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Cruise service planning considering berth availability and decreasing marginal profit

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Abstract: This paper 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) that 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 the 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.

Keywords: Cruise shipping; Cruise network design; Service planning; Berth availability; Dynamic programming.

1. Introduction

Over the past two decades, the cruising industry has developed dramatically. In 2014, there

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are 296 cruise ships in the world (Cruise Ship Statistics, 2015). With such a massive fleet, the global cruise industry generated revenues of 37.1 billion U.S. dollars, and the number of cruise passengers in the worldwide level reached a total of 22.04 million in 2014 (Cruise Industry, 2015). Those 22.04 million cruise passengers were mainly from developed countries: Among them, 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, as the cruising industry is an oligopolistic industry, the majority of the huge cruise market is shared by three cruise companies, which are Carnival, Royal Caribbean, and Norwegian Cruise Lines with market shares of 41.8%, 21.8%, and 8.2%, respectively (Cruise Industry, 2015).

For those cruise companies, a few strategic or tactical decisions have a long-lasting effect on the profitability of their cruise ships (Veronneau and Roy, 2009). This is due to the fact that the cruising market fluctuates significantly by the regional and seasonal differentiations: Some cruise ships are routinely repositioned from the Caribbean to Alaska in summer, or from the Mediterranean to the Caribbean in winter in order to appeal to more cruise passengers. Recently, a number of mass market cruise ships were relocated to the Asia to gain profit from the fast-growing Asian market. When a cruise ship is relocated to a new region for the sake of seasonal variations or market repositioning, a home port will be selected at first. Then, various loop candidate cruise services are designed for the cruise ship to operate: a candidate cruise service operated by the cruise ship is a cruise route, in which the ship picks up cruise passengers at the home port, visits the ports of call covered in the route, and returns to the home port where the passengers get off the ship.

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 construct 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 for 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 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 or not 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, firstly we build an integer linear model assuming that the marginal profit of operating a cruise service is constant. Then, an integer nonlinear model is formulated for 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 paper is organized as follows. Section 2 reviews the related works. Section 3 presents a brief problem description and proposes the mathematical models. Complexity analysis and extensive comparison with heuristics are conducted in Section 4. The results of numerical experiments are reported in Section 5. Conclusions are then outlined in the last section.

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 the 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 in 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 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 a 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 nearly 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 in essential.

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 consider 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 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 is 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.

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.

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 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 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 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 $M1$. 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 $M2$.

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 $M1$ can be formulated as follows:

$$[\boldsymbol{M1}] \quad \text{Maximize} \quad \sum_{t\in\mathbb{T}} \sum_{r\in\mathbb{R}} g_r z_{rt} \tag{1}$$

$$s.t. \quad z_{rt} \le \delta_{rt} \qquad \forall r \in \mathbb{R}, t \in \mathbb{T} \tag{2}$$

$$\sum_{r\in\mathbb{R}} \sum_{t'=\max(t-s_r+1,1)}^{t} z_{rt'} \le 1 \qquad \forall t \in \mathbb{T} \tag{3}$$

$$z_{rt} \in \{0, 1\} \qquad \forall r \in \mathbb{R}, t \in \mathbb{T}. \tag{4}$$

In the above model $M1$, Objective (1) maximizes the total profit by selecting cruise services from a set of pre-determined candidate services in the planning horizon. Constraints (2) ensure that all the designed services are operable considering the availability of berths at the ports visited. Constraints (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 (4) define the domains of the binary decision variables.

3.3. Model with decreasing marginal profit

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:

$$G_r(x_r) < G_r(x_r + 1) \tag{5}$$

$$G_r(x_r + 2) \ - G_r(x_r + 1) \leq G_r(x_r + 1) - G_r(x_r). \tag{6}$$

Figure 1 demonstrates the concavity of the function on the total profit for operating a service repeatedly.

