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Rental pricing and empty container repositioning strategy for a one-way container rental service

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ABSTRACT

This paper investigates rental pricing and empty container repositioning (ECR) strategies for a one-way container rental service (OCRS). The proposed OCRS aims to address intercontinental container imbalances and alleviate financial burdens on shipping companies by optimizing rental pricing and ECR operations. Mathematical optimization models are developed to determine optimal prices and container utilization, complemented by two practical inventory management policies, namely periodic review and continuous review policies, to enhance real-world applicability. To further validate the robustness of the proposed service in stochastic environments, two highly practical rule-based heuristics are additionally proposed. Computational experiments evaluate the service's profitability under various scenarios, revealing that the heuristic based on the continuous review policy demonstrates robust performance. The results underscore the potential of the OCRS to promote resource efficiency and to reduce logistical waste, paving the way for resilient and eco-friendly maritime logistics networks.

1. Introduction

Global trade mainly occurs through maritime transportation, which accounts for 85 percent of global trade. Among various cargo types, container trade volumes possess 15 percent of total seaborne trade (UNCTAD, 2023). However, a significant imbalance exists in intercontinental cargo volumes. When freight is transported via containers from export-oriented nations (e.g., China) to import-focused regions like North America and Europe, some of these containers should return empty or underutilized (i.e., empty backhaul). Consequently, the retrieval and repositioning of empty containers are essential but incur substantial costs for their owners, leading to a retrieval rate below 100 percent and exacerbating intercontinental container imbalances.

Containers are divided into carrier-owned and shipper-owned containers, further categorized into self-owned containers or leased containers from leasing companies (Chen et al., 2022c). Container leasing offers advantages such as flexibility in response to demand fluctuations, avoidance of capital fixation, and reduction in ancillary costs, with various lease types including long-term, short-term, round-trip, and one-way leases. Among these, one-way leasing contracts mainly offer greater flexibility to lessees. Fig. 1 illustrates the difference between the flow of owned/long-term leased containers and one-way leased containers from a carrier's perspective. Note that although there are usually many additional procedures involved in practice, such as the intermediary role of forwarders (Xu et al., 2024), this study focuses exclusively on the contract between the container lessor and the carrier. Therefore, the process has been significantly simplified in Fig. 1.

The carrier is required to continuously reposition its own containers from surplus ports to deficit ports in order to maintain its operations successfully. Although the actual costs incurred for repositioning may be reduced depending on contractual agreements with shippers, the necessity of repositioning itself remains unchanged. However, in the case of one-way leased containers, the contract terminates upon the return of the container at the destination port (Port 2), thereby releasing the carrier from the responsibility of repositioning. Due to such convenience, one-way leasing contracts come with the drawback of being more expensive, thereby posing a significant burden to the lessees (Zhao, 2007). As a result, one-way leasing contracts have primarily been utilized by carriers as a temporary solution to address sudden fluctuations in demand rather than as a consistent viable option. Moreover, research on one-way leasing, which allows for freedom in container retrieval to carriers, remains insufficient.

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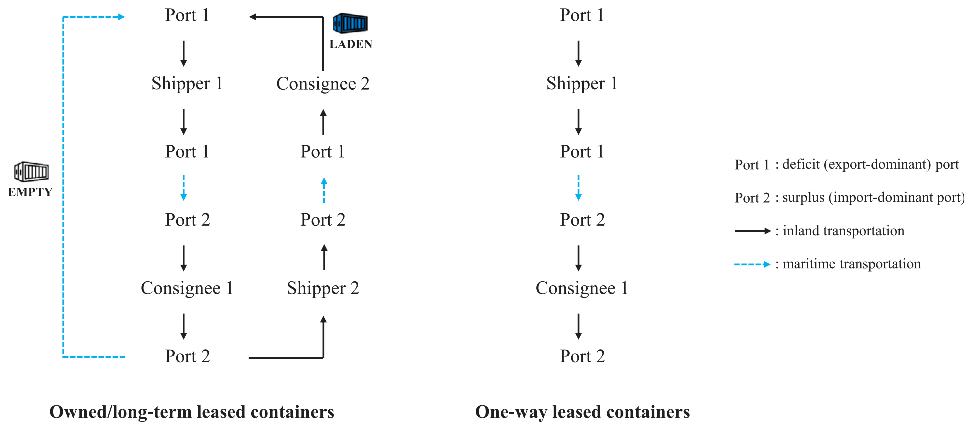

Fig. 1. Simplified container flow from a carrier's perspective.

In this paper, we propose a novel one-way container rental service (OCRS). To emphasize the difference between conventional leasing contracts and the service we propose, we intentionally adopt the term "rental" instead of "leasing". Traditional one-way leasing contracts have typically been one of the various options offered by leasing companies and thus come with the drawback of being relatively expensive. However, our proposed service is entirely based on one-way contracts, offering only this type of service to customers (probably carriers). Accordingly, the service provider (i.e., lessor) takes on the whole responsibility of empty container repositioning (ECR). Therefore, determining appropriate pricing and efficiently managing ECR constitute the core focus of the OCRS.

Restricting the contract option to a single mode facilitates ECR based on economies of scale, which enables the provision of more competitive pricing to customers. Considering that the primary target customers of this service are shipping companies, they may also act as competitors by choosing not to utilize one-way contracts and instead reposition empty containers on their own. In other words, if the rental price of an origin–destination (O–D) pair (e.g., Port 1 to Port 2) exceeds the transportation cost of the reverse route (e.g., Port 2 to Port 1), the customer enjoys no merit in utilizing the proposed service. Consequently, we aim to offer customers a rational option that can be utilized not only as a one-time solution for emergencies but also as a consistently viable choice in everyday operations.

The sharing economy has been garnering great interest in various areas recently. Specifically, one can easily experience shared mobility by such modes as car-sharing, bicycle-sharing, or scooter-sharing worldwide nowadays. However, the word "sharing" deviates considerably from its original meaning when applied to such services. Rather than indicating concepts of communal use of an object that belongs to an individual, such sharing services are closer to rentals, allowing for a very short period of use. The proposed OCRS shares several similarities with these sharing services, as it is based on one-way contracts. However, there are some critical distinctions.

In the case of shared mobility services, users exhibit highly diverse travel routes and rental periods. As a result, it is impractical to set pricing for a specific route; instead, a time-based pricing model, typically charging by usage, is adopted. Moreover, pricing in these services is determined considering the randomly distributed willingness-to-pay of individual customers. In contrast, container transportation operates on predefined routes between designated ports (Yap et al., 2023), and in the absence of disruptions, the transportation time tends to be consistent. Therefore, it is reasonable to offer route-specific pricing. In addition, as potential customers can also act as competitors, each price must be strictly constrained not to exceed the transportation cost of the reverse route.

We propose an optimization model to represent the situation in which the service provider of the OCRS determines rental pricing and the utilization of containers, assuming deterministic demand. Additionally, the model is complemented by two practical inventory management policies, and the profitability and effectiveness of the OCRS are analyzed. To relax the assumption of deterministic demand and further enhance real-world applicability, two practical rule-based heuristics are also presented. Eventually, we hope that the proposed service can successfully resolve container imbalance issues, thus alleviate shipping companies' financial burdens and suggest a new logistics paradigm.

The remainder of this study is organized as follows: Existing literature that previously studied related topics is reviewed in Section 2. In Section 3, we describe our problem. Then, the mathematical formulations are presented in Section 4. Computational experiments and the heuristics are reported in Section 5, and conclusions are offered in Section 6.

2. Literature review

2.1. Empty container repositioning (ECR)

Two distinct research streams are closely associated with our work. The first stream focuses on ECR, often called empty equipment repositioning. Since the standardization of containers, ECR has become a critical issue for the containerized trade market, as it addresses the challenge of demand imbalance. Essentially, this represents the situation of weighing the trade-off between the opportunity cost of unmet demand due to container shortages and the costs incurred by measures to address such imbalance. Striving for ECR is not limited to maritime transport but is also relevant to land transport utilizing rail networks or trucks (Kuzmicz and Pesch, 2019; Chen et al., 2022c). Consequently, research on ECR has been conducted extensively across various domains and continues to grow. Among this research, we specifically focus on ECR in the context of maritime transportation.

Dong et al. (2013) categorized ECR strategies into two major types: deterministic and stochastic/dynamic. The authors conducted a study comparing ten representative strategies from these two categories through simulation. Lee et al. (2012) investigated ECR policies based on an inventory management policy to address uncertain demand. Specifically, they employed a periodic inventory review model and applied a combination of nonlinear programming and an infinitesimal perturbation analysis-based gradient algorithm to solve the problem. In addition to the periodic inventory review model, Cai et al. (2022, 2024) explored a quantitative inventory control strategy. Upper and lower bounds are established for the empty container inventory at each port, ensuring inventory levels remain within the specified range.

As previously mentioned, ECR is carried out as a trade-off to address lost sales, and in the same vein, purchasing or leasing additional containers can also serve as a partial solution (Moon et al., 2010). Since the decline in interest in master leasing, most studies considering leasing have focused on long-term arrangements. Master leasing, which shares some similarities with the OCRS proposed in this study, allows lessees to access a flexible pool of containers on demand without long-term commitments. However, from a practical standpoint, long-term leasing has been preferred over master leasing, making the latter less commonly observed in recent years (Lumetzberger, 2010; Dong and Song, 2012). Long-term leases typically span two to eight years and are considered at the tactical or strategic decision-making level due to their lengthy contract periods (Dong and Song, 2012). Such contract durations significantly exceed the planning time horizons assumed in studies focusing on ECR at the operational level. As a result, long-term leased containers are often treated as carrier-owned containers in these studies (Jeong et al., 2018). Consequently, research on ECR that addresses leasing has predominantly concentrated on short-term leases (Moon et al., 2010; Lee et al., 2012; Lee and Moon, 2020; Lu et al., 2020).

To further reduce the ECR costs, some studies have additionally considered using foldable containers. Unlike standard containers, foldable containers can be folded and stacked, thereby reducing the space they occupy. As a result, more empty containers can be transported at once, leading to cost savings. Moon et al. (2013) explored situations involving ECR by considering not only foldable containers but also the option to purchase additional containers when available containers are insufficient. Similarly, Lee and Moon (2020) studied a robust ECR problem incorporating foldable containers and short-term leasing simultaneously. However, the authors did not explicitly consider the leasing option; instead, they treated it merely as a penalty for unmet demand. Zheng et al. (2016) and Wang et al. (2024) incorporated foldable containers and container leasing at different levels. Specifically, ECR decisions were made first by considering foldable containers, followed by an analysis of perceived container leasing prices to support decisions on whether to lease containers. Similarly, though excluding foldable containers, Hu et al. (2021) examined the impact of leasing on ECR decisions. The authors explicitly differentiated between long-term and short-term leases and determined guidance leasing prices for both options.

ECR, purchasing, and leasing options were suggested as solutions to address the issue of demand imbalance. However, these actions are fundamentally passive and merely respond to demand reactively after it arises. In contrast, there have also been attempts to control demand actively through pricing strategies. These efforts are based on the widely accepted common sense that price influences demand, which is broadly applicable across various fields (Park and Moon, 2024). Zhou and Lee (2009), Xu et al. (2015), Chen et al. (2016), and Yu et al. (2024) modeled the problem under the consideration of multiple players and assumed that demand is linearly dependent on price. Due to the significant increase in problem complexity as the number of decision-makers grows, these studies assumed a relatively simple scenario involving two ports (i.e., two depots) and single decisions, substantially simplifying ECR-related decisions. In contrast, Lu et al. (2020) examined pricing and ECR decisions over multiple time periods. The authors assumed stochastic demand, which is influenced by prices. However, again, due to the high complexity of the problem, their analysis was also limited to scenarios involving only two depots.

Note that all the studies mentioned above adopt the perspective of carriers (and forwarders also in the study of Xu et al. (2015)). In contrast, similar to our study, some research explicitly addresses the problem from the perspective of container lessors. When finite capacity is assumed, the efficient allocation of on-hand inventory becomes critical. In this context, Yang et al. (2023) investigated the optimal capacity rationing policy of a lessor. Moreover, preserving the focus on fixed capacity, Jiao et al. (2016) and Jiao (2022) additionally considered pricing policies. However, all three studies excluded considerations for repositioning empty containers, marking the most significant distinction from our work. On the other hand, Zhao (2007) concentrated on the ECR problem from the perspective of a lessor but omitted pricing decisions. To fulfill these research gaps, we focused on both pricing and ECR from the perspective of the service provider of the OCRS.

2.2. Sharing economy

The other stream is related to sharing economy. Mobility sharing systems (MSSs), which commonly involve vehicles such as cars, bicycles, or scooters, have grown and evolved over several decades and are now widely implemented globally. They offer multiple benefits, such as reducing traffic congestion and emissions. From the individual's perspective, they provide cost-effective or time-efficient options for reaching desired destinations. MSSs can generally be categorized into round-trip (or two-way) and one-way systems, with the latter further divided into station-based and free-floating models.

Round-trip systems are typically station-based, requiring users to return the vehicle to the same station where it was rented. In station-based one-way systems, users can pick up and return vehicles at designated stations, which do not have to be the same (Hosseini et al., 2024). In contrast, free-floating systems allow users to access vehicles wherever available and return them anywhere, except in restricted areas (He et al., 2020; Kypriadis et al., 2020). Still, in car-sharing systems, the users are usually required to return the vehicle to a parking spot. Unlike round-trip systems, both types of one-way systems face challenges similar to those encountered in containerized trade, namely the imbalance between regions with high demand (i.e., rentals) and regions with high supply (i.e., returns). Failure to address this imbalance results in lost sales, leading to potential losses for service providers. Therefore, service providers must carefully weigh the trade-off between lost sales and the costs associated with repositioning (often referred to as "relocating" for MSSs) and make informed decisions. Extensive research has been conducted on this topic, and we focus on one-way systems, which are more relevant to our study, rather than on round-trip systems (Zhang et al., 2023).

The imbalance between supply and demand, where some regions experience surpluses and others face shortages, cannot simply be resolved by accurately predicting demand and deploying resources accordingly. Eventually, accumulation in certain regions still occurs, necessitating the inevitable process of repositioning. However, if the initial deployment is well-planned (i.e., if the fleet size is appropriately determined), subsequent repositioning becomes significantly easier (Boyacı et al., 2015). Repositioning can be conducted in a relatively stable environment during late-night hours when demand for shared mobilities is considerably lower. In such scenarios, the locations of mobility assets can be assumed to be deterministic, and the focus is solely on how to redistribute them efficiently. This is referred to as static repositioning (Raviv et al., 2013). If the initial deployment is effective enough to cover most demand without frequent intermediate repositioning, static repositioning can be optimized during nighttime hours to efficiently redistribute resources. However, situations may arise where real-time repositioning is required during the daytime due to rapid changes in demand, or where immediate repositioning is necessitated due to station capacity issues. Such scenarios are classified as dynamic repositioning (Ghosh et al., 2017; Zhang et al., 2017).

Table 1
Comparison between the OCRS and MSSs.

