition between shipping liners, slot configurations, and slot conversion are, in practice, topics of significant importance among shipping companies (Lin et al., 2017).

Table 3.1: The capacities of the ships in the fleet used for the Yangtze Service route

No.	**Ship name**	**Capacity (TEU)**
1	ARCHIMIDIS	7,943
2	CMA CGM NABUCCO	8,488
3	CSCL EAST CHINA SEA	10,036
4	CSCL SOUTH CHINA SEA	10,036
5	NAVARINO	8,533
6	XIN DA YANG ZHOU	8,533

In maritime studies, a great deal of research effort has been devoted to container ship fleet deployment problems. This effort is mainly focused on determining the ship type for a given shipping service route (Gelareh and Meng, 2010; Meng et al., 2012; Song and Dong, 2013; Ng, 2014). In such studies, it is assumed that the container ships are categorized into different types. Moreover, all the ships belonging to a particular category are homogenous, i.e. they have the same capacity. In addition, the ship fleet deployed for a given route only consists of one type of ship. However, in reality, the ships in a fleet may not all have the same capacity (Lin and Liu, 2011; Du et al., 2017). For instance, consider the example listed in Table 3.1 (relating to the China–USA Yangtze Service route operated by France’s CMA CGM Group, the third largest shipping liner in the world). The table lists the six ships deployed in the fleet which consists of four different ship types, each with different capacity (CMA CGM, 2016).

Corresponding to the data in Table 3.1, there is a novel optimization problem which has been addressed by Wang (2016). Put briefly, how should we arrange the sequence of the ships for a given fleet in order to maximize the ship utilization of the fleet and reduce the number of delayed containers? Here, the sequence in which the ships visit each port in the shipping route is indicated using a ‘‘string’’ (Figure 3.1). If the sequence is 1→2→3→4→5→6, for example, then each port will be visited by the ARCHIMIDIS first, CMA CGM NABUCCO second, and so on. Optimization of the sequence depends on the weekly-dependent demand for container shipment (Meng and Wang, 2012). That is, shipment demand does not remain constant and will vary from week to week. Let us suppose that the demand for the Yangtze Service route is random and varies between 8,000 and 10,000 TEU. Intuitively, the sequence of 3→5→1→4→6→2 might be expected to outperform the sequence of 1→2→3→4→5→6, as the former sequence has a more uniformly distributed ship capacity (which is more likely to be able to handle an uncertain demand pattern).

This study aims to optimize the ship sequence considering the availability of dry slots and reefer slots when the ship visits each port in a given route. Note that reefer containers have a higher priority than dry containers when loaded onto visiting ships in each port. Here, to account for the randomness in the container shipment demand, we assume that a predetermined demand probability distribution can be found. Based on the optimized ship sequence found for a string subject to uncertainty, this study further optimizes the associated problem of reefer slot conversion. That is, we aim to determine whether or not a shipping line should convert some of the dry slots in the ships to reefer slots (and how many dry slots should be converted) considering that reefer slots are more flexible (i.e. can carry either dry or reefer containers).

To improve the utilization of container ships and the efficiency of container handling, much effort has been devoted to studying various different aspects, e.g. optimization of shipping networks and container terminal operation. Whether or not reefer slot conversion provides a cost-efficient approach is still an open question. Meanwhile, the open question is also meaningful as Arduino et al. (2015) have proposed many technical and operational advantages of using reefer containers and slots. Although the study conducted by Wang (2016) provided some useful rules to improve the sequencing of container ships, it does not consider the availability of reefer slots in the container ships, nor does it judge whether the slot configurations in the ships can be improved. As ships have both reefer and dry slots to include to measure the ship’s capacity, the consideration of both types of slots in sequence optimization is inevitable.

Based on the discussion above, this paper presents a practical study of optimizing reefer slot conversion for container ships in a string. First, we derive the relevant equations required to estimate the profit of a certain string/ship sequence. Then, we propose a simulation-based approach to optimizing the sequence with the objective of maximizing the profit. We solve the slot-conservation problem using a slot-conversion algorithm that embeds a simulation-based approach for sequence optimization. Furthermore, to validate the effectiveness of the proposed approach, we consider several case studies based on real shipping routes operated by CMA CGM.

3.2 ESTIMATING THE PROFIT FOR A GIVEN STRING

Figure 3.1 depicts the sequence of container ships corresponding to a given string of the weekly-serviced Yangtze Service shipping route. The sequence shown is 1→4→6→5→2→3 (which is equivalent to 4→6→5→2→3→1, and the other sequences obtained by cyclically permuting the original string, as the string of ships forms a loop). Without losing generality, we assume that the sequence is written so that the first ship in the sequence is the ship with the smallest capacity (e.g. ship 1 for the Yangtze Service route). Given such a string, we derive in this section some equations that can be used to calculate the weekly profit of the shipping route. Note that all the equations derived here are considered to be on a weekly basis. In the following subsections, the variables and parameters used in the equations will be elaborated upon in detail. We also outline some practical container delay and rejection rules to be applied when the container ships visit the ports.

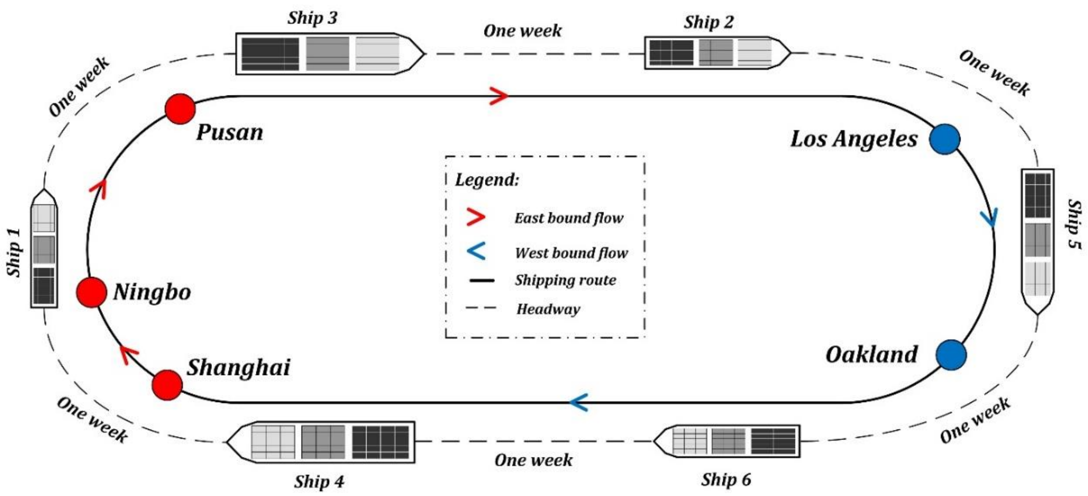


Figure 3.1: A sequence of container ships in a string

3.2.1 Decision variables and parameters

When a container ship visits a port, the containers accumulated in the past week need to be loaded into the available slots in the container ship for shipment to their destination ports. If the slots in the container ship are insufficient to stow all the accumulated containers, then some containers m be delayed for one or more weeks. Such a delay incurs additional costs for the shipping line. The main costs are: (i) the cost of storing the delayed container in the yard space of the port, (ii) the cost to customer satisfaction (who, presumably, will not be happy about the delay), and (iii) the cost incurred supplying electricity to a delayed container if it is of the reefer variety.

In the following week, when the next container ship visits the port, the containers that have been delayed will have priority when it comes to being loaded onto the ship. If some delayed containers still cannot be transported due to the limited availability of slots in the ship, then those delayed containers must be transported using slots from other shipping lines or by transshipment (Hasheminia and Jiang, 2017; Jiang et al., 2017). Such containers subsequently transported by other shipping lines are referred to as ‘‘rejected containers’’. Container rejection is the last thing that the shipping liner wants as it leads to two consequences for the shipping line: (i) it has to pay the freight rates for the shipment provided by the other shipping line, and (ii) it loses the goodwill of the customers affected. Here, one-week delays reflect the service level offered by the shipping liner with respect to guaranteeing the transit time for transportation of the container. We can adjust it to two or more weeks delay depending on the policy of the shipping liner. Meanwhile, container rejection does not mean the shipping line will lose profit. The marginal profit associated with the container transportation will decrease, but can still be positive after some additional incurred costs are deducted.

Based on the above discussion, the decision variables and parameters required are as follows.

Decision variables:

$D_{v-1}^{d}\left(D_{v-1}^{r}\right)$ **:** The number of dry (reefer) containers that were delayed from ship $v-1$ in the previous week.

$D_{v}^{d}\left(D_{v}^{r}\right)$ **:** The number of dry (reefer) containers that are delayed from ship v in the current week.

$\overline{D}^{d}\left(\overline{D}^{r}\right)$ **:** The average number of dry (reefer) containers that are delayed.

$R_{v}^{d}\left(R_{v}^{r}\right)$ **:** The number of dry (reefer) containers that are rejected from ship v in the current week.

Input parameters:

$c^{d,1}\left(c^{r,1}\right)$ **:** The loss of goodwill if a dry (reefer) container is rejected.

$c^{r,2}$ **:** The cost of electricity/fuel to transport a reefer container.

$c^{d,3}\left(c^{r,3}\right)$ **:** The cost of storing a dry (reefer) container in the yard.

$c^{r,4}$ **:** The extra electricity cost when storing a delayed reefer container.

$c^{d,5}\left(c^{r,5}\right)$ **:** The cost of customer dissatisfaction.

$g^{d}\left(g^{r}\right)$ **:** The freight rates for a dry (reefer) container.

$p_n^{d}\left(p_n^{r}\right)$ **:** The mass probability that *n* dry (reefer) containers need to be transported in the current week.

$q^{d}\left(q^{r}\right)$ **:** The expected number of dry (reefer) containers that need to be transported in the current week.

$\omega^{d}\left(\omega^{r}\right)$ **:** The new dry (reefer) container demand in the current week.

$\omega^{d}\left(\omega^{r}\right)$ **:** The realization of new dry (reefer) container demand in the current week.

$E_v^{d}\left(E_v^{r}\right)$ **:** The dry (reefer) container capacity of ship *v*.

E_v^{dr} **:** The capacity of reefer slots that are available to dry containers in the current week.

$N^{d}\left(N^{r}\right)$ **:** The maximum number of dry (reefer) containers in the current week.

V **:** The number of ships in a string.

Every week, there is a demand for dry containers, which is a random variable denoted by ω^{d}. We assume that ω^{d} is known to support integers between 0 and N^{d}. The probability mass function of the random variable ω^{d} is assumed to be known based on historical data: $\Pr(\omega^{d}=n)=p_n^{d}, n=0,1,\ldots,N^{d}$. The expectation value (E) of ω^{d} is $q^{d}:=\mathrm{E}(\omega^{d})=\sum_{n=0}^{N^{d}} np_n^{d}$. The symbols $\omega^{r}, N^{r}, p_n^{r}$ and q^{r} are correspondingly defined for reefer containers. Notice that we consider the container demands on the ''hit-haul'' leg (i.e. the leg on which the highest number of containers is carried) of the long-haul liner service routes rather than all the legs in the shipping route. For instance, for Asia–Europe service routes, the leg after the last port in Asia is normally the hit-haul leg, as the container demands from Asian ports to European ports are much higher than in the opposite direction. Thus, we only have ω^{d} and ω^{r} to denote the demands on the hit-haul leg for dry and reefer containers, respectively.

3.2.2 Container delay and rejection rules

Suppose that the V ships are in the sequence given by the string $1 \to 2 \cdots v \cdots \to V$. The dry (reefer) container capacity of the ship *v* is E_v^{d} (E_v^{r}). In a particular week, when the ship v

arrives at its destination port, the number of dry (reefer) containers that are at the port because they were delayed from the previous week is D_{v-1}^d (D_{v-1}^r). Moreover, the new dry (reefer) container demand in the current week is ω^d (ω^r), which is the realization of $\underset{\sim}{\omega}^d$ ($\underset{\sim}{\omega}^r$). Based on the values of D_{v-1}^d and D_{v-1}^r (which were determined one week ago) and the values of ω^d and ω^r (which are just observed), the shipping line needs to determine the number of dry (reefer) containers to postpone. Denote this quantity by D_v^d (D_v^r) and the number they need to reject by R_v^d (R_v^r). We analyze the decisions as follows:

(i) If $D_{v-1}^d + \omega^d \le E_v^d$ and $D_{v-1}^r + \omega^r \le E_v^r$, then all of the containers will be transported and $D_v^d = D_v^r = R_v^d = R_v^r = 0$.

(ii) As a reefer slot can also be used to transport a dry container, if $D_{v-1}^d + \omega^d > E_v^d$, $D_{v-1}^r + \omega^r \le E_v^r$, and $D_{v-1}^d + \omega^d + D_{v-1}^r + \omega^r \le E_v^d + E_v^r$, then all of the containers will be transported (some dry containers are stored in reefer slots) and $D_v^d = D_v^r = R_v^d = R_v^r = 0$.

(iii) We assume that reefer containers have higher priority because they bring in more profit than dry containers. If $D_{v-1}^r + \omega^r > E_v^r$, then not all reefer containers can be transported immediately, and we allow some reefers to be postponed to the next week. Note that in the following week, ship $v+1$ with reefer capacity of E_{v+1}^r will arrive. If $D_{v-1}^r + \omega^r - E_v^r > E_{v+1}^r$ and if all of the $D_{v-1}^r + \omega^r - E_v^r$ reefers are postponed, then some of them still cannot be transported in the following week. In this study, we assume that a container (dry or reefer) can only be postponed by one week. Hence, if $D_{v-1}^r + \omega^r > E_v^r$ and $D_{v-1}^r + \omega^r - E_v^r \le E_{v+1}^r$, then $D_{v-1}^r + \omega^r - E_v^r$ reefers are postponed, i.e. $D_v^r = D_{v-1}^r + \omega^r - E_v^r$ and $R_v^r = 0$; if $D_{v-1}^r + \omega^r > E_v^r$ and $D_{v-1}^r + \omega^r - E_v^r > E_{v+1}^r$, then E_{v+1}^r reefers are postponed, i.e. $D_v^r = E_{v+1}^r$ and $R_v^r = D_{v-1}^r + \omega^r - E_v^r - E_{v+1}^r$.

(iv) We now analyze the dry containers. We allow dry containers to occupy reefer slots that are not used in the current week, but we do not allow dry containers to reserve reefer slots in the following week. The available reefer slots in the current week are $E_v^{dr} := \max\left\{0, E_v^r - (D_{v-1}^r + \omega^r)\right\}$. If $D_{v-1}^d + \omega^d > E_v^d + E_v^{dr}$ and $D_{v-1}^d + \omega^d - E_v^d - E_v^{dr} \le E_{v+1}^d$, then $D_{v-1}^d + \omega^d - E_v^d - E_v^{dr}$ dry containers are delayed, i.e. $D_v^d = D_{v-1}^d + \omega^d - E_v^d - E_v^{dr}$ and $R_v^d = 0$; if $D_{v-1}^d + \omega^d > E_v^d + E_v^{dr}$ and $D_{v-1}^d + \omega^d - E_v^d - E_v^{dr} > E_{v+1}^d$, then E_{v+1}^d dry containers are delayed, i.e. $D_v^d = E_{v+1}^d$ and $R_v^d = D_{v-1}^d + \omega^d - E_v^d - E_v^{dr} - E_{v+1}^d$.

3.2.3 Calculation of the weekly profit

The shipping line aims to maximize their profit per week. To this end, they try to transport as many containers as possible. However, due to the randomness of the demand, it may occur that in some weeks the demand is very high and not all the containers can be transported. In this subsection, we derive an equation for the weekly profit based on a detailed analysis of the relevant cost parameters.

Let the freight rates for a dry container and reefer container be g^d and g^r, respectively, and the average number of rejected dry and reefer containers per week be $\overline{R}^d$ and $\overline{R}^r$, respectively. Then, the company's expected revenue per week is:

$$g^d\left(q^d-\overline{R}^d\right)+g^r\left(q^r-\overline{R}^r\right). \tag{3.1}$$

The container shipment also incurs some costs. First, if a dry (reefer) container is rejected, the cost associated with loss of goodwill will be denoted by $c^{d,1}$ ($c^{r,1}$). Second, reefer containers need electricity to maintain the desired temperature during transportation, and the cost of the electricity/fuel when transporting a reefer container is $c^{r,2}$. Third, if a dry (reefer) container is postponed, it has to be stored in the container yard for one week, and so we represent the corresponding storage cost of using the yard space by $c^{d,3}$ ($c^{r,3}$). Fourth, the additional electricity cost when storing a delayed reefer container is denoted by $c^{r,4}$. Fifth, if a dry (reefer) container is delayed, the cost of customer dissatisfaction is denoted by $c^{d,5}$ ($c^{r,5}$).

Denote the average number of delayed dry (reefer) containers per week by $\overline{D}^d$ ($\overline{D}^r$). Then, the expected cost per week is given by the expression

$$c^{d,1}\overline{R}^d+c^{r,1}\overline{R}^r+c^{r,2}\left(q^r-\overline{R}^r\right)+\left(c^{d,3}+c^{d,5}\right)\overline{D}^d+\left(c^{r,3}+c^{r,4}+c^{r,5}\right)\overline{D}^r. \tag{3.2}$$

Consequently, the expected profit per week is

$$\begin{aligned}
&\left[g^d\left(q^d-\overline{R}^d\right)+g^r\left(q^r-\overline{R}^r\right)\right]-\\
&\left[c^{d,1}\overline{R}^d+c^{r,1}\overline{R}^r+c^{r,2}\left(q^r-\overline{R}^r\right)+\left(c^{d,3}+c^{d,5}\right)\overline{D}^d+\left(c^{r,3}+c^{r,4}+c^{r,5}\right)\overline{D}^r\right]\\
&=\left[g^d q^d+\left(g^r-c^{r,2}\right)q^r\right]-\\
&\left[\left(g^d+c^{d,1}\right)\overline{R}^d+\left(g^r+c^{r,1}-c^{r,2}\right)\overline{R}^r+\left(c^{d,3}+c^{d,5}\right)\overline{D}^d+\left(c^{r,3}+c^{r,4}+c^{r,5}\right)\overline{D}^r\right].
\end{aligned} \tag{3.3}$$

Note that the first term in the right-hand side of Eq. (3.3) is a constant and is independent of the sequence of the ships in the string.

3.3 OPTIMIZING THE SEQUENCE OF SHIPS IN A STRING

In this section, we use the profit equation derived above to optimize the sequence of ships in the string in order to maximize the weekly profit. Note that sequence optimization is a tactical level decision, which is unchanged over the weeks. There are two major reasons why the sequence may need to be re-optimized:

(i) The capacities of the ships change. For example, some old ships in the fleet used for the shipping route may be replaced by new ships of different capacity; or the rotation time of the shipping service might be adjusted so that new ships can be added to the fleet.

(ii) The demand probability changes. In other words, the probability mass function changes to a different one. For example, new competitors may enter the shipping market which will affect the demand pattern for existing shipping liners.

Given the capacities of the ships in the fleet and demand probability mass function, we design a simulation-based approach for the optimization process. Given *V* ships, any two of which have different capacity, there will be $S = (V-1)!$ different possible ship sequences (as the sequence forms a loop, it does not matter which ship is chosen to be the first one). Let the sequence be denoted by $s = (1, 2, \cdots, S)$ and the corresponding weekly profit be $P(s)$, as determined by Eq. (3.3). (With the obvious notation that $\overline{D}^d(s)$, $\overline{D}^r(s)$, $\overline{R}^d(s)$, and $\overline{R}^r(s)$ are used in place of $\overline{D}^d$, $\overline{D}^r$, $\overline{R}^d$, and $\overline{R}^r$, respectively.) Mathematically, therefore, the weekly profit of sequence *s*, $P(s)$, is given by:

$$P(s) = \left[g^d q^d + \left(g^r - c^{r,2} \right) q^r \right] - \left[\left(g^d + c^{d,1} \right) \overline{R}^d(s) + \left(g^r + c^{r,1} - c^{r,2} \right) \overline{R}^r(s) + \left(c^{d,3} + c^{d,5} \right) \overline{D}^d(s) + \left(c^{r,3} + c^{r,4} + c^{r,5} \right) \overline{D}^r(s) \right]. \quad (3.4)$$

We use Monte-Carlo simulations to calculate $\overline{D}^d(s)$, $\overline{D}^r(s)$, $\overline{R}^d(s)$, and $\overline{R}^r(s)$ in Eq. (3.4). The essence of the approach is as follows. (i) Define the number of weeks *T* we wish to simulate (e.g. $T = 100,000$ weeks). (ii) Randomly generate the demand for each week using the probability mass function. The demand for dry (reefer) containers in the week t are denoted by ω_t^d (ω_t^r). (iii) Simulate the decision-making process from weeks 1 to *T*. For each week *t*, record the number of dry (reefer) containers postponed $D_t^d(s)$ ($D_t^r(s)$) and rejected $R_t^d(s)$ ($R_t^r(s)$). (iv) The quantities $\overline{D}^d(s)$, $\overline{D}^r(s)$, $\overline{R}^d(s)$, and $\overline{R}^r(s)$ can be subsequently estimated using

$$\overline{D}^d(s) = \frac{1}{T}\sum_{t=1}^{T} D_t^d(s), \overline{D}^r(s) = \frac{1}{T}\sum_{t=1}^{T} D_t^r(s), \overline{R}^d(s) = \frac{1}{T}\sum_{t=1}^{T} R_t^d(s), \overline{R}^r(s) = \frac{1}{T}\sum_{t=1}^{T} R_t^r(s). \quad (3.5)$$

By substituting the results from Eq. (3.5) into Eq. (3.4), we can calculate $P(s)$, and therefore choose the sequence with the maximum profit:

$$s^* = \arg \max_{s=1,2\cdots S} P(s). \quad (3.6)$$

3.3.1 A two-stage simulation approach

To find the optimal sequence, we apply the two-stage simulation method proposed by Nelson et al. (2001). In the first stage, a given number of weeks of the process are simulated for each sequence. Some sequences, those whose average profits are much smaller than that with the largest profit, are removed. The remaining sequences are evaluated in the next stage. Moreover, the variance of the weekly profit for each remaining sequence can be estimated. In the second stage, additional weeks of the process are simulated for each of the remaining sequences. In particular, sequences that had smaller variances can be simulated for a smaller number of weeks. The details of the algorithm are elaborated below.

Two-stage simulation algorithm

Step 0: (i) Select a value for δ to represent a practically significant difference. For instance, δ could be set at 1000 US$/week, meaning that we are indifferent to two solutions if their expected difference in weekly profit is less than 1000 US$. This also implies that if we find a sequence that is not the optimal one, but has a profit less than that of the optimal one by at most δ, then we also consider it to be an optimal solution. (ii) Select the overall confidence level $1-\alpha$. For example, if α is chosen to be 10%, it means that the chance that the found solution is the optimal one is at least 90% (as mentioned before, a solution is considered to be optimal if its profit is within a gap of δ relative to the optimal one).

Step 1: Select a confidence level $1-\alpha_0$ for the first stage. For example, if α_0 is 5%, it means that the probability that the optimal sequence is not removed in the first stage is at least 95%.

Step 2: Select a value for the grouping parameter *U*, e.g., 30. To appreciate the significance of this parameter, consider the following discussion of the pertinent random variable. The average profit of sequence s over UV weeks is given by $\tilde{P}_{UV}(s)$. The central limit theorem implies that $\tilde{P}_{UV}(s)$ is approximately normally distributed. Select a parameter T_1 that is related to the sample size of the first stage (e.g. T_1 might be 50). Simulate the process for each of the S sequences for T_1UV weeks. We thus obtain T_1 realizations of the random variable $\tilde{P}_{UV}(s)$ for each s, which we denote by $P_{UV,1}(s), P_{UV,2}(s), \cdots, P_{UV,T_1}(s)$. Now compute the sample mean

$$\bar{P}_{UV}(s)^{(1)} = \frac{1}{T_1}\sum_{l=1}^{T_1} P_{UV,l}(s)\,, \tag{3.7}$$

where the superscript ‘‘(1)’’ means the first stage and sample variance

$$\mathrm{Var}\left(\tilde{P}_{UV}(s)\right) = \frac{1}{T_1 - 1}\sum_{l=1}^{T_1}\left[P_{UV,l}(s) - \bar{P}_{UV}(s)^{(1)}\right]^2 . \tag{3.8}$$

Step 3: Define a value θ by

$$\theta := t_{(1-\alpha_0)^{1/(S-1)}, T_1 - 1} \tag{3.9}$$

which is the $(1-\alpha_0)^{1/(S-1)}$ quantile of the t distribution with $T_1 - 1$ degrees of freedom. Let

$$W_{s,s'} := \theta \cdot \left[\frac{1}{T_1}\mathrm{Var}\left(\tilde{P}_{UV}(s)\right) + \frac{1}{T_1}\mathrm{Var}\left(\tilde{P}_{UV}(s')\right)\right]^{\frac{1}{2}}, \quad s = 1,2,\cdots,S, \quad s' = 1,2,\cdots,S, \quad s \neq s' \tag{3.10}$$

Remove all of the $s' = 1,2,\cdots,S$ if there exists an $s = 1,2,\cdots,S$ with $s \neq s'$ such that

$$\bar{P}_{UV}(s')^{(1)} \leq \bar{P}_{UV}(s)^{(1)} - \max\left\{0, W_{s,s'} - \delta\right\} . \tag{3.11}$$

The remaining sequences comprise a set denoted by I. The probability that I contains the optimal sequence is at least $1-\alpha_0$. If I is a singleton, then stop and return the sequence in I; otherwise, go to the next step.

Step 4: The second-stage confidence level is $1-\alpha_1$ where $\alpha_1 = \alpha - \alpha_0$. For example, if $\alpha_1 = 5\%$ it means that, if the set I contains the optimal sequence, then the chance that the optimal sequence will be identified in the second stage is at least 97.5%. For each $s \in I$, compute the second-stage sample size:

$$T_{2s} = \max\left\{T_1, \left\lceil \left(\frac{h}{\delta}\right)^2 \mathrm{Var}\left(\tilde{P}_{UV}(s)\right) \right\rceil\right\} \tag{3.12}$$

where $h := h(1-\alpha_1, T_1, S)$ is Rinott's constant and $\lceil \cdot \rceil$ rounds up to the next largest integer.

Step 5: Simulate the process for each sequence $s \in I$ for more $(T_{2s} - T_1)UV$ weeks. Then, compute the overall sample mean of $\tilde{P}_{UV}(s)$:

$$\bar{P}_{UV}(s)^{(2)} = \frac{1}{T_{2s}}\sum_{l=1}^{T_{2s}} P_{UV,l}(s), \quad s \in I \tag{3.13}$$

Select the sequence with the largest $\bar{P}_{UV}(s)^{(2)}$.

Our exploratory experiments show that the above algorithm is time-consuming and not able to find the optimal sequence using a ‘‘reasonable’’ amount of computation time. (All experiments in this study were conducted using MATLAB R2016b installed on a standard PC built around an Intel Core i5 processor running at 2.83GHz and with 8GB of RAM.) The problem can be attributed to the fact that T_{2s} (in Step 4) is extremely large, ranging from 1×10^8 to 3×10^8 using the baseline settings given above. Thus, in the second stage, simulating the process for each remaining sequence for other $(T_{2s}-T_1)UV$ weeks takes a considerable amount of computation time. Essentially, based on Eqs. (3.8) and (3.12), the order of magnitude of T_{2s} is determined by $\mathrm{Var}\left(\tilde{P}_{UV}(s)\right)$, whose order of magnitude is, in turn, determined by $P_{UV,l}(s)$ (i.e. the weekly profit). Using some real-world input parameters (*vide infra*), the weekly profits $P_{UV,l}(s)$ are of the order of a few million dollars, and this is the primary cause of the problem.

To reduce computation time, we have to 'fold' the weekly profit, $P_{UV,l}(s)$, by scaling it to reduce the order of magnitude of T_{2s}. This is especially important when determining the number of dry slots to convert into reefer ones. To do this, we change the unit used for the weekly profit by dividing $P_{UV,l}(s)$ by a scaling parameter β so that:

$$P_{UV,l}(s)\mapsto\frac{1}{\beta}P_{UV,l}(s)\,. \tag{3.14}$$

For instance, if $P_{UV,l}(s)$ is 5,343,000 US$ and $\beta=1000$, the weekly profit becomes 5,343 where the units used are 1,000 US$. Such a step allows us to deal with the above problem and accelerate the algorithm. Table 3.2 shows the computation times required for different values of β.

Table 3.2: Comparison of computation times for different values of the parameter $\boldsymbol{\beta}$

$\boldsymbol{\beta}$[a]	**Computation time (s)**	**Selected sequence index**
1	–	–
5	20,346	46th
10	1,425	46th
25	306	29th
50	98	10th
100	21	113rd
1000	6	113rd

[a] *The case β =1 corresponds to the original two-stage simulation algorithm.*

As can be seen from Table 3.2, increasing the value of β accelerates the algorithm. However, we cannot increase β as much as we like in order to simply accelerate the algorithm, as there are repercussions. When $\beta=1000$, we can only claim that the selected sequence is the optimal one to an accuracy of one unit, i.e. 1,000 US$. However, this will not necessarily be the optimal sequence to the desired accuracy of 1 US$. As shown in the table, different β values lead to different sequences being selected. Therefore, we need to make a comprise between speed and accuracy. In this study, we select $\beta=10$. This should be sufficiently close to the desired accuracy (so we can be confident we have selected the correct sequence) and allow us to obtain the solution in a reasonable amount of time. In the following sections, we refer to the algorithm wherein $\beta = 10$ is used for scale reduction (i.e. via Eq. (3.14)) as the ‘‘revised two-stage simulation algorithm’’.

3.3.2 Case studies

In this section, we use the revised two-stage simulation algorithm to optimize the sequence of a string of some particular cases of interest. First of all, according to EPRI (2010) and Ting and Tzing (2004), we have to fine-tune the input parameters required. To this end, the cost coefficients which we shall use were collated and are presented in Table 3.3. Here, we take $c^{d,3}\left(c^{r,3}\right)$, the storage cost incurred to keep a dry (reefer) container in the yard for one week, as an example of how we fine-tuned the costs. According to EPRI (2010), the storage space in a yard is charged at a rate of US$0.21 per square foot per day. Thus, a twenty-foot standard container corresponds to a weekly storage cost of US$30.

Table 3.3: The relevant input costs used in the case studies

Parameter	Value (US$)
$c^{d,1}$	150
$c^{r,1}$	250
$c^{r,2}$	230
$c^{d,3}$	30
$c^{r,3}$	30
$c^{r,4}$	50
$c^{d,5}$	100
$c^{r,5}$	200
g^{d}	640
g^{r}	960

We focus in this work on three shipping routes operated by CMA CGM: ‘‘Northwest Express’’, ‘‘South Atlantic Express’’, and ‘‘Europe Pakistan India Consortium 1’’. In the interest of brevity, we denote the three shipping routes as ‘‘1N’’, ‘‘2S’’, and ‘‘3E’’, respectively. Figure 3.2 indicates the port rotations of these three shipping routes.