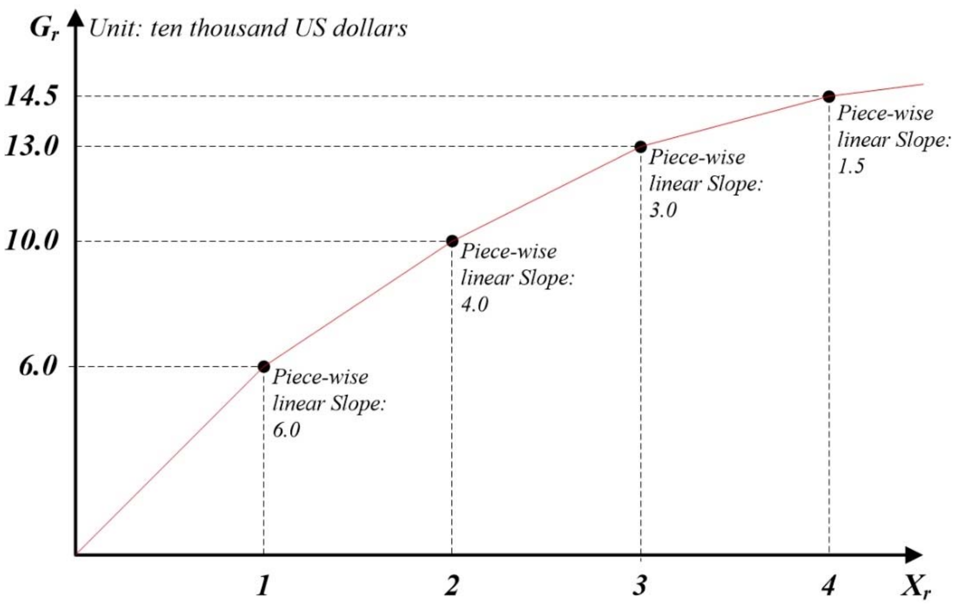

Figure 1: Concavity of the profit function

Based on the above concave function, the model with decreasing marginal profit (i.e., $M2$) can be formulated as follows:

$[\boldsymbol{M2}]$ Maximize $\sum_{r \in \mathbb{R}} G_r(x_r)$ (7)

s.t. Constraints (2-4) and;

$$x_r = \sum_{t=1}^{T} z_{rt} \qquad \forall r \in \mathbb{R}. \tag{8}$$

In this model, Objective (7) maximizes the sum of the total profits for operating services. Constraints (8) are used to calculate the number of repeats for each service.

However, $M2$ 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 $M2$. 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 simply calculated by:

$$\overline{x}_r = \left\lfloor \frac{T}{s_r} \right\rfloor \qquad \forall r \in \mathbb{R}. \tag{9}$$

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), which is a tighter upper bound compared with Eq. (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 4.3.

The first linear model:

The first linear model is defined as $M2'$, which does not take advantage of the problem structure for the linearization. In this linear model, $g_{rx} \coloneqq G_r(x) - G_r(x-1)$ 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 $M2$ 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 $M2'$ is:

$$[\boldsymbol{M2'}] \quad \text{Maximize} \quad \sum_{t\in\mathbb{T}} \sum_{r\in\mathbb{R}} \sum_{x=1}^{\overline{x}_r} g_{ry} z_{rxt} \tag{10}$$

$$\text{s.t.} \quad z_{rxt} \le \delta_{rt} \qquad \forall r \in \mathbb{R}, x \in \{1, 2 \cdots, \overline{x}_r\}, t \in \mathbb{T} \tag{11}$$

$$\sum_{r\in\mathbb{R}} \sum_{t'=\max(t-s_r+1,1)}^{t} \sum_{x=1}^{\overline{x}_r} z_{rxt'} \le 1 \qquad \forall t \in \mathbb{T} \tag{12}$$

$$\sum_{t=1}^{T} z_{rxt} \le 1 \qquad \forall r \in \mathbb{R}, x \in \{1, 2 \cdots, \overline{x}_r\} \tag{13}$$

$$\sum_{t=1}^{T} t z_{rxt} + s_r - 1 \le \sum_{t=1}^{T} t z_{r,x+1,t} + T\left(1 - \sum_{t=1}^{T} z_{r,x+1,t}\right) \qquad \forall r \in \mathbb{R}, x \in \{1, \cdots, \overline{x}_r - 1\} \tag{14}$$

$$z_{rxt} \in \{0, 1\} \qquad \forall r \in \mathbb{R}, x \in \{1, 2 \cdots, \overline{x}_r\}, t \in \mathbb{T}. \tag{15}$$