	OCRS	Bicycle/scooter-sharing	Car-sharing
Business type	B2B	B2C	B2C
Demand	Batch	Single	Single
Travel route	Predefined	Highly diverse	Highly diverse
Rental period	Long and consistent	Short and highly diverse	Short and highly diverse
Repositioning lead time	Long	Short	Short
Reposition quantity	Batch	Batch	Single

Repositioning can further be categorized based on whether it is carried out by service provider-employed staff (i.e., operator-based) or by the service users themselves (i.e., user-based) (Huang et al., 2020). Operator-based repositioning typically focuses on routing or scheduling to optimize the efficiency of staff operations (Angeloudis et al., 2014; Nourinejad et al., 2015; Folkestad et al., 2020; Yang et al., 2021). On the other hand, user-based repositioning cannot be managed in the same way as operator-based methods. In this case, the emphasis is on finding appropriate incentives to motivate users to participate in the repositioning process (Angelopoulos et al., 2018; Stokkink and Geroliminis, 2021; Zhang et al., 2025). Considering all these aspects, repositioning in MSSs can be broadly classified into operator-based static repositioning, operator-based dynamic repositioning, and user-based repositioning (Chu et al., 2023).

Table 1 provides a concise comparison between the proposed OCRS and existing MSSs. Fundamentally, the OCRS is a business-to-business (B2B) operation because its primary customers are shipping companies, whereas MSSs target individual users, making it a business-to-consumer (B2C) operation. This distinction also influences the nature of demand. In mobility sharing, an individual user cannot operate multiple vehicles simultaneously, restricting demand to one vehicle per person. In contrast, the OCRS (or container leasing) allows a single customer to rent (or lease) containers in batches.

Customers for MSSs can freely choose their travel routes, whereas containers are transported along predefined routes between designated ports. Unlike general leasing services, sharing systems usually target short-term rentals. Consequently, the rental periods in MSSs are relatively brief but vary significantly depending on each customer's travel patterns. On the other hand, even though the OCRS is proposed as a service targeting short-term rentals with one-way contracts, the nature of port-to-port transport via shipping inherently results in relatively longer rental periods compared to MSSs. Nevertheless, because containers are transported along predefined routes, the rental periods in the OCRS can generally be considered consistent. The difference in rental periods also extends to repositioning lead time. Mobility assets, even in static repositioning, are typically repositioned at least once per day. Under dynamic repositioning, the frequency increases, indicating that shared mobilities travel shorter distances, thereby reducing the time required for repositioning. Conversely, ECR again involves inter-port movements, necessitating a relatively longer repositioning lead time.

Finally, repositioning quantity may also differ. Scooters and bicycles can be loaded in batches onto a single truck, enabling batch repositioning similar to that of container operations (Legros, 2019). However, batch repositioning for cars requires car carriers, which are inefficient in terms of cost, time, and road conditions, still limiting the maximum batch size to under twelve. Therefore, except for in special cases (Iacobucci et al., 2022), cars are typically repositioned one at a time by drivers. As a result, the repositioning quantity for car-sharing systems is generally limited to one vehicle at a time. In other words, since car-sharing repositioning (whether operator- or user-based) is limited to one vehicle at a time, user-based repositioning has been predominantly applied in car-sharing systems rather than in other MSSs. Based on prior studies on MSSs, the OCRS can be regarded as a station-based one-way sharing system involving operator-based dynamic repositioning.

As previously mentioned, the OCRS can be viewed as a type of sharing system. However, several concepts regarding "container-sharing" already exist within container logistics. The first refers to container-sharing among carriers (e.g., shipping companies Zhang et al., 2019; Wang, 2024 or rail operators Tang et al., 2021), which closely aligns with the general concept of the sharing economy and is often referred to as "container-pooling". This practice involves one carrier lending its containers to another, which represents the most typical scenario of container-sharing. Nevertheless, this concept requires prior agreements among carriers, usually referred to as shipping alliances (Chen et al., 2022a,b, 2023), and is primarily utilized to promote street turns, which help reduce inland transportation within the hinterlands (Sterzik, 2013; Sterzik et al., 2015). The second form involves multiple shippers (i.e., consignors) who are unable to fill a full container load and, therefore, collectively consolidate their shipments into a less-than-container load, effectively sharing the capacity of a single container (Jamrus and Chien, 2016). However, the OCRS differs from these container-sharing models and more closely resembles MSSs.

As with containers, pricing in MSSs can serve as an alternative solution to address imbalances. Some studies have tackled demand imbalances exclusively through pricing without considering repositioning (Huang et al., 2022; Soppert et al., 2022). Additionally, several papers have addressed both pricing and repositioning decisions, aligning more closely with our problem context. For instance, Xu et al. (2018), Ren et al. (2019), Huang et al. (2021), Lu et al. (2021), Banerjee et al. (2022), and Pantuso (2022) explored dynamic pricing combined with repositioning strategies. Since MSSs typically operate as B2C businesses utilizing digital platforms, they are well-suited for implementing dynamic pricing regarding the randomly distributed willingness-to-pay of individual customers.

As previously mentioned, the proposed OCRS has an explicit upper bound on pricing, defined by the transportation cost of the reverse route. Although various factors, such as fuel prices, geopolitical issues, or disruptions, can influence transportation costs, they are generally considered to be significantly more stable compared to freight rates. In fact, studies addressing ECR commonly treat transportation costs as deterministic (refer to the studies in Section 2.1). Accordingly, the rental prices, which are constrained by these deterministic costs, are inevitably treated as static in this paper. Moreover, customers can sometimes feel uncomfortable with dynamic prices (Kim and Randhawa, 2018), and the burden is even greater for container leasing, which operates in a B2B context. Consequently, we propose a static pricing model where prices may differ by route but remain unchanged over time. Nevertheless, the prices remain static only for the specific given planning time horizon and may vary for other horizons.

As shown in Table 1, the OCRS differs significantly from mobility sharing regarding rental periods and repositioning lead times. This implies that a much larger proportion of assets remains tied up in current operations (whether for rental or for ECR) compared to that in shared mobility scenarios. As a result, the OCRS cannot directly adopt the repositioning strategies proposed in the shared mobility research stream to effectively cover demands. Thus, we propose strategies based on inventory management policies to effectively respond to demands during lengthy rental periods and repositioning lead times of the OCRS.

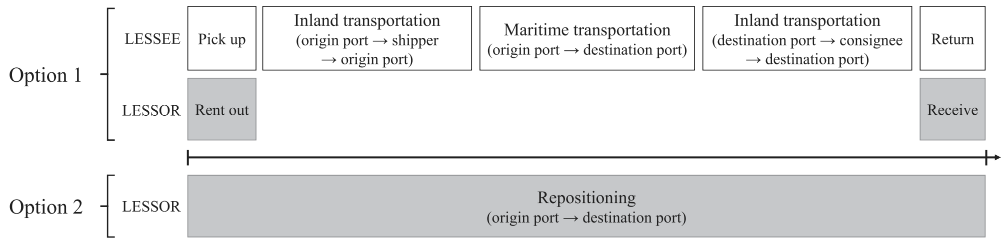

Fig. 2. Container flow based on the company's decision.

3. Problem description

We consider the problem of maximizing the profit of a container rental company via rental pricing and ECR. The company offers carriers only one-way contracts and takes on the whole responsibility for managing the ECR process. We assume all containers are identical; for example, we only treat a single type of container, such as twenty-foot containers. For each empty container, the company can choose one of three options. The first option is to rent it out to a customer. All rental contracts are defined over a route, starting from an origin port and terminating at a destination port, including the inland transportation times. In other words, a rented empty container is delivered from the origin port to a shipper, retrieved from the port after loading, transported to the destination port, delivered to the consignee, and retrieved again from the port, after which it can be returned (see Fig. 2). The second option is to reposition the container, and the third option is to do nothing. Note that this description serves as an illustrative example. In the actual model, since all containers are assumed to be identical, the options are not selected individually for each container.

The pricing scheme is fixed after the initial decision and lasts for a given period, which also stands for the period of planning the ECR. Assuming deterministic demand depending on the prices, we propose a mathematical model to handle such a problem. The core decisions are the rental pricing and the utilization of containers. In detail, the prices are set for each O–D pair, and the utilization of containers includes ECR and rental quantities in response to demands. As the pricing and rental quantity are both decisions, the optimization model is developed as a non-convex mixed-integer quadratic programming model. However, making optimal decisions for ECR is greatly difficult in practice. To resolve this issue and to derive practical insights, two ECR strategies based on inventory management policies are suggested.

Two order-up-to policies are utilized, which differ in the review process. The first is a periodic review policy, known as the (T, S) policy (Xu et al., 2023c). The term T stands for the fixed time between orders, and S is the order-up-to level. As the name indicates, the inventory position is reviewed periodically, which is every T period (a period can be any unit), and an order is placed to precisely fill the gap between the current inventory position and the order-up-to level. The other one is a continuous review policy, referred to as the (s, S) policy (Yun et al., 2011). The term S is again the order-up-to level, which is equivalent to that of the (T, S) policy, and s is the reorder point. The inventory position is continuously traced, and a new order is placed when it drops below the reorder point, regardless of the time passed since the last order. Again, the order size is the exact quantity of the difference between the order-up-to level and the current inventory position.

However, the ECR problem is not precisely equivalent to the inventory management problem. The main difference lies in the source of new orders. In a general inventory management problem, one receives the products of its orders from an external supplier. On the other hand, empty containers are just being relocated in an ECR situation, resulting in an additional demand for containers at some ports. In other words, an order of empty containers from a port decreases the inventory level of another port. Considering the difference between the two problems, we present two ECR strategies corresponding to the two inventory management policies, respectively.

Note that the aforementioned optimization model determines both the prices and container utilization, but the two ECR strategies do not regard pricing as a decision. Instead, the price determined in the optimization model is utilized, and decisions are made regarding container utilization as well as the parameters of the two strategies, such as the reorder point (s) and the order-up-to level (S). However, the order cycle (T), which is another parameter of the (T, S) policy, is not a decision and will be predetermined. The two ECR strategies are compared to the optimization model through computational experiments in Section 5.

As previously mentioned, deterministic demand is assumed. Original demands for each O–D pair are predetermined in the first place. These demands are reduced to actual demands according to the prices. In detail, the actual demand remains still, equal to the original demand if the price is free. However, the actual demand drops to zero as the price increases until it reaches the transportation cost of an empty container in the opposite direction. We further assume that the demands decrease linearly with regard to the prices in the range between the two points mentioned above. This is the standard situation of this problem, and we will later consider the price sensitivity of the customers. In addition, satisfying all the actual demands is not mandatory. As the proposed service basically serves as an additional option for shipping companies, shortages are more acceptable than are other types of contracts, and thus, any penalties related to loss of demand are not considered. Furthermore, all the unmet demands are regarded as lost sales rather than as backorders. In Section 5.3, we present two practical rule-based heuristics based on the proposed mathematical models. To verify the robustness of the OCRS and further enhance real-world applicability, the heuristics are evaluated in a stochastic environment by relaxing the assumption of deterministic demand.

4. Mathematical formulations

4.1. Notations

The model sets and parameters are defined as follows:

$\mathcal{T}$: set of periods, $\{1, 2, 3, \ldots, |\mathcal{T}|\}$

J : set of ports

$\mathcal{G}$: set of port groups

D_{ij}^{t} : original demand from port $i \in J$ to port $j \in J$ in period $t \in \mathcal{T}$

C_{ij} : transportation cost of an empty container from port $i \in J$ to port $j \in J$

R_{ij} : transportation time from port $i \in J$ to port $j \in J$

r_j : inland transportation time allied with port $j \in J$

F_G : penalty cost of inventory position difference for port group $G \in \mathcal{G}$

P_{ij} : fixed rental price of a container from port $i \in J$ to port $j \in J$

ρ : price sensitivity of demand, $0 \leq \rho \leq 1$

ϕ : weight of transportation cost, $0 \leq \phi \leq 1$

T : number of periods between orders regarding the (T, S) strategy

IL_j^0 : initial inventory level of containers at port $j \in J$

M : sufficiently large number

We consider a complete graph consisting of a finite number of ports. In other words, all routes exist between any two ports except for any two identical ones. Every element of $\mathcal{G}$ is a subset of J, in which any two of them are disjointed, and the union of all is equal to J. The parameter R_{ij} denotes the transportation time between two ports caused by shipping, whereas r_j indicates the inland transportation time depending on the port (e.g., the time between the origin port and the shipper or between the destination port and the consignee). We additionally assume that the inland transportation time for each port is constant, respectively.

The planning time horizon is based on a finite timeline, so the tail periods should be carefully considered. Specifically, one can easily suggest a superior strategy in which containers are sent from export-dominant ports to import-dominant ports without sufficient retrievals. The ECR cost can be reduced significantly, but the container imbalance will be severe in the last period. If the service provider is willing to maintain this service, the following planning time horizon is definitely waiting. Therefore, such a strategy has no merit, as it just postpones the current costs. To overcome this issue, a penalty is introduced that compares the initial and final inventory positions of containers. Note that these penalties are calculated by each port group rather than by each individual port.

The parameter P_{ij} denotes the fixed rental prices derived from the optimization model, which is utilized for the ECR strategies. The demands are assumed to decrease linearly with regard to the prices. The slope of the linear function is determined by ρ. When the value of ρ gets smaller, customers can afford higher prices, and more demands remain while the prices increase. Various factors can discount the transportation costs caused by ECR. For example, the service provider can enter into a long-term contract with a carrier for some capacity of a vessel or can effectively utilize the spot market. To further consider this matter, ϕ is introduced.

The decision variables are defined as follows:

x_{ij} : rental price of a container from port $i \in J$ to port $j \in J$

y_{ij}^{t} : demand coverage (rental quantity) from port $i \in J$ to port $j \in J$ in period $t \in \mathcal{T}$

z_{ij}^{t} : ECR quantity from port $i \in J$ to port $j \in J$ in period $t \in \mathcal{T}$

d_{ij}^{t} : actual demand from port $i \in J$ to port $j \in J$ in period $t \in \mathcal{T}$

IL_j^t : inventory level of containers at port $j \in J$ in period $t \in \mathcal{T}$

I_j^t : temporary inventory level of containers at port $j \in J$ in period $t \in \mathcal{T}$

IP_j^t : temporary inventory position of containers at port $j \in J$ in period $t \in \mathcal{T}$

SIP_j : initial inventory position of containers at port $j \in J$

TIP_j : final inventory position of containers at port $j \in J$

L_G : quantity of surplus containers at port group $G \in \mathcal{G}$

s_j : reorder point of port $j \in J$

S_j : order-up-to level of port $j \in J$

a_G, b_G : auxiliary binary variables, $G \in \mathcal{G}$

$\alpha_j^t, \beta_j^t, \gamma_j^t, \delta_j^t$: auxiliary variables, $j \in J,\ t \in \mathcal{T}$

w_j^t, μ_j^t, ν_j^t : auxiliary binary variables, $j \in J,\ t \in \mathcal{T}$

As the pricing decisions are made only once, x_{ij} is identical for all periods. Another core decision besides the pricing is the utilization of containers, consisting of (1) how many to rent out (y_{ij}^t), and (2) how many to reposition (z_{ij}^t). Inventory level (IL_j^t and I_j^t) refers to the actual on-hand quantity that can be utilized immediately. In contrast, inventory position (IP_j^t, SIP_j, and TIP_j) is calculated as the sum of the inventory level and on-order inventory, additionally accounting for the quantity that has been shipped but not yet received due to lead time (Kurian et al., 2023). The variables SIP_j, TIP_j, and L_G are introduced to calculate the previously mentioned penalties. Note that L_G is defined as the surplus, which is clearly different from the absolute difference. A surplus of containers in a port group indicates that at least one other port group is facing a deficit. In other words, defining L_G as the absolute difference results in redundancy, which can be prevented by defining it as the surplus. Auxiliary variables are utilized to linearize logical constraints. Further details will be provided after proposing the mathematical formulations.