1N

2S

3E

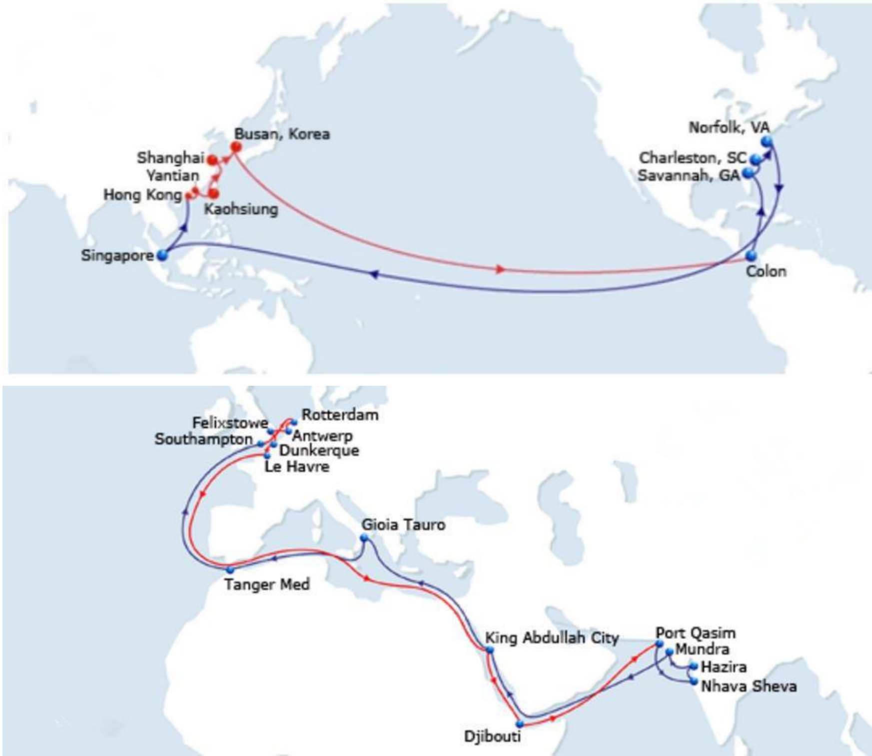


Figure 3.2: The shipping routes involved in three case studies (CMA CGM, 2017)

Some key information about the shipping routes and ships deployed are given in Table 3.4 — further details can be found by referring to CMA CGM (2017). During string optimization, the number of ships deployed is another key element that can affect the scale of the problem. This is because the number of ships determines the number of possible sequences to consider. Therefore, we chose three shipping routes that deploy different numbers of ships (determined by the rotation time, considering the weekly service frequency). We assume that the dry- and reefer-container demands follow a uniform distribution with their ranges as given in Table 3.4. The last column in this table shows the variance of the total container demand for both dry and reefer containers.

Table 3.4: Information on the shipping routes and ships deployed

Route	Name	Ship No.	Rotation time (days)	Container demand (TEUs)		Total demand variance
				Dry	Reefer	
1N	Northwest Express	6	42	[7800, 9220]	[0, 800]	4.11×10^5
2S	South Atlantic Express	7	49	[4500, 6100]	[50, 900]	5.00×10^5
3E	Europe Pakistan India Consortium 1	8	56	[7250, 9100]	[100, 1300]	7.75×10^5

To facilitate discussion of the experiment results, we list in Table 3.5 some important information about the ships deployed in each of the three shipping routes. As can be seen, in each shipping route, the deployed ships have various capacities which help address the importance of string optimization.

Table 3.5: Ships deployed in the three shipping routes

Route	Ship no.	Ship name	Capacity (TEU)	Dry slots	Reefer slots
1N	1	COSCO GUANGZHOU	9,469	8,769	700
	2	COSCO INDONESIA	8,501	8,501	0
	3	COSCO JAPAN	8,501	7,801	700
	4	COSCO PACFIC	10,020	9,220	800
	5	COSCO PHLIPPINES	8,501	7,801	700
	6	COSCO PUSAN	9,572	8,872	700
2S	1	E.R. LONDON	6,008	5,208	800
	2	MSC KATYAYNI	5,711	5,177	534
	3	MSC KRYSTAL	5,782	5,222	560
	4	MSC MARGARITA	5,770	5,138	632
	5	MSC ORIANE	5,782	5,082	700
	6	NORTHERN MAJESTIC	6,732	6,232	500
	7	RIO BARROW	5,551	5,001	550
3E	1	APL CHARLESTON	9,336	8,322	1,014
	2	CMA CGM AMAZON	9,130	8,530	600
	3	CMA CGM URUGUAY	9,130	7,630	1,500
	4	MSC ALBANY	8,762	7,762	1,000
	5	MSC ALGHERO	8,827	8,827	0
	6	MSC SILVANA	8,400	7,700	700
	7	MSC TOMOKO	8,400	7,700	700
	8	UASC AL KHOR	9,400	8,900	500

Based on the information presented on the shipping routes, we implemented the revised two-stage simulation algorithm to find the optimal sequence to employ. The results are shown in Table 3.6. The table shows that the string optimization process changes all of the original sequences used in the shipping routes. The last column shows the difference or gap in profit between the original and optimized sequences (which are all positive). As tactical-level decisions, these increases in profit can be claimed to be significant considering that the string optimization procedure is inexpensive, i.e. the approach is cost effective. The results prove the effectiveness of using the proposed algorithm for string optimization. One remarkable feature of the table is that the string optimization procedure produced a much larger profit increase for shipping route 3E than for 1N and 2S. This can be attributed to the fact that 3E involves more ships and a greater demand variance than the other two shipping routes. Therefore, it is apparent that string optimization becomes more significant when the size of the deployed fleet is large and there is a greater variance in demand.

Table 3.6: Results of the string optimization process

Route	Original sequence		Optimized sequence		Gap
	Sequence [a]	Profit (10^6 US$)	Sequence [a]	Profit (10^6 US$)	
1N	1→2→3→4→5→6	5.601	1→5→2→4→3→6	5.643	0.74%
2S	1→2→3→4→5→6→7	3.576	1→5→2→7→6→4→3	3.634	1.63%
3E	1→2→3→4→5→6→7→8	5.343	1→6→5→7→3→8→4→2	5.530	3.50%

[a] *A sequence can always be written with the first ship in the first place as the ships form a loop (so sequences such as 1→2→3→4→5→6 and 2→3→4→5→6→1 are equivalent).*

3.4 OPTIMIZING REEFER SLOT CONVERSION

The next natural question to ask is whether a shipping line should convert some of the dry slots of a ship into reefer slots. Before addressing this question, we first consider the feasibility of carrying out such conversions.

Reefer containers have an integral refrigeration unit with a water-cooling system to keep the cargo cold. This refrigeration system needs an external power supply when the container is stored in a ship. Therefore, a reefer slot has to be equipped with an electrical outlet which is connected to the power system of the ship. Thus, an electrical outlet or plug needs to be installed to convert a dry slot to a reefer slot. Technically, the conversion process is not much trouble. Container ships usually have independent power sub-distribution panels that supply power connections for refrigerated containers. When there is a need for more electrical outlets to create a reefer slot, therefore, a ship can simply group several electrical outlets and supply them with electricity using one power cable connected to a power sub-distribution panel (DNV GL SE, 2015).

The slot conversion problem is addressed in the following way. Suppose that the cost of converting one dry to one reefer slot is $\hat{c}$ (US$/week). We need to determine how many dry slots we should convert. Note that $\hat{c}$ is an average cost *per week*. The cost of slot conversion is mainly that associated with installing the electrical outlet or electrical plug which is used to power the reefer container. According to EPRI (2010), the installation cost is approximately 1,250 US$ per electrical outlet. As we measure the profit on a weekly basis, we transfer the installation cost to a depreciation cost of 48 US$ per week (i.e. $\hat{c} = 48$). This assumes that such a tactical level decision (i.e. decision to implement string optimization and slot conversion) lasts for half a year (26 weeks). Then, we solve the problem using the following algorithm.

Slot conversion algorithm

Input: V ships whose identities (IDs) are labeled $1, 2, \dots, V$. The initial number of reefer slots (i.e. that prior to conversion) of the ship with ID v is E_v^r ($v = 1, 2, ..., V$).

Step 0: Find the optimal sequence using the *revised two-stage simulation algorithm*. The optimal sequence is denoted by $\pi(1) \to \pi(2) \to \cdots \pi(V)$, where $\pi(u)$ is the ID of the uth ship in the sequence ($u = 1, 2, ..., V$). Thus, we have found $\bar{P}_{UV}(\pi)$, that is, the optimal weekly profit derived using the revised two-stage simulation algorithm.

Step 1: If the reefer slots of all of the V ships have reached the limit R, then stop the process.

Step 2: Set $u' \leftarrow 1$.

Step 3: If the reefer slots on the ship with ID $\pi(u')$ have reached the limit R, then set $u' \leftarrow u'+1$ and go to Step 5.

Step 4: Temporarily convert one dry slot on the ship with ID $\pi(u')$ into a reefer slot. The resulting new sequence is denoted by π', which is the same as sequence π except that ship $\pi'(u')$ has one more reefer slot (and, of course, one fewer dry slot) than the ship $\pi(u')$. Calculate $\bar{P}_{UV}(\pi')$:

(i) If $\bar{P}_{UV}(\pi') - \bar{P}_{UV}(\pi) \geq \hat{c}$, permanently convert the dry slot into a reefer one and set $\pi \leftarrow \pi'$ (i.e. permanently convert a dry slot into a reefer slot on the ship $\pi(u')$). Go to Step 1.

(ii) Otherwise, set $u' \leftarrow u'+1$ and go to Step 5.

Step 5: If $u' \leq V$, go to Step 4. Otherwise, this means that just converting dry slots without changing the sequence is not economically viable. Hence, we need to check what happens if we change the sequence. To this end, go to Step 6.

Step 6: If the reefer slots of all of the V ships have reached the limit R, stop.

Step 7: Set $v' \leftarrow 1$.

Step 8: If the reefer slots of all of the V ships have reached the limit R, set $v' \leftarrow v'+1$ and go to Step 10.

Step 9: Temporarily, convert one dry slot on the ship with ID v' into a reefer slot. Use the revised two-stage simulation algorithm to find the optimal sequence π'':

(i) If $\bar{P}_{UV}(\pi") - \bar{P}_{UV}(\pi) \geq \hat{c}$, permanently convert the dry slot into a reefer one, set $\pi \leftarrow \pi"$ (i.e. permanently convert a dry slot into a reefer one on the ship whose ID is v' and adjust the sequence of the ships). Go to Step 1.

(ii) Otherwise, set $v' \leftarrow v'+1$ and go to Step 10.

Step 10: If $v' \leq V$, go to Step 9. Otherwise, we can no longer improve the solution, so stop.

Considering the limited availability of electricity on a container ship, we assume in the above algorithm that the maximum number of reefer slots on a ship cannot exceed the limit $R = 1500$. The other input parameters are the same as in the previous section. In practice, a better limit to slot conversion can be derived by using information about the electrical loads in the container ships and electricity usage of the reefer containers. For instance, EPRI (2010) estimates that an electric reefer container needs 2.8875 kW per hour on average. The container ship Hanjin Paris has a generator installed with a capacity of 7,600 kW and a load factor (% of capacity) of 63%. This indicates that the ship has 2,812 kW of electrical power available (Khersonsky et al., 2007). Some detailed information on electricity demand in container ships can be found in the work of Zis et al. (2014). In the Hanjin Paris case, the container ship can be equipped with an additional 973 reefer slots (at most) considering the generator's limitations (i.e. 2812/2.8875 slots can be supplied). Normally, the larger the capacity of the ship, the greater the engine power available from the ship to support reefer slots (Zis et al., 2013).

3.4.1 Slot conversion case study

String optimization is the first step carried out in our research problem. We now want to use the slot conversion algorithm (which embeds the revised two-stage optimization algorithm to optimize strings) to conduct a further investigation of the three case studies given in Section 3.3.2 (i.e. using the shipping routes and information given in Tables 3.4 and 3.5).

Using the same input parameters, we ran the slot conversion algorithm to obtain the number of reefer slots to convert. The results are shown in Table 3.7. As can be seen, all the ships involved have some dry slots that are converted to reefer slots, apart from one (namely, the CMA CGM URUGUAY in shipping route 3E which already has the maximum number of reefer slots permitted in the conversion algorithm). This verifies that the benefits gained by the greater flexibility of reefer slots outweigh the conversion costs incurred to change the existing slot configurations of the ships.

The last column in Table 3.7 shows the ‘‘optimal increment’’ that the optimal change in a number of reefer slots represents. This quantity corresponds to the ratio of the optimal number of converted slots to the ship's capacity (in TEU) expressed as a percentage. It is important to note that the mean optimal increments for the shipping routes, as a whole, increase from 1N to 2S to 3E. This reflects the higher significance of slot conversion for those shipping routes with larger shipping fleets and higher demand variances (as is the case for the shipping route 3E).

Table 3.7: Reefer slot conversion results for the three shipping routes

Route	Ship	Name	Number of reefer slots			Optimal increment[a]
			Original	After conversion	Converted	
1N	1	COSCO GUANGZHOU	700	834	134	1.42%
	2	COSCO INDONESIA	0	443	443	5.21%
	3	COSCO JAPAN	700	861	161	1.89%
	4	COSCO PACFIC	800	940	140	1.40%
	5	COSCO PHLIPPINES	700	874	174	2.05%
	6	COSCO PUSAN	700	945	245	2.56%
						Mean: 2.42%
2S	1	E.R. LONDON	800	1,024	224	3.73%
	2	MSC KATYAYNI	534	761	227	3.97%
	3	MSC KRYSTAL	560	800	240	4.15%
	4	MSC MARGARITA	632	752	120	2.08%
	5	MSC ORIANE	700	874	174	3.01%
	6	NORTHERN MAJESTIC	500	906	406	6.03%
	7	RIO BARROW	550	650	100	1.80%
						Mean: 3.54%
3E	1	APL CHARLESTON	1,014	1,500	486	5.21%
	2	CMA CGM AMAZON	600	954	354	3.88%
	3	CMA CGM URUGUAY	1,500	1,500	0	—[b]
	4	MSC ALBANY	1,000	1,263	263	3.00%
	5	MSC ALGHERO	0	640	640	7.25%
	6	MSC SILVANA	700	876	176	2.10%
	7	MSC TOMOKO	700	1,075	375	4.46%
	8	UASC AL KHOR	500	881	381	4.05%
						Mean: 4.28%

[a] *The ratio of the number of converted slots to capacity (in TEU), as given in Table 5.*
[b] *We cannot obtain a value here as the ship has already reached the slot conversion limit (1,500).*

Overall, we have to emphasize the importance of having greater numbers of reefer slots. This is not just based on the Hamburg Süd and Hanjin cases mentioned in the Introduction in the context of competitiveness, but also because of the experimental results shown in Table 3.7.

The slot conversion algorithm is an iterative algorithm. When some dry slots have been converted to reefer slots, the previous optimal sequence may no longer be optimal as the number of reefer slots has changed. Thus, the slot conversion algorithm will not terminate until both the slot conversion and sequence rearrangement processes can no longer be further optimized. For the current examples, Table 3.8 illustrates the resulting sequences produced as a result of re-optimization during slot conversion. From the table, we can see that the optimal sequence after slot conversion is different from that obtained by just implementing string optimization. The ‘gap’ column in Table 3.8 corresponds to the loss of profit suffered if we insist on maintaining the previous optimal sequence. The numbers suggest that string optimization and slot conversion should always be carried out at the same time as an integrated optimization approach, exactly like our slot conversion algorithm does. Combining the gaps or differences given in Tables 3.8 and 3.6, we can say that the optimal sequence with slot conversion significantly outperforms the original sequence with the current slot configuration (as the weekly profit increases substantially).

Table 3.8: Sequence re-optimization and slot conversion

Route	Before slot conversion [a]		After slot conversion		Gap
	Sequence	Profit (10^6 US$)	Sequence	Profit (10^6 US$)	
1N	1→5→2→4→3→6	5.643	1→2→4→3→6→5	5.689	0.82%
2E	1→5→2→7→6→4→3	3.634	1→4→3→5→7→6→2	3.671	1.01%
3E	1→6→5→7→3→8→4→2	5.530	1→5→3→4→6→7→8→2	5.620	1.64%

[a] *Optimized results obtained using the revised two-stage simulation algorithm with the original (non-optimized) slot allocations.*

3.4.2 Shipping routes with large fleets

In the above cases, we compare weekly profits after slot conversion and after string optimization. The profit improvement is not so clear cut, as we optimized the ship fleet using string optimization in the first place. In this subsection, we conduct two further case studies based on two shipping routes with very large shipping fleets and extremely high demand variances. Our intention is to provide further motivation for integrating string optimization with slot conversion.

The two routes selected are the French Asia Line 1 and Columbus JAX (both belonging to CMA CGM) which involve 12 and 17 ships, respectively. CMA CGM (2017) gives detailed information on the two shipping routes but some of the basic information of interest is shown in Table 3.9. Compared with the previously considered routes (Table 3.4), these routes have many more ships involved and their variance in demand is much larger.

Table 3.9: Basic information on the two shipping routes

Route	Ships	Rotation time (days)	Container demand (TEU)		Total demand variance
			Dry	Reefer	
French Asia Line 1	12	84	[12000, 18000]	[650, 1900]	4.38×10^6
Columbus JAX	17	119	[5000, 10000]	[700, 1600]	2.90×10^6

We first calculated the weekly profits of the original sequences used in the shipping routes (Table 3.10). Then, we used the slot conversion algorithm (with string optimization) to optimize the sequence of ships and convert some dry slots to reefer slots. Note that the slot conversion limit was increased to 2,500 in these two case studies as the deployed ships have larger capacities. Table 3.10 shows the effectiveness of the proposed approach. Compared to the original sequences, the weekly profits of the optimized fleets were improved by 9.06% (French Asia Line 1) and 7.90% (Columbus JAX). These profit increases are very significant considering the cost-efficiency of the methods used. Note also that the two routes have larger dry-to-reefer conversion rates (8.63% and 7.12%) compared to those found in the three previous cases. This result verifies the previous finding that slot conversion is more critical for shipping routes with large fleets of ships and high demand variances.

Table 3.10: Results obtained using string optimization and slot conversion

Route	Weekly profit (10^6 US$)		Gap	Average reefer-slot conversion ratio
	Original sequence	Optimized sequence		
French Asia Line 1	10.27	11.20	9.06%	8.63%
Columbus JAX	5.444	5.874	7.90%	7.12%

3.5 CONCLUSION

This paper presents an improved algorithm to search for the optimal number of reefer slots to have on a container ship. It is assumed that all the relevant parameters (e.g. freight rates, storage costs, etc.) are already known. We first used a revised two-stage simulation approach to optimize the sequence of ships deployed. Based on this, we then formulated a slot conversion algorithm to determine the optimal slot configurations of the ships, which embeds the two-stage simulation algorithm for string optimization.

In this study, we used several real shipping routes operated by CMA CGM to highlight the effectiveness of our approach. Our results reveal that the algorithm is highly efficient and can help shipping liners to significantly improve their profits. However, there are also several issues that are worth studying further in future work:

(i) When converting the dry slots to reefer slots, draft and load capacities are not taken into consideration. This would be of great use when making ship stowage plans.

(ii) The use of power packs as a method of supplying electricity could be incorporated into the analysis. (A self-contained power pack in a standard twenty- or forty-foot container could act as a power source for multiple reefer boxes.) They are currently used to serve as a standby or prime power source for intermodal applications including rail, port, ship, and barge.

3.6 REFERENCES

Arduino, G., Carrillo Murillo, D., & Parola, F., 2015. Refrigerated container versus bulk: evidence from the banana cold chain. *Maritime Policy & Management* 42(3), 228-245.

Bell, M. G., Liu, X., Angeloudis, P., Fonzone, A., & Hosseinloo, S. H., 2011. A frequency-based maritime container assignment model. *Transportation Research Part B: Methodological* 45(8), 1152-1161.

Cheaitou, A., & Cariou, P., 2012. Liner shipping service optimisation with reefer containers capacity: an application to northern Europe–South America trade. *Maritime Policy & Management* 39(6), 589-602.

Chen, J., & Yahalom, S., 2013. Container slot co-allocation planning with joint fleet agreement in a round voyage for liner shipping. *The Journal of Navigation* 66(4), 589-603.

Cool Logistics, 2014. The Hanjin crisis: what about the reefer cargoes? http://coollogisticsresources.com/global/the-hanjin-crisis-what-about-the-reefer-cargoes. Accessed 18 January 2017.

CMA CGM, 2016. Line details: Yangtze Service. https://www.cma-cgm.com/products-services/line-services/flyer/YANGTZE. Accessed 30 June 2016.

CMA CGM, 2017. Products & Services: Search Line Services. http://www.cma-cgm.com/products-services/line-services. Accessed 20 January 2017.

DNV GL SE, 2015. Rules for Classification and Construction: Chapter 3 Electrical Installations. Hamburg, Germany. http://rules.dnvgl.com/docs/pdf/gl/maritimerules/gl_i-1-3_e.pdf. Accessed 29 April 2017.

Du, Y., Meng, Q., & Wang, S., 2017. Mathematically calculating the transit time of cargo through a liner shipping network with various trans-shipment policies. *Maritime Policy & Management* 44(2), 248-270.

EPRI., 2010. Electric Refrigerated Container Racks: Technical Analysis. http://www.epri.com/abstracts/Pages/ProductAbstract.aspx?ProductId=000000000001019926. Accessed 18 January 2017.

Gelareh, S., & Meng, Q., 2010. A novel modeling approach for the fleet deployment problem within a short-term planning horizon. *Transportation Research Part E: Logistics and Transportation Review* 46(1), 76-89.

Hasheminia, H., & Jiang, C., 2017. Strategic trade-off between vessel delay and schedule recovery: an empirical analysis of container liner shipping. *Maritime Policy & Management* 44(4), 458-473.

Hamburg Süd., 2013. Hamburg Süd 2013: Doing well under difficult business conditions. http://www.hamburgsud-line.com/hsdg/en/hsdg/regionalinformation/regional_news/regionalenewsdetails_409528.html. Accessed 18 January 2017.

Jiang, C., Wan, Y., & Zhang, A., 2017. Internalization of port congestion: strategic effect behind shipping line delays and implications for terminal charges and investment. *Maritime Policy & Management* 44(1), 112-130.

Khersonsky, Y., Islam, M., & Peterson, K., 2007. Challenges of connecting shipboard marine systems to medium voltage shoreside electrical power. *IEEE Transactions on Industry Applications* 43(3), 838-844.

Lin, D. Y., Huang, C. C., & Ng, M., 2017. The coopetition game in international liner shipping. *Maritime Policy & Management* 44(4), 474-495.

Lin, D. Y., & Liu, H. Y., 2011. Combined ship allocation, routing and freight assignment in tramp shipping. *Transportation Research Part E: Logistics and Transportation Review* 47(4), 414-431.

Lin, D. Y., & Tsai, Y. Y., 2014. The ship routing and freight assignment problem for daily frequency operation of maritime liner shipping. *Transportation Research Part E: Logistics and Transportation Review* 67, 52-70.

Wang, S., & Meng, Q., 2013. Reversing port rotation directions in a container liner shipping network. *Transportation Research Part B: Methodological* 50, 61-73.

Meng, Q., & Wang, S., 2012. Liner ship fleet deployment with week-dependent container shipment demand. *European Journal of Operational Research* 222(2), 241-252.

Meng, Q., Wang, T., & Wang, S., 2012. Short-term liner ship fleet planning with container transshipment and uncertain container shipment demand. *European Journal of Operational Research* 223(1), 96-105.

Nelson, B. L., Swann, J., Goldsman, D., & Song, W., 2001. Simple procedures for selecting the best simulated system when the number of alternatives is large. *Operations Research* 49(6), 950-963.

Ng, M., 2014. Distribution-free vessel deployment for liner shipping. *European Journal of Operational Research* 238(3), 858-862.

Ng, M., 2015. Container vessel fleet deployment for liner shipping with stochastic dependencies in shipping demand. *Transportation Research Part B: Methodological* 74, 79-87.

Rodrigue, J. P., & Notteboom, T., 2015. Looking inside the box: Evidence from the containerization of commodities and the cold chain. *Maritime Policy & Management* 42(3), 207-227.

Song, D. P., & Dong, J. X., 2013. Long-haul liner service route design with ship deployment and empty container repositioning. *Transportation Research Part B: Methodological* 55, 188-211.

Sowinski, L. L., 2015. Container, specialized carriers boost reefer investments. http://www.joc.com/international-logistics/cool-cargoes/container-specialized-carriers-boost-reefer-investments_20150301.html, Accessed 18 January 2017.

Ting, S. C., & Tzeng, G. H., 2004. An optimal containership slot allocation for liner shipping revenue management. *Maritime Policy & Management* 31(3), 199-211.

Wang, S., 2015. Optimal sequence of container ships in a string. *European Journal of Operational Research* 246(3), 850-857.

Wang, S., 2017. Formulating cargo inventory costs for liner shipping network design. *Maritime Policy & Management* 44(1), 62-80.

Zis, T., North, R. J., Angeloudis, P., & Bell, M. G., 2013. A Systematic Evaluation of Alternative Options for the Reduction of Vessel Emissions in Ports. *In Proceedings of Transportation Research Board 92nd Annual Meeting* (No. 13-5346).

Zis, T., North, R. J., Angeloudis, P., Ochieng, W. Y., & Bell, M. G. H., 2014. Evaluation of cold ironing and speed reduction policies to reduce ship emissions near and at ports. *Maritime Economics & Logistics* 16(4), 371-398.

Chapter 4: Cruise Itinerary Schedule Design

This chapter addresses the cruise itinerary schedule design problem for a cruise ship. This problem determines the optimal sequence of a given set of ports of call (a port of call is an intermediate stop in a cruise itinerary) and the arrival and departure times at each port of call for maximizing the monetary value of the utility at ports of call minus the fuel cost. To solve the problem, in view of the practical observations that most cruise itineraries do not have many ports of call, we first enumerate all sequences of ports of call and then optimize the arrival and departure times at each port of call by developing a dynamic programming approach. To improve the computational efficiency, we propose effective bounds on the monetary value of each sequence of ports of call, eliminating non-optimal sequences without invoking the dynamic programming algorithm. Extensive computational experiments are conducted and the results show that, first, using the bounds on the profit of each sequence of ports of call considerably improves the computational efficiency; second, the total profit of the cruise itinerary is sensitive to the fuel price and hence an accurate estimation of the fuel price is highly desirable; third, the optimal sequence of ports of call is not necessarily the sequence with the shortest voyage distance, especially when the ports do not have a naturally geographical sequence.

4.1 INTRODUCTION

A cruise itinerary is a cruise route operated by a cruise company: A cruise ship picks up cruise passengers at an embarkation port, calls at a set of ports of call for cruise passengers to visit the port cities, and returns to a disembarkation port where cruise passengers get off the cruise ship. The ship that is deployed on the itinerary, the embarkation port, the sequence of ports of call, the disembarkation port, and the time schedule are all pre-determined in a cruise itinerary. Cruise ships are different from other ships such as tankers, bulk carriers and containerships in that transportation is not the purpose of cruise ships.

The cruising industry has maintained a steady increase in supply for the past 20 years. In 2014, the number of cruise passengers reached a total of 22.04 million and the global cruise industry generated revenues of 37.1 billion U.S. dollars (Statista, 2015). Meantime, the world cruise fleet had 296 ships (Cruise Industry News, 2015) with a total of 482,000 lower berths[1] (Statista, 2015). The Caribbean and the Mediterranean areas are the most important cruising

[1] *It is often considered that one cabin has two beds (two lower berths) when calculating the capacity of cruise ships. Any extra beds in a cabin are referred to as "upper berths". The actual average number of beds per cabin in a cruise ship is usually higher than two.*

destinations and hence they are also where most ship capacity is deployed. Cruise passengers are mainly from developed countries. Among the 22.04 million cruise passengers in 2014, 12.16 million (55%) were from North America, 6.39 million (29%) were from Europe and 3.49 million (16%) were from the rest of the world. However, Cruising is an oligopolistic industry: Carnival, Royal Caribbean, and Norwegian Cruise Lines are the three largest companies with market shares of 41.8%, 21.8%, and 8.2%, respectively (Statista, 2015).

A few strategic decisions have a long-lasting effect on the profitability of a cruise company (Veronneau and Roy, 2009). The first one is the cruise fleet planning. A large cruise ship has over 5000 lower berths and may cost over one billion US dollars to construct. Companies book new ships in order to replace the scrapped, damaged, or lost ships, fulfill the rising trend of the cruising market, and provide extra capacity to block potential entrants to the market. The second one is ship deployment. Some cruise ships are repositioned from the Caribbean to Alaska in summer, or from the Mediterranean to the Caribbean in winter. Recently, a number of mass-market cruise ships were relocated to Asia to gain profit from the fast-growing Asian market. The third one is the itinerary planning. A cruise itinerary is similar to a container liner service (Fransoo and Lee, 2013; Pang and Liu, 2014): both have fixed sequences of ports of call and fixed schedules (arrival and departure time at each port of call); the itineraries are announced in advance to attract bookings and cruise ships have to adhere to the announced itineraries irrespective of whether they are full or not. Moreover, both industries are markedly capital-intensive and characterized by high fixed costs for operators, who seek a high volume of bookings to fill their capacity (Wang et al., 2015).

Most itineraries are loops with a home port: the itinerary starts and ends at the home port and most cruise passengers embark and disembark at the home port. The choice of home ports by cruise companies depends on the passenger market, the air-lift capacity of the port city, and the infrastructure and services of the port. Typical examples of home ports include Miami and Barcelona. Some itineraries are one-way in that they start and end at different home ports: for instance, trans-Atlantic itineraries. A cruise company also needs to determine which ports of call to include into an itinerary for a cruise ship. Ports of call are chosen based on the attractions of the port cities, the infrastructure and services of the ports, and the proximity to other ports in the itinerary. Under the background, the sequence of visiting the ports of call and the arrival and departure times at the ports of call needs to be determined.

This study assumes that the home port (or home ports in case of one-way itinerary) and the ports of call have been chosen in advance and addresses the Cruise Itinerary Schedule Design (CISD) problem that determines the optimal sequence of the ports of call to visit and the arrival and departure times at the ports of call. The optimal sequence of the ports of call to visit is mainly determined by geographical distances. In general, a shorter overall itinerary distance means less fuel consumption and thereby significant fuel cost savings. As reported by Statista

(2015), the fuel cost was 220 US dollars per cruise passenger on average, which is 15% of the cruise expenses. Therefore, one percent reduction in the fuel cost is translated to savings of 48 million US dollars (220 US dollars per cruise passenger times 1% and then times 22.04 million cruise passengers in 2014) for the industry.

Determining the sequence of ports of call simply based on the overall itinerary distance may not be optimal. For example, quite often the ports of call are close to each other, as is the case for the Caribbean and Mediterranean areas, and different sequences may not have much effect on the overall distance. Moreover, some itineraries are along the coast of a continent (e.g., from Sydney to the north along the east coast of Australia) and whether a port of call is included in the direction away from the home port or back to the home port does not affect the overall itinerary distance. These observations motivate the development of more sophisticated models that formulate factors beyond the port distances to determine the sequence of visiting the ports of call. In particular, we take into account the arrival and departure times at each port of call. A cruise ship generally visits a port of call in the early morning and departs in the late afternoon so that cruise passengers can go onshore to have a tour to the port city. In extreme cases, a cruise ship may stay at a port of call for as short as two hours or as long as two days. In reality, it may not be possible for a cruise ship to visit all of the ports of call at the same time of a day because it will mean the ship often has to sail very fast or very slowly from the previous port of call. In other words, although it is preferable for cruise passengers to spend more hours in the daytime at each port of call, it comes at the cost of reducing the sailing time at sea, resulting in higher sailing speed and possibly higher fuel consumption.