In the above model $M2'$, Objective (10) maximizes the sum of the total profits in the planning horizon. Constraints (11) guarantee that all the selected services satisfy the availability constraints of berths at the ports visited. Constraints (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 (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 (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 (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 (14) could be removed to reduce the computation time for the model $M2'$. Without Constraints (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 $M2''$, 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 $M2'$ is:

$[\boldsymbol{M2''}]$ Maximize $\sum_{r\in\mathbb{R}} u_r$ (16)

s.t. Constraints (2-4); (8);

$$u_r \le G_r(x) + \frac{G_r(x+1)-G_r(x)}{(x+1)-x}(x_r - x) \qquad \forall r \in \mathbb{R}, x \in \{0,1,\cdots,\overline{x}_r - 1\}. \qquad (17)$$

In this model, Objective (16) maximizes the sum of the total profits for operating services by repeating different times. Constraints (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., $M2$), which will be further compared in Section 5 for the computation efficiency to solve the problem.

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 $M1$ and the model $M2$ respectively. Some properties on commonly used heuristic methods for the CSP problem are also investigated and proved.

4.1. Complexity of the problem of $M1$ with constant marginal profit

Proposition 1: The problem of $M1$ 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 $M1$ becomes a problem of maximizing the total profit by choosing 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 $M1$ is also NP-hard. ■

Proposition 2: The problem of $M1$ is weakly NP-hard.

Proof: We can propose a DP based pseudo-polynomial algorithm for the problem, which could demonstrate that the problem of $M1$ is weakly NP-hard. The procedures of the DP algorithm are elaborated as follows:

To apply the DP for the problem of $M1$, 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:

$$U(t) = -\infty \qquad t = T+2, T+3, \ldots \tag{18}$$

$$U(t) = 0 \qquad t = T+1. \tag{19}$$

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:

$$U(t) = max_{r \in \mathbb{R}} \left\{ (1 - z_{rt}) \cdot U(t+1) + z_{rt} \cdot \left(g_r + U(t + s_r) \right) \;\middle|\; z_{rt} \leq \delta_{rt}, z_{rt} \in \{0, 1\} \right\}$$

$$\forall t \in \mathbb{T}. \tag{20}$$

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 (i.e., 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.

Finally, we will obtain the value $U(1)$, the objective value of $M1$, 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 1*:

Algorithm 1. *The dynamic programming based algorithm for the model M1*

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

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 $M1$ is weakly NP-hard. ■

4.2. Complexity of the problem of $M2$ with decreasing marginal profit

Corollary 1: The problem of $M2$ is NP-hard.

Proof: The problem of $M2$ nests the problem of $M1$ as a special case. If we change Eq. (6) to $G_r(x_r+2)-G_r(x_r+1)=G_r(x_r+1)-G_r(x_r)$, $M2$ becomes $M1$. As $M2$ is more general than $M1$, and the problem of $M1$ is NP-hard, the problem of $M2$ is also NP-hard. ■

Here, we would like to investigate the problem of $M2$ 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 3: The problem of $M2$ 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 $M2$, 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 $M1$ as the decreasing pattern of the service marginal profit has been considered in the problem of $M2$. Enlightened by the formulation of $M2'$, in the DP for the special case of $M2$, we assume that each combination of (r,x) is a "detailed service" with the marginal profit $g_{rx}:=G_r(x)-G_r(x-1)$, 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 $\mathbb{S} = \{(1,1), (1,2), \cdots, (1, \overline{x}_1), \cdots, (r, 1), (r, 2), \cdots, (r, \overline{x}_r)\}$. The upper bound for $|\mathbb{S}|$ is $|\mathbb{R}| \cdot T$.