4.2. The optimization model

The optimization model is as follows:

$$\max \quad \sum_{t \in \mathcal{T}} \sum_{j \in J} \sum_{i \in J} \left(x_{ij} y_{ij}^{t} - \phi C_{ij} z_{ij}^{t} \right) - \sum_{G \in \mathcal{G}} F_G L_G$$

$$\text{s.t.} \quad d_{ij}^t = D_{ij}^t \left(1 - \frac{\rho}{C_{ji}} x_{ij}\right) \qquad i,j \in J,\ t \in \mathcal{T} \tag{1}$$

$$x_{ij} \le C_{ji} \qquad i,j \in J \tag{2}$$

$$y_{ij}^t \le d_{ij}^t \qquad i,j \in J,\ t \in \mathcal{T} \tag{3}$$

$$IL_j^t = IL_j^{t-1} + \sum_{i \in J} \left(y_{ij}^{t-r_i-r_j-R_{ij}} + z_{ij}^{t-R_{ij}}\right) - \sum_{k \in J} \left(y_{jk}^t + z_{jk}^t\right) \qquad j \in J,\ t \in \mathcal{T} \tag{4}$$

$$SIP_j = IL_j^0 + \sum_{i \in J} \left(\sum_{\tau=0}^{r_i+r_j+R_{ij}-1} y_{ij}^{0-\tau} + \sum_{\tau=0}^{R_{ij}-1} z_{ij}^{0-\tau} \right) \qquad j \in J \tag{5}$$

$$TIP_j = IL_j^{|\mathcal{T}|} + \sum_{i \in J} \left(\sum_{\tau=0}^{r_i+r_j+R_{ij}-1} y_{ij}^{|\mathcal{T}|-\tau} + \sum_{\tau=0}^{R_{ij}-1} z_{ij}^{|\mathcal{T}|-\tau} \right) \qquad j \in J \tag{6}$$

$$L_G \ge \sum_{j \in G} \left(TIP_j - SIP_j\right) \qquad G \in \mathcal{G} \tag{7}$$

$$L_G \le \sum_{j \in G} \left(TIP_j - SIP_j\right) + M a_G \qquad G \in \mathcal{G} \tag{8}$$

$$L_G \le M b_G \qquad G \in \mathcal{G} \tag{9}$$

$$a_G + b_G \le 1 \qquad G \in \mathcal{G} \tag{10}$$

$$x_{ij} \ge 0 \qquad i,j \in J \tag{11}$$

$$y_{ij}^t, z_{ij}^t, d_{ij}^t \ge 0 \qquad i,j \in J,\ t \in \mathcal{T} \tag{12}$$

$$IL_j^t \ge 0 \qquad j \in J,\ t \in \mathcal{T} \tag{13}$$

$$SIP_j, TIP_j \ge 0 \qquad j \in J \tag{14}$$

$$L_G \ge 0 \qquad G \in \mathcal{G} \tag{15}$$

$$a_G, b_G \in \{0,1\} \qquad G \in \mathcal{G} \tag{16}$$

As previously assumed, the actual demands decrease linearly depending on the prices, as demonstrated by Constraint (1). When x_{ij} exceeds C_{ji}, the actual demand drops below zero (assuming $\rho = 1$, $1 - x_{ij}/C_{ji} < 0$ if $x_{ij} > C_{ji}$), which is logically meaningless. Consequently, Constraint (2) prohibits x_{ij} from being greater than C_{ji}. The company cannot rent out more containers than the demand and does not need to fulfill the exact demand (i.e., $y_{ij}^t = d_{ij}^t$ is not mandatory), as stated by Constraint (3). Constraint (4) indicates the balance equation of the inventory levels of containers in each port. Specifically, the inventory level in period t has to be updated by considering the containers arriving (the second term) and the ones being sent during that period (the third term).

Note that for a small value of t, the summation of y_{ij}^ts and z_{ij}^ts can be out of range (e.g., $t - R_{ij} < 0$ if $t = 1$ and $R_{ij} = 2$). We assume the values out of range are given as initial conditions to prevent such an issue. We previously mentioned that the tail periods should be carefully treated as a finite time horizon is assumed. Similarly, the early periods are also critical when considering a finite time horizon. Except for the launch of a new service, preceding decisions always exist in advance of the current planning time horizon. Consequently, it is reasonable to treat the values corresponding to the preceding periods as deterministic, which will be considered as parameters. The initialization of these parameters will be specified in Section 5.1.

Constraints (5) and (6) calculate the initial and final inventory positions of each port, which are necessary to assess the penalties. Recall that the inventory position equals the sum of the inventory level and the on-order inventory. The latter terms of Constraints (5) and (6) represent the number of containers currently in transit. Constraints (7)–(10) are presented to linearize $L_G = \left(\sum_{j \in G} \left(TIP_j - SIP_j\right)\right)^+$, indicating the number of surplus containers of each port group (note that $(A)^+$ denotes $\max\{A, 0\}$). Constraints (11)–(16) define the domains of the variables. The objective function consists of the revenue earned by renting out the containers, the transportation costs induced by ECR, and the penalty costs. For the revenue, one can easily observe that two variables are multiplied ($x_{ij} y_{ij}^t$), which makes this formulation a non-convex mixed-integer quadratic programming model.

4.3. The (T, S) strategy

The first strategy is named the (T, S) strategy, which is naturally based on the (T, S) policy. The mathematical model of the (T, S) strategy is as follows:

$$\max \quad \sum_{t \in \mathcal{T}} \sum_{j \in J} \sum_{i \in J} \left(P_{ij} y_{ij}^t - \phi C_{ij} z_{ij}^t\right) - \sum_{G \in \mathcal{G}} F_G L_G$$

$$\text{s.t.} \quad y_{ij}^t \le \left(D_{ij}^t \left(1 - \frac{\rho}{C_{ji}} P_{ij}\right)\right)^+ \qquad i,j \in J,\ t \in \mathcal{T} \tag{17}$$

$$I_j^t = IL_j^{t-1} + \sum_{i \in J} \left(y_{ij}^{t-r_i-r_j-R_{ij}} + z_{ij}^{t-R_{ij}}\right) - \sum_{k \in J} y_{jk}^t \qquad j \in J,\ t \in \mathcal{T} \tag{18}$$

$$IP_j^t = I_j^t + \sum_{i \in J} \left(\sum_{\tau=0}^{r_i+r_j+R_{ij}-1} y_{ij}^{t-\tau} + \sum_{\tau=0}^{R_{ij}-1} z_{ij}^{t-\tau} \right) \qquad j \in J,\ t \in \mathcal{T} \tag{19}$$

$$IP_j^t + \sum_{i \in J} z_{ij}^t = S_j \qquad j \in J,\ t \in \mathcal{T} : t \equiv 0 \pmod{T} \tag{20}$$

$$z_{ij}^t = 0 \qquad i, j \in J,\ t \in \mathcal{T} : t \not\equiv 0 \pmod{T} \tag{21}$$

$$IL_j^t = I_j^t - \sum_{k \in J} z_{jk}^t \qquad j \in J,\ t \in \mathcal{T} \tag{22}$$

$$SIP_j = IL_j^0 + \sum_{i \in J} \left(\sum_{\tau=0}^{r_i + r_j + R_{ij} - 1} y_{ij}^{0-\tau} + \sum_{\tau=0}^{R_{ij}-1} z_{ij}^{0-\tau} \right) \qquad j \in J \tag{23}$$

$$TIP_j = IL_j^{|\mathcal{T}|} + \sum_{i \in J} \left(\sum_{\tau=0}^{r_i + r_j + R_{ij} - 1} y_{ij}^{|\mathcal{T}|-\tau} + \sum_{\tau=0}^{R_{ij}-1} z_{ij}^{|\mathcal{T}|-\tau} \right) \qquad j \in J \tag{24}$$

$$L_G \geq \sum_{j \in G} \left(TIP_j - SIP_j \right) \qquad G \in \mathcal{G} \tag{25}$$

$$L_G \leq \sum_{j \in G} \left(TIP_j - SIP_j \right) + M a_G \qquad G \in \mathcal{G} \tag{26}$$

$$L_G \leq M b_G \qquad G \in \mathcal{G} \tag{27}$$

$$a_G + b_G \leq 1 \qquad G \in \mathcal{G} \tag{28}$$

$$y_{ij}^t, z_{ij}^t \geq 0 \qquad i, j \in J,\ t \in \mathcal{T} \tag{29}$$

$$I_j^t, IL_j^t, IP_j^t \geq 0 \qquad j \in J,\ t \in \mathcal{T} \tag{30}$$

$$SIP_j, TIP_j, S_j \geq 0 \qquad j \in J \tag{31}$$

$$L_G \geq 0 \qquad G \in \mathcal{G} \tag{32}$$

$$a_G, b_G \in \{0, 1\} \qquad G \in \mathcal{G} \tag{33}$$

As the prices are no longer variables, the actual demands are deterministic in Constraint (17). Constraint (18) partially updates the inventory levels, only considering the number of containers being rented out (compared to Constraint (4), only the y_{jk}^t terms are subtracted). Then, Constraint (19) updates the inventory positions regarding the containers expected to be received based on the partially updated inventory levels. With these temporary inventory positions, the quantities of ECR are designated based on the order-up-to levels in Constraint (20). Specifically, empty containers must be repositioned to fill the gap between the temporary inventory positions and the order-up-to levels. However, ECR only takes place periodically and should not be held for the other periods, as stated in Constraint (21). Finally, Constraint (22) updates the inventory levels considering the quantities of ECR. Constraints (23)–(28) are introduced again to assess the penalties. Constraints (29)–(33) define the domains of the variables, and the objective function is similar to the previous one, except for the difference between x_{ij} and P_{ij}. Due to this difference, the formulation of the (T, S) strategy becomes a mixed-integer linear programming model.

4.4. The (s, S) strategy

The second strategy is named the (s, S) strategy, which is naturally based on the (s, S) policy. The mathematical model of the (s, S) strategy is as follows:

$$\max \quad \sum_{t \in \mathcal{T}} \sum_{j \in J} \sum_{i \in J} \left(P_{ij} y_{ij}^t - \phi C_{ij} z_{ij}^t \right) - \sum_{G \in \mathcal{G}} F_G L_G$$

$$\text{s.t.} \quad y_{ij}^t \leq \left(D_{ij}^t \left(1 - \frac{\rho}{C_{ji}} P_{ij} \right) \right)^+ \qquad i, j \in J,\ t \in \mathcal{T} \tag{34}$$

$$I_j^t = IL_j^{t-1} + \sum_{i \in J} \left(y_{ij}^{t - r_i - r_j - R_{ij}} + z_{ij}^{t - R_{ij}} \right) - \sum_{k \in J} y_{jk}^t \qquad j \in J,\ t \in \mathcal{T} \tag{35}$$

$$IP_j^t = I_j^t + \sum_{i \in J} \left(\sum_{\tau=0}^{r_i + r_j + R_{ij} - 1} y_{ij}^{t-\tau} + \sum_{\tau=0}^{R_{ij}-1} z_{ij}^{t-\tau} \right) \qquad j \in J,\ t \in \mathcal{T} \tag{36}$$

$$\gamma_j^t \leq s_j + M \mu_j^t \qquad j \in J,\ t \in \mathcal{T} \tag{37}$$

$$\gamma_j^t \geq s_j \qquad j \in J,\ t \in \mathcal{T} \tag{38}$$

$$\gamma_j^t \leq IP_j^t + M \nu_j^t \qquad j \in J,\ t \in \mathcal{T} \tag{39}$$

$$\gamma_j^t \geq IP_j^t \qquad j \in J,\ t \in \mathcal{T} \tag{40}$$

$$\mu_j^t + \nu_j^t \leq 1 \qquad j \in J,\ t \in \mathcal{T} \tag{41}$$

$$\alpha_j^t = \gamma_j^t - IP_j^t \qquad j \in J,\ t \in \mathcal{T} \tag{42}$$

$$\beta_j^t = S_j^t - \gamma_j^t \qquad j \in J,\ t \in \mathcal{T} \tag{43}$$

$$w_j^t \leq M \alpha_j^t \qquad j \in J,\ t \in \mathcal{T} \tag{44}$$

$$w_j^t \geq \frac{\alpha_j^t}{M} \qquad j \in J,\ t \in \mathcal{T} \tag{45}$$

$$\delta_j^t \leq \alpha_j^t + \beta_j^t \qquad j \in J,\ t \in \mathcal{T} \tag{46}$$

$$\delta_j^t \leq M w_j^t \qquad j \in J,\ t \in \mathcal{T} \tag{47}$$

$$\delta_j^t \geq \alpha_j^t + \beta_j^t + M\left(w_j^t - 1\right) \qquad j \in J,\, t \in \mathcal{T} \tag{48}$$

$$\sum_{i \in J} z_{ij}^t = \delta_j^t \qquad j \in J,\, t \in \mathcal{T} \tag{49}$$

$$IL_j^t = I_j^t - \sum_{k \in J} z_{jk}^t \qquad j \in J,\, t \in \mathcal{T} \tag{50}$$

$$SIP_j = IL_j^0 + \sum_{i \in J}\left(\sum_{\tau=0}^{r_i+r_j+R_{ij}-1} y_{ij}^{0-\tau} + \sum_{\tau=0}^{R_{ij}-1} z_{ij}^{0-\tau}\right) \qquad j \in J \tag{51}$$

$$TIP_j = IL_j^{|\mathcal{T}|} + \sum_{i \in J}\left(\sum_{\tau=0}^{r_i+r_j+R_{ij}-1} y_{ij}^{|\mathcal{T}|-\tau} + \sum_{\tau=0}^{R_{ij}-1} z_{ij}^{|\mathcal{T}|-\tau}\right) \qquad j \in J \tag{52}$$

$$L_G \geq \sum_{j \in G}\left(TIP_j - SIP_j\right) \qquad G \in \mathcal{G} \tag{53}$$

$$L_G \leq \sum_{j \in G}\left(TIP_j - SIP_j\right) + M a_G \qquad G \in \mathcal{G} \tag{54}$$

$$L_G \leq M b_G \qquad G \in \mathcal{G} \tag{55}$$

$$a_G + b_G \leq 1 \qquad G \in \mathcal{G} \tag{56}$$

$$y_{ij}^t, z_{ij}^t \geq 0 \qquad i, j \in J,\, t \in \mathcal{T} \tag{57}$$

$$I_j^t, IL_j^t, IP_j^t, \alpha_j^t, \beta_j^t, \gamma_j^t, \delta_j^t \geq 0 \qquad j \in J,\, t \in \mathcal{T} \tag{58}$$

$$SIP_j, TIP_j, S_j, s_j \geq 0 \qquad j \in J \tag{59}$$

$$w_j^t, \mu_j^t, \nu_j^t \in \{0, 1\} \qquad j \in J,\, t \in \mathcal{T} \tag{60}$$

$$L_G \geq 0 \qquad G \in \mathcal{G} \tag{61}$$

$$a_G, b_G \in \{0, 1\} \qquad G \in \mathcal{G} \tag{62}$$

Constraints (37)–(49) are introduced to determine whether repositioning is required and, if so, to calculate the necessary quantity. In other words, empty containers are repositioned to increase the temporary inventory positions up to the order-up-to levels, but only when they fall below the reorder points. Accordingly, Constraints (37)–(49) linearize the following conditional statement: If $IP_j^t < s_j$, then $\sum_{i \in J} z_{ij}^t = S_j - IP_j^t$. Specifically, Constraints (37)–(41) linearize $\gamma_j^t = \max\{s_j, IP_j^t\}$. When $IP_j^t < s_j$ holds, $\alpha_j^t = s_j - IP_j^t > 0$ by Constraint (42) and $\beta_j^t = S_j - s_j$ by Constraint (43). Moreover, as $\alpha_j^t > 0$ holds, $w_j^t = 1$ by Constraints (44) and (45), considering that w_j^t are binary variables. Constraints (46)–(48) linearize $\delta_j^t = \left(\alpha_j^t + \beta_j^t\right) w_j^t$. As $w_j^t = 1$ holds, $\delta_j^t = \alpha_j^t + \beta_j^t = S_j - IP_j^t$, and Constraint (49) designates the quantity of ECR. On the other hand, if $IP_j^t \geq s_j$ holds, $\alpha_j^t = 0$, and $\beta_j^t = S_j - IP_j^t$. As $\alpha_j^t = 0$ holds, $w_j^t = 0$, and $\delta_j^t = 0$. Therefore, no ECR takes place. Constraints (34)–(36), (50)–(56), and the objective function are the same as in the previous model, and Constraints (57)–(62) define the domains of the variables. In addition, the formulation of the (s, S) strategy is also a mixed-integer linear programming model.