Based on the above analysis, this paper presents an explorative study on the CISD problem, in which the optimal sequence of visiting a given set of ports of call and the arrival time and departure time at each port of call is to be determined. In view of the practical observations that most cruise itineraries do not have many ports of call, we first enumerate all sequences of ports of call and then optimize the arrival and departure times at each port of call by developing a dynamic programming approach. To improve the computational efficiency, we propose effective bounds on the profit of each sequence of ports of call, eliminating non-optimal sequences without invoking the dynamic programming algorithm. Extensive computational experiments are conducted and the results show that, first, using the bounds on the profit of each sequence of ports of call considerably improves the computational efficiency; second, the total profit of the cruise itinerary is sensitive to the fuel price and hence an accurate estimation of the fuel price is highly desirable; third, determining the sequence of ports of call solely by minimizing the overall voyage distance leads to significant reduction in the total profit when the ports do not have a naturally geographical sequence.

The existing researches on cruise shipping, such as the above-mentioned works, are mainly descriptive. There are few quantitative studies on cruise shipping such as Maddah et al. (2010).

Given that cruise itineraries have fixed sequences of ports of call and fixed schedules, optimization-based service planning tools should be able to increase the profit or save the cost for cruise shipping companies and improve the service quality for cruise passengers. Such tools are urgent in view of the fast-growing cruise market and the gigantism of cruise ships. This paper develops quantitative models on the CISD problem and thus contributes to the state-of-the-art research and practice by developing such a tool.

4.2 LITERATURE REVIEW

We first review academic literature on cruise shipping. As the work is also related to maritime freight transportation and land transportation, we also relate our work to these studies after introducing some research works on cruise operations.

4.2.1 Cruise operations

There is not much research about cruise shipping in academic literature. This might be attributed to the reason that tourism researchers have not paid much attention as worldwide cruise ship tourism accounts for just about 2% of world tourism (Gui and Russo, 2011), and maritime researchers mainly focus on freight transportation.

Soriani et al. (2009) investigated the structural aspects and evolutionary trends for cruising in the Mediterranean region. They identified three crucial issues for the future development of the region. Gui and Russo (2011) introduced a global value chain framework that connects the global structure of cruise value chains to the regionally land-based cruise services and reflects some strategies that local agents can adapt to enhance the generation of value at the local level. Veronneau and Roy (2009) were amongst the first to lay a descriptive theoretical foundation of a cruise ship supply chain. They pointed out that in the strategic plan, what is unique to the cruise industry is that the itinerary planning will affect the supply chain design, demand forecasts, and product mix. Rodrigue and Notteboom (2013) conducted a deep market investigation in the cruise industry. They mentioned that vessel deployment strategies and itinerary design are primordial.

Revenue management (RM) in the cruise industry was a hot topic among researchers. According to Kimies (1989), cruise lines, just like hotels and airlines, can be deemed as traditional RM industries. Talluri and van Ryzin (2004) stated that the cruise ships are nothing more than floating hotels. However, Biehn (2006) strongly disagreed with the common idea that running a cruise ship is identical to managing a hotel, and claimed that hotel management guidelines should not be directly used for cruise lines in terms of RM strategies. Meanwhile, He proposed deterministic linear programming to maximize revenue for a cruise ship considering the capacity limitations on the number of cabins and the number of lifeboat seats. Based on his study, Maddah et al. (2010) built a discrete-time dynamic capacity control model to improve the profit of cruise ships, in which the orders from arrival customers follow a stochastic process and request one type of cabin combined with one or more lifeboats. Further review of the cruise operations can be referred to Wang et al. (2016).

4.2.2 Maritime freight transportation

Cruise shipping is akin to container liner services as both of them have fixed port rotation and schedule. Moreover, the fuel consumption of cruise ships and container ships are both related to the speeds of the ships. We refer to Meng et al. (2014) for a review of container liner service operations and planning. Generally, there are two major differences between the modeling approaches for the two types of operations. First, one liner service alone is usually not sufficient to transport containers from their origins to their destinations as containers are often transshipped during their trips (Ng, 2014, 2015). As a result, a liner service cannot be designed independently without considering other services, and cargo routing among multiple shipping service routes is critical (Song and Dong, 2012). However, in cruising shipping, only one cruise ship is deployed on a cruise itinerary and passengers do not transfer between different itineraries. Therefore, the schedule design for an itinerary can be implemented separately. Second, the purpose of docking at ports by container ships is to load and unload containers. Consequently, it is always desirable for a container ship to spend less time at ports (Song and Dong, 2011; Du et al., 2015). Different from container shipping, the purpose of docking at ports by cruise ships is for cruise passengers to visit the port city and hence a longer port time could be advantageous.

Compared with limited research papers on the cruise shipping, tremendous research works have been devoted to the container liner shipping. Take the research topic of route design and schedule design in the container liner shipping as an example: Shintani et al. (2007) proposed a problem for liner shipping networks design, which consists of dozens of shipping routes. Qi and Song (2012) worked on the problem of designing an optimal schedule in order to minimize the total fuel consumption. For the uncertainties in port operations, Wang and Meng (2012a) studied a robust schedule design problem. Meantime, Wang and Meng (2012b) further considered sea contingency time for the schedule design problem. Song and Dong (2013) combined both ship deployment and empty container repositioning into a long-haul shipping route design.

4.2.3 Land transportation

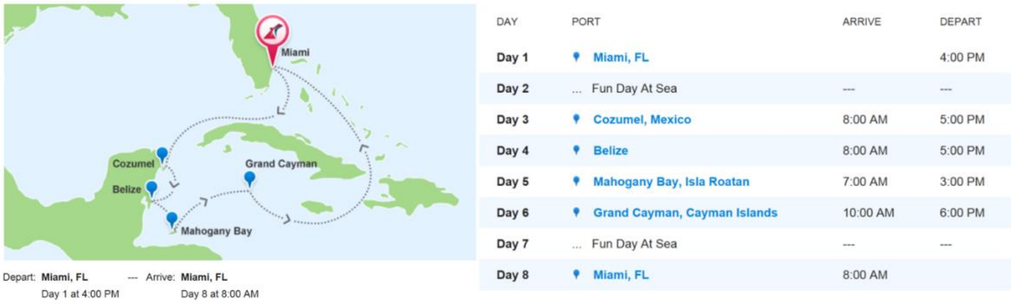
Land transportation, such as the traveling salesman problem (Applegate et al., 2011) and the vehicle routing problem (Toth and Vigo, 2001), is also relevant to cruise shipping in that a vehicle/vessel visits several locations. However, land transportation is different from maritime transportation because the travel speed inland transportation is largely determined by the traffic conditions and vehicles usually travel at the highest possible safe speed in the exogenous traffic conditions. On the contrary, ships can sail freely at sea without congestion and they do not often sail at their highest speed mainly for economic reasons: a ship burns more fuel when it sails faster. As the relation between speed and fuel consumption is nonlinear, optimization models for cruise itinerary are also nonlinear. A more relevant category of research is vehicle routing problems with time windows (VRPTW) (Cordeau et al., 2001). The time window at a customer in VRPTW is a time interval, e.g., 9:00 am to 2:00 pm and the planning horizon in vehicle routing problems is usually one day. However, the cruise ship schedule design problem covers a planning horizon of many days and the cruise ship can visit a port in the daytime on any day; hence the “time window” at a port is a set of disconnected time intervals. Cruise ship schedule design is also relevant to the traveling salesman problem with profits (Feillet et al., 2005) as passengers gain extra utility by spending time at ports. The difference is: the amount of extra utility gained by cruise passengers at a port depends on the time of visit and duration of visit, rather than a fixed value.

The above literature review shows that existing research on cruise shipping is mainly descriptive with just a few exceptions (e.g. Maddah et al., 2010). Moreover, cruise shipping modeling is inherently different from other maritime transportation analysis and land transportation formulations. Given that cruise services have fixed sequences of ports of call and fixed schedules, optimization-based service planning tools should be able to increase the profit or save the cost for cruise shipping companies and improve the service quality for cruise passengers. Such tools are urgent in view of the fast-growing cruise market and the gigantism of cruise ships. This paper develops a quantitative solution approach to the CISD problem and thus contributes to the state-of-the-art research and practice by developing such a tool.

4.3 PROBLEM DESCRIPTION

The CISD problem focuses on schedule design for a cruise itinerary with a given home port and a set of given ports of call (two home ports will be given in case of one-way itineraries). The optimal sequence of the ports of call to visit and the arrival and departure time at the ports of call are to be determined. In the CISD, the deployed cruise ship departs from the home port, denoted by Port 1, visits a set of given ports of call, denoted by Ports $2, \cdots, N-1$, the sequence of which is to be determined, and finally returns to the home port, denoted by Port N, which is the same port as Port 1 in looped itineraries or is a different port in one-way itineraries. We use $P_c \coloneqq \{2, \cdots, N-1\}$ to represent the set of ports of call, and $P \coloneqq \{1, \cdots, N\}$ to represent the set of all of the ports (both the homeports and ports of call). For the example of a cruise itinerary in Figure 4.1, Miami is the home port (i.e., Port 1 and Port $N = 6$), at which the cruise itinerary starts and terminates; there are four selected ports of call for the cruise itinerary and we can define Cozumel as Port 2, Belize as Port 3, Mahogany Bay as Port 4, and Grand Cayman as Port 5. Figure 4.1 shows that the cruise ship on the cruise itinerary starts from the home port at 4:00 pm (Day 1), visits Cozumel at 8:00 am (Day 3), spends nine hours at

Cozumel, departs at 5:00 pm (Day 3), visits Belize (Day 4), Mahogany Bay (Day 5), Grand Cayman (Day 6), and returns to the home port (Day 8). As shown in Figure 4.1, an instance of the solution for the CISD problem is presented, in which the sequence of the ports of call and the times when the cruise ship arrives at and departs from each port of call are displayed.



DAY	PORT	ARRIVE	DEPART
Day 1	Miami, FL		4:00 PM
Day 2	Fun Day At Sea	---	---
Day 3	Cozumel, Mexico	8:00 AM	5:00 PM
Day 4	Belize	8:00 AM	5:00 PM
Day 5	Mahogany Bay, Isla Roatan	7:00 AM	3:00 PM
Day 6	Grand Cayman, Cayman Islands	10:00 AM	6:00 PM
Day 7	Fun Day At Sea	---	---
Day 8	Miami, FL	8:00 AM	

Figure 4.1: Itinerary of 7 Day Western Caribbean of Carnival (Carnival Cruise Line, 2016)

In the CISD problem, the following information is required as inputs: (i) The departure time when a cruise ship leaves the home port and its arrival (return) time at the home port for termination; (ii) The utility distribution at each port of call for the cruise passengers to experience (for instance, the utility for the cruise passengers to spend time at a port city at 3:00 am is marginal); (iii) The relationship between bunker consumption and speed on each leg (a leg is the voyage from one port to the next port). Then, based on these inputs, we make two critical decisions: (i) The sequence of ports of call for the cruise ship to visit; and (ii) The arrival and departure time at each port of call. The sequence displays the order list of ports, in which ports of call must be visited by the cruise ship one by one. The arrival and departure times confirm the staying time that the ship spends at each port of call and the voyage time on each leg. The objective of the CISD problem is to maximize the total monetary value from the utilities brought to cruise passengers at port cities minus the bunker cost of the cruise ship.

4.3.1 Departure time from the home port and the return time

We assume that the cruise ship departs from the home port and returns to the home port at a pre-determined time. This assumption does not restrict the model but simply aims to simplify the notation. Without loss of generality, we define that the cruise ship departs at Time 0 and returns at Time T. Hence, there are a total of $T+1$ time points to complete the cruise, denoted by set $\mathbb{T}=\{0,\cdots,T\}$. Here, one time period could be set as one hour, as using one hour in the schedule for cruise itineraries is precise enough (our model can also handle other time periods, e.g., half an hour). Note that when we mention "at time $t \in \mathbb{T}$" we refer to the time at the end of the tth time period (or equivalently, at the beginning of the $(t+1)$th time period).

4.3.2 Utility distribution at ports

Regarding the time spent at port cities, we notice that cruise ships generally visit a port in the morning and leave in the evening so that cruise passengers can have a tour in the port city.

Evidently, if a cruise ship visits a port at e.g. 3:00 am, then there is no transport available for the cruise passengers and there is no place for the cruise passengers to visit.

To capture the impact of arrival and departure times on the cruise itinerary, we need to know the utility of a port in different hours of a day. One example of the utility distribution at a port is showed in Figure 4.2. In the daytime hours, the utility is positive. In the night hours when the port is closed, the utility is zero. The utility for each hour can be estimated by expert judgment or by analyzing existing cruise itineraries, details of which will be discussed in Section 4.6.1 and Section 4.7.

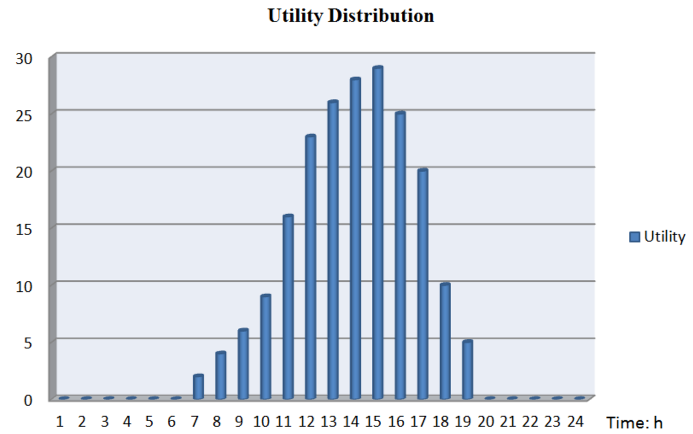


Figure 4.2: Utility distribution for one day

We make three comments on the utility shown in Figure 4.2. (i) The utility mentioned here actually refers to the extra utility by spending time at port cities compared with spending time at sea on cruise ships (as cruise passengers also have a lot of fun at sea). (ii) Different ports have different utility distributions. For instance, a world-renowned city like Rome should have high utilities; cities in which people tend to go to bed and wake up early, have different profiles from those in which people stay late at nights in bars. (iii) It is possible that the ship stays at a port when the utility is zero. For instance, in Figure 4.3, when two ports are very close, e.g, two hours' sailing, it is possible that the ship stays in Port j overnight, when there is no utility, and leaves the port at 8:00 am on the next day.

To facilitate the solution approach development, we define $g_i(t)$ as the utility at Port i in Time period $t \in \{1,2,\cdots,T\}$. $g_i(t)$ can be derived based on the daily distribution of the utility. Considering the example in Figure 4.2, if the cruise ship leaves the home port at 4:00 pm (which, by our definition, is Time 0), then 6:00-7:00 am of the next day corresponds to Time period 15 and we thus have $g_i(15) = 2$ as the utility for the hour from 6:00 am to 7:00 am is two. Similarly, we have $g_i(15 + 24) = 2$ and $g_i(15 + 48) = 2$ in which 24 means one day and 48 means two days.

To synthesize the total amount of utility that the cruise passengers will experience with the bunker cost in the objective function, we denote p^u as the monetary value for the cruise company from one unit of utility. The product of the unit monetary value (i.e., p^u) and the total utility that the cruise passengers would experience at ports of call is the total monetary value for visiting the ports of call during the cruise.

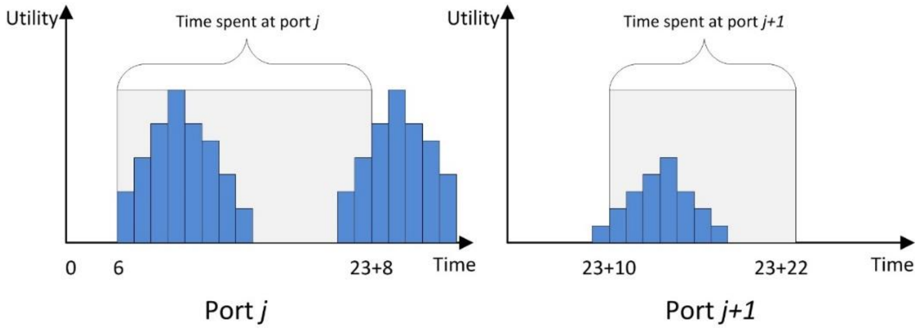


Figure 4.3: Utility distributions and time spent at two ports

4.3.3 Fuel consumption

Different arrival and departure times at ports affect the sailing speed, which impacts the fuel consumption by the main engine of the cruise ship. According to the research conducted by Du et al. (2011), the fuel consumption rate of a ship is determined by the speed and can be estimated as follows.

$$k + k' \cdot (v)^s \tag{4.1}$$

Here k and k' are regression coefficients, v is the sailing speed, and $s \in \{3.5, 4, 4.5\}$. For feeders, $s = 3.5$; for medium-sized vessels, $s = 4$; and for jumbo vessels, $s = 4.5$. To calculate the fuel consumption of a leg, let d be the distance of the leg and τ be the sailing time on the voyage, implying that the speed is $v = d/\tau$. Therefore, the bunker consumption on the leg, denoted by function $\tilde{F}(d, \tau)$, is

$$\tilde{F}(d, \tau) = [k + k' \cdot (v)^s] \cdot \tau = k\tau + k' d^s \tau^{1-s} \tag{4.2}$$

There exists an optimal sailing speed, denoted by v^*, to save the fuel, which can be derived by minimizing the consumption in Eq. (4.2). The calculation for the optimal sailing speed is:

$$v^* = \left(\frac{k}{k' \cdot (s-1)}\right)^{1/s} \tag{4.3}$$

The cruise ship can decelerate (or accelerate) if its sailing speed exceeds (or is lower than) the optimal speed in order to save fuel.

Given d and τ, the average speed is d/τ. If $d/\tau \geq v^*$, the ship should sail at a constant speed that is equal to d/τ for saving fuel consumption. Otherwise, the ship should sail at its optimal speed to the destination and then wait at the destination (Wang et al., 2013). Thus, given d and τ, the minimum fuel consumption, denoted by function $F(d, \tau)$, is denoted as:

$$F(d, \tau) = \begin{cases} \tilde{F}(d, \tau) & , if \;\; d/\tau \geq v^* \\ [k + k' \cdot (v^*)^s] \cdot (d/v^*) & , otherwise \end{cases} \tag{4.4}$$

In the CISD, we define d_{ij} and τ_{ij} as the voyage distance and voyage time between Port i and Port j. d_{ij} is an input data, which can be easily obtained from a geographical database. τ_{ij} is meaningful only if the cruise ship visits Port j directly after Port i; if this is the case, τ_{ij} is the time interval between the departure from Port i and the arrival at Port j, and hence is a decision variable. Given d_{ij} and τ_{ij}, the minimum bunker consumption between Port i and Port j can be calculated by $F(d_{ij},\ \tau_{ij})$ in Eq. (4.4). To convert the fuel consumption into the fuel cost, the unit price of fuel, denoted by c^F, is needed as an input.

4.3.4 Sequence of ports of call

Determining the sequence of ports of call is a crucial decision that we should make for the CISD problem. To represent the sequence in the manner of mathematical models, here, we use the same way to define it as many vehicle routing problems (VRPs) do: Set x_{ij} to one if the cruise ship visits Port j immediately after visiting Port i, and zero otherwise.

It is worthwhile to mention that visa restrictions of cruise passengers should be considered when designing the sequence of ports of call. Specifically, some ports of call belong to the same country and must be visited without interruption. For instance, if the cruise itinerary is Shanghai (China) →Nagoya (Japan) →Busan (Korea) →Kobe (Japan) →Shanghai (China), then the cruise passengers from China must obtain a tourist visa for Japan that allows multiple entries to Japan. If this is difficult for the cruise passengers, the two Japanese ports should be visited without interruption, for example, Shanghai (China) →Busan (Korea) →Nagoya (Japan) →Kobe (Japan) →Shanghai (China). To capture this practical consideration, we define $\mathbb{H}$ as the set of countries that can only be entered once, H_r as the set of ports belonging to Country $r \in \mathbb{H}$, and N_r as the number of ports in Country r, $N_r \coloneqq |H_r|$.

4.3.5 Arrival and departure times at ports of call

For arrival time and departure times at ports of call, it does not make sense for a cruise ship to arrive at a time when the port is closed, for instance, at 3:00 am or leave too late. Therefore, we define sets of possible arrival and departure times based on realistic situations as follows. First, we note that different ports may be located in different time zones and ignoring the difference in time zones will lead to incorrect decisions. Second, given the opening hours in a day for a port of call (evidently, the opening hours refer to the local time zone), the time zones of the home port and the port of call, we can define the time windows of the port of call in the planning horizon (i.e., from Time 0 to Time T). For instance, if a cruise ship departs from the home port (time zone: UTC+8) at 8:00 pm (i.e., Time 0 in our model), Port of call i is in time zone UTC+9 and opens every day from 7:00 am to 3:00 pm, then, the time windows of Port of call i is $\mathcal{T}_i = [10, 18] \cup [(10 + 24), (18 + 24)] \cup [(10 + 48), (18 + 48)] \cdots$. The arrival and departure times of the cruise ship at Port of call i, denoted by a_i and b_i, respectively, must be in the set, $a_i \in \mathcal{T}_i, b_i \in \mathcal{T}_i, i \in P_c$.

We define m_i as the minimum time (e.g., five consecutive hours) that the cruise ship should stay at Port i before the port closes when it arrives at a port during its opening hours $\mathcal{T}_i$. During the m_i hours, the cruise ship could replenish consumables or fuel and the cruise passengers could have a tour around the city. Given minimal staying hours in ports, we can refine the set of arrival time windows at Port of call i, for instance, if $m_i = 6$ and $\mathcal{T}_i = [10, 18] \cup [(10 + 24), (18 + 24)] \cup [(10 + 48), (18 + 48)] \cdots$, the set of possible arrival times (i.e., a_i) is $\mathcal{T}_i{}' = [10, 12] \cup [(10 + 24), (12 + 24)] \cup [(10 + 48), (12 + 48)] \cdots$.

4.3.6 Model for Cruise Itinerary Schedule Design (CISD)

This section formulates a mathematical model for the general CISD problem, denoted by $F0$. Then, to reduce the amount of input data required, we make some modifications on the model to solve a special case, denoted by $F0'$. Before presenting the models for the CISD problem, we list the notation below.

Indices and sets:

i: index of a port

t: index of a time period

P: set of all ports of call and home ports, $P = \{1,2, \cdots, N-1, N\}$, where 1 and N represent home ports

P_c: set of all ports of call, $P_c = \{2,3, \cdots, N-2, N-1\}$, excluding home ports

$\mathbb{T}$: set of all time periods in one cruise, $\mathbb{T} = \{0,1,2, \cdots, T-1, T\}$

Decision variables:

a_i: time when the cruise ship arrives at Port i

b_i: time when the cruise ship departs from Port i

x_{ij}: binary, set to one if Port i is immediately followed by Port i in the voyage of the cruise ship

θ_{ij}: sailing time on the leg from Port i to Port j

Input data:

$F(d,\ t)$: fuel consumption (tones) of the cruise ship if the voyage distance is d and the sailing time is t

c^F: unit fuel price of the cruise ship

d_{ij}: voyage distance between Port i and Port j

$g_i(t)$: number of the utility at Port i for Time period t

m_i: minimum time that the cruise ship should stay in Port of call i

p^u: unit monetary value of the utility

v^{max}: maximum speed of the cruise ship

$\mathcal{T}_i$: set of all possible visiting time windows of Port i

$\mathcal{T}_i'$: set of all possible arrival time windows of Port i

H_r: set of ports that belong to Country $r \in \mathbb{H}$

$\mathbb{H}$: set of countries that can only be entered once

N_r: number of ports in H_r

M: a sufficiently large number

Mathematical model:

$$[\boldsymbol{F0}] \quad \text{Maximize } Z = p^u \cdot \sum_{i \in P_c} \sum_{t=a_i}^{b_i - 1} g_i(t) - c^F \cdot \sum_{i \in P} \sum_{j \in P} x_{ij} \cdot F(d_{ij},\ \theta_{ij}) \tag{4.5}$$

s.t.

$$\sum_{j \in P} x_{ij} = 1 \qquad \forall i \in P_c \tag{4.6}$$

$$\sum_{i \in P} x_{ik} - \sum_{j \in P} x_{kj} = 0 \qquad \forall k \in P_c \tag{4.7}$$

$$\sum_{j \in P_c} x_{1,j} = 1 \tag{4.8}$$

$$\sum_{i \in P_c} x_{i,N} = 1 \tag{4.9}$$

$$\sum_{i \in H_r} \sum_{j \in H_r} x_{ij} = N_r - 1 \qquad \forall H_r \in \mathbb{H} \tag{4.10}$$

$$b_i + \theta_{ij} - M \cdot (1 - x_{ij}) \le a_j \qquad \forall i \in P \backslash \{N\}, j \in P \backslash \{1\}, i \ne j \tag{4.11}$$

$$a_i + m_i \le b_i \qquad \forall i \in P_c \tag{4.12}$$

$$\theta_{ij} \ge \lceil d_{ij} / v^{max} \rceil \qquad \forall i, j \in P, i \ne j \tag{4.13}$$

$$b_1 \coloneqq 0 \tag{4.14}$$

$$a_N \coloneqq T \tag{4.15}$$

$$x_{ij} \in \{0,1\} \qquad \forall i, j \in P \tag{4.16}$$

$$a_i \in \mathcal{T}_i' \qquad \forall i \in P_c \tag{4.17}$$

$$b_i \in \mathcal{T}_i \qquad \forall i \in P_c \tag{4.18}$$

In the above model $F0$, Objective (4.5) maximizes the monetary value of the total utilities minus the bunker costs. Constraints (4.6) and (4.7) guarantee that the cruise ship visits each port of call exactly once. Constraints (4.8) and (4.9) ensure that each cruise starts at the home port and goes back to the home port finally. Constraints (4.10) states that ports of call in the same country must be visited without interruption for the sake of the visa restrictions. Constraints (4.11) show the relationship between the departure time at one port and the arrival time at the next visited port. Constraints (4.12) ensures that the cruise ship dwells in each port for at least a certain period of time (i.e., m_i). Constraints (4.13) ensure that the real voyage time between two ports should be more than the minimal voyage time, in which the cruise ship sails at the maximum speed. Constraint (4.14) and Constraint (4.15) guarantee that the cruise ship departs from the home port and returns to it at specified times. Constraints (4.16) indicate that there is no partial connection between two ports. Constraints (4.17) and Constraints (4.18) ensure that the cruise ship must arrive at one port and leave from it during its opening hours.

In reality, it may be difficult for a cruise company to define the utility distribution of each port (i.e., $g_i(t)$), then we consider a new special case of the model, in which the staying time in each Port i (i.e., $b_i - a_i$) is not influenced by the utility profiles. Instead, $b_i - a_i$ just needs to exceed the minimal staying hours in port i (i.e., m_i). The model, denoted by $F0'$ for this special case is formulated as follow:

[$\boldsymbol{F0'}$]: *Minimize* $Z = c^F \cdot \sum_{i \in P} \sum_{j \in P} x_{ij} \cdot F(d_{ij},\ \theta_{ij})$ (4.19)

s.t. Constraints (4.6-4.18)

4.4 SOLUTION APPROACH FOR CISD

In this section, we develop an efficient solution algorithm to obtain optimal solutions by analyzing some special features of the problem.

4.4.1 Complexity of the CISD problem

Proposition 4.1: The CISD problem is NP-hard.

Proof: Suppose that all of the utilities $g_i(t)$ are zero, all of the minimum staying times m_i are zero, all of the time windows $\mathcal{T}_i' = \mathcal{T}_i = \mathbb{T}$, and the fuel consumption function $F(d,\ t)$ is proportional to the distance d and there is no visa restriction. Then the CISD problem becomes the one that finds the shortest distance to visit all of the ports of call from the homeport and then returns to the homeport, which is exactly the travelling salesman problem (TSP). Since the TSP is NP-hard (Cormen et al., 2009), the general version of the CISD problem is also NP-hard. ■

4.4.2 Dynamic programming for the model

Despite the NP-hardness of the problem in nature, we find that in realistic cases the number of ports of call is not large. Figure 4.4 shows the statistics on the trips in 2016 of the biggest cruise ship—The Carnival Vista—owned by Carnival Cruise Line. From the figure, we note that the number of ports of call and cycle time in a cruise itinerary is not large, ranging from two to nine and 5 days to 13 days, respectively. Thus, we could enumerate all of the sequences of visiting the ports of call for one specific cruise itinerary. Meanwhile, as can be seen in the third part of the figure, the ports of call among the trips are normally located in several countries. When considering the visa restrictions, some infeasible sequences for the ports of call can be deleted directly without exploring.

The total number of possible sequences for $(N-2)$ ports of call is $(N-2)!$. Let s denote the index of a sequence, $s \in S = \{1,2,\cdots,(N-2)!-1,(N-2)!\}$. Then, for each sequence s, we develop a dynamic programming (DP) approach to find the optimal arrival and departure times for each port of call. As mentioned in Section 4.4.3, the sequence (denoted by $x_{ij}, \forall i \in P\backslash\{N\}, j \in P\backslash\{1\}, i \neq j$) and the arrival and departure times of each port of call (i.e.,a_i and

$b_i, \forall i \in P_c$) are two critical decisions in the CISD. The combined enumeration and DP approach could hence obtain the optimal solution for the CISD problem.

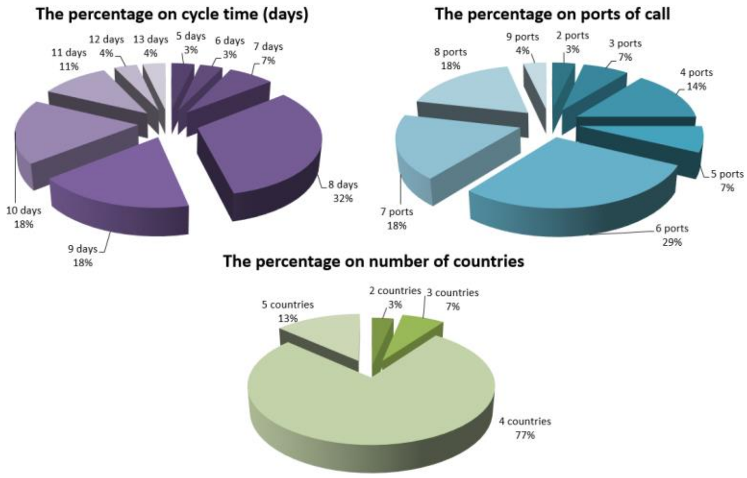


Figure 4.4: Statistic on trips for the Carnival Vista (Cruise Ship Schedule, 2016)

We now consider a special sequence s that visits the ports of call according to their IDs, i.e., $1, \cdots j, j+1 \cdots N$, in which 1 and N refer to the home ports and j is the j^{th} port visited on the cruise itinerary. The cruise ship leaves Port 1 at Time 0 (i.e., $b_1 = 0$), and returns to Port N at Time T (i.e., $a_N = T$). We need to determine the optimal arrival and departure times at each Port $2, \cdots j, j+1 \cdots N-1$. The purpose of examining this special case is for notational convenience; any sequence can be addressed using the same DP approach.