In the case of the problem of $M2$, 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:

$$V(0, t) := 0 \qquad \forall \ t \in \{0, 1, \cdots T\} \tag{21}$$

$$V(\beta, 0) := 0 \qquad \beta = 1, 2, \ldots, |\mathbb{S}|. \tag{22}$$

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:

$$V(\beta, t) = \begin{cases} V(\beta - 1, t) & , if \quad t < s'_\beta \\ \max\{V(\beta - 1, t),\ V(\beta - 1, t - s'_\beta) + g'_\beta\}, if & s'_\beta \leq t \end{cases} \quad \forall \beta \in \mathbb{S}, t \in \mathcal{T} \tag{23}$$

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 2*:

Algorithm 2. *The dynamic programming based algorithm for the model M2 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 $M2'$ 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 pseudo-polynomial algorithm, which show that the special case is weekly NP-hard. ∎

For the general case of the problem of $M2$ considering the berth availability and decreasing marginal profit, we cannot propose a pseudo-polynomial algorithm using DP. Therefore, the two linear models $M2'$ and $M2''$ are solved directly by CPLEX for the optimal solutions of $M2$.

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 $M2$ 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 $M2$ 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 considering the berth availability (i.e., $\forall r,\ \delta_{rt} = 1$). Based on the 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 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 4: In the worst case, the ratio between the optimal profit obtained by the model $M2$ and the profit obtained by Myopic Rule_1 or Myopic Rule_2 is close to infinity.

Proof: See Appendix A. ■

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 one day to the next. 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: 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 $M2$.

Proof: See Appendix B. ■

Proposition 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. (9). The greedy algorithm is better than Eq. (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. (9) will be given in Section 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 $M2'$ and $M2''$ are solved by CPLEX12.5 with concert technology of C#(2012).

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 5.4.

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 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 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 with 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 $M2$ 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.

5.2. Efficiency of solving the models

In this section, we compare the model $M2'$ with Constraints (14) and without Constraints (14), which are solved by CPLEX in different instance groups. The comparison results are shown in Table 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 $M2'$ without Constraints (14) much faster than the model $M2'$ with Constraints (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 $M2'$ to solve the problem, Constraints (14) should be removed for saving the CPU time. The solution obtained by the model $M2'$ without Constraints (14) can be sorted manually for the optimal solution by adjusting the chronological order for the repeats of each cruise service, as discussed in Section 3.3.

Table 2: Comparison between the model $M2'$ 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.

In Section 3.3, we have proposed two linear models $M2'$ and $M2''$ for the nonlinear model $M2$. Here, we test which linear model has a higher efficiency to derive solutions for the problem. As we have verified that the model $M2'$ without Constraints (14) can be solved faster, the comparison is conducted between this case of the model $M2'$ and the model $M2''$. Table 3 illustrates the comparison between the model $M2'$ and $M2''$. 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 $M2''$ can be solved much faster than the model $M2'$ 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 $M2'$ 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 3: Comparison between the two linear models

Instance		The first model			The second model			Comparison	LP-relaxation	
# of candidate service	Instance id	Z_f (US$)	T_f (s)	B&B nodes	Z_s (US$)	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.

5.3. Performance of myopic approaches

In this section, we aim to validate the effectiveness of the model $M2''$ (the second linear model for the model $M2$) and investigate the performance of the two myopic approaches proposed in Section 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 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 $M2''$, which validates the effectiveness of the model and addresses the importance of having the optimization-based service planning tool.

Table 4: Comparison between the model $M2$ and two myopic rules

Instance		$M2''$	**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.

5.4. 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 of 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 passenger 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 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 and the locations of the port cities visited by those cruise services are shown in Figure 2.