5. Computational experiments

5.1. Setting of the experiments

The mathematical models were solved with FICO Xpress version 8.12. The main east–west route connecting East Asia and North America accounts for more than 30 percent of global containerized trade. However, the imbalance between the two directions keeps getting more severe. Based on the majority of the main east–west route, we considered five ports included in this route: Ningbo-Zhoushan (NB, China), Shanghai (SH, China), Busan (BS, Republic of Korea), Vancouver (VC, Canada), and Los Angeles-Long Beach (LA, U.S.). Three concerns, namely the balance between continents, the volatility of demand, and the number of containers, are additionally considered.

The first concern is about the balance between the Asian ports and the North American ports. Two situations are investigated: one representing imbalanced cases and the other significantly imbalanced cases, denoted as "balanced" and "imbalanced" respectively. The volatility of demand demonstrates how much demand fluctuates and is related to the standard deviations of the demands. Again, two situations are represented as "stable" and "fluctuating". The number of containers shows how many containers the service provider is utilizing. The number of containers in three cases each of "insufficient", "adequate", and "ample" are examined. The three concerns are applied independently, and therefore, a total of twelve independent cases are analyzed. Throughout this section, $T = 1$ is assumed for the (T, S) strategy. The data for the demand were obtained from the Container Trade Statistics Ltd (https://cedar.containerstatistics.com/) and are reported in Tables 2 and 3, after refining.

Table 2 presents the mean and standard deviation of each route's demand for a balanced situation. For example, the values in the second column and the third row indicate the demand heading to Busan from Shanghai. On the other hand, Table 3 corresponds to an imbalanced situation. Note that the only difference between Tables 2 and 3 are the values for the routes heading to Asian ports from North American ports. Specifically, the demand for these routes has decreased, aggravating the asymmetry. The standard deviations reported in Tables 2 and 3 illustrate stable situations. For a fluctuating case, we assume the values of the standard deviations to be double.

The number of containers is given based on the sum of average outbound demands. In detail, the values multiplying the sum of average outbound demands by 2, 3, and 4 are applied for each situation, respectively. For instance, the average outbound demand of NB is 800, and those of the other ports are 800, 700, 210, and 285, respectively, for the balanced situation (Table 2). The sum of these values equals 2795, resulting in a total of 5590 containers in the balanced and insufficient case. Moreover, the adequate and ample cases assume 8385 and 11,180 containers under the balanced situation, respectively.

Table 2
Parameters of demand for a balanced and stable situation.

	NB	SH	BS	VC	LA
NB	–	(50, 6.57)	(50, 6.57)	(300, 48.38)	(400, 64.50)
SH	(50, 6.57)	–	(50, 6.57)	(300, 48.38)	(400, 64.50)
BS	(100, 13.14)	(100, 13.14)	–	(200, 32.25)	(300, 48.38)
VC	(75, 7.72)	(75, 7.72)	(50, 5.14)	–	(10, 1.43)
LA	(100, 10.29)	(100, 10.29)	(75, 7.72)	(10, 1.43)	–

Table 3
Parameters of demand for an imbalanced and stable situation.

	NB	SH	BS	VC	LA
NB	–	(50, 6.57)	(50, 6.57)	(300, 48.38)	(400, 64.50)
SH	(50, 6.57)	–	(50, 6.57)	(300, 48.38)	(400, 64.50)
BS	(100, 13.14)	(100, 13.14)	–	(200, 32.25)	(300, 48.38)
VC	(30, 3.09)	(30, 3.09)	(20, 2.06)	–	(10, 1.43)
LA	(40, 4.12)	(40, 4.12)	(30, 3.09)	(10, 1.43)	–

Table 4
Transportation cost of an empty container for each route.

C_{ij}	NB	SH	BS	VC	LA
NB	–	1	1	2	2
SH	1	–	1	2	2
BS	1	1	–	2	2
VC	2	2	2	–	1
LA	2	2	2	1	–

Table 5
Transportation time for each route.

R_{ij}	NB	SH	BS	VC	LA
NB	–	1	1	4	4
SH	1	–	1	4	4
BS	1	1	–	4	4
VC	4	4	4	–	2
LA	4	4	4	2	–

The parameters refer to Lee and Moon (2020) and are organized in Tables 4 and 5. One period is set to be equal to four days, indicating that transportation time between Asian ports takes four days, while 16 days are required to transport containers from an Asian port to a North American port. In addition, we assume that the inland transportation time, r_j, is one base period for all ports, and the length of the planning time horizon, $|\mathcal{T}|$, is 30. Considering the amount of demand and the motivation of the penalties, each Asian port constructs an individual port group, whereas the two North American ports are merged into a single port. Moreover, as empty containers tend to pile up in North American ports, the penalty costs are set to be equal to the transportation costs heading to Asian ports. Specifically, the penalty cost of the North American port group is set to be 2, while the penalty costs of the Asian port groups are all assumed to be 1. The default values of ρ and ϕ are 1, and the impacts of changing these values will be further explored.

As previously mentioned, in most cases, preceding and succeeding periods exist relative to the current planning time horizon. Consequently, an appropriate initialization of data is important. The initialization of data and other experimental procedures are carried out in the following order:

(i) Set the initial inventory level of each port to the values, multiplying the average outbound demands by 2, 3, and 4, depending on the number of containers.
(ii) Generate ten independent demand sets based on the parameters in Table 2 or Table 3, assuming normal distributions.
(iii) Apply the optimization model to the ten demand sets respectively and obtain ten independent price matrices (i.e., the values of x_{ij}). In this context, all the values of y_{ij}^t and z_{ij}^t for $t \leq 0$ and IL_j^0 should be restricted to be zero.
(iv) Average the obtained prices and apply the (T, S) and (s, S) strategies, respectively, based on the ten demand sets. Acquire ten independent values of the order-up-to levels (for each strategy) and the reorder point.
(v) Generate 30 additional independent demand sets based on the parameters in Table 2 or Table 3, assuming normal distributions.
(vi) Apply the three models respectively based on the 30 demand sets. The same prices used in (iv) are utilized again. In addition, the order-up-to levels and reorder point values are assumed to equal the average of the values retrieved in (iv).
(vii) Average the 30 results of y_{ij}^t, z_{ij}^t, and IL_j^t, and utilize as the initialized data.
(viii) Repeat (ii) to (vi), except for that the values of y_{ij}^t and z_{ij}^t for $t \leq 0$ and IL_j^0 are no longer restricted to be zero, but are set to be equal to the initialized data in (vii).

A sensitivity analysis investigating the impacts of ρ and ϕ is presented together. Note that the sensitivity analysis is executed in the same procedure of (iii) to (iv) and (vi) to (viii) while utilizing the same demand sets generated in (ii) and (v). Four values of ρ and ϕ each were considered, with ϕ and ρ being fixed as the default values, respectively. In detail, the value of ρ was changed from 1 to 3/4, 1/2, and 1/4, with ϕ fixed as 1. Then the value of ϕ was also changed from 1 to 3/4, 1/2, and 1/4, with ρ fixed as 1. All the results are analyzed based on the average of the 30 instances for each case.

Table 6
Results of $\rho = 1$; $\phi = 1$.

Index	Stable												Fluctuating											
	Balanced						Imbalanced						Balanced						Imbalanced					
	Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample	
	1		2		3		4		5		6		7		8		9		10		11		12	
Optimal	25,593	4.15	25,650	0.00	25,651	0.00	13,217	0.00	13,209	0.00	13,207	0.00	25,250	14.80	25,366	1.89	25,371	0.00	13,068	0.00	13,053	0.00	13,057	0.00
(T,S)	24,934	24.74	24,947	13.82	24,948	13.81	12,861	0.37	12,855	0.97	12,854	0.76	23,944	109.45	23,879	44.99	23,880	45.14	12,329	12.99	12,316	13.47	12,325	11.41
(s,S)	25,565	0.00	25,621	0.00	25,626	0.00	13,206	0.00	13,199	0.00	13,196	0.00	25,201	0.00	25,304	0.00	25,307	0.00	13,019	0.00	13,016	0.00	13,015	0.00

Table 7
Results of $\rho = 3/4$; $\phi = 1$.

Index	Stable												Fluctuating											
	Balanced						Imbalanced						Balanced						Imbalanced					
	Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample	
	1		2		3		4		5		6		7		8		9		10		11		12	
Optimal	33,026	256.71	33,227	1,001.87	33,226	1,512.41	14,780	5,706.89	14,535	5,820.56	14,535	3,343.95	32,810	260.94	33,090	1,246.83	33,088	1,481.24	15,799	5,544.07	14,518	5,754.59	14,518	3,279.49
(T,S)	32,202	115.89	32,863	617.13	32,863	604.74	14,780	1,677.54	14,535	3,084.42	14,535	2,910.07	31,427	236.25	31,981	937.51	31,970	1,006.82	15,681	1,709.29	14,508	4,233.24	14,509	3,602.44
(s,S)	33,020	0.00	33,216	0.00	33,215	0.00	14,780	0.00	14,535	0.00	14,535	0.00	32,789	0.00	33,066	8.62	33,075	0.00	15,778	224.53	14,518	0.00	14,518	0.00

Table 8
Results of $\rho = 1/2$; $\phi = 1$.

Index	Stable												Fluctuating											
	Balanced						Imbalanced						Balanced						Imbalanced					
	Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample	
	1		2		3		4		5		6		7		8		9		10		11		12	
Optimal	38,206	1,201.68	38,185	8,597.49	38,425	11,850.79	19,027	6,797.75	19,020	12,812.37	19,106	16,456.04	38,080	745.03	38,061	8,555.69	38,286	12,017.31	19,006	6,418.83	19,000	12,891.29	19,100	16,272.47
(T,S)	37,575	380.53	37,507	1,470.80	38,425	6,387.30	18,703	1,244.64	18,686	2,325.63	19,106	9,491.31	37,135	362.07	37,069	1,351.70	38,276	6,957.83	18,474	1,229.54	18,458	2,511.38	19,100	9,785.80
(s,S)	38,206	19.11	38,185	18.51	38,425	0.00	18,996	408.68	18,990	756.76	19,106	30.26	38,080	25.82	38,061	0.00	38,286	0.00	18,999	1,048.86	18,982	838.73	19,100	213.67

Table 9
Results of $\rho = 1/4$; $\phi = 1$.

Index	Stable												Fluctuating											
	Balanced						Imbalanced						Balanced						Imbalanced					
	Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample	
	1		2		3		4		5		6		7		8		9		10		11		12	
Optimal	52,269	320.31	52,268	7,508.61	52,271	13,533.27	26,485	5,326.55	26,485	12,434.47	26,492	17,848.60	52,069	161.38	52,068	6,142.85	52,072	13,308.39	26,455	4,602.05	26,455	12,380.63	26,463	16,941.57
(T,S)	52,133	150.61	52,126	1,179.56	52,152	2,469.30	26,263	1,756.08	26,261	2,492.50	26,295	3,668.38	51,598	350.80	51,589	1,653.39	51,619	2,908.52	25,978	1,767.85	25,974	2,613.08	26,015	3,826.19
(s,S)	52,269	0.00	52,268	0.00	52,271	20.19	26,453	1,669.31	26,452	1,772.85	26,492	1,809.17	52,069	0.00	52,068	49.75	52,072	66.01	26,419	2,683.81	26,446	3,786.33	26,463	2,728.83

5.2. Results

The results are summarized in Tables 6 through 13. Tables 6 to 9 show the results of the cases with a fixed ϕ, whereas Tables 10 to 13 deliver the results with a fixed ρ. Note that Tables 6 and 10 are indeed the same but are reported twice, for convenience. A total of twelve situations is considered, as previously mentioned, and is indexed as 1 through 12. Every cell contains two values: The first indicates the value of the objective function (i.e., profit), and the latter represents the total quantity of ECR within the given planning time horizon. Recall that each value is the average of the values obtained from 30 instances.

A smaller value of ρ (price sensitivity of demand) indicates that customers are more tolerant of higher prices. In other words, the service provider can increase the price to meet a similar level of demand or can enjoy more demand while maintaining the current price. Assuming that the value of ϕ (weight of transportation cost) is fixed (Tables 6 to 9), one might expect that the quantity of ECR will not change significantly as ρ decreases. However, the quantities of ECR show considerable increments for smaller values of ρ. Such a result implies that securing higher demand is more profitable, though greater losses occur due to ECR. It is evident that the profit certainly increases as ρ decreases. Balanced situations are indeed more profitable than imbalanced ones and induce less ECR. On the other hand, the volatility of demand does not substantially affect the profit or the quantity of ECR.

Focusing on the profit, the optimization model undoubtedly promises the highest profit, which can serve as an upper limit and a benchmark for the two strategies. The (s, S) strategy retrieves a comparable profit compared to the optimum (within a 0.37% gap for every case). The gap drops below 0.16% as ρ gets smaller than 1, and in some cases, the (s, S) strategy reaches the optimum. The (T, S) strategy performs less satisfactorily than does the (s, S) strategy. Compared to the optimum, the gap is within 5.88%. However, the gap steadily diminishes as ρ decreases.