To apply DP, we firstly define $U_j(t)$ as the maximum possible profit (to be determined) from Time t to T, if the cruise ship arrives at Port j at Time t, and $V_j(t)$ as the maximum possible profit (to be determined) from Time t to T, if the cruise ship leaves Port j at Time t. Then, we define τ_j^v as the voyage time from the j^{th} port to the $(j+1)^{th}$ port, and τ_j^p as the staying time at the j^{th} port. The τ_j^v and τ_j^p are two decision variables in the DP algorithm. Third, since the cruise ship has a maximum sailing speed v^{max} and the minimum time spent at Port j is m_j, the earliest possible arrival time at Port j can be computed by assuming the cruise ship sails at its highest speed and spends the least time at previous ports of call:

$$a_j^{min} = \begin{cases} \sum_{k=1}^{j-1} \left\lceil \frac{d_{k,k+1}}{v^{max}} \right\rceil & , j = 2 \\ \sum_{k=1}^{j-1} \left\lceil \frac{d_{k,k+1}}{v^{max}} \right\rceil + \sum_{k=2}^{j-1} m_k & , j = \{3,4, \cdots N-1\} \end{cases} \tag{4.20}$$

The latest departure time is:

$$b_j^{max} = \begin{cases} T - \left(\sum_{k=j}^{N-1} \left\lceil \frac{d_{k,k+1}}{v^{max}} \right\rceil + \sum_{k=j+1}^{N-1} m_k \right) & , j = \{2,3, \cdots N-2\} \\ T - \sum_{k=j}^{N-1} \left\lceil \frac{d_{k,k+1}}{v^{max}} \right\rceil & , j = N-1 \end{cases} \tag{4.21}$$

Define

$$a_j^{max} := b_j^{max} - m_j, \; b_j^{min} := a_j^{min} + m_j \qquad \forall j \in P_c \tag{4.22}$$

To be feasible, the arrival time at Port j must be in the interval $[a_j^{min}, a_j^{max}]$ and the departure time must be in $[b_j^{min}, b_j^{max}]$.

In the DP approach, we have the boundary conditions:

$$U_N(t) = \begin{cases} -\infty, t \neq T \\ 0 \quad , t = T \end{cases} \qquad \forall t \in \mathbb{T} \tag{4.23}$$

and the recursive relations between $V_j(t)$ and $U_j(t)$ for all $t \in \mathbb{T},\ j \in \{1, 2, \cdots N-1\}$ are:

$$V_j(t) = \begin{cases} max_{\lceil d_{j,j+1}/v^{max} \rceil \leq \tau_j^v \leq T-t} \{-c^F \cdot F(d_{j,j+1}, \tau_j^v) + U_{j+1}(t + \tau_j^v)\}, t \in \mathcal{T}_j \cap [b_j^{min}, b_j^{max}] \\ -\infty \qquad , otherwise \end{cases} \tag{4.24}$$

$$U_j(t) = \begin{cases} \max_{m_j \leq \tau_j^p \leq T-t} \left\{p^u \cdot \sum_{h=t}^{t+\tau_j^p-1} g_j(h) + V_j(t + \tau_j^p)\right\}, t \in \mathcal{T}_j' \cap [a_j^{min}, a_j^{max}] \\ -\infty \qquad , otherwise \end{cases} \tag{4.25}$$

Eq. (4.24) is used to maximize the profit from Time t to T given that the cruise ship leaves Port j at Time t. Here, the possible departure times at Port j should be restricted in the intersection of $\mathcal{T}_j$ and $[b_j^{min}, b_j^{max}]$. The $\mathcal{T}_j$ is the set of opening hours of Port j. To enforce that the ship must leave Port j within its opening hours (i.e., time windows), we also need to include $\mathcal{T}_j$ in Eq. (4.24). The $[b_j^{min}, b_j^{max}]$ is the possible departure time range defined by Eq. (4.20), (4.21) and (4.22) based on the speed of the ship and minimal staying hours at the ports of call. It is impossible for the cruise ship to depart from Port j at Time t if the t is out of the range (i.e., $[b_j^{min}, b_j^{max}]$). The intersection of these two parts offers a strict limit on the possible departure time at Port j. This is crucial for Eq. (4.24), because the $V_j(t)$ with impossible Time t should be set to $-\infty$ in order to avoid unexpected problems in processing DP. For all possible Time t, the $V_j(t)$ is calculated by $U_{j+1}(t + \tau_j^v)$ and $-c^F \cdot F(d_{j,j+1}, \tau_j^v)$. The former is the maximal profit from Time $t + \tau_j^v$ to T, if the cruise ship arrives at Port $j+1$ at time $t + \tau_j^v$. As this maximal profit of Port $j+1$ has been obtained beforehand in the DP process, the $V_j(t)$ can be easily achieved by adding the bunker fuel profit (i.e., $-c^F \cdot F(d_{j,j+1}, \tau_j^v)$) between Port j and Port $j+1$. For the maximum $V_j(t)$, we need to determine the optimal voyage time (i.e., τ_j^v) between two ports, which is selected within the possible range (i.e., $\lceil d_{j,j+1}/v^{max} \rceil \leq \tau_j^v \leq T - t$). Here, we notice that the range may be infeasible when time t is large. For instance, when $t = T$, the upper bound of the range is zero, which is less than the lower bound of the range. To avoid these infeasible cases, we set $V_j(t)$ to $-\infty$ directly without calculation when the upper bound is less than the lower bound.

Eq. (4.25) is used to maximize the profit from Time t to T given that the cruise ship arrives at Port j at Time t. Similar to Eq. (4.24), the possible arrival time set at port j is also to be defined before calculation, which is the intersection of $\mathcal{T}_j'$ and $[a_j^{min}, a_j^{max}]$. The possible arrival time range (i.e., $[a_j^{min}, a_j^{max}]$) based on the speed of the ship and minimal staying hours at the ports of call is also achieved by Eq. (4.20), (4.21) and (4.22). For all possible arrival

Time t, the $U_j(t)$ is determined by $V_j\left(t+\tau_j^p\right)$ and $p^u \cdot \sum_{h=t}^{t+\tau_j^p-1} g_j(h)$. The former is the maximal profit from time $t+\tau_j^p$ to T, if the cruise ship leaves Port j at time $t+\tau_j^p$. As this maximal profit of Port j in terms of departure times has been obtained previously, the $U_j(t)$ can be easily obtained by adding the utility profit (i.e., $p^u \cdot \sum_{h=t}^{t+\tau_j^p-1} g_j(h)$) at Port j. For the maximum $U_j(t)$, we need to determine the optimal staying time (i.e., τ_j^p) at Port j, which is chose within the possible range (i.e., $m_j \le \tau_j^p \le T-t$). Similar to Eq. (4.24), the range could also be feasible. Thus, we set $U_j(t)$ to minus infinity when the upper bound of the range is less than the lower bound of the range (i.e., $T-t<m_j$).

$V_1(0)$ represents the maximum possible profit from Time 0 to T if the cruise ship departs from Port 1 at Time 0 and the value of $V_1(0)$ is obtained by executing the above algorithm. In essence, the value of the $V_1(0)$ is the optimal objective value for the sequence. The optimal arrival and departure times at each port of call under this sequence can be calculated by using the optimal decision variables $(\tau_j^v)^*$ and $(\tau_j^p)^*$ in DP, which is shown as follow.

$$a_j{}^* = \begin{cases} \sum_{k=1}^{j-1}(\tau_j^v)^* & ,j=2 \\ \sum_{k=1}^{j-1}(\tau_j^v)^* + \sum_{k=2}^{j-1}(\tau_j^p)^* & ,j=3,4,\cdots N-1 \end{cases} \tag{4.26}$$

$$b_j{}^* = a_j{}^* + (\tau_j^p)^* \quad ,j=2,3,\cdots N-1. \tag{4.27}$$

The detailed algorithm for the above-mentioned DP is given as follows:

Algorithm 4.1: Dynamic programming

Initialize $U_N(t), \forall t \in \mathbb{T}$ according to Eq. (4.23);
For $j=N-1 \ to \ j=1$
  If $j \neq 1$ **Then**
    For $t=0 \ to \ t=T$
      If $T-t \ge \lceil d_{j,j+1}/v^{max} \rceil$ **Then**
        Calculate $V_j(t)$ by using Eq. (4.24);
      Else
        $V_j(t) = -\infty$;
      End If
    End For
    For $t=0 \ to \ t=T$
      If $T-t \ge \ m_j$ **Then**
        Calculate $U_j(t)$ by using Eq. (4.25);
      Else
        $U_j(t) = -\infty$;
      End If
    End For
  Else // $j=1$
    Calculate $V_j(0)$ by using Eq. (4.24), output the optimal values of the decision variables τ_j^v and τ_j^p, and return.
  End If
End For

4.4.3 Improving the enumeration

When we enumerate all of the sequences, we may stop once we know that this sequence cannot be better than the incumbent best one. To this end, we develop an efficient method to find a high-quality upper bound on the profit of a sequence.

To begin with, the total cruise rotation time (i.e., T) is divided into the sailing time $\hat{T}$ (i.e., the total voyage time at sea) and port time $T - \hat{T}$ (i.e., the total staying hours in the ports of call). The optimal division is to be determined. Then, given a sequence s, we let $j(s)$ be the ID of the physical port of the j^{th} port visited on s. Here, we need to note that there is an underlying bound for the total sailing time (i.e., $\hat{T}$) when considering the speed restriction on sail (i.e., the speed cannot exceed v^{max}) and staying time restriction in ports (i.e., the stating in each port of call must exceed m_i). The bound for the total sailing time in each sequence s is.

$$\sum_{j=1}^{N-1} \lceil d_{j(s),(j+1)(s)} / v^{max} \rceil \le \hat{T} \le T - \sum_{i=1}^{N-1} m_i \tag{4.28}$$

where we notice that for some sequences s, the upper bound in (4.28) (i.e., $T - \sum_{i=1}^{N-1} m_i$) could be less than the lower bound in (4.28) (i.e., $\sum_{j=1}^{N-1} \lceil d_{j(s),(j+1)(s)} / v^{max} \rceil$), which means under these sequences, it is impossible for the cruise ship to return to the home port on time even if it sails at the maximum speed in the whole cruise. To improve the enumeration, we just drop these sequences and calculate the next one.

An upper bound on the profit from the negative fuel cost when the total sailing time is $\hat{T}$, denoted by $UB_s(\hat{T}, s)$, can be calculated as follow.

$$UB_s(\hat{T}, s) = \begin{cases} -c^F \cdot F\left(\sum_{j=1}^{N-1} d_{j(s),(j+1)(s)}, \hat{T}\right) & ,\hat{T}\ satisfies\ (4.28) \\ -\infty & ,otherwise \end{cases} \tag{4.29}$$

where fuel consumption is the lowest when the cruise ship sails at a constant speed.

An upper bound on the monetary value of the total utilities when the total port time is $T - \hat{T}$, denoted by $UB_p(T - \hat{T})$, can be calculated by solving an integer-linear program. First, we let

$$G_j(\delta_j) := max_{0 \le \tau \le 23} \sum_{h=\tau}^{\tau+\delta_j-1} p^u \cdot g_j(h) \tag{4.30}$$

That is, $G_j(\delta_j)$ is the maximum monetary value from the utility for spending δ_j consecutive hours at Port j. To obtain $UB_p(T - \hat{T})$, we let binary variable $z_{j\delta_j}$ be one if and only if the time spent at Port j is δ_j. Since the minimum time spent at Port j is m_j, to have a feasible port time solution, the time spent at Port j must be between m_j and $T - \hat{T} - \sum_{i \in P_c \setminus \{j\}} m_i$. The model for obtaining $UB_p(T - \hat{T})$ is:

$$[\boldsymbol{F1}]\ UB_p(T - \hat{T}) = max \sum_{j \in P_c} \sum_{\delta_j = m_j}^{T - \hat{T} - \sum_{i \in P_c \setminus \{j\}} m_i} G_j(\delta_j) z_{j\delta_j} \tag{4.31}$$

subject to:

$$\sum_{\delta_j=m_j}^{T-\hat{T}-\sum_{i\in P_c\backslash\{j\}} m_i} z_{j\delta_j} = 1 \qquad \forall j \in P_c \tag{4.32}$$

$$\sum_{j\in P_c} \sum_{\delta_j=m_j}^{T-\hat{T}-\sum_{i\in P_c\backslash\{j\}} m_i} \delta_j z_{j\delta_j} = T - \hat{T} \tag{4.33}$$

$$z_{j\delta_j} \in \{0,1\} \qquad \forall j \in P_c, \delta_j \in \left\{m_j, m_j+1, \cdots, T-\hat{T}-\sum_{i\in P_c\backslash\{j\}} m_i\right\} \tag{4.34}$$

Note that although $\boldsymbol{F1}$ is an integer linear program, we only need to solve it once for each possible value of $T-\hat{T}$ in one CISD problem.

An upper bound on the profit of a sequence s can now be easily obtained:

$$UB(s) = max_{\sum_{j=1}^{N-1}\lceil d_{j(s),(j+1)(s)}/v^{max}\rceil \le \hat{T} \le T-\sum_{i=1}^{N-1} m_i}\left[UB_s(\hat{T}, s) + UB_p(T-\hat{T})\right] \tag{4.35}$$

Based on above-mentioned definitions and formulations, the algorithm for improving the enumeration can be designed (denoted as *Algorithm 4.2*) and is shown as:

Algorithm 4.2: Improving the enumeration:

Define the incumbent best profit: $UB_{best} = -\infty$;
Calculate $UB_p(T-\hat{T})$ for all possible values of $T-\hat{T}$;
Enumerate each sequence: sequence $s \in S$;
For $s = 1\ to\ s = (N-2)!$
  If the sequence s violates the visa restriction **Then**
    Continue;
  End If
  If $T - \sum_{i=1}^{N-1} m_i < \sum_{j=1}^{N-1}\lceil d_{j(s),(j+1)(s)}/v^{max}\rceil$ **Then**
    Continue;
  End If
  Calculate the upper bound on the profit of the sequence s by Eq. (4.35)
  If $UB(s) \le UB_{best}$ **Then**
    Continue;
  Else
    Use DP (i.e., *Algorithm 4.1*) to find the maximum profit of the sequence s, denoted by UB_s^{DP}.
    If $UB_{best} < UB_s^{DP}$ **Then**
      Set $UB_{best} = UB_s^{DP}$ and record the sequence s;
    End If
  End If
End For

When the procedure for *Algorithm 4.2* is finished, the optimal profit for the CISD problem is achieved, which is UB_{best}, and the best sequence s^* is recorded. The details of arrival times and departure times can also be checked in the results of the DP for the sequence s^*.

4.5 COMPUTATIONAL EXPERIMENT

In order to validate the effectiveness of the proposed model $F1$ and the efficiency of the developed solution method, we conduct numerical experiments by using a PC (Intel Core i5, 2.1G Hz; Memory, 4G). The solution method is implemented by Matlab R2013b. The integer linear program $M1$ is solved by CPLEX12.1 with concert technology of C# (VS2008).

Before conducting experiments, we need to notice that the objective of our model does not represent the final profit for a cruise. To calculate the final profit, the incomes (e.g., tickets for cruise passengers) and the costs (e.g., operating cost of the cruise ship) should be included. To combine these incomes and costs together, a margin for per cruise passenger per day is assumed, denoted by p^m. In practice, this margin can be easily achieved by cruise companies to analyze the previous profit reports of cruises. Here, we take US$100 as the value of p^m. The total number of cruise passengers and the cycle time for one cruise are denoted by φ and π respectively. Thus, the final profit can be calculated by $profit = p^m \times \varphi \times \pi + Z$, in which Z is the optimal result obtained by the proposed method. In the following experiments, the final profit will be used as the optimal profit to be displayed in tables. Note that the newly added term $p^m \times \varphi \times \pi$ does not affect the optimization of our model objective Z since we assume the passenger demand φ is constant in response to different itineraries. We will discuss in the conclusion a future research to capture that the itinerary will affect the demand.

For the bunker cost function of the cruise ship deployed on the itinerary, according to Du et al (2011), the coefficients in bunker consumption function (i.e., k, k' and s in Eq. (4.2)) are related to the size of cruise ships. Here, we take the Explorer of the Seas (a cruise ship that belongs to the Royal Caribbean) as the example, which is a jumbo ship with 138,000 deadweight tons. We set the coefficients in Eq. (4.2) as $k = 698$, $k' = 0.000865$ and $s = 4.5$. The fuel price for the ship is assumed to be US$251.50 per metric ton, which is the price of IFO 380 at the port of Singapore on 8 September 2015 according to Ship & Bunker (2015).

4.5.1 Estimation of utility distribution

When using the above-mentioned method to design itineraries, cruise companies may find it difficult to evaluate the monetary value of the utilities in ports of call. To facilitate their designing, we propose a rational idea to help them derive utility profit. This utility profit is calculated based on analyzing the announced itineraries of their own or other cruise companies. For example, if we are helping Carnival Cruise Line to design a new itinerary, we could analyze the itineraries from the Royal Caribbean, which is the biggest competitor for Carnival Cruise Line, in order to obtain the adopted utility profit.

Our idea to derive the utility profit of ports of call comes from the observation of the different arrival times at these ports in announced itineraries. Take the "*11 Night Middle East & Asia Cruise*" operated by the Royal Caribbean International as an example. In Day 5 of the itinerary, the cruise ship arrives at the port of Mormugao, India at 6:00 am. In Day 10 of the itinerary, the ship arrives at the port of Penang, Malaysia at 12:00 pm. Here, we have the question: why does not the ship arrive at these ports one hour earlier or one hour later? For the port of Mormugao, the ship cannot arrive at 5:00 am because the port closes for service at that time, but it is possible to arrive at 7:00 am. However, the cruise ship does not postpone the arrival time for one hour even if this means a saving of US$780.65 in the bunker cost, which is calculated by the bunker cost function. One reasonable explanation for this is that the cruise ship could earn more than US$780.65 from the utility in the time period from 6:00 am to 7:00 am at the port of Mormugao. For the port of Penang, the cruise ship could arrive at 11:00 am (or 1:00 pm) if possible, which increases (or decreases) the bunker cost by US$855.02 (or US$784.45). This means that the utility profit of the port of Penang from 11:00 am to12:00 pm is less than US$855.02 (or from 12:00 pm to 1:00 pm is more than US$784.45).

According to the above analysis, the main idea for the method is: we derive the utility profit based on the announced itineraries operated by the other cruise companies. This method for estimating the utility profit might not be the best, but a rational alternative for the estimation of utility distribution. In Section 4.7, we will also propose a potential marketing method to estimate the utility.

4.5.2 Impact of different units of time period

In Section 4.3.1, we mentioned that we use one hour as a time period when implementing the CISD and the method can also handle time periods, e.g., half an hour. Here, we conduct some experiments on two types of settings of the time unit, including one hour and half an hour setting. The input data for testing the settings are randomly generated. Based on the above-mentioned method of the estimation, we randomly generate the utility distribution under the principles that bigger ports have higher utilities than small ports and noon hours have higher utilities than other opening hours. The results of the experiments are shown in Table 4.1.

Table 4.1: Comparison between different settings of the time unit

Instance			**One hour**		**Half an hour**		**Comparison**	
# of ports of call	**Cycle time**	**Instance id**	Z_o	T_o	Z_h	T_h	$(Z_h - Z_o) / Z_o$	$\frac{T_h}{T_o}$
3	6	3_6	1.237	2	1.240	5	0.25%	2.50
	7	3_7	2.115	4	2.122	11	0.33%	2.75
	8	3_8	3.196	5	3.208	16	0.38%	3.20
	9	3_9	3.690	8	3.710	26	0.54%	3.25
5	8	5_8	1.545	6	1.553	29	0.51%	4.83
	9	5_9	2.440	10	2.447	41	0.30%	4.10
	10	5_10	3.374	13	3.392	70	0.53%	5.38
	11	5_11	4.070	15	4.079	90	0.22%	6.00
7	10	7_10	1.934	16	1.939	113	0.23%	7.06
	11	7_11	2.646	22	2.653	173	0.24%	7.86
	12	7_12	3.573	53	3.583	434	0.27%	8.19
	13	7_13	4.404	85	4.426	732	0.49%	8.61
						Average:	**0.36%**	**5.31**

Note: *(i) "# of ports of call" column denotes the total number of ports of call involved in one cruise. This does not include two home ports. (ii) "Cycle time" column indicates the total days for one cruise. (iii) "Z_o" and "Z_h" columns list the optimal profits in the two settings of time unit with the unit of one million US dollars. (iv) "T_o" and "T_h" columns show the CPU time (seconds) to solve the problem.*

From Table 4.1, we observe that half an hour setting brings more profit than that of the one-hour setting. On average, the former increases the profit by 0.36%. However, the smaller time unit causes trouble in computational time. In the half an hour setting, the time to find the optimal results is longer than that of the one-hour setting. The average ratio between the two settings is 5.31. Moreover, the ratio keeps increasing when the scale of instances becomes larger. For the cruise companies, half an hour setting can still be used to improve the total profit, as the problem is a strategic decision problem. In the following experiments, in order to save the CPU time, we will use the one-hour setting rather than half an hour setting to solve the CISD problem.

4.5.3 Performance of the enumeration improving method

We have proposed two exact solution methods. One enumerates all sequences of ports of call and applies DP to calculate all these sequences in order to find the optimal one; while the other one considers the enumeration improving (i.e., *Algorithm 4.2*). In order to test the efficiency of the method with the enumeration improving, we conduct experiments under different instance-scales by using the two methods. The comparisons are listed in Table 4.2.

Table 4.2: Computational efficiency with and without using enumeration improving

Instance			**Enumeration improving method**		**No enumeration improving**		**Time ratio**
# of ports of call	**Cycle time**	**Instance id**	Z_0	T_0	Z_1	T_1	$\frac{T_1}{T_0}$
3	7	3_7	2.115	4	2.115	5	1.25
	8	3_8	3.196	5	3.196	8	1.60
	9	3_9	3.690	8	3.690	20	2.50
5	9	5_9	2.440	10	2.440	14	1.40
	10	5_10	3.374	13	3.374	25	1.92
	11	5_11	4.096	15	4.096	43	2.87
7	11	7_11	2.646	22	2.646	62	2.82
	12	7_12	3.573	53	3.573	198	3.74
	13	7_13	4.404	85	4.404	552	6.49
9	13	9_13	3.803	236	3.803	2035	8.62
	14	9_14	4.697	374	4.697	3961	10.59
	15	9_15	5.413	642	5.413	9753	15.19
						Average:	**4.92**

Note: *(i) "Z_0" and "Z_1" columns list the optimal profits obtained by two methods with the unit of one million US dollars. (ii) "T_0" and "T_1" columns show the CPU time (seconds) to solve the problem.*

As can be seen in Table 4.2, both two methods obtain optimal results. This is verified by the same optimal profits shown in the column "Z_0" and the column "Z_1". However, the method without using the enumeration improving is extremely time-consuming. The average ratio of CPU time between this enumeration method and the method with the enumeration improving is on average 4.92, which implies the proposed method saves approximately 80% of the computational time on average. More importantly, the time ratio between two methods increases dramatically with the growth of the instance-scale, which is shown in the last column of the table. This demonstrates that the enumeration improved method is quite efficient to find the optimal solutions for the problem.

4.5.4 Sensitivity analysis for a real case with a natural geographical sequence

As we have already tested the efficiency of the proposed method, we will use this method to conduct sensitivity analysis in terms of three inputs, which are fuel price for the ship, minimal staying hours of ports of call and opening hours of ports of call. Here, we take a popular cruise line from the Royal Caribbean, “*14 Night Singapore to Fremantle Cruise*”, as an example, and suppose that we are helping the Carnival Cruise Line to design a similar one-way cruise. The nine ports involved in this cruise are shown in Figure 4.5, and it can easily be seen that this itinerary has a naturally geographical sequence, under which we may design a good visiting sequence by direct observation.

Figure 4.5: City ports in “14 Night Singapore to Fremantle Cruise” (Google Map, 2018a)

Table 4.3: Information of selected ports in a real case

Port index	Port	Country	Latitude (N+,S–)	Longitude (W–,E+)	Minimal staying hours
1	Singapore	Singapore	1.35	103.82	***Home Port***
2	Phuket	Thailand	7.88	98.39	9
3	Langkawi	Malaysia	6.35	99.80	6
4	Kuala Lumpur	Malaysia	3.14	101.69	6
5	Geraldton	Australia	–28.77	114.61	6
6	Bali	Indonesia	–8.41	115.19	9
7	Lombok	Indonesia	–8.65	116.32	7
8	Broome	Australia	–17.95	122.24	6
9	Fremantle	Australia	–31.95	115.86	***Home Port***

For this cruise, assume that we deploy the Carnival Vista, which is the biggest cruise ship of the Carnival Cruise Line. It has 133,500 deadweight tons. Same as the “*14 Night Singapore to Fremantle Cruise*” operated by the Royal Caribbean International, in this cruise, the cruise ship departs from the port of Singapore at 5:00 pm on Day 1 and arrives at the port of Fermantle, Australia at 7:00 am on Day 15. Singapore and Fermantle are the home ports. The information about the seven selected ports of call (i.e., Phuket, Langkawi, Kuala Lumpur, Geraldton, Bali, Lombok, and Broome) and the two home ports are shown in Table 4.3. We assume that each port opens for the cruise ship at 7:00 am and closes at 7:00 pm on a daily basis. The fuel price for the cruise ship has been mentioned in Section 4.6.1, which is US$251.50 per metric ton.

The above-mentioned information is deemed as the baseline setting for the following sensitivity analysis. The sensitivity analysis of the fuel price is implemented at first, which is shown in Table 4.4. As it is shown in the table, there are two port sequences for different fuel prices. For the optimal profit, we notice that with the rising of the fuel price, the profit decreases evidently. If the fuel price increases by 20%, the profit drops by 0.81%. The number of voyage hours also changes in different settings of the fuel price. It keeps rising and stays unchanged for 268 hours when the fuel price increases by more than 40% compared with the baseline setting. The increasing tendency for the voyage hours in response to the rising fuel price is reasonable. This is because that lower fuel price may induce the cruise ship to sail faster in order to gain more utility profit from the ports of call, and the higher fuel price may impede the cruise ship to sail faster, because the bunker consumption increases significantly when speeding up, meaning that the extra bunker cost is higher at a higher fuel price.

Table 4.4: Sensitivity analysis on fuel price

Differentiation	**Solved optimal port sequence**	**Optimal profit**	**Deviation**	**Voyage hours**
0.40	[1 4 3 2 6 7 8 5 9]	5.969	2.52%	240
0.60	[1 4 3 2 6 7 8 5 9]	5.918	1.64%	263
0.80	[1 4 3 2 6 7 8 5 9]	5.870	0.82%	264
Baseline setting	[1 4 3 2 6 7 8 5 9]	5.822	0.00%	265
1.20	[1 4 3 2 6 7 8 5 9]	5.775	–0.81%	267
1.40	[1 2 3 4 6 7 8 5 9]	5.728	–1.62%	268
1.60	[1 2 3 4 6 7 8 5 9]	5.681	–2.43%	268

Note: *(i) the coefficients in "Differentiation" column (i.e., {0.40, 0.60, 0.80, 1.20, 1.40, 1.60}) are used to multiply the baseline setting of the fuel price (i.e., US$251.50 per metric ton) to represent the price in each instance, e.g.,* $0.40 \times 251.50 = 100.60$. *(ii) "Deviation" column lists the gap between the current setting and the baseline setting with respect to the optimal profit. (iii) "Optimal profit" column list the optimal profits obtained under different settings with the unit of one million US dollars.*

Table 4.5: Sensitivity analysis on minimum staying hours

Differentiation	**Solved optimal port sequence**	**Optimal profit**	**Deviation**	**Staying hours**
–3	[1 2 3 4 6 7 8 5 9]	5.823	0.02%	55
–2	[1 2 3 4 6 7 8 5 9]	5.823	0.02%	55
–1	[1 2 3 4 6 7 8 5 9]	5.823	0.01%	57
Baseline setting	[1 4 3 2 6 7 8 5 9]	5.822	0.00%	60
+1	[1 4 3 2 6 7 8 5 9]	5.821	–0.02%	61
+2	[1 4 3 2 6 7 8 5 9]	5.819	–0.06%	64
+3	[1 4 3 2 6 7 8 5 9]	5.814	–0.14%	70

Note: (i) the coefficients in "Differentiation" column (i.e., $\{-3,-2,-1,+1,+2,+3\}$*) are used to add the baseline setting of the minimal staying hours of each port call (i.e., the last column in Table 4.4 to obtain the minimal staying hours in each instance, e.g., for Port 2:* $-3+9=6$*.*

Table 4.5 shows the results of sensitivity analysis on minimal staying hours for the cruise ship dwelling in all ports of call. With the decreasing of minimal staying hours, the optimal profit increases steadily until the minimal staying hours of all ports of call decrease by two hours compared with the baseline setting. This is the point when the minimal staying hours lose its effect as the restriction. It is also observed from the table that the cruise ship tends to reduce its total staying hours in all ports of call with the minimal staying hours decreasing. However, it stands at 55 hours even when the minimal staying hours decrease further, which means the cruise ship still needs to stay in the ports of call for enough hours in order to obtain decent profits from the utility of these ports.

The results of sensitivity analysis on the opening hours of the ports of call are given in Table 4.6. In the baseline setting, all ports of call open to the cruise ship for twelve hours daily, which starts at 7:00 am and ends at 7:00 pm. Here, in the table, we change the daily opening hours for all ports of call by one hour each time. As can be seen from the table, the cruise ship tends to earn more profit as the ports open for a longer time. However, the effect on the profit increasing from the increase of opening hours is not obvious, which is generally less than 0.05% per hour in the instances shown in the table. Therefore, it is highly recommended that cruise companies need to be considerate when they want to increase the profit by requiring more opening hours from the ports of call. In the table, the total staying hours also increase steadily with more opening hours offered by the ports of call, which is the direct reason for the increase of the optimal profit as more utility profit is earned from the ports of call.

Table 4.6: Sensitivity analysis on opening hours

Differentiation	**Solved optimal port sequence**	**Optimal profit**	**Deviation**	**Staying hours**
–3	[1 4 3 2 6 7 8 5 9]	5.817	–0.09%	55
–2	[1 4 3 2 6 7 8 5 9]	5.820	–0.04%	56
–1	[1 4 3 2 6 7 8 5 9]	5.820	–0.04%	58
Baseline setting	[1 4 3 2 6 7 8 5 9]	5.822	0.00%	60
+1	[1 4 3 2 6 7 8 5 9]	5.822	0.00%	60
+2	[1 2 3 4 6 7 8 5 9]	5.823	0.02%	61
+3	[1 2 3 4 6 7 8 5 9]	5.823	0.02%	66

***Note:** (i) The coefficients in "Differentiation" column (i.e.,* $\{-3,-2,-1,+1,+2,+3\}$*) are used to add the baseline setting of the opening hours of each port call (i.e., twelve hours) to achieve the opening hours in each instance, e.g.,* $-3+12=9$*.*

In sum, if the ports on an itinerary have a naturally geographical sequence, then port distance will dominate the design of the itinerary and other parameters have a marginal effect on the results. In the next section, we will examine cases in which the ports do not have a naturally geographical sequence.

4.5.5 Further analysis for cases without a natural geographical sequence

In some cruise areas with scattered ports and islands, such as the Caribbean Sea area (see Figure 4.6), the ports of call in some cruise itineraries may not have a natural geographical sequence, and there are many potentially good sequences given a set of ports of call. In this section, we examine the value of sophisticated models for the itinerary design in such cruise areas, in which a geographical sequence may not be easy to derive by direct observation.