Table 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.

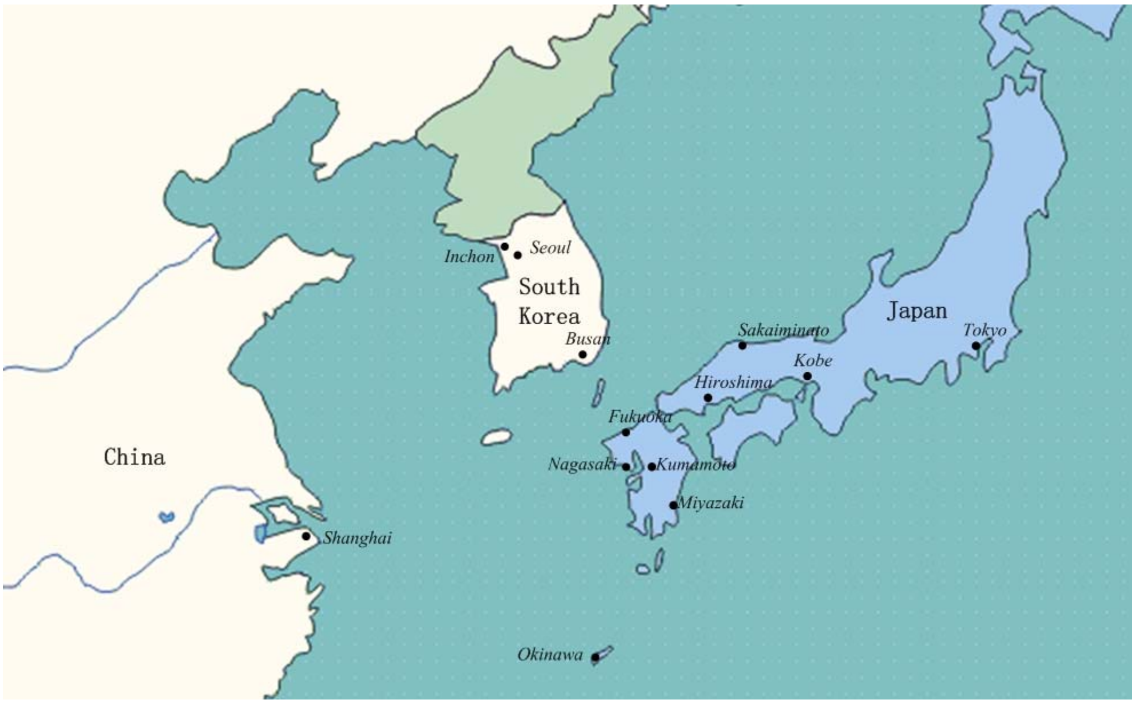

Figure 2: Locations of the port cities

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 profit 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 following ways: firstly, we set the p for each cruise service based on the assumption in Section 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 indicate 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.