Considering the quantity of ECR, the optimization model demonstrates the most inferiority, and the (s, S) strategy induces the least. Specifically, the (s, S) strategy triggers less ECR than does the optimization model for every case, and even the (T, S) strategy utilizes less ECR than does the optimization model for most of the cases. For some cases, the (s, S) strategy fetches the same profit with the optimization model but incurs much less ECR (e.g., case 12 in Table 9). Moreover, the (s, S) strategy induces less ECR than does the (T, S) strategy for most of the cases, except for only two cases in particular: case 10 and case 11 in Table 9. It is apparent that when $\rho \leq 1/2$ (Tables 8 and 9), the quantity of ECR surges as more containers are utilized for the optimization model and the (T, S) strategy. This result implies that actively utilizing ECR to circulate containers continuously may be an option to increase the profit, even if it incurs substantial costs. Such an occasion will be specifically discussed later.

A smaller value of ϕ (weight of transportation cost) results in a lower burden on ECR to the service provider. In other words, the service provider can aggressively reposition the empty containers to gain more profit. Consequently, Tables 10 to 13 clearly illustrate that the quantities of ECR substantially escalate as ϕ decreases, regardless of the model. In addition, the profits also increase along with the decrement of ϕ, which is more prominent for imbalanced situations. When balanced situations are compared with imbalanced ones and stable situations with fluctuating ones, the aspects resemble those of the previous. Again, balanced situations are more profitable and induce less ECR, while the volatility of demand does not significantly affect the profit or the quantity of ECR.

Table 10
Results of $\phi = 1;\ \rho = 1$.

Index	Stable												Fluctuating											
	Balanced						Imbalanced						Balanced						Imbalanced					
	Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample	
	1		2		3		4		5		6		7		8		9		10		11		12	
Optimal	25,593	4.15	25,650	0.00	25,651	0.00	13,217	0.00	13,209	0.00	13,207	0.00	25,250	14.80	25,366	1.89	25,371	0.00	13,068	0.00	13,053	0.00	13,057	0.00
(T,S)	24,934	24.74	24,947	13.82	24,948	13.81	12,861	0.37	12,855	0.97	12,854	0.76	23,944	109.45	23,879	44.99	23,880	45.14	12,329	12.99	12,316	13.47	12,325	11.41
(s,S)	25,565	0.00	25,621	0.00	25,626	0.00	13,206	0.00	13,199	0.00	13,196	0.00	25,201	0.00	25,304	0.00	25,307	0.00	13,019	0.00	13,016	0.00	13,015	0.00

Table 11
Results of $\phi = 3/4;\ \rho = 1$.

Index	Stable												Fluctuating											
	Balanced						Imbalanced						Balanced						Imbalanced					
	Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample	
	1		2		3		4		5		6		7		8		9		10		11		12	
Optimal	25,631	105.41	25,660	81.80	25,660	81.28	13,630	2,109.93	13,628	2,098.96	13,630	2,125.53	25,259	440.24	25,388	173.89	25,388	170.83	13,578	2,090.59	13,579	2,104.61	13,581	2,115.62
(T,S)	24,981	275.80	24,976	296.42	24,976	294.82	13,425	2,070.05	13,422	2,074.98	13,424	2,097.65	24,006	641.96	23,979	633.17	23,976	633.08	13,145	1,999.35	13,148	2,005.64	13,150	2,005.30
(s,S)	25,594	3.04	25,630	1.18	25,630	0.00	13,614	2,071.91	13,623	2,090.83	13,613	2,081.94	25,205	212.93	25,306	0.00	25,313	0.00	13,557	2,071.42	13,549	2,067.12	13,557	2,089.56

Table 12
Results of $\phi = 1/2;\ \rho = 1$.

Index	Stable												Fluctuating											
	Balanced						Imbalanced						Balanced						Imbalanced					
	Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample	
	1		2		3		4		5		6		7		8		9		10		11		12	
Optimal	26,108	2,090.56	26,330	3,513.60	26,330	3,524.71	16,397	7,781.08	16,664	9,829.60	16,670	9,952.01	25,889	1,987.65	26,218	3,484.17	26,218	3,491.04	16,298	7,342.33	16,614	9,790.63	16,628	9,892.62
(T,S)	25,577	1,949.52	25,987	3,550.34	25,989	3,558.21	15,970	7,959.54	16,347	10,039.47	16,361	10,118.92	24,981	2,144.55	25,489	3,789.38	25,491	3,808.17	15,637	7,558.92	15,975	10,170.39	16,001	10,223.18
(s,S)	26,028	1,978.21	26,315	3,515.06	26,292	3,514.71	16,273	7,745.46	16,622	9,841.04	16,646	9,994.15	25,784	1,803.94	26,179	3,487.24	26,180	3,483.53	16,124	7,311.42	16,565	9,801.02	16,567	9,949.87

Table 13
Results of $\phi = 1/4;\ \rho = 1$.

Index	Stable												Fluctuating											
	Balanced						Imbalanced						Balanced						Imbalanced					
	Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample		Insufficient		Adequate		Ample	
	1		2		3		4		5		6		7		8		9		10		11		12	
Optimal	27,834	4,830.07	30,253	11,758.64	30,318	12,438.53	20,718	9,277.05	23,363	15,750.48	23,602	17,724.39	27,563	4,758.59	30,047	11,410.30	30,187	12,370.74	20,527	9,136.81	23,186	15,146.40	23,511	17,648.55
(T,S)	27,459	5,256.73	29,756	12,377.91	29,961	13,197.72	20,393	9,668.08	22,905	16,614.02	23,225	18,742.59	26,890	5,494.59	29,206	12,531.34	29,499	13,801.82	19,927	9,827.91	22,389	16,473.72	22,758	19,650.22
(s,S)	27,584	4,931.58	30,044	11,973.62	30,171	12,506.82	20,566	9,409.71	23,217	15,995.56	23,453	18,109.28	27,301	4,884.23	29,751	11,651.50	30,131	12,516.80	20,194	9,461.07	22,917	15,568.53	23,402	17,730.25

The optimization model again sets the upper limit for the profit. However, it is evident that its profits are deficient compared to the cases of decreasing ρ. Consequently, the profits of the two strategies also decreased compared to the profits of the former cases. In addition, the (s, S) strategy's profit exposes a wider gap with the optimum, though it is still worthwhile. While the maximum gap was 0.16% when $\rho < 1$ and $\phi = 1$, it grew up to 1.62% for $\phi < 1$ and $\rho = 1$. Moreover, the (s, S) strategy failed to achieve the optimal profit in all cases. Structurally, compared to the previous cases, how actively ECR can be done is the primary concern when ϕ decreases. In this respect, the two strategies are more restricted than in the optimization model in repositioning empty containers and, thus, suffer wider gaps in terms of profit. Although the (T, S) strategy also demonstrates wider gaps, the gap is reduced progressively as ϕ decreases, similar to the decrement of ρ. Unlike the previous cases, the quantity of ECR shows no significant difference among the three models. Because of the low costs, all models actively utilize ECR, resulting in fair surges.

The observed results can be further summarized as follows:

1. An excessive number of containers is not recommended.
2. The balance between continents significantly affects the results.
3. The volatility of demand does not have a significant impact.
4. Decreasing ECR costs (ϕ) makes a tremendous difference in imbalanced situations, which are highly likely to occur in practice.
5. Lowering customers' price sensitivity (ρ) should be prioritized over ECR costs (ϕ).
6. The (s, S) strategy demonstrates sufficient profitability, and the (T, S) strategy is also practically applicable.
7. The difference in the quantities of ECR is insignificant among the three models when ϕ decreases, but the (s, S) strategy induces considerably less ECR than does the optimization model as ρ decreases.

The results of the optimal pricing setup are also analyzed. Figs. 3, 5, 7, and 9 show the averaged optimal prices for each route for each case, decreasing the value of ρ from 1 to 1/4 while assuming $\phi = 1$. As we are considering a total of 20 routes, some of the graphs corresponding to similar routes are overlapped (e.g., heading to the same destination while departing from NB or SH, and vice versa). For clarity, the exact values are reported in Tables A.14 to A.20 in Appendix.

Figs. 4, 6, 8, and 10 illustrate how the profit, cost, and penalty of the three models change as ρ decreases. Specifically, each figure presents bar charts for the twelve different cases, with bars corresponding to the results of the optimization model, the (T, S) strategy, and the (s, S) strategy, respectively. Each bar consists of three stacked segments: the bottom segment represents profit, the middle segment represents cost, and the top segment represents penalty. In other words, each complete bar corresponding to a model represents its total revenue.

Fig. 3 illustrates the default situation, assuming $\rho = \phi = 1$. Recall that each price is restricted to be not higher than the transportation cost in the opposite direction (Constraint (1)). We can observe four prominent trends in Fig. 3 and in Table A.14. First, the prices corresponding to the routes within the same continent (i.e., intra-continental routes) are highly stable. This is due to the fact that these routes are relatively balanced. Second, compared to the Chinese ports, departing from BS is more expensive, while heading to BS is cheaper. When considering the five ports

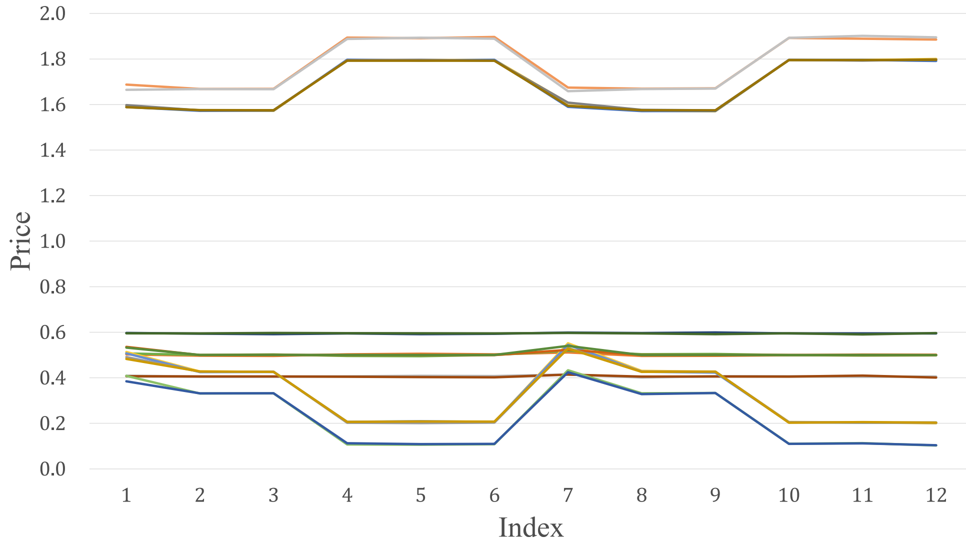

Fig. 3. Optimal prices assuming $\rho = 1$; $\phi = 1$.

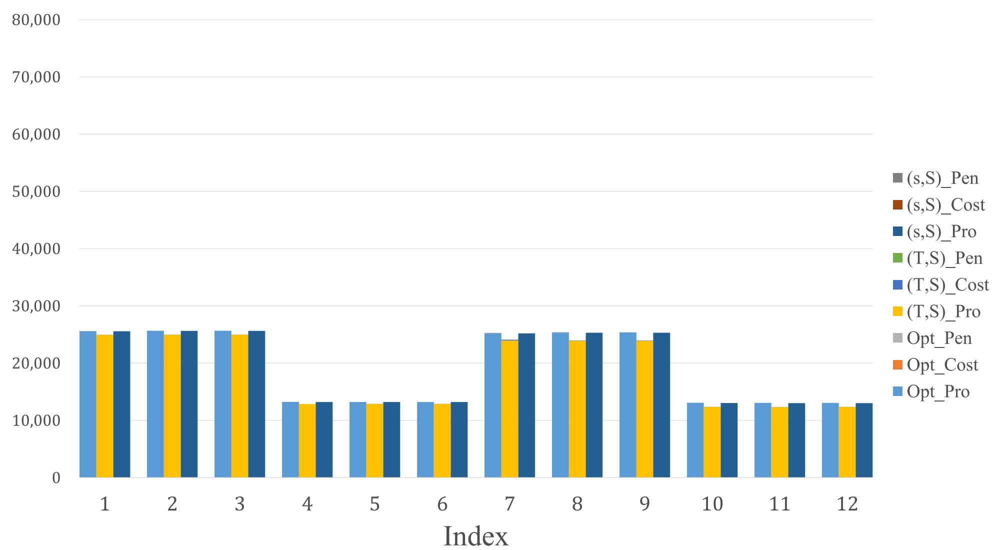

Fig. 4. Financial performances assuming $\rho = 1$; $\phi = 1$.

divided into three groups, BS, China, and North America, it is fundamentally beneficial to strengthen the circulation in the order of BS → China → North America → BS. However, as the demand from North America to Asia is insufficient and as ECR is yet burdensome, such circulation is not fully vitalized. In other words, the demand from China to North America can only be addressed conservatively. Consequently, the importance of the bidirectional routes between BS and the Chinese ports rises.

To prevent empty containers from flocking to China, the route from BS to China is set to be more expensive, whereas the route from China to BS is made cheaper. Moreover, intending to secure more demand in the routes between BS to China (as opposed to BS to North America), between China to North America (as opposed to BS to North America), and between North America to BS (as opposed to North America to China) can all result in the aforementioned trend related to BS. The intention to strengthen such a circulation is also evident in Fig. 4. The most notable observation is that costs and penalties are negligible, indicating that profits account for the majority of the total revenues. This outcome reflects the fact that ECR has rarely been executed at this stage due to its excessive burden.

Third, the balance significantly affects the prices representing the intercontinental routes. In imbalanced situations (i.e., indices 4, 5, 6, 10, 11, and 12), routes from North America to Asia become cheaper, while routes from Asia to North America become more expensive. As the demand from North America to Asia diminishes, prices are also decreased to capture as much demand as possible. Nevertheless, the circulation is still depressed, restraining the Asia → North America route. As a result, the corresponding prices rose.

Finally, departing from North America is more expensive in balanced and insufficient circumstances (i.e., indices 1 and 7), regardless of the volatility of demand. In imbalanced scenarios, there is no capacity for flexibility, necessitating the unconditional establishment of low prices. In contrast, under balanced conditions, the presence of moderate demand mitigates the need for excessively low pricing, as the scarcity of containers inherently limits the ability to meet all demand. Furthermore, the insufficient availability of containers results in the underutilization of routes from Asia to North America. Therefore, the prices increased only for those specific conditions.