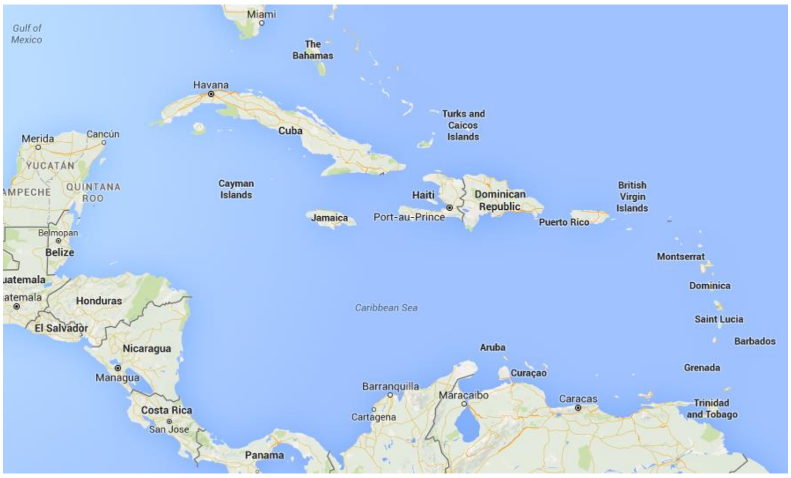


Figure 4.6: City ports around the Caribbean Sea (Google Map, 2018b)

As the bunker cost is one of the major concerns for cruise companies, we would like to further conduct analysis on the fuel price to see how important an optimal port sequence is needed when the fuel price fluctuates. In order to conduct such analysis, we select 16 real cruise services operated by Royal Caribbean International in the Caribbean Sea area (Royal Caribbean International, 2016). Before conducting the analysis, we first redesign the itinerary schedules for the 16 real cruise service. The comparisons in terms of port sequence and port staying hours between the 16 designed itineraries and the 16 actual itineraries are listed in Figure 4.7. Here, the y-axis shows the total port staying hours for each itinerary, and the x-axis indicates the index of each cruise service. Symbol "Y" (Symbol "N") above pairs of bars indicates that the designed itinerary and the actual itinerary have the same port sequence (different port sequences) for the corresponding cruise service.

For further analysis of the fuel price, based on the above-mentioned 16 cruise services, the optimal sequence under the baseline setting of the fuel price is obtained by using the proposed method at first. Then, the profits under other fuel price settings of this optimal sequence (i.e., Baseline itinerary) are calculated, which are defined as Baseline itinerary profit. The optimal sequences and the optimal profits under other fuel price settings are also re-optimized by using the proposed method, which is compared with the Baseline itinerary and Baseline itinerary profit. The results of the comparisons are reported in Table 4.7.

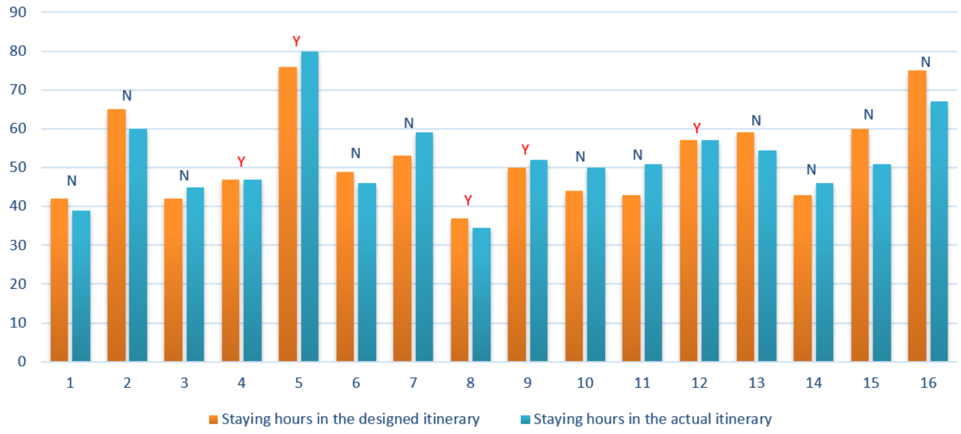


Figure 4.7: Comparisons between the designed and actual itineraries

From Table 4.7, we can observe that when the fuel price fluctuates, the optimal sequences for the itineraries are highly likely to change. Especially for large degrees of fluctuation, such as the 0.4-differentiation and the 1.6-differentiation on the fuel price, the majority of optimal sequences in the 16 cruise services are different from the optimal sequences obtained under the baseline setting of the fuel price. However, when the fuel price fluctuates, if the optimal sequence obtained in the baseline setting is fixed for the itinerary, there is significant profit loss based on the average deviation in the table. In extreme cases, for instance, with 0.4-differentiation on the fuel price, the average profit loss is 4.52%. Therefore, it is critical for the cruise companies to re-optimize the visiting sequence when the fuel price fluctuates significantly in order to achieve a higher profit.

Table 4.7: Further analysis of fuel price

Differentiation on the fuel price	Number of instances having the same optimal port sequence as the baseline setting	Average optimal profit	Average Baseline itinerary profit	Average deviation
0.4	3	5.022	4.805	4.52%
0.6	6	4.894	4.772	2.56%
0.8	8	4.779	4.721	1.23%
Baseline setting	16	4.663	4.663	0.00%
1.2	10	4.538	4.490	1.07%
1.4	6	4.424	4.317	2.48%
1.6	5	4.322	4.159	3.92%

Note: (i) "Average optimal profit" column list the average profit among the 16 cruise services under each fuel price setting. (ii) "Average optimality gap" column shows the gap between the average optimal profit and the average Baseline itinerary profit.

Based on the 16 selected cruise services from Royal Caribbean International, we also conduct some sensitivity analysis on the utility distributions of the ports of call. For each port of call in one instance, its utility distribution among hours in one day may have different values of mean and standard deviation (SD). The SD indicates the degree of variation of the utility among 24 hours. Here, we change the SD of the utility distribution for each port of call by multiplying a coefficient, which generates a new case of the instance for the sensitivity analysis. Given the 16 cruise services, we test each instance in different SDs. The effects on the optimal sequence and the optimal profit by different SDs (i.e., different variations of the utility distribution) are shown in Table 4.8. As can be seen from Table 4.8, the differentiation on the SD of the utility distribution has limited impacts on the optimal sequence and the optimal profit. For the majority of the 16 cruise services, the optimal sequence under different SDs is still the same as the optimal sequence under the baseline setting. Meanwhile, if we insist on using the baseline optimal sequence under different SDs in large differentiations such as 0.8-differentiation and 1.2 differentiation, the profit loss is around 0.5%.

Table 4.8: Sensitivity analysis on the utility distributions

Differentiation on the standard deviation	**Number of instances having the same optimal port sequence as the baseline setting**	**Average optimal profit**	**Average baseline itinerary profit**	**Average deviation**
0.8	12	4.551	4.526	0.55%
0.9	14	4.615	4.601	0.30%
Baseline setting	16	4.663	4.663	0.00%
1.1	14	4.675	4.667	0.17%
1.2	13	4.717	4.694	0.49%

Note: (i) the coefficients in "Differentiation" column (i.e., {0.80, 0.90, 1.10, 1.20}) are used to multiply the baseline setting of the standard deviations (SDs) of the utility distributions of all ports of call to represent the SDs in each instance.

4.5.6 Comparison between the proposed method and two heuristics

To test how important the proposed method is needed for the CISD, we compare our method with two heuristics, which are the minimum fuel cost heuristic and the shortest path heuristic. For both heuristics, we first find the sequence with the shortest voyage distance. Then, in the minimum fuel cost heuristic, we design the itinerary schedule by minimizing the total fuel consumption among all the voyage legs in the sequence without considering the port staying profit. In the shortest path heuristic, assuming that we also consider the port staying profit, the itinerary schedule is derived by using *Algorithm 4.1* based on the sequence. The total profits of the itinerary schedules obtained by the proposed method and the two heuristics under different problem scales are compared in Table 4.9.

As can be seen in Table 4.9, the deviation in the sense of the average profit between the proposed method and the minimum fuel cost heuristic is 7.54% on average. Such deviation suggests that when designing the itinerary schedule, only focusing on the fuel cost minimization would lead to significant profit loss, as the port staying profit is ignored in the optimization. Although the port staying profit is considered in the shortest path heuristic, there is still an average of 3.16% deviation to the optimal profit, which implies that the sequence with the shortest voyage is not necessarily the optimal sequence, especially when the ports do not have a naturally geographical sequence.

Table 4.9: Comparisons between the proposed method and two heuristics

Instance group		The proposed method	Minimum fuel cost heuristic		The shortest path heuristic	
# of ports of call	Cycle time	Average profit	Average profit	Average deviation	Average profit	Average deviation
5	9	2.352	2.225	5.40%	2.325	1.15%
	10	3.249	3.044	6.31%	3.184	2.00%
	11	3.894	3.551	8.81%	3.764	3.34%
7	11	2.501	2.352	5.96%	2.457	1.76%
	12	3.297	3.084	6.46%	3.194	3.12%
	13	4.235	3.814	9.94%	4.074	3.80%
9	13	3.712	3.478	6.30%	3.604	2.91%
	14	4.494	4.121	8.30%	4.284	4.67%
	15	5.108	4.578	10.38%	4.818	5.68%
Average:				**7.54%**		**3.16%**

Note: *(i) In each instance group, there are 10 instances, which are randomly generated based on major ports or islands in the Caribbean Sea area. (ii) The average profit of 10 instances in one group is calculated for the proposed method and the two heuristics. (iii) "Average deviation" shows the deviations between the average profit by the proposed method and the average profits by the heuristics.*

4.5.7 Managerial Implications

The above numerical experiments shed lights on the nature of the CISD problem and enable us to discover a number of useful managerial implications for cruise companies summarized as follow.

First, when designing itineraries, using smaller time unit causes an increase in computational time, but it could bring more profits. As the planning of cruise itineraries is a strategic decision, it is recommended that cruise companies use smaller time unit in order to obtain more profits. The resulting schedule could be an "internal" schedule and the published schedule could be the one that rounds the internal schedule to one hour or half an hour. For instance, if it is calculated that the ship should arrive at a port of call at 6:50 am, then the cruise company can inform the captain to try to arrive at 6:50 am and can inform the cruise passengers that the ship arrives at 7:00 am.

Second, when the ports of call on an itinerary have a naturally geographical sequence, then the distances between ports dominate the design of the schedule. In other words, the sequence of the ports of call with the shortest total distance is generally the optimal choice, and the impacts of minimum staying hours at ports and the opening hours at ports are marginal. The bunker fuel price has a larger effect on the total profit in the following way: when the fuel price is higher, the voyage time is longer, leading to lower fuel consumption and thereby lower fuel costs, and vice versa.

Third, when the ports of call on an itinerary do not have a naturally geographical sequence, as is the case for the largest cruise destination—the Caribbean Sea area, there are many potentially good schedules. We find that the fuel price has a much larger impact on the design of schedule. Specifically, when the fuel price deviates from the estimated price by 60%, sticking to the optimal schedule based on the estimated price will lead to a profit reduction of around 4% (cf. Table 4.7). Hence, it is highly desirable for a cruise company to have an accurate estimation of the fuel price.

4.6 UTILITY ESTIMATION BY MARKETING TECHNIQUES

In this paper, a big challenge to implement the model in practice is the utility distribution estimation. We have proposed a method for the estimation in Section 4.6.1. Such a method might not be the best, but a rational alternative. In this section, we further construct a potential utility estimation approach by using some marketing techniques. Here we design a *conjoint analysis* (Green et al., 1996; Ding et al., 2009) for evaluating customers' preference on cruise itinerary schedules. A choice-based conjoint experiment (Toubia et al., 2007; Gilbride et al., 2008) is conducted to obtain conjoint data. Then, the conjoint data is analyzed by a basic *multinomial logit model* (Hongmin and Woonghee, 2011; Li, 2011; Paat and Huseyin, 2012), and henceforth the utility distribution can be obtained. Note that this approach will not be implemented in this paper, as it involves tremendous research efforts in collecting conjoint data by interviewing many potential cruise passengers. However, this approach will be explored and developed in our future study.

4.6.1 Choice data collection

Before illustrating our analysis procedure, we would introduce the background of the analysis. Our conjoint experiment is conducted for the cruise itinerary schedules in a specific region (e.g., Asia region) rather than the global. It is due to that: firstly, loop cruise itineraries only traverse a set of ports in the same region, and secondly, the customers from different regions have different preferences on cruise itinerary schedules. For instance, the China-Japan-Korea cruise services are popular in China. In those services, cruise passengers in China would leave from the home port in China (such as Shanghai and Tianjin), visit some ports of call in Japan and Korea (such as Nagasaki (Japan), Fukuoka (Japan) and Busan (Korea)), and return to the home port finally. In the background of China-Japan-Korea area, many cruise itinerary schedules can be designed based on the cruise passengers' preference in China.

The first step in the *conjoint analysis* is to define the attributes (or factors) of a cruise service (or a cruise itinerary schedule) that have effects on customers' preference on cruise itinerary schedules. A straightforward attribute is the ticket price for the cruise service, which is an explanatory variable on how the attribute motivates the customers to buy the service. Each attribute has different levels, i.e., the possible values for the attributes. For example, for the ticket price attribute, there are possible levels at \$800, \$850, \$900 and so on. Xie et al. (2012)

have proposed several attributes of a cruise ship that affect the customers' preference. In our analysis, we focus on some attributes related to the itinerary schedule design.

Table 4.10 lists the attributes and levels used in our analysis under the background of China-Japan-Korea area. Apart from some regular variables (such as price, home port, and rotation time), there are some important hourly dummy binary variables (i.e., time-of-day variables), which are defined to show whether the cruise ship stays at a certain port of call during a certain hourly time period (e.g., 6:00 – 7:00 am) or not. The purpose of defining the hourly dummy binary variables is to estimate the utility distribution in each port of call (see Koppelman et al. (2008) for the application of time-of-day variables). Here, we denote E as the set of all the regular variables, and R as the set of all the hourly dummy binary variables. Assume that there is a mock-up cruise schedule: the ticket price is \$850, the rotation time is 6 days, the home port is Shanghai, and it only has one port of call (Fukuoka (Japan), arrival time: 7:00 am, departure time: 5:00 pm). Then based on Table 4.10, the cruise service can be depicted in: "Price" with value 850; "Rotation time" with value 6; "Home port" with value 1; the binary variables in "Staying hours in Fukuoka(Japan)" corresponding to the staying hours from 7:00 am to 5:00 pm with value 1, and all other variables with value 0.

Table 4.10: Attributes and levels used in the conjoint analysis

Attributes	**Levels**
Price	A continuous variable (such as \$800, \$850 and \$900)
Rotation time	A discrete variable (such as 5 days, 6 ports and 7 ports)
Homeport	A discrete variable (1 for Shanghai, and 2 for Tianjin)
Staying hours at Nagasaki (Japan): 6:00 – 7:00 am 7:00 – 8:00 am 8:00 – 9:00 am and so on	A dummy binary variable for each hourly time period (for example, 6:00 – 7:00 am in Nagasaki (Japan): 1 for the cruise ship staying at the port in 6:00 – 7:00 am; otherwise 0)
Staying hours at Fukuoka (Japan): 6:00 – 7:00 am 7:00 – 8:00 am 8:00 – 9:00 am and so on	A dummy binary variable for each hourly time period (for example, 6:00 – 7:00 am in Fukuoka (Japan): 1 for the cruise ship staying at the port in 6:00 – 7:00 am; otherwise 0)
Staying hours at Busan (Korea): 6:00 – 7:00 am 7:00 – 8:00 am 8:00 – 9:00 am and so on	A dummy binary variable for each hourly time period (for example, 6:00 – 7:00 am in Busan (Korea): 1 for the cruise ship staying at the port in 6:00 – 7:00 am; otherwise 0)

Note: (i) In "Staying hours at Nagasaki (Japan)" attributes, each hourly time period (e.g., 6:00 – 7:00 am in Nagasaki (Japan)) has a corresponding attribute. (ii) For "Staying hours in Nagasaki (Japan)" attribute, if the cruise ship for a cruise schedule arrives at Nagasaki(Japan) at 7:00 am and departs from the port at 11:00 am. Then, this schedule has the dummy binary variables (corresponding to 7:00 – 8:00 am, 8:00 – 9:00 am, 9:00 – 10:00 am and 10:00 – 11:00 am) equalling to one, and all other dummy binary variables equalling to zero.

As we have decomposed the cruise schedule into such attributes and levels in Table 4.10. The next step is to generate some mock-up cruise schedules, which will be used in the interview with potential cruise passengers. $\mathbb{S}$ denotes the set for all generated cruise schedules. Those generated mock-up cruise schedules will be clustered into some choice sets. The schedule generation and cluster process can be done by Efficient Factorial Design in the statistical package of SAS (Kuhfeld, 2010). Each choice set contains a certain number of mock-up cruise schedules (denoted as J). Thereafter, the conjoint choice data is collected by interviewing potential cruise passengers (i.e., respondents), and asking them to choose one preferred cruise schedule (i.e., alternative) form each choice set. Here, we denote w and q as the index for the choice set and respondent, respectively, where $w \in \mathbb{W}$ and $q \in \mathbb{Q}$. For instance, we have generated 20 (i.e., $|\mathbb{S}| = 20$) unique mock-up cruise schedules, which are clustered into 12 choice sets (i.e., $|\mathbb{W}| = 12$) with 3 alternatives in each set ($J = 3$). Note that a mock-up cruise schedule can exist in several choice sets. Assuming that the choice set 1 contains the alternative 1, 2 and 4, each respondent q will be asked to choose one of the three alternatives for the choice set.

4.6.2 Choice data analysis

After collecting the conjoint choice data, the following step is to analyze the conjoint data. The most popular model to analyze the choice data is the *multinomial logit model* (Vermeulen et al., 2008). By using aggregate logit share techniques (Koppelman et al., 2008), we can derive the utility experienced by the respondent q when facing the jth alternative ($j \in \{1,..,J\}$) in the choice set w as follows:

$$\mathbb{U}_{qwj} = \sum_{e \in E} \alpha_e X_{wje} + \sum_{r \in R} \beta_r Y_{wjr} + \varepsilon_{qwj} \tag{4.36}$$

where α_e represents the partial utility (i.e., the coefficient or "partworths") for the eth regular variable (e.g., the variable for the price), and X_{wse} is the value of the eth no time-of-day variable for the jth cruise schedule in the choice set w (e.g., \$850 for the price). Similarly, β_r and Y_{wjr} are corresponding to the rth hourly dummy binary variable. ε_{qwj} is the error term. Note that $\beta_r, \forall r \in R$ indicate the utility distribution for all the ports of call.

Then, all the error terms are assumed to be i.i.d., under which we can calculate the probability that the cruise passenger q will choose the jth alternative in the choice set w:

$$P_{qwj} = \frac{\exp(\sum_{e \in E} \alpha_e X_{wje} + \sum_{r \in R} \beta_r Y_{wjr})}{\sum_{j' \in \{1,2,..,J\}} \exp(\sum_{e \in E} \alpha_e X_{wj'e} + \sum_{r \in R} \beta_r Y_{wj'r})} \tag{4.37}$$

Based on the probability function, we can derive its log-likelihood function:

$$\ln(F(\alpha, \beta)) = \sum_{q \in \mathbb{Q}} \sum_{w \in \mathbb{W}} \sum_{j \in \{1,2,..,J\}} Z_{qwj} \ln(P_{qwj}) \tag{4.38}$$

where Z_{qwj} shows the conjoint choice data collected in Section 4.7.1, which equals one if and only if the cruise passenger q choose the jth alternative in the choice set w. In order to estimate $\hat{\alpha}_e, \forall e \in E$ and $\hat{\beta}_r, \forall r \in R$, we can maximize the above log-likelihood function by using the conjoint choice data as the input parameters. This procedure can also be done by SAS (Kuhfeld, 2000), and some technical issues are discussed in Vermeulen et al. (2008). Till now, the estimated coefficient $\hat{\beta}_r, \forall r \in R$ are obtained and indicate the utility distribution for each hour in each port of call.

Based on the estimated coefficient $\hat{\alpha}_e, \forall e \in E$ and $\hat{\beta}_r, \forall r \in R$, we further estimate the possible demand for a newly designed cruise schedule (denoted as γ): firstly, we investigate all the existing cruise schedule $s \in \mathbb{S}$ in the specific region (e.g., the China-Japan-Korea area) as well as the total regional market share (denoted as $\mathbb{M}$). The total regional market share can be easily obtained from some industry reports, such as Statista (2015). Then, the utility is calculated for each existing cruise schedule and the newly designed cruise schedule by: $\mathbb{U}_s = \sum_{e \in E} \hat{\alpha}_e X_{se} + \sum_{r \in R} \hat{\beta}_r Y_{sr}$ and $\mathbb{U}_\gamma = \sum_{e \in E} \hat{\alpha}_e X_{\gamma e} + \sum_{r \in R} \hat{\beta}_r Y_{\gamma r}$ (X and Y parameters here have the same meanings with that in Eq.(21)). Thereafter, the probability that potential cruise passengers in the regional market will choose the newly designed cruise schedule is $P(\gamma) = \frac{\exp(\mathbb{U}_\gamma)}{\sum_{s \in \mathbb{S}} \exp(\mathbb{U}_s) + \exp(\mathbb{U}_\gamma)}$. Next, the demand in the regional market for the newly designed cruise schedule γ is estimated as: $\mathbb{M} \cdot P(\gamma)$.

4.7 CONCLUSION

This paper addresses the cruise itinerary schedule design problem that determines the optimal sequence of a given set of ports of call and the arrival and departure times at each port to maximize the monetary value of the utility minus the fuel cost. In view of the practical observations that most cruise itineraries do not have many ports of call, we first enumerate all sequences of ports of call and then optimize the arrival and departure times at each port of call by developing a dynamic programming approach. To improve the computational efficiency, we propose effective bounds on the profit of each sequence of ports of call, eliminating non-optimal sequences without invoking the dynamic programming algorithm. The computational experiments show that, first, the proposed bounds on the profit of each sequence of ports of call can considerably improve the computational efficiency; second, the total profit of the cruise itinerary is sensitive to the fuel price and hence, it is acceptable to use the shortest voyage distance method to design the schedule when the ports of call have a naturally geographical distance; in contrast, determining the sequence of ports of call solely by minimizing the overall voyage distance frequently leads to a significant reduction in the total profit when the ports do not have a naturally geographical sequence.

Given that cruise itineraries have fixed sequences of ports of call and fixed schedules, optimization-based itineraries planning tools should be able to increase the profit or save the cost for cruise shipping companies and improve the service quality for cruise passengers. Compared with other areas of transportation such as a truck, rail, and air (we note that transportation is not the purpose of cruising, but the cruise shipping is a part of transportation), there are few quantitative studies on cruise shipping. Nevertheless, cruise shipping has its own characteristics that need to be explored by industrial engineers/operations researchers. Moreover, the cruise market has maintained steady growth over the past 20 years despite the economic crisis in 2008 and cruising companies have ordered a number of large cruise ships to serve the mass market of cruising. We believe that there is a broad range of research topics in cruise shipping.

In this study, we have a limitation on assuming that the utility increase for the cruise passengers is additive over the port staying hours. However, in reality, cruise passengers' utility may depend on the time period that they want to stay in the ports, and the incremental utility of an extra port staying hour may decrease over time. Under this circumstance, the proposed solution can still be applied by analyzing the utility for each possible port staying period (e.g., 7:00 am to 6:00 pm) rather than each port staying hour. Our future study will further explore the relationship between the utility increase for cruise passengers and the port staying hour increase. Another limitation is that we assume the itinerary design has no effect on the passenger demand. However, if we consider the multinomial logit model in Section 4.6, given any new schedule, the utility of this schedule will be different and thus the demand will change accordingly. A future study should also embed the multinomial logit model to measure the potential demand in response to different itinerary schedules. Meanwhile, we may also determine the number of days while designing a cruise service rather than follow the fixed time periods for planning. Henceforth, the pricing strategies should be considered, because the number of days for a cruise service will affect the pricing, and thus further affect the demand.

For future research topics on the cruise industry, there are some recommendations. (i) The cruise itinerary design topic: based on the limitation of this study, we do not consider some practical constraints for the cruise ship to dwell in the ports of call, such as berth availability and tide effects in ports. Therefore, a more general cruise itinerary design problem can be studied. (ii) The cruise ship fleet deployment topic: cruise ships are frequently repositioned from one region to another region. From the perspective of the cruise lines, there are several decision problems on how cruise ships are repositioned. (iii) The cruise ticket pricing topic: in airlines, many pricing policies, and strategies have been developed to increase revenue. However, the pricing in cruise shipping is not so flexible than that of the airlines. Thus, future studies can be conducted on cruise pricing by borrowing some ideas from the pricing of the airlines.

4.8 REFERENCES

Applegate, D.L., Bixby, R.E., Chvatal, V., Cook, W.J., 2011. *The Traveling Salesman Problem: A Computational Study*. Princeton University Press, New Jersey.

Biehn, N., 2006. A cruise ship is not a floating hotel. *Journal of Revenue and Pricing Management* 5, 135–142.

Cormen, T.H., Leiserson, C.E., Rivest, R.L., Stein, C., 2009. *Introduction to Algorithms, Third Edition*. The MIT Press, London, England.

Cordeau, J. F., Laporte, G., Mercier, A., 2001. A unified tabu search heuristic for vehicle routing problems with time windows, *Journal of the Operational Research Society* 52(8), 928–936.

Carnival Cruise Line, 2016. 7 day Western Caribbean from Miami, FL. http://www.carnival.com/itinerary/7-day-western-caribbean-cruise/miami/glory/7-days/wek. Accessed 4 April 2016.

Cruise Industry News, 2015. Cruise Industry Statistics—Cruise Ship Statistics. http://www.cruiseindustrynews.com/cruise-industry-stats.html. Accessed 28 Aug 2015.

Cruise Ship Schedule, 2015. Carnival Vista itinerary 2016 cruises. http://www.cruiseshipschedule.com/carnival-cruise-lines/carnival-vista-schedule/. Accessed 12 September 2015.

Ding, M., Park, Y.H., Bradlow, E.T., 2009. Barter markets for conjoint analysis, *Management Science* 55(6), 1003–1017.

Du, Y., Chen, Q., Quan, X., Long, L., Fung, R.Y.K., 2011. Berth allocation considering fuel consumption and vessel emissions, *Transportation Research Part E* 47, 1021–1037.

Du, Y., Chen, Q., Lam, J. S. L., Xu, Y., Cao, J. X., 2015. Modeling the impacts of tides and the virtual arrival policy in berth allocation, *Transportation Science* 49(4), 939-956.

Feillet, D., Dejax, P., Gendreau, M., 2005. Traveling salesman problems with profits, *Transportation Science* 39(2), 188–205.

Fransoo, J.C., Lee, C.Y., 2013. The critical role of ocean container transport in global supply chain performance, *Production and Operations Management* 22(2), 253–268.

Gilbride, T.J., Lenk, P.J., Brazell, J.D., 2008. Market share constraints and the loss function in choice-based conjoint analysis, *Marketing Science* 27(6), 995–1011.

Google Map, 2018a. https://www.google.com/maps/@-9.689449,127.0193577,5.17z. Accessed 4 April 2018.

Google Map, 2018b. https://www.google.com/maps/@15.264912,-75.719404,6.17z. Accessed 4 April 2018.

Green, P.E., Krieger, A.M., 1996. Individualized hybrid models for conjoint analysis, *Management Science* 42(6), 850–867.

Gui, L., Russo, A.P., 2011. Cruise ports: a strategic nexus between regions and global lines—evidence from the Mediterranean, *Maritime Policy & Management* 38(2), 129–150.

Hongmin, L., Woonghee, T.H., 2011. Pricing multiple products with the multinomial logit and nested logit models: concavity and implications, *Manufacturing & Service Operations Management* 13(4), 549–563.

Kimes, S.E., 1989. Yield management: a tool for capacity-considered service firms, *Journal of Operations Management* 8, 348–363.

Koppelman, F.S., Goldren, G.M., Parker, R.A., 2008. Schedule delay impacts on air-travel itinerary demand, T*ransportation Research Part B: Methodological* 42, 263–273.

Kuhfeld, W., 2000. *An Introduction to Designing Choice Experiments, and Collecting, Processing, and Analyzing Choice Data with the SAS System*. Cary: SAS Institute Inc..

Kuhfeld, W., 2010. *Marketing research methods in SAS*. Cary: SAS Institute Inc..

Li, B., 2011. The multinomial logit model revisited: A semi-parametric approach in discrete choice analysis, T*ransportation Research Part B: Methodological* 45(3), 461–473.

Maddah, B., Moussawi-Haidar, L., El-Taha, M., Rida, H., 2010. Dynamic cruise ship revenue management, *European Journal of Operational Research* 207(1), 445–455.

Meng, Q., Wang, S., Andersson, H., Thun, K., 2014. Containership routing and scheduling in liner shipping: overview and future research directions, *Transportation Science* 48 (2), 265–280.

Ng, M.W., 2014. Distribution-free vessel deployment for liner shipping, *European Journal of Operational Research* 238(3), 858–862.

Ng, M.W., 2015. Container vessel fleet deployment for liner shipping with stochastic dependencies in shipping demand, *Transportation Research Part B* 74, 79–87.

Paat, R., Huseyin, T., 2012. Robust assortment optimization in revenue management under the multinomial logit choice model, *Operation Research* 60(4), 865–882.

Pang, K.W., Liu, J., 2014. An integrated model for ship routing with transshipment and berth allocation, *IIE Transactions* 46(12), 1357–1370.

Qi, X.T., Song, D.P., 2012. Minimizing fuel emissions by optimizing vessel schedules in liner shipping with uncertain port times, *Transportation Research Part E* 48(4), 863–880.

Rodrigue, J., Notteboom, T., 2013. The geography of cruises: Itineraries, not destinations, *Applied Geography* 38, 31–42.

Royal Caribbean International, 2016. Cruise itineraries sailing to the Caribbean area. http://www.royalcaribbean.com/cruises?destinationRegionCode_CARIB=true. Accessed 22 Aug 2016.

Shintani, K., Imai, A., Nishimura, E., Papadimitriou, S., 2007. The container shipping network design problem with empty container repositioning, *Transportation Research Part E* 43(1), 39–59.

Ship & Bunker, 2015. Bunker prices. http://shipandbunker.com/prices#IFO380. Accessed 8 September 2015.

Song, D.P. and Dong, J.X. 2011. Effectiveness of an empty container repositioning policy with flexible destination ports, *Transport Policy* 18 (1), 92–101.

Song, D.P. and Dong, J.X. 2012. Cargo routing and empty container repositioning in multiple shipping service routes, *Transportation Research Part B* 46(10), 1556–1575.

Song, D.P. and Dong, J.X. 2013. Long-haul liner service route design with ship deployment and empty container repositioning, *Transportation Research Part B* 55, 188–211.

Soriani, S., Bertazzon, S., Cesare, F.D., Rech, G., 2009. Cruising in the Mediterranean: structural aspects and evolutionary trends, *Maritime Policy & Management* 36(3), 235–251.

Statista, 2015. Cruise industry—Statista Dossier: Facts and statistics on the cruise industry. http://www.statista.com/study/11547/cruise-line-industry-statista-dossier/. Accessed 28 Aug 2015.

Talluri, K., van Ryzin, J., 2004. *The Theory and Practice of Revenue Management*, Kluwer Academic, Boston.

Toubia, O., Hauser, J., Garcia, R., 2007. Probabilistic polyhedral methods for adaptive choice-based conjoint analysis: theory and application, *Marketing Science* 26(5), 596–610.

Toth, P., Vigo, D., 2001. *The Vehicle Routing Problem*. Society for Industrial and Applied Mathematics, Philadelphia.

Vermeulen, B., Goos, P., & Vandebroek, M., 2008. Models and optimal designs for conjoint choice experiments including a no-choice option. *International Journal of Research in Marketing* 25(2), 94–103.

Veronneau, S., Roy, J., 2009. Global service supply chains: An empirical study of current practices and challenges of a cruise line corporation, *Tourism Management* 30, 128–139.

Veronneau, S., Roy, J., Beaulieu, M., 2015. Cruise ship suppliers: A field study of the supplier relationship characteristics in a service supply chain, *Tourism Management Perspectives* 16, 76–84.

Wang, K., Wang, S., Zhen, L., Qu, X., 2016. Cruise shipping review: Operations planning and research planning. *Maritime Business Review* 1(2), 133-148.