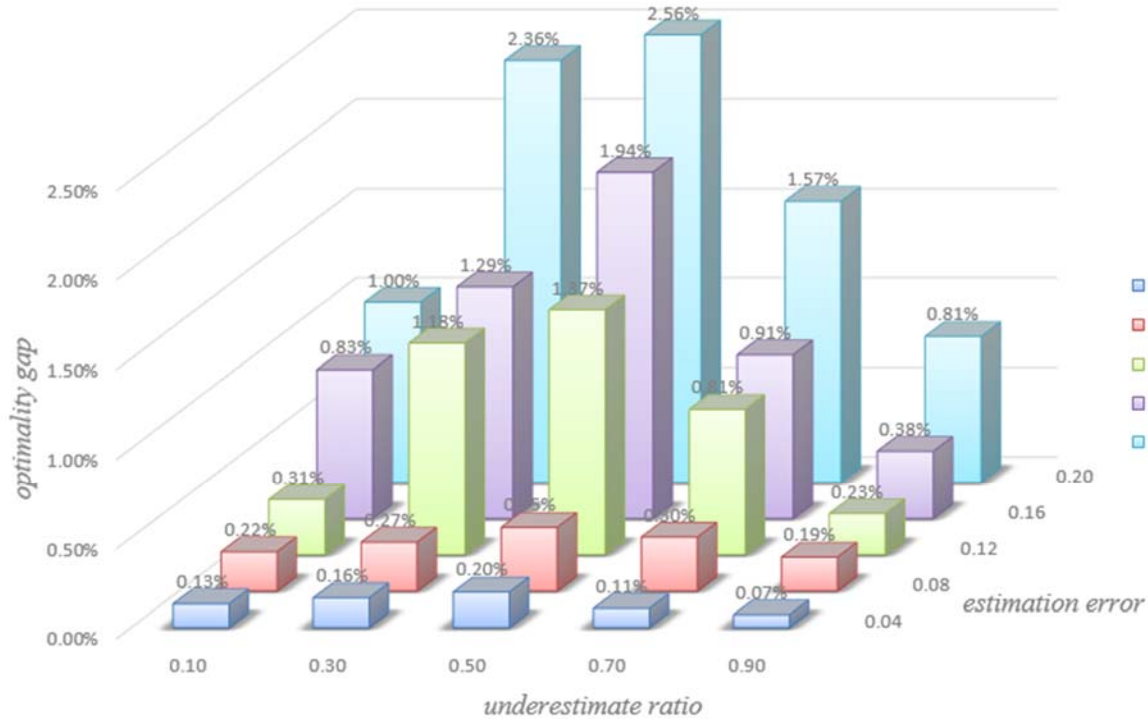

Figure 3: The robustness test on p

The robustness test on the average profit per cruise passenger for cruise services is illustrated in Figure 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 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 color), 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.

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 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 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 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.