Fig. 5 and Table A.15 present the situation with $\rho = 3/4$, while ϕ remains still. Some resemblances to the previous case can be easily observed. Compared to the Chinese ports, routes departing from BS remain more expensive, while those heading to BS are still cheaper. The prices for the

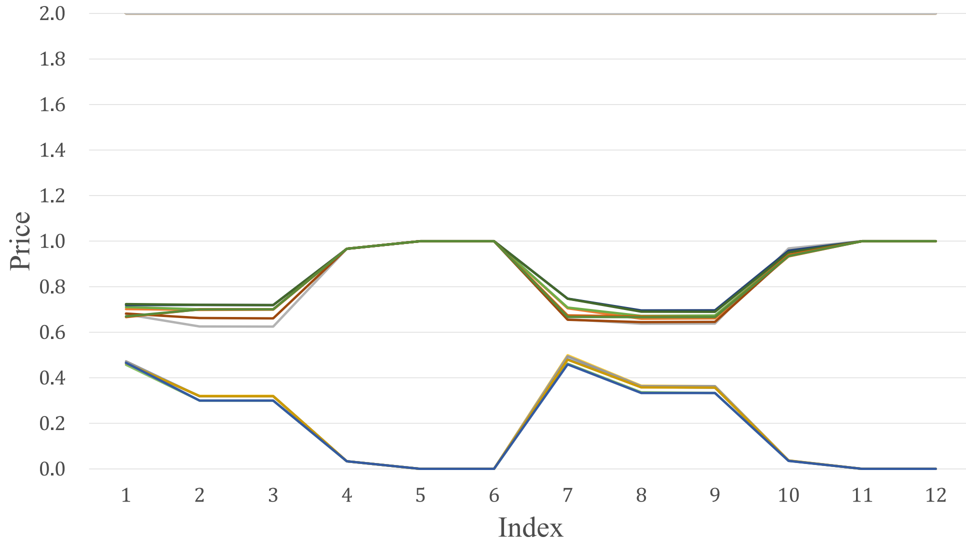

Fig. 5. Optimal prices assuming $\rho = 3/4$; $\phi = 1$.

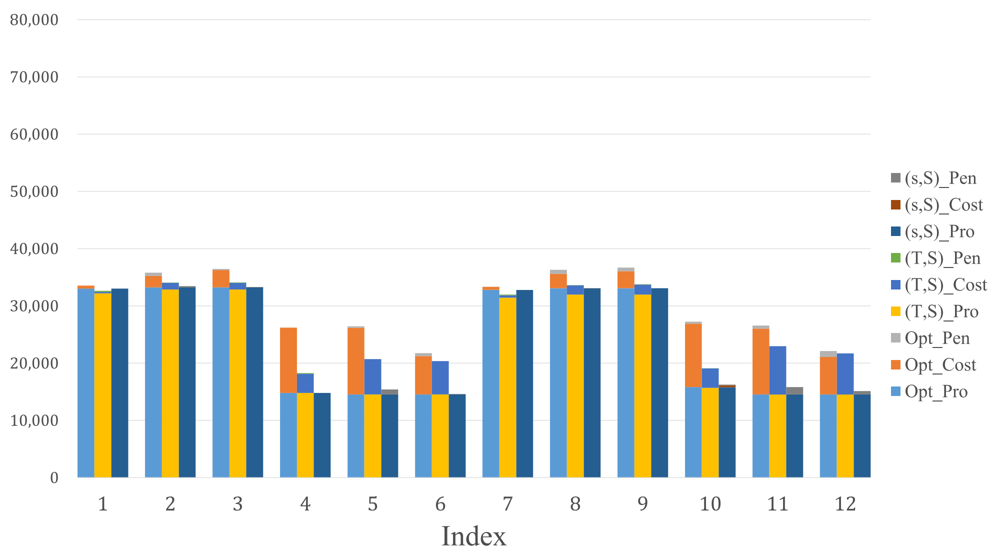

Fig. 6. Financial performances assuming $\rho = 3/4$; $\phi = 1$.

intercontinental routes are again substantially influenced by the balance, and North America → Asia routes are yet more expensive in balanced and insufficient circumstances. In contrast, some differences are also notable. All prices, except for those corresponding to North America → Asia, escalated. Such a result is reasonable, considering the decrement of ρ. Recall that the optimization model determines the prices, and the quantity of ECR increased for this model, compared to $\rho = 1$. Consequently, we can conclude that the optimal strategy is to enhance the aforementioned circulation, though ECR costs increase.

The most remarkable change is that routes from Asia to North America are now adopting their possibly highest prices (i.e., the same as the upper limits), regardless of any situation. These routes are undoubtedly the largest potential market, and the demands can be sufficiently secured though the prices are set to maximum, as ρ has decreased. Therefore, profits heavily rely on these routes. Note that the demands actually increase though the prices are equal to 2. All the prices representing the routes from Asia to North America were higher than 1.57 when $\rho = 1$, regardless of circumstances. Accordingly, the following inequality holds for these routes: $d_{ij}^t = D_{ij}^t \left(1 - \rho x_{ij}/C_{ji}\right) = D_{ij}^t \left(1 - x_{ij}/2\right) \leq D_{ij}^t \left(1 - 1.57/2\right) = 0.215 D_{ij}^t$. On the other hand, now that such prices are fixed to 2, the actual demands can be expressed as $d_{ij}^t = D_{ij}^t \left(1 - \rho x_{ij}/C_{ji}\right) = D_{ij}^t \left(1 - 3x_{ij}/8\right) = 0.25 D_{ij}^t$, which are always bigger than were the previous demands.

However, the prices corresponding to North America → Asia became cheaper. As previously mentioned, the demands for the opposite direction increased. To successfully respond to this growth, the necessity of securing additional demands for backhauls is emphasized. Consequently, the corresponding prices are lowered. In other words, such a strategy involves sacrificing the profitability of North America → Asia routes to focus on Asia → North America routes. Considering the insufficient demands of North America → Asia, this approach necessitates increasing ECR. In essence, this strategy is justified by the guarantee of higher profits outweighing the ECR costs. In extreme cases, during imbalanced scenarios, prices may be set close to zero or even at zero. Such a result implies a willingness to lend containers for free and to rely on the customers to retrieve them, rather than incurring ECR costs, though it merely serves as a partial substitute for ECR.

The last difference compared to the previous case is that the prices for the intra-continental routes are no longer stable. Nevertheless, the patterns for the routes within Asia and within North America remain consistent. Recall that the routes connecting BS and Chinese ports were emphasized

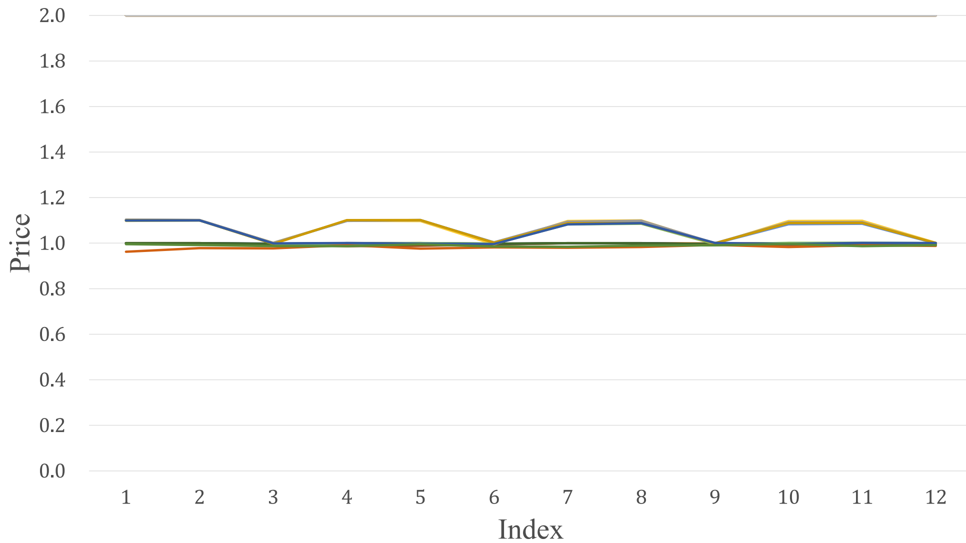

Fig. 7. Optimal prices assuming $\rho = 1/2$; $\phi = 1$.

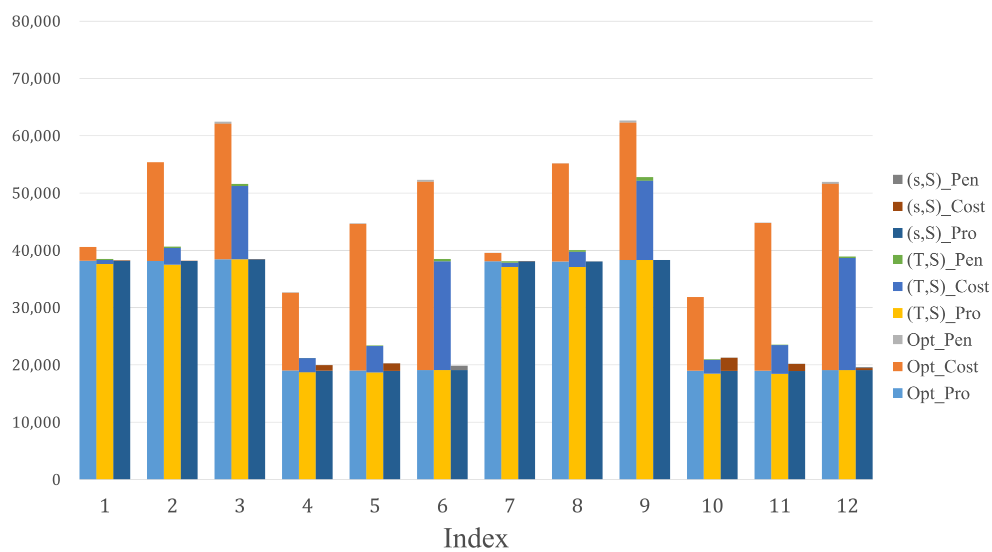

Fig. 8. Financial performances assuming $\rho = 1/2$; $\phi = 1$.

in the previous case. Thus, the intra-continental routes previously exhibited price stability, with additional consideration of the absence of demand differences caused by balance disparities. Furthermore, in imbalanced scenarios, the Asia → North America routes became more expensive, but they are now fixed at a price of 2 and remain unchanged. Consequently, in the current focus on strengthening the circulation, a different approach is adopted to enhance the routes from Asia to North America.

Previously, due to the burdens associated with ECR, the optimal strategy in imbalanced situations was to raise the prices for the Asia → North America routes, thereby reducing the corresponding demands and concentrating on intra-continental demands. However, Asia → North America routes are now the primary source of revenue, and demand control through price adjustment is no longer feasible due to the upper limit. Therefore, the chosen strategy in imbalanced scenarios is to increase the prices for the intra-continental routes, thereby reducing demand for these routes and preventing containers from being occupied by these routes. In other words, ECR is actively executed to maintain the circulation, as the profits outweigh the ECR costs, and naturally, the quantity of ECR increases in imbalanced scenarios. Fig. 6 explicitly demonstrates this. In imbalanced scenarios, although total revenue increases significantly compared to the previous case, the majority of the additional revenue is spent on covering the increased costs. Nevertheless, profits still show overall improvements.

Fig. 7 and Table A.16 demonstrate the situation with $\rho = 1/2$ and $\phi = 1$. Compared to the previous case, the quantity of ECR has increased significantly, and the number of containers substantially impacts ECR. This is because sufficient demand exists despite the high prices, making the number of containers a critical factor in determining the demand that can be covered. The Asia → North America routes remain fixed at a price of 2, while the prices for the intra-continental routes converge to 1. In other words, most prices have reached their maximum values. When $\rho = 3/4$, the prices for the North America → Asia routes decreased, but now even these prices have risen.

As the prices can be set higher, the burden of ECR costs has relatively decreased, enabling a more active implementation of ECR without the necessity of securing backhaul demand. Accordingly, Fig. 8 shows that significant costs are incurred not only in imbalanced scenarios but also in balanced scenarios. As in the previous case, total revenues increase substantially; however, the associated costs also rise considerably. While

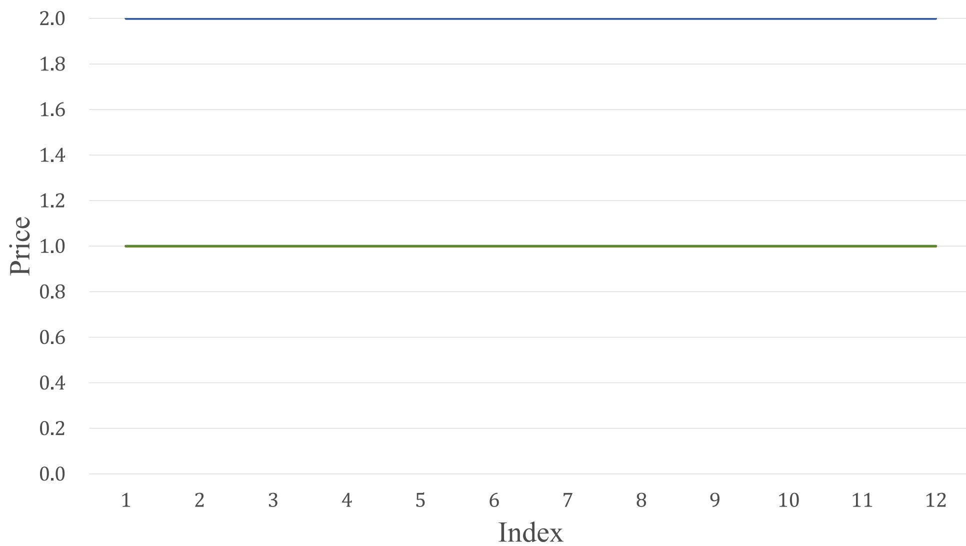

Fig. 9. Optimal prices assuming $\rho = 1/4$; $\phi = 1$.

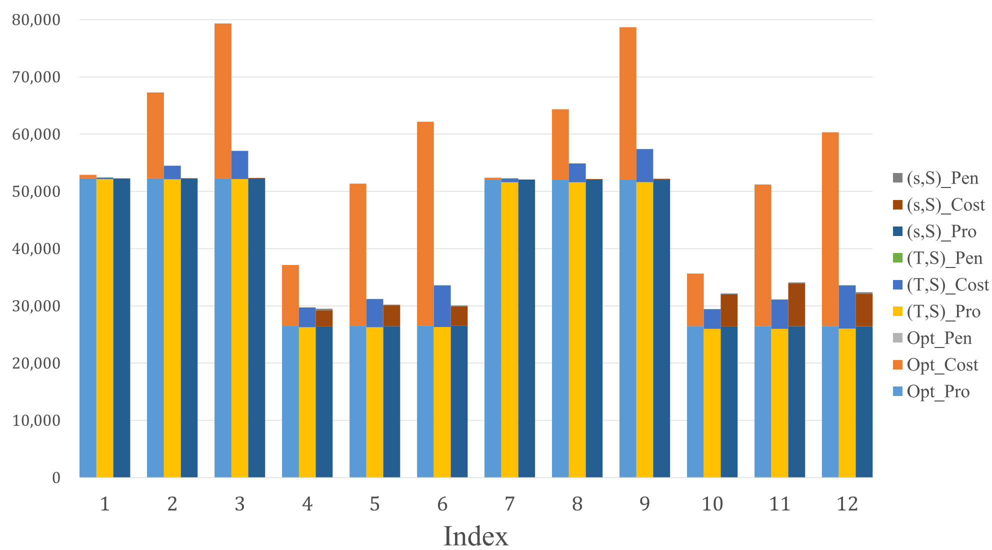

Fig. 10. Financial performances assuming $\rho = 1/4$; $\phi = 1$.

in cases with fewer containers, most of the additional revenues directly translate into increased profits, as the number of containers increases, a larger portion of the additional revenues are absorbed by costs. As a result, even when the number of containers increases, costs escalate sharply, whereas profits remain relatively unchanged.