Wang, S., Meng, Q., 2012a. Robust schedule design for liner shipping services, *Transportation Research Part E* 48(6), 1093–1106

Wang, S., Meng, Q., 2012b. Liner ship route schedule design with sea contingency time and port time uncertainty, *Transportation Research Part B* 46(5), 615–633.

Wang. S., Meng. Q., Liu. Z., 2013. Bunker consumption optimization methods in shipping: A critical review and extensions, *Transportation Research Part E: Logistics and Transportation Review* 53, 49–62.

Wang. S., Wang. H., Meng. Q., 2015. Itinerary provision and pricing in container liner shipping revenue management, *Transportation Research Part E: Logistics and Transportation Review* 77, 135–146.

Xie, H., Kerstetter, D.L., Mattila, A.S., 2012. The attributes of a cruise ship that influence the decision making of cruisers and potential cruisers, *International Journal of Hospitality Management* 31, 152–159.

Chapter 5: Cruise Ship Service Planning

This chapter addresses a decision problem on planning cruise services for a cruise ship so as to maximize the total profit during a planning horizon. The service is a sequence of ports (harbor cities) the cruise ship visits. In this decision problem, the constraint about the availability of berths at each port is taken into account. In reality, if a cruise service is executed by the ship repeatedly for several times, the profit earned by the cruise service in each time decreases gradually. This effect of decreasing marginal profit is also considered in this study. We propose a nonlinear integer programming model to cater to the concavity of the function for the profit of operating a cruise service repeatedly. To solve the nonlinear model, two linearization methods are developed, one of which takes advantage of the concavity for a tailored linearization. Some properties of the problem are also investigated and proved by using dynamic programming (DP) and two commonly used heuristics. In particular, we prove that if there is only one candidate cruise service, a greedy algorithm can derive the optimal solution. Numerical experiments are conducted to validate the effectiveness of the proposed models and the efficiency of the proposed linearization methods. In case some parameters needed by the model are estimated inexactly, the proposed decision model demonstrates its robustness and can still obtain a near-optimal plan, which is verified by experiments based on extensive real cases.

5.1 INTRODUCTION

In the cruising industry, service planning is often independent among different cruise ships, and planning problems of different cruise ships can be solved individually. According to Rodrigue and Notteboom (2013), the cruise ship deployment focuses on a specific cruise ship rather than a fleet of cruise ships. Cruise ships are often unique, even if the cruise ships have the same capacity (in passengers), different cruise ships have significantly different onboard activities, which are part of cruising experience. The same cruise route traversed by two cruise ships constructs two different cruise services, as the onboard activities are different. Our research is applicable to this situation. If two ships are very similar and serve the same region and visit common ports of call, then the competition between the services provided by the ships have to be accounted for.

This study assumes that when a cruise ship is repositioned to a new region, a home port and a set of candidate cruise services are chosen in advance and addresses the Cruise Service Planning (CSP) problem. This problem aims to determine how to plan cruise services for the cruise ship to operate in the region for a period of time. In other words, over the period of time, how to choose cruise services from the candidate cruise services for the cruise ship to operate in order to maximize total profit. However, the solution to the problem is not as straightforward as it seems. In a cruise service, there are several ports of call for the cruise ship to visit. Therefore, the berth availability of the ports of call should be considered when operating a cruise service. For instance, Wusong Kou terminal is a cruise terminal in Shanghai (China) with two available berths. Based on the arrival schedule of the terminal for the incoming cruise ships in the Year 2016, on a specific day, there might be two cruise ships scheduled to moor at the terminal. If the cruise service operated by the cruise ship also arrives at the terminal on that day on schedule, the cruise service is unable to be operated due to the lack of berth.

Determining whether to choose a cruise service for the cruise ship is based on the scheduled rotation time of the service and the marginal profit of operating the service (i.e., the operating profit). Empirically, operating a cruise service with a high daily operating profit (i.e., the operating profit divided by the service's rotation time) is more likely to cater to the preference of the cruise ship. Whereas, a preferable cruise service might not be always profitable in a planning horizon: the marginal profit of operating a cruise service is not constant in the real situation. If a cruise service is repeated several times, its marginal profit decreases gradually. This phenomenon attributes to that few potential cruise passengers would order a cruise service if the cruise service has been repeated many times. Therefore, the effect of the decreasing marginal profit should also be considered in the CSP problem.

Based on the above analysis, this paper presents an explorative study on the CSP problem considering berth availability and decreasing marginal profit, in which optimal services for a cruise ship to operate are to be determined. In our study, we first build an integer linear model assuming that the marginal profit of operating a cruise service is constant. Then, an integer nonlinear model is formulated as a general problem, and two methods are proposed to linearize the model. One of the two methods takes advantage of the concavity for a tailored linearization, and the model linearized by this method is more efficient to be solved based on computational results. Some properties of the problem are also investigated and proved. By using DP, we investigate the NP-hardness of the problem under different cases. By analyzing some commonly used heuristics, we prove some useful theorems, for example, we prove that if there is only one candidate cruise service, a greedy algorithm can derive the optimal solution. The effectiveness of the proposed models is verified by extensive numerical experiments. Lastly, based on extensive real cases, robustness tests are conducted to show that in case some parameters needed by the model are estimated inexactly, the proposed decision model has its robustness and can still obtain a near-optimal plan.

The remainder of this chapter is organized as follows. Section 5.2 reviews the related works. Section 5.3 presents a brief problem description and proposes mathematical models. Complexity analysis and extensive comparison with heuristics are conducted in Section 5.4.

The results of numerical experiments are reported in Section 5.5. Conclusions are then outlined in the last section.

5.2 LITERATURE REVIEW

The cruise shipping related studies could belong to the area of tourism research as cruise ships provide cruise passengers with tourism service. Meanwhile, it can be also sorted into the area of maritime research as the cruise services are akin to container liner services. However, the past research on cruise shipping is limited, the reason of which may include: (i) the worldwide cruise ship tourism just accounts for about 2% of the world tourism market revenue, thus the tourism-related researchers have not paid much attention to the cruise shipping related studies (Gui and Russo, 2011); (ii) the maritime logistic related researchers mainly focus on freight transportation (e.g., Bell et al., 2011; Meng and Wang, 2012; Song et al., 2015).

The majority of past research on the cruise shipping analyzed the cruising industry as a tourism service supply chain. Gui and Russo (2011) constructed an analytic framework connecting the global structure of cruise value chains to the regional land-based cruise services. The demand side and the supply side of the cruise shipping at the worldwide level were analyzed by Soriani et al. (2009). They also investigated the main characteristics of the cruising in the Mediterranean region and examined the main cruising ports in the region. A field study of a large Florida-based global cruise company's practices in re-supplying ships globally was conducted by Veronneau and Roy (2009), which makes them amongst the first to take a comprehensive study of a specific service supply chain. Veronneau et al. (2015) investigated the relationships between a major cruise line corporation and its suppliers by a field study. Rodrigue and Notteboom (2013) focused on capacity deployment and itineraries in two important markets: the Caribbean and Mediterranean. They found that these two market areas interact with each other due to seasonal variations in demand.

Although those researchers devoted significant efforts into cruising shipping research, their works are mainly descriptive and belong to empirical studies. The majority of existing related works did not provide the cruise industry with quantitative analysis on cruise shipping, which could be critical for some detailed problems. Maddah et al. (2010) conducted a quantitative study on cruise shipping, in which a discrete-time dynamic capacity control model was built to improve the profit of cruise ships. Their model could give cruise ship managers some suggestions about which requests from customers should be accepted based on the remaining cabin and lifeboat capacities and the type of requests. The research is adaptable for cruise companies to improve profit, and it focuses on an operational level problem. As the cruising industry has developed dramatically, more research efforts should be made on the problems in strategic level or tactical level.

The cruise shipping and the container liner shipping have something in common in the sense of research. They both follow a designed itinerary to finish service for customers on the sea and visit selected ports of call in the route. However, in contrast to the cruise shipping, there are tremendous research works on the container liner shipping. The examples are given as follows. Meng et al. (2012) proposed a liner ship fleet planning problem considering container transshipment and uncertain container shipment demand. A liner container seasonal shipping revenue management problem for a container shipping company was researched by Wang et al. (2015). Song et al. (2015) addressed a joint tactical planning problem for deciding the number of ships, the planned maximum sailing speed, and the liner service schedule. Ship deployment and empty container repositioning related problems were investigated by Song et al. (2012) and Song et al. (2013). Ng (2014, 2015) studied fleet deployment-related problems for liner shipping under stochastic environment. A cost-based maritime container assignment model was formulated by Bell et al. (2013) to assign containers to routes to minimize the total operational cost. More related works can be referred to Meng et al. (2014) for a review of container liner service operations and planning. The majority of those works drew attention to practical problems existing in the container liner shipping and developed useful optimization-based planning tools.

Although the cruise services are akin to the container liner services, we cannot simply transfer the methods used in the container liner shipping to the applications for the problems related to the cruise shipping. There are some essential differences between them. For example, the problems in the container liner shipping normally did not consider the berth availability in ports of call. This is due to that the major container transshipment terminals (e.g., the container terminals in Hong Kong and Singapore) have abundant berth resource, and useful berth allocation techniques have been proposed by port logistic researchers (e.g., Meisel and Bierwirth, 2009; Giallombardo et al., 2010; Zhen et al., 2011; Vacca et al., 2012; Iris et al., 2015; Zhen, 2015), which give more flexibility for liner companies on the berth availability. However, the berths in major cruise terminals are quite limited. For example, Wusong Kou cruise terminal (Shanghai) and Kai Tak cruise terminal (Hong Kong) just have the berth capacity to serve two cruise ships simultaneously. Therefore, the berth availability should be emphasized in the cruise shipping-related problems. Moreover, the container liner services are normally designed for repeats on a weekly basis, and the weekly demands from customers are close to constant (except for some special weeks, such as the Chinese New Year week and the Christmas week). Thus, the fluctuation of the profit for a container liner service is little. In comparison, the cruise services appeal to the cruise passengers for their feeling of freshness (Esteve-Perez and Garcia-Sanchez, 2014), which requires the diversity of the cruise services. New and interesting cruise services should be provided frequently, and the multiple repeats on a cruise service would bring significant decreasing on its marginal profit. Based on these facts and discussions, the problems arising in the cruise shipping are different from the problems existing in the container liner shipping inessential.

The decreasing marginal profit phenomenon is widely considered in the research works in operations management or operations research area (Arthur and Ronald, 2000; Hongmin and Woonghee, 2011; Li, 2011; Paat and Huseyin, 2012). However, there are limited research works in maritime transportation area that considers the decreasing marginal profit or decreasing marginal productivity. Meisel and Bierwirth (2009) and Iris et al. (2015) investigated the integrated problem of berth allocation and quay crane assignment for container terminals, in which they considered the decrease of marginal productivity of quay cranes assigned to the vessels.

In our research, we address a tactical problem in cruise shipping: the cruise service planning problem considering the berth availability and decreasing marginal profit. In fact, this problem is a variant of knapsack problem (will be elaborated in Section 5.4). The major structural difference between our problem and some nonlinear/nonconvex extensions to the knapsack problem (Bretthauer and Shetty, 2002; Kameshwaran and Narahari, 2009; Poirriez et al., 2009) is that the berth availability constraints in our setting are not well structured in the past extensions. We cannot simply take advantage of the existing algorithms for the knapsack problem and its extensions, all of which exploit the special structure that there are only linear constraints in the problems. Thus, for our problem, we explore optimization-based service planning tools to increase the profit by planning cruise services. Some mathematical models (both linear and nonlinear models) of the problem are formulated in order to contribute to the state-of-the-art research in a quantitative manner.

5.3 MATHEMATICAL MODEL

In this section, we provide a brief description of the CSP problem for a cruise ship considering the decreasing marginal profit and the berth availability and formulate it as integer programming models.

5.3.1 Problem description

The problem focuses on service planning for a specific cruise ship. Given a set of pre-determined candidate services (denoted by $\mathbb{R} = \{1, 2, \ldots, |\mathbb{R}|\}$) and a set of all days in a planning horizon with T days in total (denoted by $\mathbb{T} = \{1, 2, \ldots, T\}$), the optimization of the problem aims at selecting services for the cruise ship to operate in the planning horizon. Each candidate service $r \in \mathbb{R}$ has a pre-determined rotation time, defined as s_r (days), which indicates the number of days needed for the cruise ship to operate such a service. The marginal profit of operating Service r is denoted as g_r. The objective of the optimization is to maximize the total profit by the cruise ship to operate the services selected from the set R in the planning horizon.

In this problem, we consider the berth availability of the visiting ports of call in all the candidate services. In each day in the planning horizon, each port either has an available berth or not for the cruise ship, which is known to the cruise ship in advance. A service can be operated if and only if each port in the service has an available berth for the cruise ship. To indicate the availability of berths at the ports visited during the planning horizon, we further define a binary parameter $\delta_{rt}, \forall r \in \mathbb{R}, t \in \mathbb{T}$. Here, δ_{rt} equals one if and only if Service r can be operated starting from 0:00 am in Day t, which means that all the visiting ports in Service r have available berths for the cruise ship in future arrival times if the service starts from 0:00 am (Day t). For instance, suppose there is a cruise service r': Shanghai (China)→Cheju (Korea)→Fukuoka (Japan)→Shanghai (China). The itinerary for the cruise service is given in Table 5.1. $\delta_{r'2}$ is set to one when the cruise ship can operate the cruise service r' starting from Day 2 of the planning horizon. Meanwhile, along the cruise route in the planning horizon, it has all available berths to moor at Shanghai (China) in Day 2, Cheju (Korea) in Day 3, Fukuoka (Japan) in Day 5 & Day 6, and Shanghai (China) in Day 10. Normally, the cruise ship arrives at a port around 6:00 am, and leaves from the port around 5:00 pm such that the cruise passengers could tour around the port city in daytime. Thus, the berth in the port is usually occupied by the cruise ship for a whole day. However, the berth can be occupied by the cruise ship for two or three days if more tour time is arranged for onshore activities.

Table 5.1: The itinerary for the cruise service

Day 1	**Day 2**	**Day 3**	**Day 4**	**Day 5**	**Day 6**	**Day 7**	**Day 8**	**Day 9**
Shanghai	Cheju	*Sea*	Fukuoka	Fukuoka	*Sea*	*Sea*	*Sea*	Shanghai

When planning services for the cruise ship in the planning horizon, we assume that all the services must be finished before T. To ensure this assumption, we initially set input data δ_{rt} in the following way: for each candidate service r with rotation time s_r, $\delta_{rt} \coloneqq 0$ if t is bigger than $T - s_r + 1$. This setting can guarantee that all the services are finished within the planning horizon.

For the interest of simplicity, firstly, this study assumes that the marginal profit of operating Service r is constant when the service is repeated several times. Under this assumption, an integer programming model is formulated, denoted as model $FM1$. Then, in order to be close to the real situation, we change the profit setting to that the marginal profit of operating a service decreases when the service is repeated several times. Based on this, a nonlinear integer programming model is formulated, denoted as model $FM2$.

5.3.2 Model with constant marginal profit

As we have defined the rotation times of services $s_r, \forall r \in \mathbb{R}$, the profits of operating services $g_r, \forall r \in \mathbb{R}$, the planning horizon $t \in \mathbb{T} = \{1, 2, \cdots, T-1, T\}$, and the berth availability $\delta_{rt}, \forall r \in \mathbb{R}, t \in \mathbb{T}$, we further define decision variables as $z_{rt}, \forall r \in \mathbb{R}, t \in \mathbb{T}$, which equals one if and only if Service r is operated starting from 0:00 am (Day t). Then, the model $FM1$ can be formulated as follows:

$$[\boldsymbol{FM1}] \text{ Maximize } \quad \sum_{t\in\mathbb{T}} \sum_{r\in\mathbb{R}} g_r z_{rt} \tag{5.1}$$

$$s.t. \quad z_{rt} \leq \delta_{rt} \qquad \forall r \in \mathbb{R}, t \in \mathbb{T} \tag{5.2}$$

$$\sum_{r\in\mathbb{R}} \sum_{t'=\max(t-s_r+1,1)}^{t} z_{rt'} \leq 1 \qquad \forall t \in \mathbb{T} \tag{5.3}$$

$$z_{rt} \in \{0, 1\} \qquad \forall r \in \mathbb{R}, t \in \mathbb{T}. \tag{5.4}$$

In the above model $FM1$, Objective (5.1) maximizes the total profit by selecting cruise services from a set of pre-determined candidate services in the planning horizon. Constraints (5.2) ensure that all the designed services are operable considering the availability of berths at the ports visited. Constraints (5.3) guarantee that in each day, the cruise ship operates at most one cruise service, and once a cruise service is finished, the next cruise service can be started. There is no rotation time overlap between the two selected cruise services in the planning horizon. Constraints (5.4) define the domains of the binary decision variables.

5.3.3 Model with decreasing marginal profit

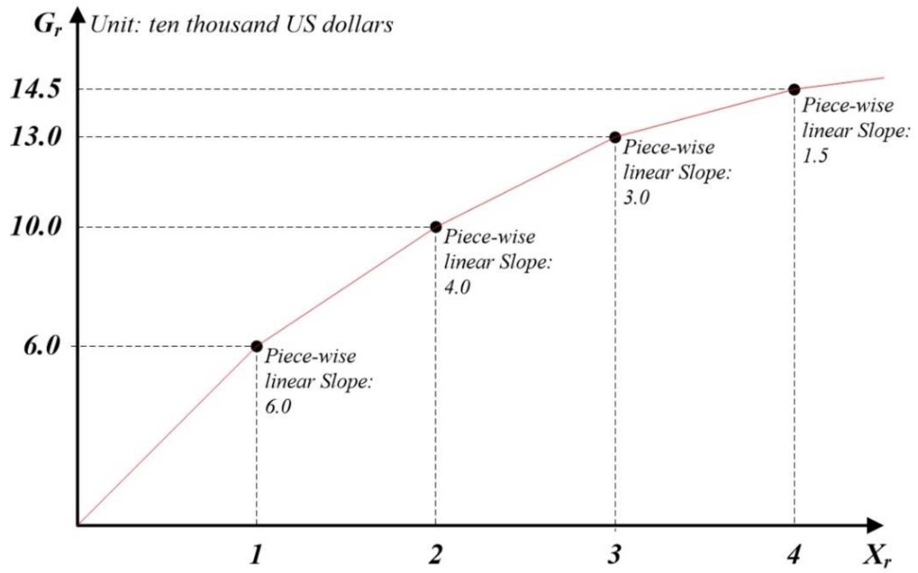


Figure 5.1: Concavity of the profit function

In the model with decreasing marginal profit, we assume that when a service is repeated for several times, the marginal profit of the service will decrease gradually. This consideration makes the problem close to the reality as few potential passengers would choose a cruise service when the cruise service has been repeated many times. To show the decreasing pattern of the marginal profit in the model, we define a strictly increasing concave function $G_r(x_r)$ as the total profit for operating Service $r \in \mathbb{R}$ by a total of x_r times, which can be designed as follows:

$$G_r(x_r) < G_r(x_r + 1) \tag{5.5}$$

$$G_r(x_r + 2) - G_r(x_r + 1) \leq G_r(x_r + 1) - G_r(x_r). \tag{5.6}$$

Figure 5.1 demonstrates the concavity of the function on the total profit for operating a service repeatedly.

Based on the above concave function, the model with decreasing marginal profit (i.e., $FM2$) can be formulated as follows:

$$[\boldsymbol{FM2}] \text{ Maximize } \quad \sum_{r\in\mathbb{R}} G_r(x_r) \tag{5.7}$$

s.t. Constraints (5.2)-(5.4) and;

$$x_r = \sum_{t=1}^{T} z_{rt} \qquad \forall r \in \mathbb{R}. \tag{5.8}$$

In this model, Objective (5.7) maximizes the sum of the total profits for operating services. Constraints (5.8) are used to calculate the number of repeats for each service.

However, $FM2$ is a nonlinear model as it involves the concave objective function, which makes it hard to be solved by some efficient solution methods. Thus, we present two transformed linear models for $FM2$. Before building the two linear models, we define $\overline{x}_r$ as an upper bound of the number of repeats x_r for Service r. $\overline{x}_r$ can be calculated by:

$$\overline{x}_r = \left\lfloor \frac{T}{s_r} \right\rfloor \qquad \forall r \in \mathbb{R}. \tag{5.9}$$

Here, it is worthwhile to mention that there is a better way to derive the upper bound of the number of repeats for Service r. We propose a greedy algorithm to find the maximum number of repeats for Service r in the planning horizon (note that the greedy algorithm is applied to derive optimal $\overline{x}_r$ in the numerical experiments in Section 5.5), which is a tighter upper bound compared with Eq. (5.9). The details of the greedy algorithm and why the greedy algorithm can find the optimal number of repeats for Service r will be given in the proof of Proposition 5 in Section 5.4.3.

The first linear model:

The first linear model is defined as $FM2'$, which does not take advantage of the problem structure for the linearization. In this linear model, $g_{rx} := G_r(x) - G_r(x-1)$ is used to define the marginal profit of the x^{th} repeat of Service r. Meanwhile, the binary decision variable (i.e., z_{rt},) in $FM2$ is changed to another binary decision variable denoted by z_{rxt} , $\forall r \in \mathbb{R}, x \in \{1, 2 \cdots \overline{x}_r\}, t \in \mathbb{T}$. Here, z_{rxt} equals one if and only if Service r is operated for the x^{th} time starting from 0:00 am (Day t). Based on the above redefinition of some variables, the formulation of $FM2'$ is:

$$[\boldsymbol{FM2'}] \text{ Maximize } \quad \sum_{t\in\mathbb{T}} \sum_{r\in\mathbb{R}} \sum_{x=1}^{\overline{x}_r} g_{ry} z_{rxt} \tag{5.10}$$

$$s.t. \quad z_{rxt} \leq \delta_{rt} \qquad \forall r \in \mathbb{R}, x \in \{1, 2 \cdots, \overline{x}_r\}, t \in \mathbb{T} \tag{5.11}$$

$$\sum_{r\in\mathbb{R}}\sum_{t'=\max(t-s_r+1,1)}^{t}\sum_{x=1}^{\overline{x}_r} z_{rxt'} \leq 1 \qquad \forall t \in \mathbb{T} \tag{5.12}$$

$$\sum_{t=1}^{T} z_{rxt} \leq 1 \qquad \forall r \in \mathbb{R}, x \in \{1, 2 \cdots, \overline{x}_r\} \tag{5.13}$$

$$\sum_{t=1}^{T} tz_{rxt} + s_r - 1 \leq \sum_{t=1}^{T} tz_{r,x+1,t} + T\left(1 - \sum_{t=1}^{T} z_{r,x+1,t}\right) \quad \forall r \in \mathbb{R}, x \in \{1, \cdots, \overline{x}_r - 1\} \tag{5.14}$$

$$z_{rxt} \in \{0, 1\} \qquad \forall r \in \mathbb{R}, x \in \{1, 2 \cdots, \overline{x}_r\}, t \in \mathbb{T}. \tag{5.15}$$

In the above model $FM2'$, Objective (5.10) maximizes the sum of the total profits in the planning horizon. Constraints (5.11) guarantee that all the selected services satisfy the availability constraints of berths at the ports visited. Constraints (5.12) limit that the cruise ship can only provide one service in one day and once a service r starts, the ship cannot provide other services in s_r days. Constraints (5.13) guarantee that each repeat of each service (e.g., the x^{th} repeat of Service r) can only be operated by the cruise ship at most one time. Constraints (5.14) enforce that for each service, all the repeats must have a chronological order, which means a latter repeat cannot be started before a former repeat. Constraints (5.15) define the domains of the binary decision variables. Note that in the above formulation, for each service, a former repeat will be selected prior to a latter repeat as the marginal profit of the former is higher than that of the latter.

Constraints (5.14) could be removed to reduce the computational time for the model $FM2'$. Without Constraints (5.14), the optimal objective value is still the same, but the optimal solution for the model might be infeasible for the problem as some latter repeats might be started before some former repeats in a chronological order. However, the infeasible situation can be sorted manually by adjusting the chronological order for the repeats of a cruise service. The above tactic will be tested and verified in the computational experiment section.

The second linear model:

The second linear model is defined as $FM2''$, which is formulated by taking advantage of the concavity of $G_r(x_r)$ (Premoli, 1986). In order to build this linear model, we introduce continuous variables $u_r, \forall r \in \mathbb{R}$ that represent the total profit by operating Service r repeatedly. With the continuous variables, the formulation of $FM2'$ is:

$$[\boldsymbol{FM2''}] \quad \text{Maximize} \quad \sum_{r\in\mathbb{R}} u_r \tag{5.16}$$

s.t. Constraints (5.2-5.4); (5.8);

$$u_r \leq G_r(x) + \frac{G_r(x+1) - G_r(x)}{(x+1) - x}(x_r - x) \qquad \forall r \in \mathbb{R}, x \in \{0,1, \cdots, \overline{x}_r - 1\}. \tag{5.17}$$

In this model, Objective (5.16) maximizes the sum of the total profits for operating services by repeating different times. Constraints (5.17) are used to calculate the total profit of each service in a linear manner. Here, notice that $G_r(0) \coloneqq 0, \forall r \in \mathbb{R}$.

Both linear models provide the linearization for the nonlinear model (i.e., $FM2$), which will be further compared in Section 5.5 for the computation efficiency to solve the problem.

5.4 COMPLEXITY ANALYSIS AND COMPARISON WITH HEURISTICS

In this section, for the complexity analysis, two dynamic programming (DP) based pseudo-polynomial algorithms are developed for the model $FM1$ and the model $FM2$ respectively. Some properties on commonly used heuristic methods for the CSP problem are also investigated and proved.

5.4.1 Complexity of the problem of $FM1$ with constant marginal profit

Proposition 5.1: The problem of $FM1$ is NP-hard.

Proof: Suppose all ports always have berths for the cruise ship, which means no matter which services have been chosen for the planning horizon, the cruise ship always has the available berths to dwelling whenever it arrives at the ports in the services. Then, the $FM1$ becomes a problem of maximizing the total profit by choosing a number of services from the set of candidate services with different rotation times and profits. This is exactly an unbounded knapsack (Poirriez et al., 2009). Since the knapsack problem is NP-hard, the general version of the problem of $FM1$ is also NP-hard. ■

Proposition 5.2: The problem of $FM1$ is weakly NP-hard.

Proof: We can propose a DP based pseudo-polynomial algorithm for the problem, which could demonstrate that the problem of $FM1$ is weakly NP-hard. The procedures of the DP algorithm are elaborated as follows:

To apply the DP for the problem of $FM1$, we firstly define $U(t)$ as the maximum possible total profit of operating services (to be determined) from 0:00 am (Day t) to the end of Day T, i.e., 0:00 am (Day $T+1$). Then, we make the decision for each day whether choosing a service to start or designating the cruise ship to stay in the harbor of the home port. Let z_{rt} denote the binary variable of the decision, which equals one if and only if Service r is started in Day t. We initially have the boundary conditions as:

$$U(t) = -\infty \qquad t = T+2, T+3, \dots \tag{5.18}$$

$$U(t) = 0 \qquad t = T+1. \tag{5.19}$$

The DP consists of T stages (for t decreasing from T to 1) and computes the total profit at each stage $t \in \mathbb{T}$ based on choosing a service to start or designating the cruise ship to stay in the harbor of the home port for one day, by using classical Bellman recursion:

$$U(t) = max_{r \in \mathbb{R}} \left\{ (1 - z_{rt}) \cdot U(t+1) + z_{rt} \cdot \left(g_r + U(t + s_r)\right) \,\middle|\, z_{rt} \le \delta_{rt}, z_{rt} \in \{0, 1\} \right\}$$
$$\forall t \in \mathbb{T}. \tag{5.20}$$

To calculate $U(t)$ at each stage, we firstly enumerate all the services and select feasible services by considering the availability of berths at the ports visited (δ_{rt}). Then, we start the feasible services one by one to derive the profits for the feasible services, and also calculate the profit when no service is started. Those profits are compared to obtain the maximal profit $U(t)$ at each stage.

Algorithm 5.1. *DP-based algorithm for the model FM1*

Input: A set of candidate services $r \in \mathbb{R}$, with operating profit g_r and rotation time s_r
Output: An optimal schedule to operate cruise services
// initialization
for $t \leftarrow T+1$ **to** 1 **do**
    $U(t) \leftarrow 0$
end for
for $t \leftarrow T+2$ **to** $T + \max\{s_r | \forall r \in \mathbb{R}\}$ **do**
    $U(t) \leftarrow -\infty$
end for
// the DP procedure
for $t \leftarrow T$ **to** 1 **do**
    $U(t) \leftarrow U(t+1)$
    for $r \leftarrow 1$ **to** $|\mathbb{R}|$ **do**
        if $U(t) < g_r + U(t+s_r)$ **and** $\delta_{rt} = 1$ **then**
            $U(t) \leftarrow g_r + U(t+s_r)$
        end if
    end for
end for

Finally, we will obtain the value $U(1)$, the objective value of $FM1$, which represents the maximum total profit of operating services from 0:00 am (Day t) to the end of Day T. The optimal solution can be extracted from the values of z^*_{rt}, $\forall r \in \mathbb{R}, t \in \mathbb{T}$. The pseudocode of this DP based algorithm is elaborated in *Algorithm 5.1*.

In summary, the proposed algorithm runs in $O(T \cdot |\mathbb{R}|)$ time for the solution. There are T stages in the proposed DP. The decision at each stage is which service $r \in \mathbb{R}$ to start or designating the cruise ship to stay in the harbor of the home port for one day. Therefore, the computational complexity for the DP is $T \cdot |\mathbb{R}|$, which demonstrates that the problem of $FM1$ is weakly NP-hard. ■

5.4.2 Complexity of the problem of $FM2$ with decreasing marginal profit

Corollary 5.1: The problem of $FM2$ is NP-hard.

Proof: The problem of $FM2$ nests the problem of $FM1$ as a special case. If we change Eq. (6) to $G_r(x_r+2) - G_r(x_r+1) = G_r(x_r+1) - G_r(x_r)$, $FM2$ becomes $FM1$. As $FM2$ is more general than $FM1$, and the problem of $FM1$ is NP-hard, the problem of $FM2$ is also NP-hard. ■

Here, we would like to investigate the problem of $FM2$ in a special case, in which we assume that all the ports in the candidate services have sufficient berth availability at any time for the cruise ship. The reasons for such investigation are listed as follows: (i) it can be used as a benchmark for cruise companies in the sense of the total profit. They could assess the maximal profit that can be earned when the berth availability is in a perfect condition. (ii)

Some cruise terminals are operated by cruise companies, thus, the investigation on the special case is meaningful for them to make investment decisions on berth construction. (iii) The special case is also useful for cruise port policy makers to evaluate whether the berth availability is the limitation for the local cruise shipping development.

Proposition 5.3: The problem of $FM2$ is weakly NP-hard in the special case with sufficient berth availability.

Proof: We can propose a DP based pseudo-polynomial algorithm for the special case of the problem, which demonstrates that special case is weekly NP-hard. The procedures of the DP algorithm are elaborated as follows:

In the special case for $FM2$, the availability of berths at the ports visited is sufficient, which means that all the ports in the services have available berths for the cruise ship at any time. The application of the DP is significantly different from that for the problem of $FM1$ as the decreasing pattern of the service marginal profit has been considered in the problem of $FM2$. Enlightened by the formulation of $FM2'$, in the DP for the special case of $FM2$, we assume that each combination of (r, x) is a "detailed service" with the marginal profit $g_{rx} \coloneqq G_r(x) - G_r(x-1)$, which denotes the x^{th} time for the repeat of Service r. Each "detailed service" can only be started for once in the planning horizon. Meanwhile, a latter "detailed service" cannot be started before a former "detailed service". For instance, $(r, 5)$ cannot be started if $(r, 4)$ has not been started. Here, we define an index β and a set $\mathbb{S}$, $\beta \in \mathbb{S}$ for all the possible "detailed services"; here $\mathbb{S} = \{(1,1), (1,2), \cdots, (1, \bar{x}_1), \cdots, (r, 1), (r, 2), \cdots, (r, \bar{x}_r)\}$. The upper bound for $|\mathbb{S}|$ is $|\mathbb{R}| \cdot T$.