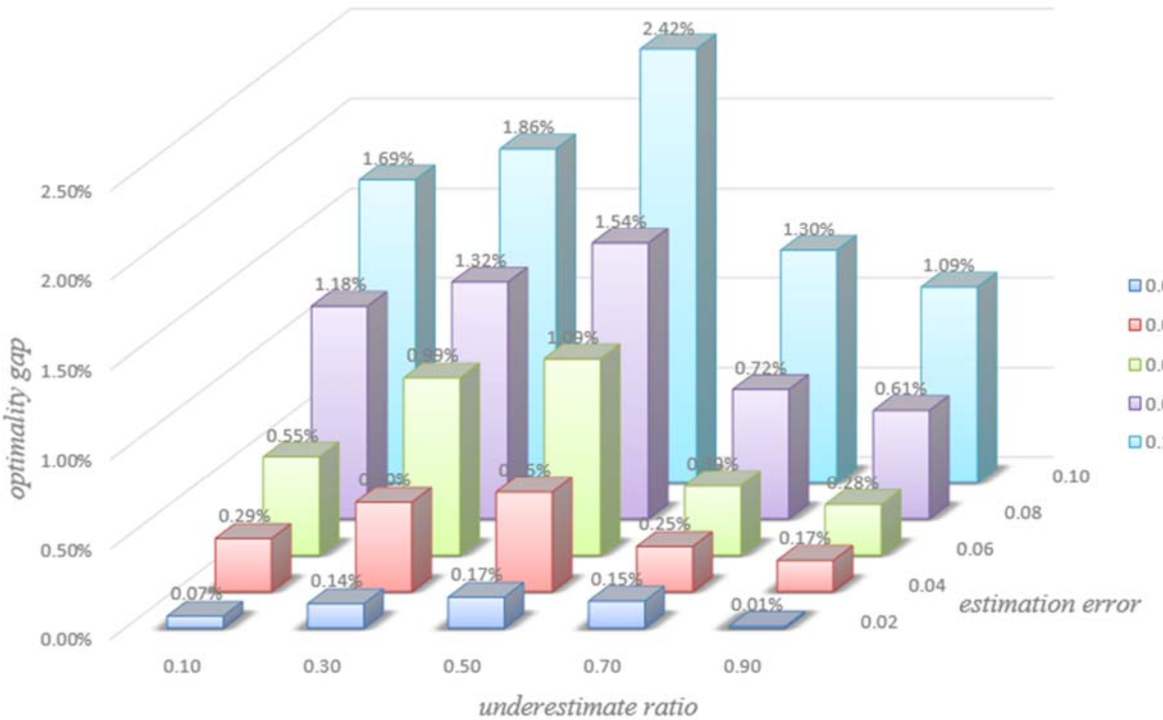

Figure 4: The robustness test on a

The two 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 considering the berth availability.

5.5. Sensitivity analysis for the berth availability

In this section, based on 13 real candidate cruise services given by Table 5, we further conduct some sensitivity analysis for the berth availability as the berth availability plays the dominant role in the optimization. In Section 5.1, 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, Figure 6, and Table 6, and are analyzed below.

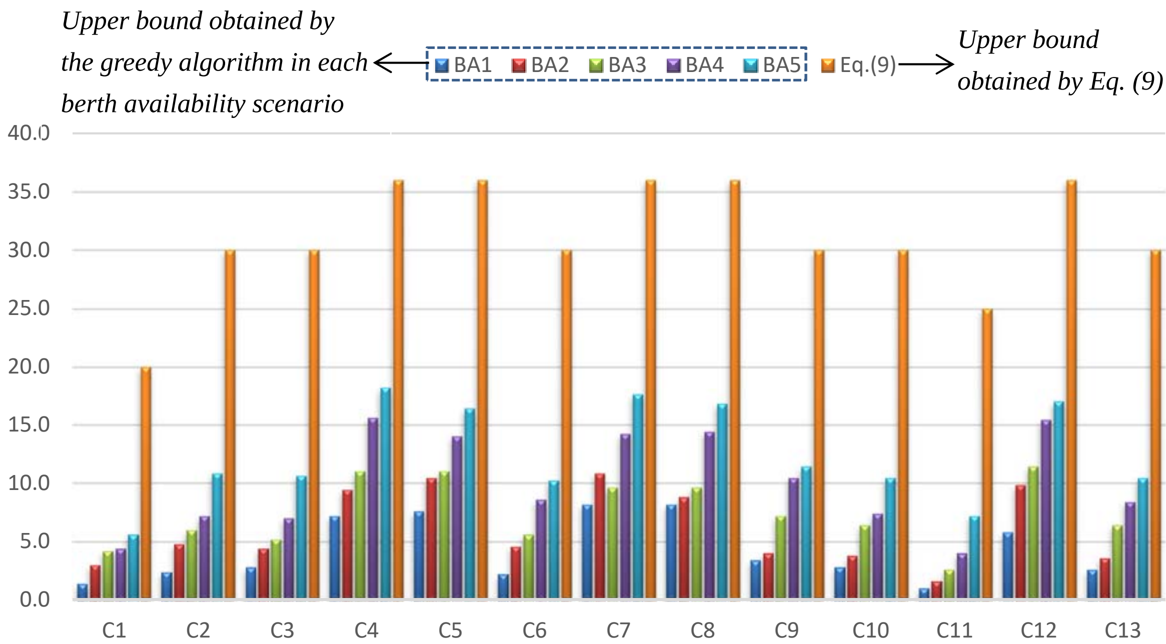

Figure 5: Upper bound $\overline{x}_r$ obtained by the greedy algorithm and Eq. (9)

Figure 5 reports $\overline{x}_r$, upper bound of the number of repeats for Service r in one planning horizon. Eq. (9) exhibits a way to approximate $\overline{x}_r$. In Proposition 5, we proved that the greedy algorithm can obtain the optimal $\overline{x}_r$. Here, we report $\overline{x}_r$ obtained by the greedy algorithm under the five berth availability scenarios and by Eq. (9) are given in Figure 5. Note that the $\overline{x}_r$ obtained by Eq. (9) is constant under different berth availability (given by Bar Eq. (9)), as it is derived by $\left\lfloor \frac{T}{s_r} \right\rfloor$, and the $\overline{x}_r$ 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 contains six bars. As can be seen, the upper bound $\overline{x}_r$ obtained by Eq. (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 $\overline{x}_r$ obtained by Eq. (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 $\overline{x}_r$.