A notable observation is that prices are lower only when there are ample containers for the North America → China routes. This adjustment is made to mitigate the slight burden of relying solely on ECR in cases of container surplus. In addition to this, the North America → BS routes exhibit lower prices even in imbalanced situations. This is because the North America → BS routes inherently have lower demands than do the North America → China routes, regardless of whether balanced or not. Therefore, such adjustment is attributed to considerations of ECR costs, similar to in the case of the North America → China routes.

Fig. 9 and Table A.17 show the results assuming $\rho = 1/4$. At this point, all prices have reached their maximum values without exception. ECR still heavily depends on the number of containers. In Fig. 10, unlike the previous case, the increase in revenue has a significant impact on profit growth. Demand remains sufficiently high even with elevated pricing, allowing for a substantial rise in revenue. In addition, as demand from North America to Asia has also increased, the need for ECR has not increased significantly. As a result, the increase in revenue is effectively translated into profit growth. Eventually, when ρ changes, determining how much of the ECR cost can be tolerated becomes critical, and prices and demands are adjusted accordingly.

Now we examine the scenarios where ρ is fixed and ϕ is reduced. Fig. 11 and Table A.18 illustrate the case where $\phi = 3/4$ and $\rho = 1$. Unlike in previous cases, increasing the prices is no longer possible. Instead, increasing demand and leveraging cost-effective ECR to improve efficiency are now the main concerns, leading to price reductions. Consequently, profit does not increase as dramatically as when ρ is varied. The routes departing from North America remain expensive in balanced and insufficient scenarios, but the difference has narrowed.

When classified by balance, the results exhibit highly consistent patterns. In balanced scenarios, the prices are very similar to those when $\phi = 1$, but entirely different patterns emerge in imbalanced situations. In imbalanced scenarios, the characteristics of BS observed previously

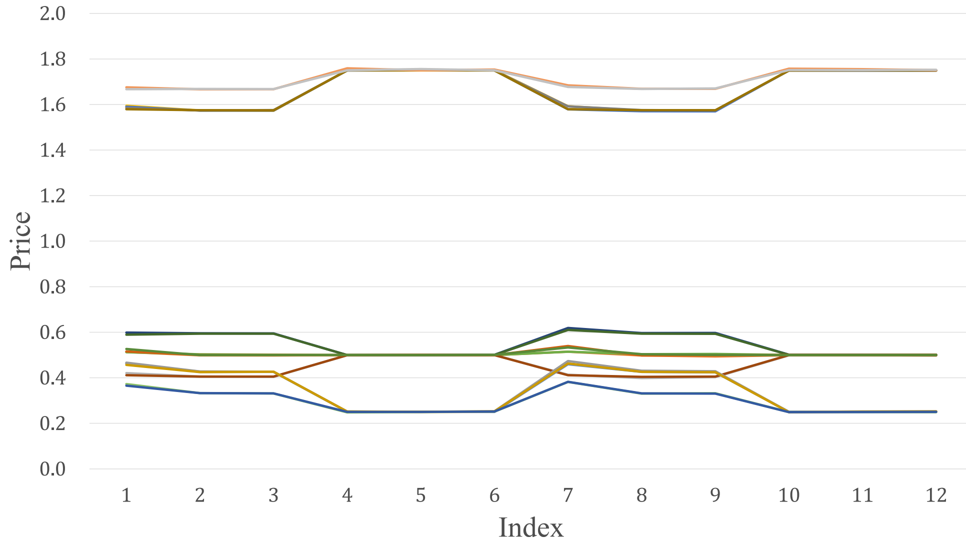

Fig. 11. Optimal prices assuming $\phi = 3/4$; $\rho = 1$.

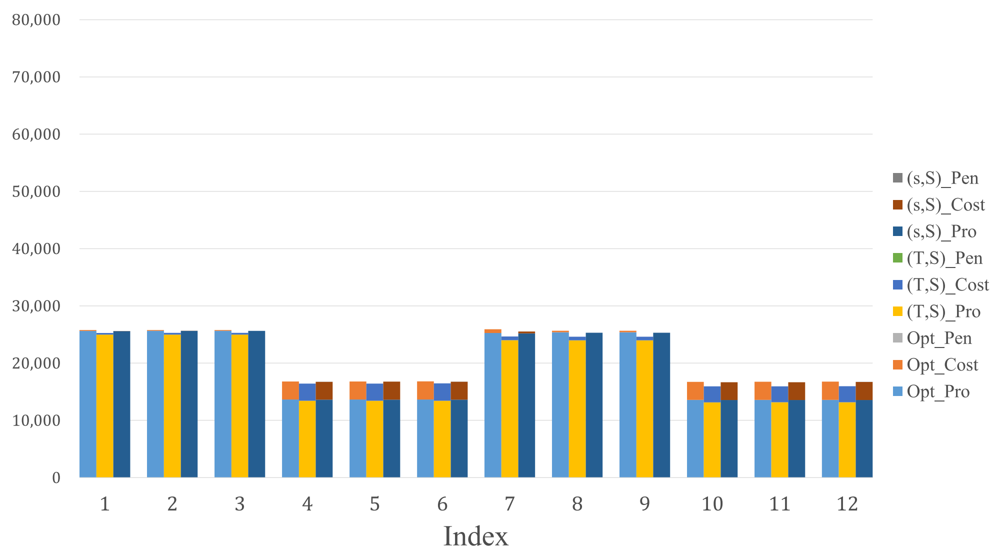

Fig. 12. Financial performances assuming $\phi = 3/4$; $\rho = 1$.

disappear entirely, and outcomes are determined solely by intercontinental differences. Additionally, the prices for the North America → China routes have increased, and even more so for the North America → BS routes, in imbalanced circumstances. Despite the reduction in ϕ, ECR remains a considerable burden. In balanced scenarios, the circulation could be maintained with minimal ECR, which is not attainable in imbalanced cases. Instead, a strategy of relinquishing the North America → Asia routes and actively performing ECR is adopted.

The same result can be observed in Fig. 12. Under imbalanced scenarios, maintaining a profit level comparable to the case of $\phi = \rho = 1$ (i.e., Fig. 4) inevitably requires accepting an increase in ECR costs. Therefore, the increase in revenue leads to higher costs, resulting in only a marginal improvement in profit. The primary concern for now is to focus on the main east–west route connecting Asia and North America, though the North America → Asia routes may be mostly handled via ECR. In other words, the motivation to maintain the circulation of BS → China → North America → BS no longer exists, naturally diminishing the individuality of BS. Accordingly, prices for the Asia → North America routes have been lowered to increase demand, while prices for the North America → Asia routes have been raised.

The results assuming $\phi = 1/2$ are reported in Fig. 13, Table A.19, and Fig. 14. The quantity of ECR and its associated costs increased significantly not only in imbalanced scenarios but also in balanced situations. The prices exhibit highly consistent patterns depending on the type of route. The Asia → North America routes have prices roughly ranging from 1.5 to 1.6, while the North America → Asia and intra-continental routes have prices around 0.5. With the burden of ECR significantly reduced, there is no longer a compelling reason to prioritize the circulation, as mentioned earlier in the previous case. All the prices for the Asia → North America routes have decreased, reflecting the intention to secure more demand. Conversely, all the prices for the North America → Asia routes have increased, indicating a willingness to relinquish these routes and actively perform ECR. Intra-continental routes have prices around 0.5, similar to the imbalanced cases of $\phi = 3/4$. Moreover, with the increasing proportion of ECR, price differences due to balance disparities have become less pronounced, while differences related to the number of containers have become more apparent. Regardless of other conditions, prices for all routes increase when the number of containers is insufficient. Such a result reflects the intention to raise prices and reduce demand when excessive demand cannot be covered due to container shortages.

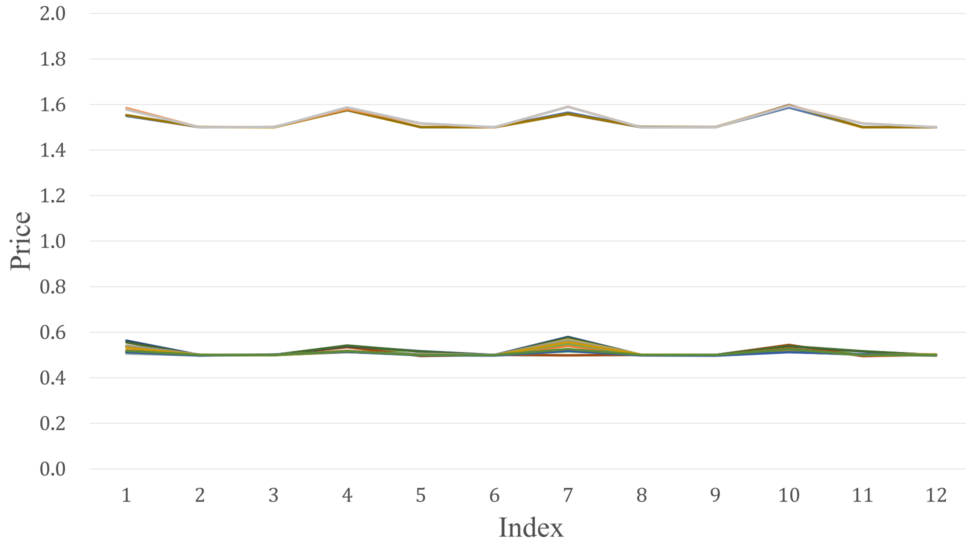

Fig. 13. Optimal prices assuming $\phi = 1/2$; $\rho = 1$.

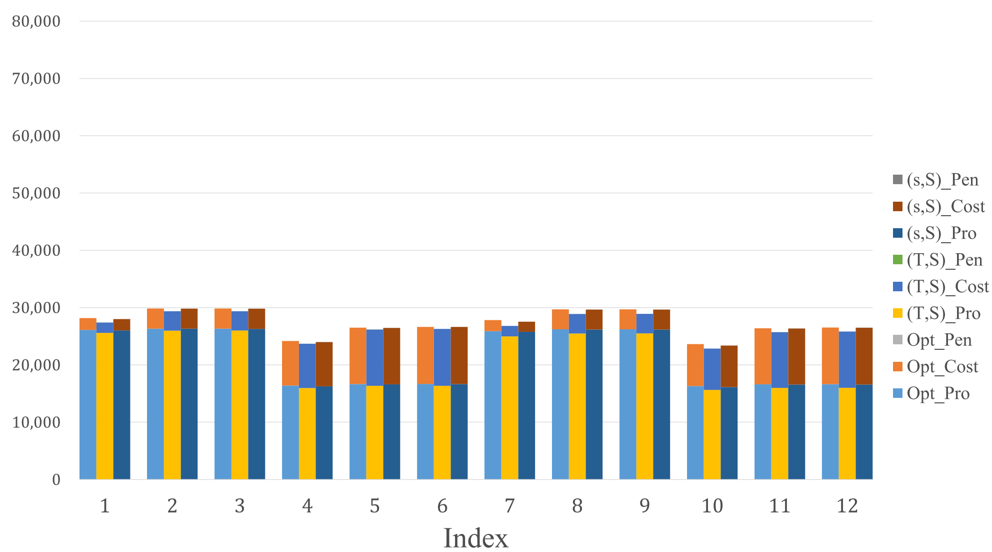

Fig. 14. Financial performances assuming $\phi = 1/2$; $\rho = 1$.

Finally, Fig. 15, Table A.20, and Fig. 16 present the case where $\phi = 1/4$. The quantity of ECR has increased even more significantly compared to in the previous case. However, in the imbalanced scenarios, the associated costs actually decreased. When ϕ decreased from 3/4 to 1/2, the quantity of ECR surged dramatically, both in absolute and relative terms, regardless of the scenario. As a result, costs increased in all scenarios. In the current situation, however, although the quantity of ECR has increased significantly in absolute terms across all scenarios, the relative increase is less severe compared to the previous case. Specifically, in the balanced scenarios, the quantity of ECR increased by 2.3 to 3.7 times, whereas in the imbalanced scenarios, it increased by only 1.2 to 1.9 times. In other words, all balanced scenarios saw an increase of more than twice, while all imbalanced scenarios experienced less than a twofold increase. Consequently, since ϕ was reduced by half, from 1/2 to 1/4, the balanced scenarios ultimately experienced an increase in costs, whereas the imbalanced scenarios resulted in a decrease in costs.

All the prices for the Asia → North America routes have decreased again, aiming to secure additional demand. The prices for the North America → Asia routes have increased significantly, indicating an intent to abandon backhaul demand and rely solely on ECR due to its low cost. In addition, the prices for intra-continental routes have slightly increased, reflecting a focus on the main east–west route. Resembling the previous case, the increased proportion of ECR has minimized price differences caused by balance disparities, while differences based on the number of containers have become more evident. With the ability to perform ECR extensively, there are now considerable differences between adequate and ample scenarios. In other words, it is natural to focus on securing more demand as the number of containers increases. Consequently, the logic is consistent with the case of $\phi = 1/2$, though the changes are more extreme.

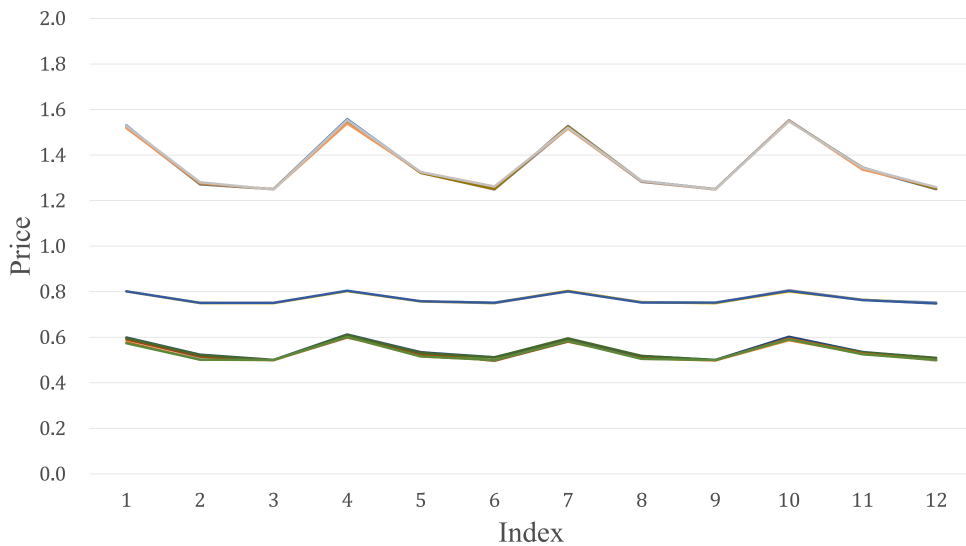

Fig. 15. Optimal prices assuming $\phi = 1/4$; $\rho = 1$.