In the case of the problem of $FM2$, we can deem the problem as: we are packing $|\mathbb{S}|$ "detailed services" with different profits and rotation times into a period of time T, which is a 0/1 knapsack problem. To build the DP for the case, We further define $V(\beta, t)$ as the maximum possible total profit of operating services (to be determined) from 0:00 am (Day 1) to the end of Day t (0:00 am of Day $t+1$) by choosing the services from first β "detailed services"; all of the operated services must finish by the end of Day t. Then, we make decisions at each stage on whether to place "detailed service" β to finish at the end of Day t or not. Based on the above information, we initially have the boundary conditions as:

$$V(0, t) := 0 \qquad \forall\, t \in \{0, 1, \cdots T\} \tag{5.21}$$

$$V(\beta, 0) := 0 \qquad \forall\, \beta = 1, 2, \ldots, |\mathbb{S}|. \tag{5.22}$$

The DP procedure consists of $|\mathbb{S}|$ service stages (for β increasing from 1 to $|\mathbb{S}|$) and computes the total profit at each stage $\beta \in \mathbb{S}$ with the time stage t increasing from 1 to T. The DP procedure uses the classical Bellman recursion as follows:

$$V(\beta, t) = \begin{cases} V(\beta - 1, t) & , if\ \ t < s'_\beta \\ \max\{V(\beta - 1, t),\ V(\beta - 1, t - s'_\beta) + g'_\beta\}, & if\ s'_\beta \le t \end{cases} \quad \forall \beta \in \mathbb{S}, t \in \mathcal{T} \tag{5.23}$$

where, s'_β, g'_β and $\delta'_{\beta t}$ equal to s_r, g_{rx} and δ_{rt}, respectively, if "detailed service" β is the x^{th} repeat for Service r ("detailed service" β is the combination of (r, x)). By conducting the recursion, we will obtain the value $V(|\mathbb{S}|, T)$, which represents the maximum total profit without considering the availability of berths at the ports (i.e., the availability of berths at the ports visited is sufficient all the time). The pseudocode of this DP based algorithm is elaborated in *Algorithm 5.2.*

Algorithm 5.2. *DP-based algorithm for the model FM2 in a special case*

Input: A set of candidate "detailed service" $\beta, \forall \beta \in \mathbb{S}$, with operating profit g'_β and rotation time s'_β
Output: An optimal schedule to operate "detailed service"
// initialization
for $t \leftarrow 0$ **to** T **do**
    $V(0, t) \leftarrow 0$
end for
for $\beta \leftarrow 1$ **to** $|\mathbb{S}|$ **do**
    $V(\beta, 0) \leftarrow 0$
end for
// the DP procedure
for $\beta \leftarrow 1$ **to** $|\mathbb{S}|$ **do**
    for $t \leftarrow 0$ **to** T **do**
        if $t < s'_\beta$ **then**
            $V(\beta, t) \leftarrow V(\beta - 1, t)$
        else
            if $V(\beta - 1, t) < V(\beta - 1, t - s'_\beta) + g'_\beta$ **then**
                $V(\beta, t) \leftarrow V(\beta - 1, t - s'_\beta) + g'_\beta$
            else
                $V(\beta, t) \leftarrow V(\beta - 1, t)$
            end if
        end if
    end for
end for

In summary, the model $FM2'$ enlightens us to consider each combination of (r, x) as a "detailed service". The problem becomes how to place detailed services into a period of time T to maximize the profit. Time complexity of the DP is $O(|\mathbb{S}| \cdot T)$, where $|\mathbb{S}| \leq |\mathbb{R}| \cdot T$. Thus, time complexity of the DP is bounded by $O(|\mathbb{R}| \cdot T^2)$ and the DP algorithm is a pseudo-polynomial algorithm, which show that the special case is weekly NP-hard. ■

For the general case of the problem of $FM2$ with considering the berth availability and decreasing marginal profit, we cannot propose a pseudo-polynomial algorithm using DP. Therefore, the two linear models $FM2'$ and $FM2''$ are solved directly by CPLEX for the optimal solutions of $FM2$.

5.4.3 Comparison with commonly used heuristics

The models and the solution methods (the DP-based algorithms) solve the CSP problem optimally under different assumptions. However, in a real situation, there are some commonly used myopic heuristics to solve the CSP problem. In this section, the properties of the solutions obtained by those heuristics and the optimal solutions are investigated for the general case with decreasing marginal profit.

In the knapsack problem and its variants, there are two commonly used heuristics: operating-profit-first heuristic and unit-profit-first heuristic. For the example of the special case of the model $FM2$ mentioned in the previous section (a variant of the knapsack problem), the two heuristics are as follows. (i) The operating-profit-first heuristic: according to the sequence of the profits of "detailed services" such that $g'_1 \geq g'_2 \geq \cdots \geq g'_{|\mathbb{S}|}$, we put the "detailed services" into the planning horizon sequentially until it is not possible to place more "detailed services". (ii) The unit-profit-first heuristic: a service's unit profit is the service's operational profit divided by the service's rotation time. According to the sequence of the unit profits of the "detailed services" such that $\frac{g'_1}{s'_1} \geq \frac{g'_2}{s'_2} \geq \cdots \geq \frac{g'_{|\mathbb{S}|}}{s'_{|\mathbb{S}|}}$, we put the "detailed services" into the planning horizon sequentially until it is impossible to place more "detailed services".

Based on the above two commonly used heuristics, we can design two myopic heuristic rules to solve the general case of the model $FM2$ when considering the berth availability, in which the decision is made on a daily basis from Day 1 to Day T.

Myopic Rule_1: For a specified Day t, we determine all the cruise services that can be operated with considering the berth availability (i.e., $\forall r,\ \delta_{rt} = 1$). Based on those cruise services, we select the optimal cruise service r^* with the maximal daily operating profit (i.e., g_{r^*}/s_{r^*}). Then, the time is updated to Day $t + s_{r^*}$ for the next selection. If no cruise service can be operated, the time is updated to Day $t + 1$ for the next selection.

Myopic Rule_2: For a specified Day t, we determine all the cruise services that can be operated with considering the berth availability (i.e., $\forall r,\ \delta_{rt} = 1$) at first. Among those cruise services, we select the optimal cruise service r^* with the maximal operating profit (i.e., g_{r^*}) to operate. Then, the time is updated to Day $t + s_{r^*}$ for the next selection. If no cruise service can be operated, the time is updated to Day $t + 1$ for the next selection. Notice that if two cruise services have the same daily operating profit or the same operating profit in the rules, the priority will be given to the cruise service with shorter rotation time as it would occupy few days in the planning horizon.

Here, Myopic Rule_1 (Myopic Rule_2) is designed by the unit-profit-first heuristic (the operating-profit-first heuristic) as it selects the optimal cruise service r^* with the maximal daily operating profit g_{r^*}/s_{r^*} (with the maximal operating profit g_{r^*}). The solutions obtained by two myopic rules will be further compared with the optimal solutions in Section 5.3.

Proposition 5.4: In the worst case, the ratio between the optimal profit obtained by the model $FM2$ and the profit obtained by Myopic Rule_1 or Myopic Rule_2 is close to infinity.

Proof: Let Z^* be the optimal total profit derived by the model $FM2$, $\ddot{Z}$ the total profit derived by the Myopic Rule_1, and $\hat{Z}$ the total profit derived by the Myopic Rule_2.

Assuming that the number of days in the planning horizon is $T > 2$, and there are two candidate cruise services with the operating profits and rotation times as follows: $g_1 = k,\ s_1' = 2$; $g_2 = n \cdot k,\ s_2' = T - 1$. Here, k is a profit constant with unit of US$, and n is a ratio that is bigger than one. Assume that Cruise service 1 can be operated on Day 1 and Cruise service 2 cannot be operated on Day 1 due to berth unavailability. Then, Cruise service 2 can be in Day 2 and Cruise service 1 cannot be operated since Day 2 due to the berth availability. In such situation, the profits derived by two heuristic rules are $\ddot{Z} = \hat{Z} = g_1 = k$, but the optimal total profit is $Z^* = n \cdot k$. Thus, the ratio between the optimal total profit and the total profit obtained by Myopic Rule_1 or Myopic Rule_2 is n. When $n \to +\infty$, the ratio is close to infinity. ■

For the CSP problem considering berth availability, the two commonly used heuristic rules do not give the priority on the berth availability, which leads to tremendous profit loss. Thus, in cruise shipping, the operation managers should keep well informed about the berth availability from cruise terminals. Based on the information, the managers should make schedules on the overall picture for a whole period rather than from day to day. In reality, it is impossible to guarantee the sufficient berth availability in all cruise terminals, but we do encourage that the cruise lines own some cruise terminals such that they have more flexibility on berths to operate their cruise services.

Proposition 5.5: When there is only one candidate cruise service r', the solution obtained by Myopic Rule_1 or Myopic Rule_2 is the optimal solution of the model $FM2$.

Proof: When there is only one candidate cruise service r', the rotation time is constant, then we can transfer the two myopic heuristic rules to a greedy algorithm for the problem, in which the decision is made on a daily basis from Day 1 to Day T: for a specified Day t, if the cruise service r' can be operated with considering the berth availability, this cruise service is settled for the operation. Then, the time is updated to Day $t + s_{r'}$ for the next decision. Otherwise, the time is updated to Day $t + 1$ for the next decision.

As there is only and one candidate cruise service (the cruise service r'), the objective of the model $FM2$ aims to maximize the total profit earned by the one cruise service (maximize $Z = G_{r'}(x_{r'})$). Based on the concavity of the function $G_{r'}(x_{r'})$, as it is shown in Figure 5.1, the objective of the model $FM2$ is consistent with aiming to maximize $x_{r'}$ (i.e., maximize the number of repeats of the cruise service r').

Here, we define the number of repeats $x_{r'}$ obtained by the greedy algorithm as N, and the optimal number of repeats obtained by the model $FM2$ as M^*, where $M^* \geq N$. We denote φ_i ($\forall i \in \{1,2,\dots,N\}$) as the start time of i^{th} repeat in the solution obtained by the greedy algorithm, and denote ϕ_j ($\forall j \in \{1,2,\dots,M^*\}$) as the start time of j^{th} repeat in the optimal solution obtained by the model $FM2$.

Firstly, we arbitrarily assume that $M^* > N$. As the greedy algorithm would start a repeat as early as possible once it finds a day when the berths are available, we can have a conclusion that is $\varphi_1 \leq \phi_1$. As $M^* > N$, there must exist a k such that $\varphi_k > \phi_k$, where $k \in [2, N]$. If there is no such k, there exist $\varphi_N \leq \phi_N$, which means the last repeat (the N^{th} repeat) in the solution obtained by the greedy algorithm starts the repeat earlier than the N^{th} repeat in the optimal solution, and the former N^{th} repeat ends before the latter N^{th} repeat. This suggests that the greedy algorithm still have enough residual time space in the planning horizon to operate the $N+1^{th}$ repeat, which is in the conflict with the definition. Therefore, there must exist a k such that $\varphi_k > \phi_k$. As we have proved that $\varphi_1 \leq \phi_1$, there exist $\varphi_i \leq \phi_i, \forall i \in \{1,2,\dots,k-1\}$ and $\varphi_j > \phi_j, \forall j \in \{k, k+1, \dots, N\}$. Here, comes another conflict: in the solution obtained by the greedy algorithm, the $(k-1)^{th}$ repeat starts to be operated earlier than the $(k-1)^{th}$ repeat in the optimal solution such that $\varphi_{k-1} \leq \phi_{k-1}$, which implies that the former $(k-1)^{th}$ repeat ends before the latter $(k-1)^{th}$ repeat. Then, as the greedy algorithm would start a repeat as early as possible in principle, how could the k^{th} repeat from the greedy algorithm starts to be operated later than the k^{th} repeat in the optimal solution such that $\varphi_k > \phi_k$. This is where the other conflict rises.

In summary, all the above conflicts point out that the initial assumption $M^* > N$ is wrong. As we have $M^* \geq N$, we could easily conclude that $M^* = N$, which implies the solution obtained by the greedy algorithm is the optimal solution obtained by the model $FM2$ when there is only and one candidate cruise service r'. ■

Proposition 5.5 shows, when there is only one candidate cruise service, the two myopic rules work the same as a greedy algorithm to obtain the optimal solution. Such a greedy algorithm can be applied to derive a better upper bound $\overline{x}_r$ for the number of repeats for each candidate cruise service than that estimated by Eq. (5.9). The greedy algorithm is better than Eq. (5.9) for the approximation because the former one obtains the optimal number of repeats. The comparison of the approximation by the greedy algorithm and Eq. (5.9) will be given in Section 5.5.5.

5.5 COMPUTATIONAL EXPERIMENT

In this section, in order to validate the effectiveness of the proposed models and efficiency of solving the models, we conduct extensive numerical experiments by using a PC (Intel Core i5, 2.3G Hz; Memory, 8G). The integer programs $FM2'$ and $FM2''$ are solved by CPLEX12.5 with concert technology of C# (2012).

5.5.1 Generation of test instances

The planning horizon for the problem is 180 days (about half a year). The decisions (z_{rt} or z_{rxt} in the proposed models) are made on each day. The generation of the set of candidate services is different in the following four subsections of computational experiments. In Section 5.2 and Section 5.3, which aim to test the efficiency and the effectiveness of models, the candidate services are randomly generated with the rotation time assigned as $s_r \in U[4,11]$, where U denotes uniformly distributed integer pseudorandom numbers. In Section 5.4 and Section 5.5, which focus on the robustness test and sensitivity analysis on the model for Quantum of the Seas (one of cruise ship belonging to Royal Caribbean), the candidate services for the cruise ship are inputted referring to the published schedule by Royal Caribbean International (Cruise route: Quantum of the Seas, 2016). The details of those cruise services will be illustrated in Section 5.5.4.

For the berth availability (δ_{rt}), we derived the input parameters from the website of cruise terminals: firstly, we analyzed the arrival times for all the incoming cruise ships in the Year 2016 at Wusong Kou Cruise Terminal (Shanghai) from Arrival Time (2016). Based on the statistical results, there are 43% days left in the whole year that the terminal has available berths. Therefore, we assume that the cruise terminal of each port city has randomly 40% to 50% days left for having available berths. Then, the berth availability of each port in a specified day is randomly generated based on the random percentage obtained, which further forms a berth availability sheet for each port in the planning horizon. Finally, the berth availability for each cruise service (δ_{rt}) can be derived by referring to the berth availability sheets of the ports that the cruise service will visit. However, for the berth availability applied in practical applications, the cruise ship managers could contact all the cruise terminals for the arrival time sheets in advance.

To generate the profits of operating services (g_r or g_{rx}), two input parameters are further involved, which are the number of possible cruise passengers (denoted as n) and the average profit per cruise passenger (denoted as p) of a cruise service. The profit of operating a service could be calculated by: $g = n \times p$. According to Cruise Industry (2015), the average revenue per cruise passenger is US$1,728, and the average profit per cruise passenger is US$185, which suggests that the ratio between the average profit and the average revenue is 0.107. Meanwhile, according to Cruise Market Watch (2016), the ratio between the ticket price and the average revenue per cruise passenger of a cruise service is 0.759. With these two ratios, we could estimate that around 14% of the ticket price contributing to the average profit per cruise passenger. The ticket price of a cruise service can be found easily. Thus, for a given cruise service, the average profit per cruise passenger p is also assessable.

Here, notice that in the model $FM2$ with decreasing marginal profit setting, we assume p (the average profit per cruise passenger) keeps unchanged for a cruise service, but the number of cruise passenger n decreases if the cruise service is repeated many times. We assume that n decreases in an equal ratio pattern, which means once a cruise service is repeated one more time, the number of the cruise passengers for the new repeat is $n \cdot a$, here a is the ratio, and $a \in (0,1)$. Initially, we randomly set the ratio a from 0.80 to 0.90 for each candidate cruise service.

5.5.2 Efficiency of solving the models

In this section, we compare the model $FM2'$ with Constraints (5.14) and without Constraints (5.14), which are solved by CPLEX in different instance groups. The comparison results are shown in Table 5.2. As can be seen, in both cases, the optimal solution of each instance can be obtained. However, in terms of the computational time, CPLEX solves the model $FM2'$ without Constraints (5.14) much faster than the model $FM2'$ with Constraints (5.14). On average, solving the former case only needs around 32% CPU time of the latter case based on the ratio between T_o and T_w. More importantly, the ratio keeps decreasing with the increase of the problem size. Thus, when using the model $FM2'$ to solve the problem, Constraints (5.14) should be removed for saving the CPU time. The solution obtained by the model $FM2'$without Constraints (5.14) can be sorted manually for the optimal solution by adjusting the chronological order for the repeats of each service, as discussed in Section 5.3.3.

In Section 5.3.3, we have proposed two linear models $FM2'$ and $FM2''$ for the nonlinear model $FM2$. Here, we test which linear model has a higher efficiency to derive solutions for the problem. As we have verified that the model $FM2'$ without Constraints (5.14) can be solved faster, the comparison is conducted between this case of the model $FM2'$ and the model $FM2''$. Table 5.3 illustrates the comparison between the model $FM2'$ and $FM2''$. Both linear models are valid for the linearization of the nonlinear model as the optimal solutions are obtained in all instance groups. Whereas, the model $FM2''$ can be solved much faster than the model $FM2'$ by CPLEX. The ratio of CPU times between two models is 0.23 on average, which shows the advantage of using the concavity of $G_r(x_r)$ for the linearization. In a technical perspective of CPLEX, the model $FM2'$ spends too much CPU time on pre-solving the problem, and the nodes explored in CPLEX for two models are more or less the same, shown by “B&B nodes”.

Table 5.2: Comparison between the model $\boldsymbol{FM2'}$ with and without Constraints (14)

Instance		**With the constraints**		**Without the constraints**		**Comparison**
# of candidate service	Instance ID	Z_w (US$)	T_w (s)	Z_o (US$)	T_o (s)	T_o / T_w
20	2_20_1	1.156	35	1.156	16	0.46
	2_20_2	1.093	47	1.093	18	0.38
	2_20_3	1.136	29	1.136	15	0.52
	2_20_4	1.084	33	1.084	22	0.67
	2_20_5	1.217	24	1.217	11	0.46
40	2_40_1	1.312	218	1.312	29	0.13
	2_40_2	1.311	56	1.311	20	0.36
	2_40_3	1.313	90	1.313	38	0.42
	2_40_4	1.349	47	1.349	21	0.45
	2_40_5	1.304	124	1.304	43	0.35
80	2_80_1	1.392	236	1.392	39	0.17
	2_80_2	1.378	504	1.378	57	0.11
	2_80_3	1.446	378	1.446	38	0.10
	2_80_4	1.405	870	1.405	67	0.08
	2_80_5	1.407	573	1.407	88	0.15
					Average:	***0.32***

Note: *(i) "# of candidate service" column denotes the total number of candidate services. (ii) "Z_w" and "Z_o" columns list the optimal profits under two cases with the unit of ten million US dollars. (iii) "T_w" and "T_0" columns show the CPU time (seconds) to solve the problem.*

Table 5.3: Comparison between the two linear models

Instance		**The first model**			**The second model**			**Comparison**	**LP-relaxation**	
# of candidate service	Instance id	Z_f ($)	T_f (s)	B&B nodes	Z_s ($)	T_s (s)	B&B nodes	T_s/T_f	Z_l	Gap
20	3_20_1	1.182	19	1	1.182	4	1	0.21	1.185	0.23%
	3_20_2	1.154	20	1	1.154	5	1	0.25	1.158	0.37%
	3_20_3	1.127	13	1	1.127	5	1	0.38	1.131	0.36%
	3_20_4	1.147	12	1	1.147	2	1	0.17	1.150	0.26%
	3_20_5	1.167	18	1	1.167	5	1	0.28	1.173	0.55%
40	3_40_1	1.321	28	162	1.321	6	141	0.21	1.323	0.19%
	3_40_2	1.308	21	41	1.308	7	60	0.33	1.312	0.31%
	3_40_3	1.294	33	453	1.294	10	407	0.30	1.299	0.37%
	3_40_4	1.313	28	79	1.313	7	83	0.25	1.317	0.32%
	3_40_5	1.301	54	179	1.301	8	303	0.15	1.306	0.39%
80	3_80_1	1.398	134	593	1.398	17	537	0.13	1.400	0.13%
	3_80_2	1.387	64	83	1.387	15	100	0.23	1.389	0.13%
	3_80_3	1.412	85	154	1.412	14	294	0.16	1.414	0.17%
	3_80_4	1.405	101	317	1.405	20	357	0.20	1.407	0.12%
	3_80_5	1.394	88	177	1.394	16	326	0.18	1.396	0.16%
							Average:	***0.23***	***1.291***	***0.27%***

Note: (i) " Z_f " and " Z_s " columns list the optimal profits of two linear models with the unit of ten million US dollars. (ii) " T_f " and " T_s " columns show the CPU time (seconds) to solve the problem. (iii) "B&B nodes" shows the number of nodes explored by CPLEX. (iv) "LP-relaxation" shows the objective value Z_l of the LP solution obtained by LP-relaxation of the model and the objective gap $(Z_l - Z_s)/Z_s$ with the optimal solution. Two linear models have the same LP solution.

5.5.3 Performance of myopic approaches

In this section, we aim to validate the effectiveness of the model $FM2''$ (the second linear model for the model $FM2$) and investigate the performance of the two myopic approaches proposed in Section 5.4.3 for the CSP problem. In both rules, the decision is made on a daily basis from Day 1 to Day T. Based on different preferences in two heuristic rules and the berth availability of each day, an optimal cruise service is selected to operate for the day.

The comparisons between the model and two myopic rules are presented in Table 5.4. It shows Myopic Rule_1 is better than Myopic Rule_2 as more profit can be earned in the majority of the instances. However, it does not mean Myopic Rule_1 is good enough for the cruise ship to plan cruise services. There is still 5.23% optimality gap on average between Myopic Rule_1 and the optimal solution of the model $FM2''$, which validates the effectiveness of the model and addresses the importance of having the optimization-based service planning tool.

Table 5.4: Comparison between the model $\boldsymbol{FM2''}$ and two myopic rules

Instance		$\boldsymbol{FM2''}$	**Myopic Rule_1**		**Myopic Rule_2**	
# of candidate service	Instance ID	Z_m (US$)	Z_f (US$)	Gap	Z_s (US$)	Gap
20	4_20_1	1.209	1.125	7.41%	1.124	6.99%
	4_20_2	1.123	1.062	5.75%	1.061	5.51%
	4_20_3	1.156	1.033	11.93%	1.082	6.35%
	4_20_4	1.174	1.112	5.59%	1.097	6.58%
	4_20_5	1.220	1.168	4.41%	1.124	7.81%
40	4_40_1	1.327	1.253	5.90%	1.219	8.10%
	4_40_2	1.310	1.267	3.45%	1.222	6.74%
	4_40_3	1.277	1.224	4.36%	1.189	6.88%
	4_40_4	1.326	1.272	4.21%	1.179	11.03%
	4_40_5	1.305	1.231	6.09%	1.208	7.46%
80	4_80_1	1.413	1.359	3.94%	1.231	12.83%
	4_80_2	1.382	1.335	3.46%	1.217	11.96%
	4_80_3	1.380	1.322	4.44%	1.244	9.92%
	4_80_4	1.395	1.344	3.86%	1.255	10.08%
	4_80_5	1.402	1.353	3.62%	1.230	12.26%
Average:				***5.23%***		***8.70%***

Note: (i) " Z_m " column lists the optimal profit of the model with the unit of ten million US dollars. (ii) "Gap" columns show the optimality gap between the model and the myopic rule, which are calculated by $(Z_m - Z_f)/Z_m$ and $(Z_m - Z_s)/Z_m$ respectively.

5.5.4 Robustness tests for a real case

In this section, we take Quantum of the Seas as our targeted cruise ship for some robustness tests. Quantum of the Seas is a cruise ship for Royal Caribbean International (RCI). As the lead ship of the Quantum class of cruise ships, Quantum of the Seas has a large capacity to carry 4180 cruise passengers for double occupancy and 4905 for maximum occupancy. The deadweight of this cruise ship is near 168,666 tons. Currently, this cruise ship is designated in the Asian area with the home port Shanghai (China). According to the schedule published by Royal Caribbean International (Cruise route: Quantum of the Seas, 2016), there are 13 cruise services operated by this cruise ship in the Year 2016, and all the cruise services are a loop with the home port. The information of these 13 cruise services are given in Table 5.5 and the locations of the port cities visited by those cruise services are shown in Figure 5.2.

Table 5.5: Information on the cruise services

Cruise Index	Cruise route	Ticket price	Rotation time
1	Shanghai(1)→Hiroshima(3)→Tokyo(5)→Kobe(6)→Shanghai(9)	$1,110	9 days
2	Shanghai(1)→Busan(3)→Fukuoka(4)→Shanghai(6)	$745	6 days
3	Shanghai(1)→Nagasaki(3)→Busan(4)→Shanghai(6)	$610	6 days
4	Shanghai(1)→Kumamoto(3)→Shanghai(5)	$762	5 days
5	Shanghai(1)→Seoul(3)→Shanghai(5)	$732	5 days
6	Shanghai(1)→Kumamoto(3)→Miyazaki(4)→Shanghai(6)	$1,296	6 days
7	Shanghai(1)→Inchon(3)→Shanghai(5)	$561	5 days
8	Shanghai(1)→Busan(3)→Shanghai(5)	$671	5 days
9	Shanghai(1)→Busan(3)→Sakaiminato(4)→Shanghai(6)	$761	6 days
10	Shanghai(1)→Busan(3)→Nagasaki(4)→Shanghai(6)	$595	6 days
11	Shanghai(1)→Busan(3)→Fukuoka(4)→Nagasaki(5)→Shanghai(7)	$610	7 days
12	Shanghai(1)→Okinawa(3)→Shanghai(5)	$610	5 days
13	Shanghai(1)→Busan(3)→Nagasaki(4)→Shanghai(6)	$701	6 days

Note: *(i) the numbers inside the brackets indicate the index of the day when the cruise ship moors in the port cities, for example, Hiroshima(3) suggest that the cruise ship moors in Hiroshima on Day 3.*

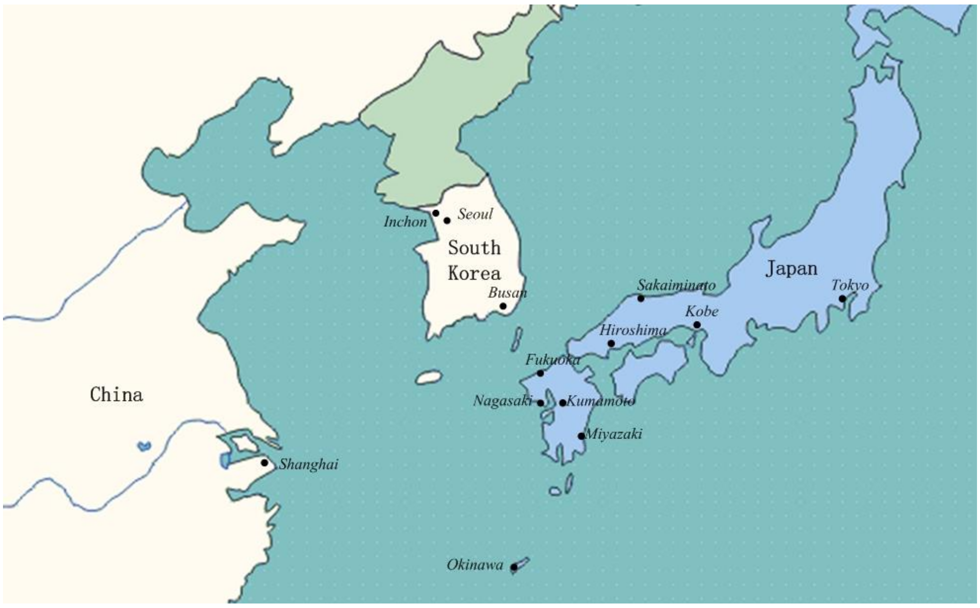


Figure 5.2: Locations of the port cities

For decision makers of a cruise ship, a challenge of implementing our model is to estimate the marginal profit of operating a cruise service accurately. Usually, as the money spent by cruise passengers during the cruising is uncertain, the operating profit cannot be finalized until a cruise service is finished. However, we have involved three input parameters for the estimation of the operating profit of a cruise service, which are the number of possible cruise passengers n, the average profit per cruise passenger p and the cruise passenger decreasing ratio for the cruise repeat a. However, the parameters p and a could be hard to be estimated accurately by cruise companies. Thus, we conduct two robustness tests on these two parameters to see how many profits will be lost compared with the optimal total profit if the two parameters are estimated inaccurately.

The robustness test for the p is conducted in the following ways: firstly, we set the p for each cruise service based on the assumption in Section 5.5.1. By implementing the model, we can obtain an optimal solution (i.e., optimal cruise service operation plan, denoted as Plan A) for the current setting of p. Then, assuming that after operating cruise services, it turns out that we estimate the p with e estimation error (e is a input parameter ratio, and $e \in (0,1)$) for all cruise services, among which u cruise services are underestimated (u is also a input parameter ratio, and $u \in (0,1)$) and $1 - u$ cruise services are overestimated. Thus, for the cruise services underestimated, the real average profit per cruise passenger $\hat{p} = (1 + e) \times p$. For the cruise services overestimated, the real average profit per cruise passenger $\hat{p} = (1 - e) \times p$. With all the $\hat{p}$ of the cruise services and Plan A, we can calculate the total profit (denoted as Z_{real}) that the cruise ship earned in real. Lastly, supposing that we can estimate all the parameters accurately at the beginning (based on all the $\hat{p}$), we implement our model again for the optimal total profit (denoted as $Z_{optimal}$) that could be earned by the cruise ship. The gap between Z_{real} and $Z_{optimal}$ is the optimality gap calculated by $(Z_{optimal} - Z_{real})/Z_{optimal}$, which is also the percentage of the profit lost due to the inaccurate estimation.

The procedure for the robustness test for a (the cruise passenger decreasing ratio for the cruise repeat) is the same as the robustness test for p. For the robustness test, we have two testing input parameters, which are u (underestimate ratio) and e (estimate error). The underestimate ratio indicates both the percentage of the cruise services underestimated u and the percentage of the cruise services overestimated $1 - u$. The estimate error suggests the deviation of our estimation from the real situation. For each combination of u and e, we conduct ten random instances. The average optimality gap obtained from the ten instances is taken as the output parameter for the two testing input parameters.

The robustness test on the average profit per cruise passenger for cruise services is illustrated in Figure 5.3. In the test, we set the estimation error e from 0.04 to 0.20 with 0.04 interval, and the underestimate ratio u from 0.10 to 0.90 with 0.10 interval. In the figure, all the optimality gaps are less than 2.0% with the estimation error less than 0.16, which implies that near-optimal solutions can be obtained the estimation error is less than 16%. Figure 5.3

also shows that the optimality gap would increase when the estimation error increase (see any five bars with a same underestimate ratio). However, there is an interesting phenomenon: for the same estimation error (see any five bars with a same colour), 0.50 underestimate ratio (i.e., a half cruise services underestimated and a half cruise services overestimated) dominates the optimality gap. This phenomenon provides the cruise company with a useful hint: when estimating the marginal profits of cruise services, the cruise company should use the same method rather than use different methods to estimate the marginal profits of different cruise services. Using different methods for the cruise services could be more likely to cause the half-underestimate-half-overestimate result.