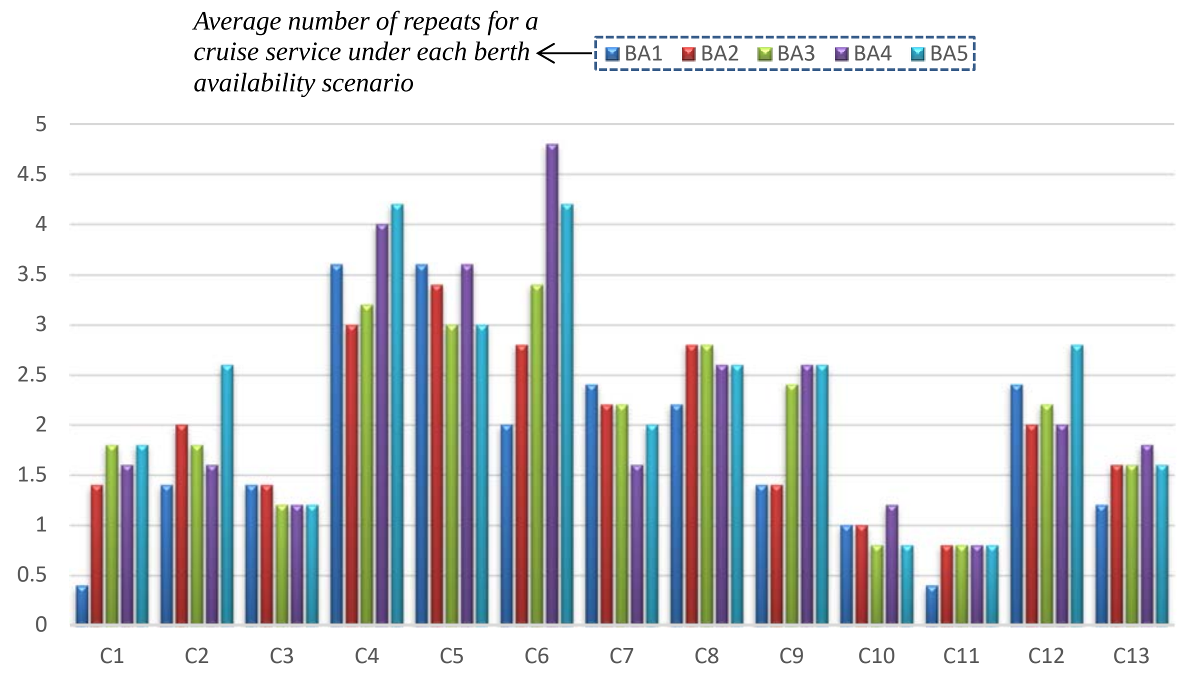

Figure 6: Number of repeats of cruise services under different berth availability scenarios

Figure 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). 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.

Table 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.

Table 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, average profit per operation day keeps nearly unchanged when the berth availability fluctuates.

6. Conclusions

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. 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 be interacted 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. All of the above issues will be the research directions for our future studies.

Appendices

Appendix A: Proof of Proposition 4

Proposition 4: In the worst case, the ratio between the optimal profit obtained by the model $M2$ 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 $M2$, $\ddot{Z}$ 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. ■

Appendix B: Proof of Proposition 5

Proposition 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 $M2$.

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 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 $M2$ 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 1, the objective of the model $M2$ 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 $M2$ 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 $M2$.

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 $M2$ when there is only and one candidate cruise service r'. ∎

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