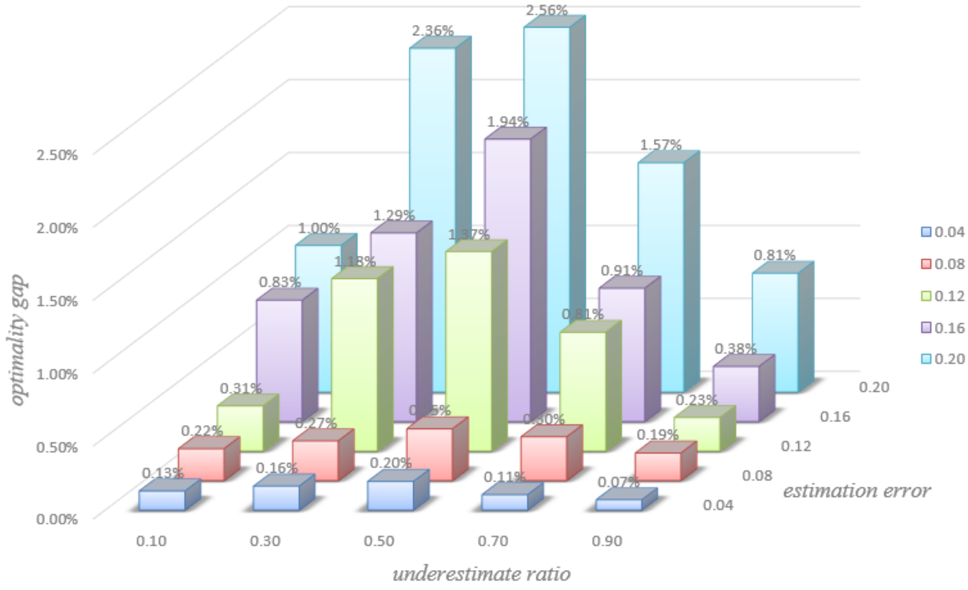


Figure 5.3: The robustness test on $\boldsymbol{p}$

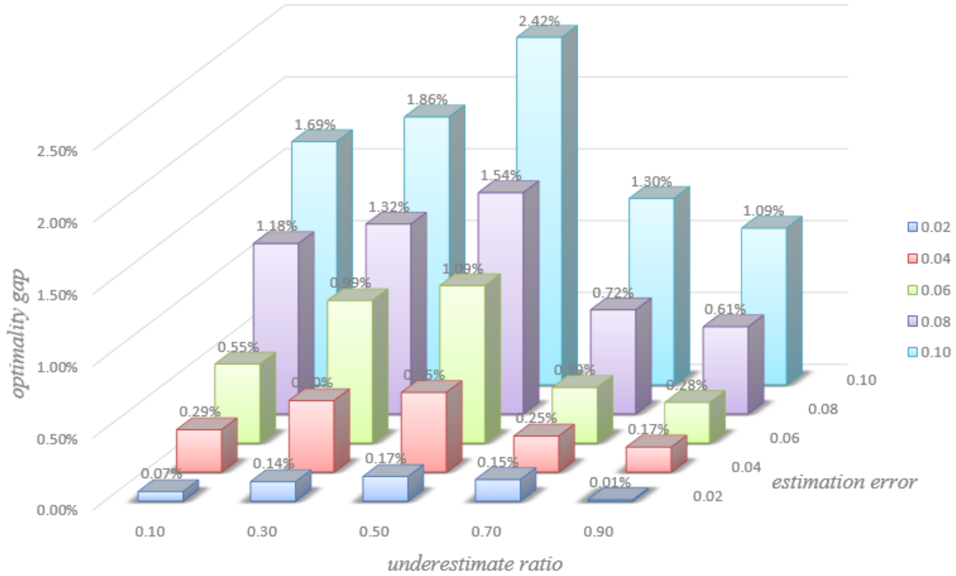


Figure 5.4: The robustness test on $\boldsymbol{a}$

The results of the robustness test on the cruise passenger decreasing ratio for the cruise repeat a are consistent with the results of the former robustness test. The robustness test on a is shown in Figure 5.4, where we set the estimation error e from 0.02 to 0.10 with 0.02 as the step, and the underestimate ratio u from 0.10 to 0.90 with 0.10 as the step. Figure 5.4 shows that the optimality gaps are less than 2% when the estimation error is less than 0.08, which shows our model could derive near-optimal solutions (optimality gap less than about 1.5%) as long as the estimation error on the a is less than 8%. Meanwhile, Figure 5.4 also shows that 0.50 underestimate ratio could bring the most profit lost for the cruise ship, which further emphasizes the importance of the aforementioned hint.

The two above robustness tests demonstrate the robustness of our proposed model. Even if some input parameters cannot be estimated accurately by the decision makers, our models can still obtain a near-optimal solution for the CSP problem, so long as the estimation errors can be controlled in reasonable ranges. The reason why the model has the robustness in the sense of error estimations on p and a can be explained as follows: the two error terms actually determine the error estimation on the marginal profits of services. However, in the optimization of the model, the berth availability plays the dominant role rather than the marginal profits. We can image that the daily operating profits g_r/s_r of cruise services are not significantly different from each other, as the cruise services with extremely low daily operating profits cannot be candidate services. However, the berth availability is significantly different among the cruise services, especially for some cruise services that have many ports of call. Thus, we can arbitrarily conclude that the prior optimization is to ensure that the cruise ship is operated for as many as possible days in the planning horizon with considering the berth availability.

5.5.5 Sensitivity analysis for the berth availability

In this section, based on 13 real candidate cruise services given by Table 5.5, we further conduct some sensitivity analysis for the berth availability as the berth availability plays the dominant role in the optimization. In Section 5.5.1, we have assumed that the cruise terminal of each port city has randomly 40% to 50% days left for having available berths and generated the berth availability scenario for each port of call accordingly. Here, we define five different berth availability scenarios, labeled by BA1, BA2, BA3, BA4, and BA5, by changing the percentages of the days left for having available berths. For BA1, we decrease the percentages by 20%; for BA2, we decrease the percentages by 10%; for BA3, we keep the percentages unchanged; for BA4, we increase the percentages by 10%; for BA5, we increase the percentages by 20%. From BA1 to BA5, the probability that each port of call has available berths increases. Ten random instances are generated for each berth availability scenario and are solved by the proposed model. The average results of the random instances are reported in Figure 5.5, Figure 5.6, and Table 5.6, and are analyzed below.

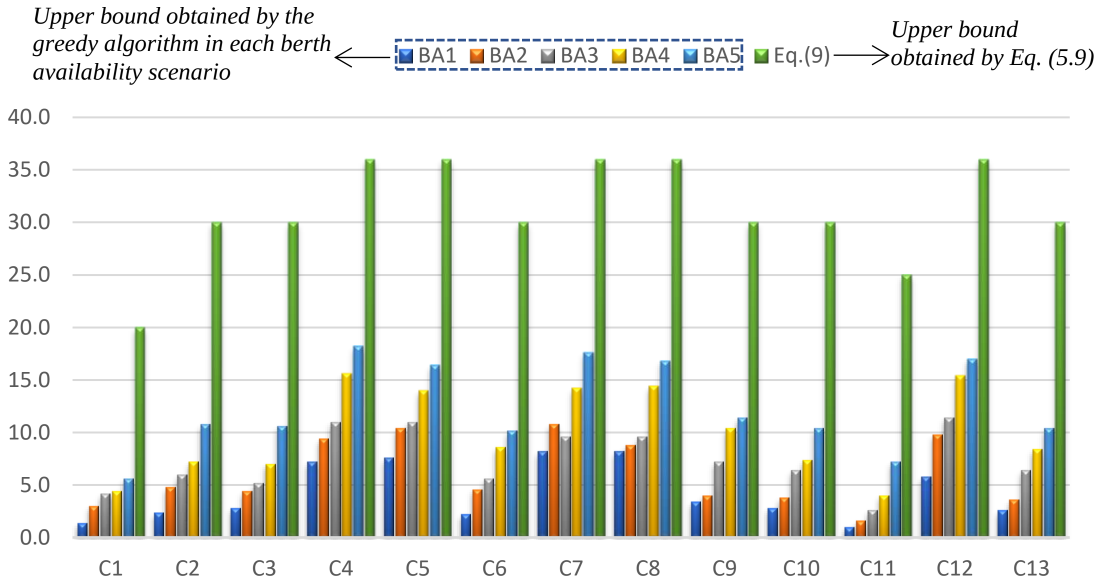


Figure 5.5: Upper bound $\bar{x}_r$ obtained by the greedy algorithm and Eq. (5.9)

Figure 5.5 reports $\bar{x}_r$, upper bound of the number of repeats for Service r in one planning horizon. Eq. (5.9) exhibits a way to approximate $\bar{x}_r$. In Proposition 5, we proved that the greedy algorithm can obtain the optimal $\bar{x}_r$. Here, we report $\bar{x}_r$ obtained by the greedy algorithm under the five berth availability scenarios and by Eq. (5.9) are given in Figure 5.5. Note that the $\bar{x}_r$ obtained by Eq. (5.9) is constant under different berth availability (given by Bar Eq. (5.9)), as it is derived by $\left\lfloor \frac{T}{s_r} \right\rfloor$, and the $\bar{x}_r$ obtained by the greedy algorithm is different under different berth availability scenarios (given by five bars from BA1 to BA5). Therefore, each candidate cruise service (indexed by C1 to C13) in Figure 5.5 contains six bars. As can be seen, the upper bound $\bar{x}_r$ obtained by Eq. (5.9) is much worse than that of the greedy algorithm, especially when the berth availability is low (BA1). For example, for Cruise service 13, the $\bar{x}_r$ obtained by Eq. (5.9) is more than ten times as large as that of the greedy algorithm under the berth availability scenario BA1. Thus, to implement our proposed model, the greedy algorithm should be applied to approximate $\bar{x}_r$.

Figure 5.6 illustrates the average number of repeats of each cruise service under each berth availability scenario. In general, cruise services 4, 5 and 6 outperform other cruise services with a higher average number of repeats. This is due to the fact that those cruise services have comparatively higher marginal profits and shorter rotation times (cf. Table 5.5). Cruise service 11 is the least selected cruise service to be operated, especially when the berth availability is low. The cruise service with the longest rotation time (cruise service 1) also performs badly in BA1, but the performance improves when the berth availability increases and around 1.5

repeats of the cruise service 1 are operated in berth availability BA2 to BA5 (shown by the last four bars in “C1” of the figure) for the sake of its high marginal profit.

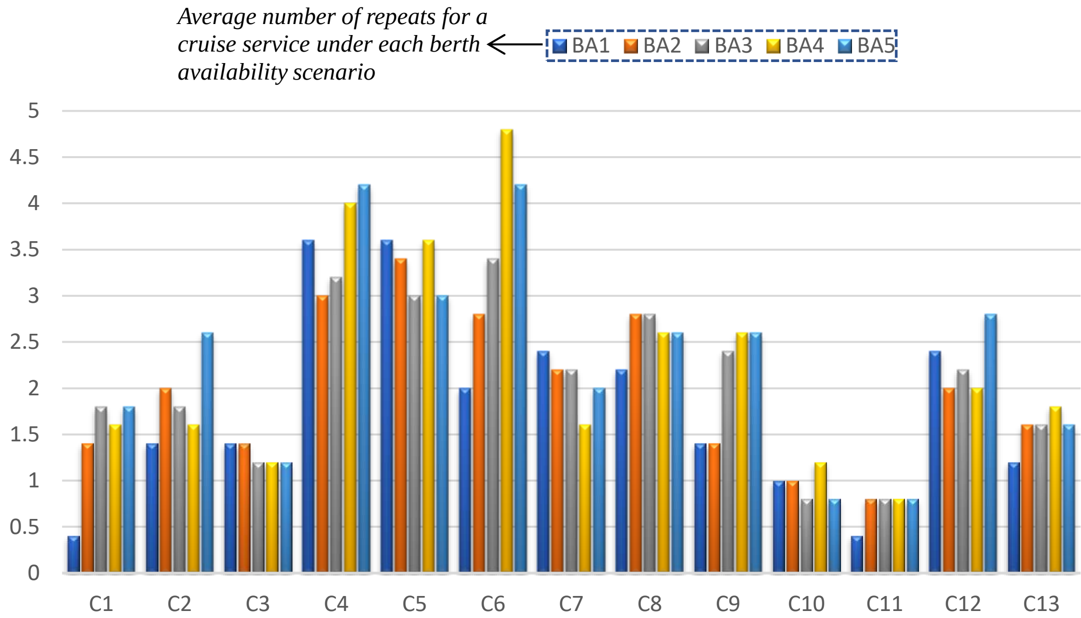


Figure 5.6: Number of repeats of cruise services under different berth availability scenarios

Table 5.6 shows the effects of different berth availability scenarios on major outputs of the model. When the berth availability increases, operation days and total profit rise simultaneously. However, the increase of operation days or total profit does not keep the pace with the increase of the berth availability. For instance, from BA3 to BA5, the berth availability grows by 20%, but the total profit increases by 9.8%. Average profit per day shares the same trend as the total profit because the number of total days is constant. By comparison, the average profit per operation day keeps nearly unchanged when the berth availability fluctuates.

Table 5.6: Outputs of the model under different berth availability scenarios

ID	Total days	Operation days	Deviation 1	Total profit	Deviation 2	Average profit per day	Average profit per operation day
BA1	180	127.8	−18.1%	8,568,362	−19.1%	47,602	67,043
BA2	180	146.4	−6.2%	9,839,851	−7.1%	54,666	67,186
BA3	180	156.0	0.0%	10,588,128	0.0%	58,823	67,901
BA4	180	168.2	7.8%	11,363,633	7.3%	63,131	67,577
BA5	180	172.8	10.8%	11,622,052	9.8%	64,567	67,266

Note: *(i) “Total days” shows the length of one planning horizon. (ii) “Operation days” indicates the number of days that the cruise ship operates cruise services, i.e., the cruise ship is traveling. (iii) “Deviation 1” lists the deviation of the operation days between the corresponding berth availability and BA3. (iv) “Deviation 2” lists the deviation of the total profit between the corresponding berth availability and BA3.*

5.6 CONCLUSION

This paper addresses a CSP problem that plans cruise services for a cruise ship, in order to maximize the total profit during a planning horizon. Considering the fact that major cruise terminals have limited berths, the berth availability is incorporated into the planning. Then, the problem also considers the phenomenon that the marginal profit of operating a cruise service would decrease gradually when a cruise service is repeated several times. To solve the problem, a nonlinear programming model is built, for which two linearization methods are suggested. By conducting computational experiments, we find that the linearization method using the concavity of $G_r(x_r)$ could improve the efficiency on solving the problem significantly. Some properties of the problem in different assumptions are also investigated. In particular, if there is only one candidate cruise service for the problem, a greedy algorithm can derive the optimal solution. The effectiveness of the proposed models is verified by extensive numerical experiments. Lastly, based on real-world cases, the robustness tests are conducted to show that if there are some parameters needed by the model cannot be estimated accurately, the proposed model has its robustness and can still obtain a near-optimal plan. Sensitivity analysis is also conducted for the berth availability to see its effects on some outputs of the model.

This study also contains limitations. For example, this study assumes all the candidate services' home port is identical. This assumption holds in the majority of real situations. However, when a cruise ship is repositioned to a new region, the candidate services for the ship may have more than one home port. This case may be more common for some cruise ships that are operated globally. For the cruise service planning problem under the context of multiple home ports, the models in this study need to be extended. Another challenge embedded in this extension may lie in that the repositioning cost between two home ports should be taken into account. Meanwhile, if a set of candidate cruise services are not available at first hand, the CSP problem is more complicated as the priority is to design profitable candidate cruise services. In addition, although we have claimed that service planning is independent among different cruise ships in the first section, two cruise ships can interact with each other if have some common ports of call in their candidate cruise services or itineraries. This is due to that the two cruise ships might compete for an available berth of a common port in a day. Thus, a joint optimization should be designed for such an interaction, especially when the two cruise ships belong to one cruise line corporation. If we plan to extend our problem to multiple ships, our model may be revised from a variant of knapsack problem to a variant of bin packing problem. The main techniques and results in this paper shall be extended and applied as well, because we can potentially use some decomposition algorithms to decompose the extended problem into subproblems of individual ships, and each of them corresponds to the problem studied in this paper. All of the above issues will be the research directions for our future studies.

5.7 REFERENCES

Arrival Time, 2016. Arrival Time—Wusong Kou Cruise Terminal. http://www.wskcruise.com/article/48.html. Accessed 22 February 2016.

Arthur, H., Ronald, T.W., 2000. Stochastic prediction in multinomial logit models. *Management Science* 46(8), 1137–1144.

Bell, M.G.H., Liu, X., Rioult, J., Angeloudis, P., 2013. A cost-based maritime container assignment model. *Transportation Research Part B* 58, 58–70.

Bell, M.G.H., Liu, X., Angeloudis, P., Fonzone, A., Hosseinloo, S.H., 2011. A frequency-based maritime container assignment model. *Transportation Research Part B* 45 (8), 1152–1161.

Bretthauer, K., Shetty, B., 2002. The non-linear knapsack problem - algorithms and applications. *European Journal of Operational Research* 138, 459–472.

Cruise Industry, 2015. Cruise industry—Statista Dossier: Facts and statistics on the cruise industry. http://www.statista.com/study/11547/cruise-line-industry-statista-dossier/. Accessed 26 December 2015.

Cruise Market Watch, 2016. Growth of the Cruise Line Industry. http://www.cruisemarketwatch.com/growth/. Accessed 22 February 2016.

Cruise route: Quantum of the Seas, 2016. Royal Caribbean itinerary 2016 cruises. http://www.wskcruise.com/tours /. Accessed 22 February 2016.

Cruise Ship Schedule, 2016. Carnival Vista itinerary 2016 cruises. http://www.cruiseshipschedule.com/carnival-cruise-lines/carnival-vista-schedule/. Accessed 8 January 2016.

Cruise Ship Statistics, 2015. Cruise Industry Statistics—Cruise Ship Statistics. http://www.cruiseindustrynews.com/cruise-industry-stats.html. Accessed 26 December 2015.

Esteve-Perez, J., Garcia-Sanchez, A., 2014. Cruise market: Stakeholders and the role of ports and tourist hinterland. *Maritime Economics and Logistics* 17(3), 1–18.

Fransoo, J.C., Lee, C.Y., 2013. The critical role of ocean container transport in global supply chain performance. *Production and Operations Management* 22(2), 253–268.

Giallombardo, G., Moccia L., Salani, M., Vacca, I., 2010. Modeling and solving the tactical berth allocation problem. *Transportation Research Part B* 44(2), 232–245.

Gui, L., Russo, A.P., 2011. Cruise ports: a strategic nexus between regions and global lines—evidence from the Mediterranean. *Maritime Policy & Management* 38(2), 129–150.

Hongmin, L., Woonghee, T.H., 2011. Pricing multiple products with the multinomial logit and nested logit models: concavity and implications. *Manufacturing & Service Operations Management* 13(4), 549 –563.

Iris, C., Pacino, D., Ropke, S., and Larsen, A., 2015. Integrated berth allocation and quay crane assignment problem: Set partitioning models and computational results. *Transportation Research Part E* 81, 75–97.

Kameshwaran, S., Narahari, Y., 2009. Nonconvex Piecewise Linear Knapsack Problems. *European Journal of Operational Research* 192, 56–68.

Li, B., 2011. The multinomial logit model revisited: A semi-parametric approach in discrete choice analysis. T*ransportation Research Part B* 45(3), 461 –473.

Maddah, B., Moussawi-Haidar, L., El-Taha, M., Rida, H., 2010. Dynamic cruise ship revenue management. *European Journal of Operational Research* 207(1), 445–455.

Meisel, F., Bierwirth. C., 2009. Heuristics for the integration of crane productivity in the berth allocation problem. *Transportation Research Part E* 45(1), 196–209.

Meng, Q., Wang, S., 2012. Liner ship fleet deployment with week-dependent container shipment demand. *European Journal of Operational Research* 222(2), 241–252.

Meng, Q., Wang, S., Andersson, H., Thun, K., 2014. Containership routing and scheduling in liner shipping: overview and future research directions. *Transportation Science* 48 (2), 265–280.

Meng, Q., Wang, T., Wang, S., 2012. Short-term liner ship fleet planning with container transshipment and uncertain container shipment demand. *European Journal of Operational Research* 223(1), 96–105.

Ng, M.W., 2014. Distribution-free vessel deployment for liner shipping. *European Journal of Operational Research* 238(3), 858-862.

Ng, M.W., 2015. Container vessel fleet deployment for liner shipping with stochastic dependencies in shipping demand. *Transportation Research Part B* 74, 79-87.

Pang, K.W., Liu, J., 2014. An integrated model for ship routing with transshipment and berth allocation. *IIE Transactions* 46(12), 1357–1370.

Paat, R., Huseyin, T., 2012. Robust assortment optimization in revenue management under the multinomial logit choice model. *Operation Research* 60(4), 865–882.

Poirriez, V., Yanev, N., Andonov, R., 2009. A hybrid algorithm for the unbounded knapsack problem. *Discrete Optimization* 6, 110–124.

Premoli, A., 1986. Piecewise-linear programming: The compact (CPLP) algorithm. *Mathematical Programming* 36(2), 210–227.

Rodrigue, J., Notteboom, T., 2013. The geography of cruises: Itineraries, not destinations. *Applied Geography* 38, 31–42.

Soriani, S., Bertazzon, S., Cesare, F.D., Rech, G., 2009. Cruising in the Mediterranean: structural aspects and evolutionary trends. *Maritime Policy & Management* 36(3), 235–251.

Song, D.P., Dong, J., 2012. Cargo routing and empty container repositioning in multiple shipping service routes. *Transportation Research Part B* 46 (10), 1556–1575.

Song, D.P., Dong, J.-X., 2013. Long-haul liner service route design with ship deployment and empty container repositioning. *Transportation Research Part B* 55, 188–211.

Song, D. P., Li, D., Drake, P., 2015. Multi-objective optimization for planning liner shipping service with uncertain port times. *Transportation Research Part E* 84, 1–22.

Statista, 2015. Passenger capacity of the global cruise industry from 2007 to 2017. http://www.statista.com/statistics/301582/passenger-capacity-of-the-global-cruise-industry/. Accessed 28 Aug 2015.

Tang, L., Sun, D., Liu, J., 2015. Integrated storage space allocation and ship scheduling problem in bulk cargo terminals. *IIE Transactions* 48(5), 428-439.

Vacca, I., Salani, M., Bierlaire, M., 2012. An Exact Algorithm for the Integrated Planning of Berth Allocation and Quay Crane Assignment. *Transportation Science* 47(2), 148–161.

Veronneau, S., Roy, J., 2009. Global service supply chains: An empirical study of current practices and challenges of a cruise line corporation. *Tourism Management* 30, 128–139.

Veronneau, S., Roy, J., Beaulieu, M., 2015. Cruise ship suppliers: A field study of the supplier relationship characteristics in a service supply chain. *Tourism Management Perspectives* 16, 76–84.

Wang, Y., Meng, Q., Du, Y., 2015. Liner container seasonal shipping revenue management. *Transportation Research Part B* 82, 141–161.

Zhen, L., Chew, E.P., Lee, L.H., 2011. An integrated model for berth template and yard template planning in transshipment hubs. *Transportation Science* 45(4), 483–504.

Zhen, L. 2015. Tactical berth allocation under uncertainty. *European Journal of Operational Research* 247, 928–944.

Chapter 6: Conclusions

This thesis investigates four problems in maritime logistics and operations, where the first two problems are related to container ships that transport cargos and other two problems are related to cruise ships that transport passengers. The first problem focuses on the ship type decision considering empty container repositioning and foldable containers. In this study, given the ship type with a certain capacity, the problem transfers to a nonstandard minimum cost flow problem. Then, a network flow model for the problem is formulated. When considering both standard containers and foldable containers, trouble arises in the network construction that is some parallel arcs share the same capacity restriction. To overcome this trouble, a revised network simplex algorithm that changes the standard pivot operation is designed. Based on the algorithm, a solution approach is proposed to solve the optimization problem. Some useful managerial implications of this study are obtained after conducting real-case experiments, which mainly includes three perspectives, i.e., ship type decision, foldable container usage, and container devanning time.

The second problem addresses the optimal reefer slot conversion for container freight transportation. This study presents an algorithm to search for the optimal number of reefer slots to have on a container ship. It is assumed that all the relevant parameters (e.g. freight rates, storage costs, etc.) are already known. To optimize the sequence of ships deployed, a revised two-stage simulation approach is proposed. Based on this, a slot conversion algorithm that determines the optimal slot configurations of the ships is formulated, which embeds the two-stage simulation algorithm for string optimization. In this study, to highlight the effectiveness of our approach, several real shipping routes operated by CMA CGM are investigated. The overall results reveal that the algorithm is highly efficient and can help shipping liners to significantly improve their profits.

The third problem concerns the cruise itinerary schedule design. It aims to determine the optimal sequence of a given set of ports of call and the arrival and departure times at each port to maximize the monetary value of the utility minus the fuel cost. To solve the problem, it first enumerates all sequences of ports of call and then optimizes the arrival and departure times at each port of call by developing a dynamic programming approach. To improve the computational efficiency, effective bounds on the profit of each sequence of ports of call are proposed. The computational experiments show that, first, the proposed bounds on the profit of each sequence of ports of call can considerably improve the computational efficiency. Second, the total profit of the cruise itinerary is sensitive to the fuel price and hence, it is acceptable to use the shortest voyage distance method to design the schedule when the ports of call have a naturally geographical distance. In contrast, determining the sequence of ports of call solely by minimizing the overall voyage distance frequently leads to a significant reduction in the total profit when the ports do not have a naturally geographical sequence.

The last problem investigates the cruise service planning, which plans cruise services for a cruise ship, in order to maximize the total profit during a planning horizon. Considering the fact that major cruise terminals have limited berths as like the container terminals (Zhen wet al., 2016; Wang et al., 2018), the berth availability is incorporated into the planning. The problem also considers the phenomenon that the marginal profit of operating a cruise service would decrease gradually when a cruise service is repeated several times. To solve the problem, a nonlinear programming model is built, for which two linearization methods are suggested. By conducting computational experiments, it is founded that the linearization method using the concavity of the objective function could improve computational efficiency significantly. Some properties of the problem in different assumptions are also investigated. In particular, if there is only one candidate cruise service for the problem, a greedy algorithm can derive the optimal solution. Based on real-world cases, the robustness tests are conducted to show that if there are some parameters needed by the model cannot be estimated accurately, the proposed model has its robustness and can still obtain a near-optimal plan. Sensitivity analysis is also conducted for the berth availability to see its effects on outputs of the model.

Based on the above studies, three future research directions are worthwhile to be further explored. (i) Integrating the optimizations: although the first two problems (container ship type decision and container reefer slot conversion) or the other two problems (cruise itinerary schedule design and cruise ship service planning) are treated in isolation, they actually interact with each other. For instance, in the cruise ship service planning problem, we take the cruise itinerary schedules exogenously given. However, if we integrate the cruise itinerary schedule design and cruise ship service planning, we can expect more profits compared with the original two-stage optimizations since the schedule design can take the inconvenience of the service planning into account. (ii) Considering the information ambiguity: We now study the problems by supposing that we have full data information, for example, in the container ship type decision problem, we assume that the container transportation demand is known and is deterministic. However, in practice, there may be high uncertainty on the information. Therefore, we need to obtain robust solutions by designing more solid solution approaches in response to the information ambiguity. (iii) Extending the problems to generalized cases: The first two problems of container shipping are based on a single shipping route. It is worthwhile to extend the problems to consider the whole shipping network of a shipping liner that may involve many shipping routes. The other two problems of cruise shipping are based on a single cruise ship. If we consider that, a cruise line owns a fleet of cruise ships. It would be interesting to extend the problems to the ones that also address the cruise ship fleet management.

Appendices

Appendix A: Specification of standard containers and foldable containers

Table A.1 shows the major specifications of standard containers and foldable containers, which are almost the same. The specifications of standard containers are collected from APL (2017) and the specifications of foldable containers are collected from Holland Container Innovations (2017).

Table A.1: Specifications of foldable and standard containers

Description	Standard containers	Foldable containers
Cubic capacity	67.7 cubic meters	72.9 cubic meters
Maximum payload	26,760 kg	26,600 kg
Gross weight	30,480 kg	32500 kg
External length	12.192 m	12.192 m
External width	2.438 m	2.438 m
External height	2.591 m	2.896 m
Internal length	12.032 m	12.012 m
Internal width	2.352 m	2.324 m
Internal height	2.392 m	2.615 m
Door opening width	2.340 m	2.172 m
Door opening height	2.280 m	2.508 m
Bundle (4 into 1) height	—	2.896 m

Appendix B: Proof for the results of Figure 2.10

Informal, we can prove the non-increasing trend by using a simplified mathematical model. Assuming X represents the vector for the number of standard containers in ports and Y represents the vector for the number of foldable containers in ports. Then, $\rho = \frac{Ye^T}{Xe^T+Ye^T}$ shows the percentage of foldable container usage, where $e = \{1, \dots, 1\}$ and e^T is the transposition of e. Given the defined vector variables X and Y, we can use the following simplified standard model to represent the formulation of our problem.

$$Min\ C_1X + C_2Y$$

$$s.t.\ A_1X + A_2Y = B$$

$$X, Y \geq 0$$

where all coefficient matrixes or vectors (C_1, C_2, A_1, A_2, B) are positive. In the next, we can derive:

$$X = A_1^{-1}B - A_1^{-1}A_2Y$$

By substituting it to the objective, we have,

$$Min\ C_1A_1^{-1}B - C_1A_1^{-1}A_2Y + C_2Y$$

Based on which, if the cost coefficient C_2 for foldable containers increase, Y will decrease. As a result, X will increase. As we have $\frac{1}{\rho} = \frac{Xe^T + Ye^T}{Ye^T} = \frac{Xe^T}{Ye^T} + 1$, the increasing of cost coefficient C_2 will lead to the increasing of $\frac{1}{\rho}$, that is the decreasing of ρ. Such a proof verifies the result shown in Figure 2.10.

References

APL, 2017. The perfect fit for all your different needs: your APL equipment guide, https://www.apl.com/wps/wcm/connect/659ca9b6-7eb3-4c16-82de-8de04abab7e9/Equipment+guide.pdf?MOD=AJPERES. Accessed on 10 August 2017.

Holland Container Innovations, 2017. 4FOLD foldable container. http://hcinnovations.nl/4fold-foldable-container/. Accessed on 10 August 2017.

Wang, K., Wang, S., Zhen, L., & Qu, X., 2016. Cruise shipping review: operations planning and research opportunities. *Maritime Business Review* 1(2), 133-148.

Wang, K., Wang, S., Zhen, L., & Qu, X., 2017. Cruise service planning considering berth availability and decreasing marginal profit. *Transportation Research Part B: Methodological* 95, 1-18.

Wang, K., Zhen, L., Wang, S., & Laporte, G., 2018. Column generation for the integrated berth allocation, quay crane assignment, and yard assignment problem. *Transportation Science* 52(4), 812-834.

Xia, J., Wang, K., & Wang, S., 2019. Drone scheduling to monitor vessels in emission control areas. *Transportation Research Part B: Methodological* 119, 174-196.

Zhen, L., Wang, S., & Wang, K., 2016. Terminal allocation problem in a transshipment hub considering bunker consumption. *Naval Research Logistics* 63(7), 529-548.