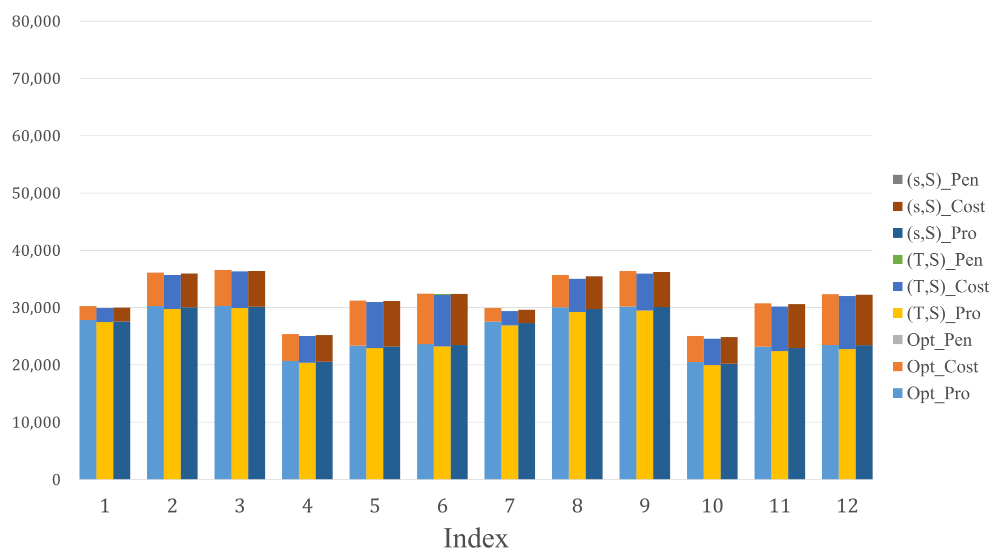

Fig. 16. Financial performances assuming $\phi = 1/4$; $\rho = 1$.

5.3. Heuristics

With the rapid development of artificial intelligence and machine learning technologies, the accuracy of forecasting has significantly improved. Naturally, research and practical applications of demand forecasting, one of the most critical components in business, have become increasingly active (Huang et al., 2023; Wong et al., 2024; Zhang et al., 2024a). Nevertheless, it remains practically impossible to eliminate uncertainty entirely. The mathematical models we previously proposed assume deterministic demand. However, as previously mentioned, the uncertainty associated with demand is still substantial, raising concerns about the practical effectiveness of our models under the deterministic demand assumption. To address these concerns, we propose two simple and highly applicable heuristics, each based on the optimization model and the (s, S) strategy, respectively. These heuristics are hereafter referred to as the "Opt heuristic" and the "(s, S) heuristic", respectively.

For both heuristics, we utilize all 40 demand sets used in the previous experiments to evaluate their robustness in responding to stochastic demand. Both heuristics fundamentally follow steps (ii) to (v) after the initialization in (vii) from the previous experiments. Specifically, the optimization model is applied to the first ten demand sets to determine the optimal prices. In addition, the resulting optimal values of y_{ij}^t and z_{ij}^t obtained from the optimization model will also be utilized. Based on the optimal prices, the (s, S) strategy is then applied to compute the optimal s_j and S_j values, and the corresponding optimal values of y_{ij}^t are also retained. By using all these parameters, both heuristics are subsequently applied to the remaining 30 demand sets.

For each demand set, demand for each period is generated sequentially. Accordingly, decisions must also be made sequentially, without any information regarding the demand in future periods. In other words, we aim to examine how robustly the optimal prices and parameters derived from historical data (i.e., the first ten demand sets) perform under stochastic demand conditions (i.e., the subsequent 30 demand sets). The two heuristics differ only in their approaches to ECR, while all other components remain identical. Further details are provided in Algorithms 1 and 2 in Appendix.

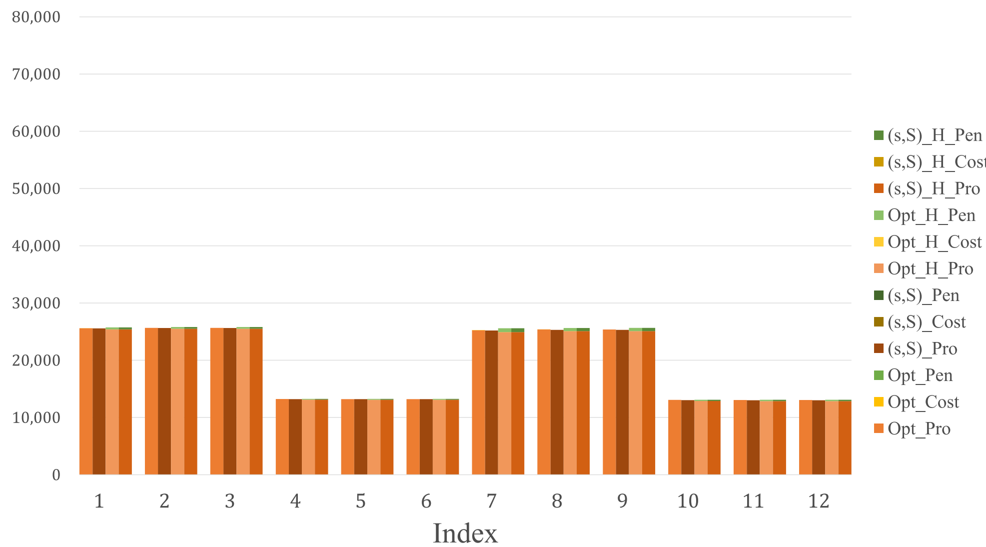

Fig. 17. Financial performances of the heuristics assuming $\rho = 1$; $\phi = 1$.

The initialized data from the previous experiments is directly utilized. For the rental decisions, the optimal y_{ij}^{t} values previously obtained from the ten demand sets are used. Specifically, for each demand set, the average value Y_{ij} is calculated for each route by taking the mean of the quantities rented out in each period. Additionally, in each period, the difference between the cumulative quantity that should have been rented out and the cumulative quantity actually rented out is computed. This difference is compensated by renting out additional containers if the available inventory allows. The most significant distinction from the previous mathematical models emerges here.

The mathematical models assume deterministic demand and do not impose penalties for lost sales, which may result in seemingly irrational but optimal decisions, such as completely ignoring demand despite having available containers. In contrast, the heuristics are designed to operate under demand uncertainty and aim to be as responsive to demand as possible, making them more practical. Following this, the ECR strategies of the two heuristics diverge. The ECR strategy of the Opt heuristic resembles the approach used for responding to demand. It performs repositioning in each period according to the average value Z_{ij}, which is calculated from the optimal z_{ij}^{t} values obtained by the optimization model applied to the initial ten demand sets, resulting in a simple and straightforward policy.

In the case of the (s, S) heuristic, the approach is again based on the conventional (s, S) inventory management policy. Using the predetermined s_j and S_j values, repositioning is carried out whenever the inventory position falls below s_j so that it is replenished up to S_j. However, as previously mentioned, the choice of source for replenishment is a critical issue (i.e., from where to bring the containers?). An analysis of the optimal decisions derived from the (s, S) strategy shows that, in all cases, the repositioning on routes other than North America to Asia is negligible. Moreover, due to the nature of the demand we applied, the quantity repositioned from LA to Asia is consistently higher than that from VC to Asia. Similarly, the repositioning quantity from North America to BS is greater than that from North America to China. Note that SH and NB are considered indifferent in this study. Therefore, we adopt the principle of prioritizing LA over VC as the supply source for empty containers from North America. Furthermore, without loss of generality, BS, SH, and NB are prioritized in that order. In summary, ECR is performed in the following sequence: LA → BS, VC → BS, LA → SH, VC → SH, LA → NB, and VC → NB.

We now compare the results of the heuristics with those of the mathematical models that assume deterministic demand. The (T, S) strategy is excluded from the comparison, as it did not demonstrate competitive performance in the previous experiments. Accordingly, bar charts are employed once again to illustrate the profits, costs, and penalties of the four approaches, presented in the order of the optimization model, the (s, S) strategy, the Opt heuristic, and the (s, S) heuristic.

Under the default setting ($\rho = \phi = 1$), the results show minimal deviation from those obtained under the deterministic demand assumption (Fig. 17). In all cases, both heuristics achieve profits comparable to those of the optimal and the (s, S) strategy while incurring negligible costs. Specifically, across all cases, both heuristics show a profit gap of less than 1.6% compared to the optimal profit. This gap tends to be larger in imbalanced scenarios than in balanced ones and in fluctuating scenarios compared to stable ones, reflecting the influence of stochastic demand.

As ρ decreases to 3/4, noticeable differences begin to emerge (Fig. 18). Compared to the optimal, the profit gap increases to as much as 3.3% in balanced scenarios and up to 16% in imbalanced ones. However, the gap narrows as the number of containers increases; even in imbalanced scenarios, it falls within 1.7% when the number of containers is ample.

When ρ decreases, the performance difference between the two heuristics remains insignificant, but the gap from the optimal profit gradually widens. Specifically, when ρ is reduced to 1/2, the profit gap remains within 10% in balanced scenarios and within 26% in imbalanced ones (Fig. 19). When ρ further decreases to 1/4, the gap increases to within 13% in balanced scenarios and up to 30% in imbalanced ones (Fig. 20). In other words, as ρ declines, the performance of the heuristics deteriorates. As ρ decreases, prices increase, and it becomes increasingly important to ensure that containers are not inefficiently occupied but are instead efficiently allocated to meet demand in order to maintain profitability. Accordingly, the mathematical models that assume deterministic demand were able to respond ideally to demand. In other words, the models could make decisions to withhold rentals even when sufficient containers were available in preparation for future demand. However, the heuristics always respond to current demand, which can lead to containers being inefficiently occupied. Such inefficiency, in turn, results in profit loss.

When ϕ decreases to 3/4, the profit gap does not increase significantly, unlike the case when ρ decreases (Fig. 21). For the Opt heuristic, the profit gap remains within 2.8% across all cases, while the (s, S) heuristic shows an even smaller gap within 1.9% in all cases. Unlike previous results, it is apparent that the (s, S) heuristic begins to dominate the Opt heuristic. This pattern becomes more evident as ϕ decreases further.

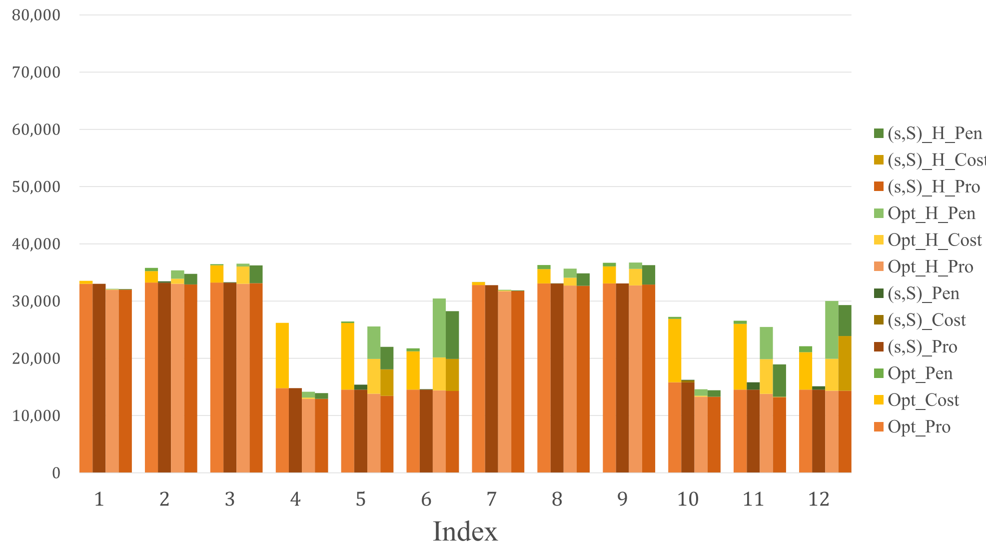

Fig. 18. Financial performances of the heuristics assuming $\rho = 3/4$; $\phi = 1$.

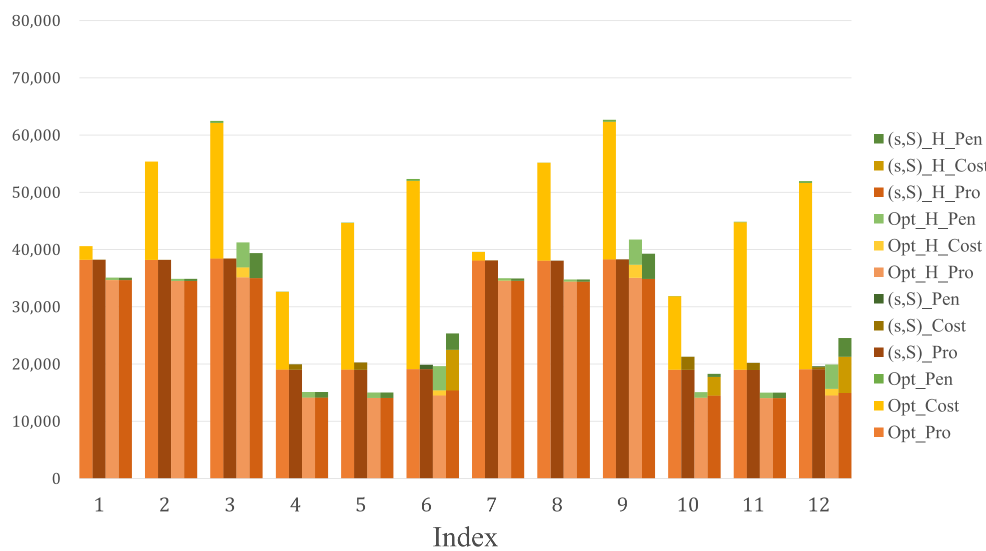

Fig. 19. Financial performances of the heuristics assuming $\rho = 1/2$; $\phi = 1$.

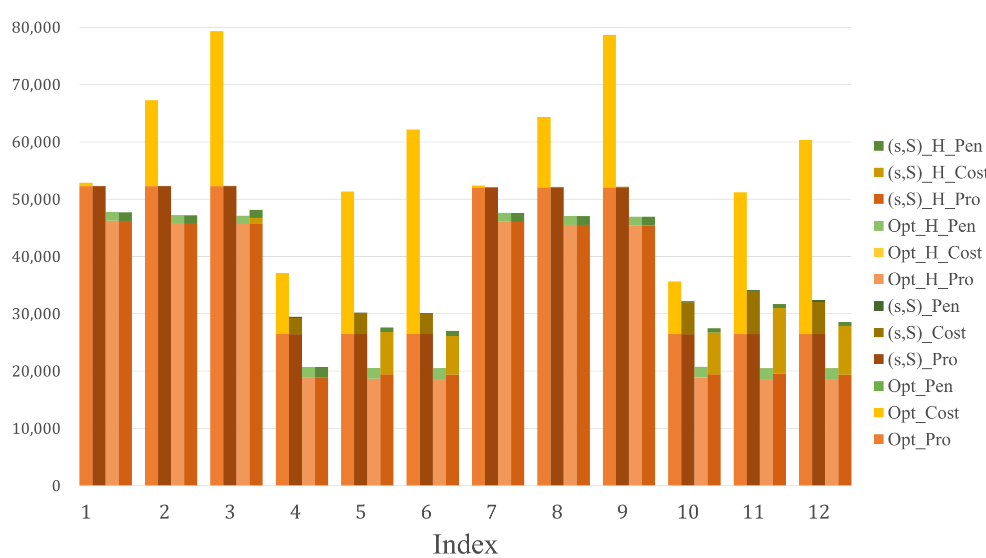

Fig. 20. Financial performances of the heuristics assuming $\rho = 1/4$; $\phi = 1$.

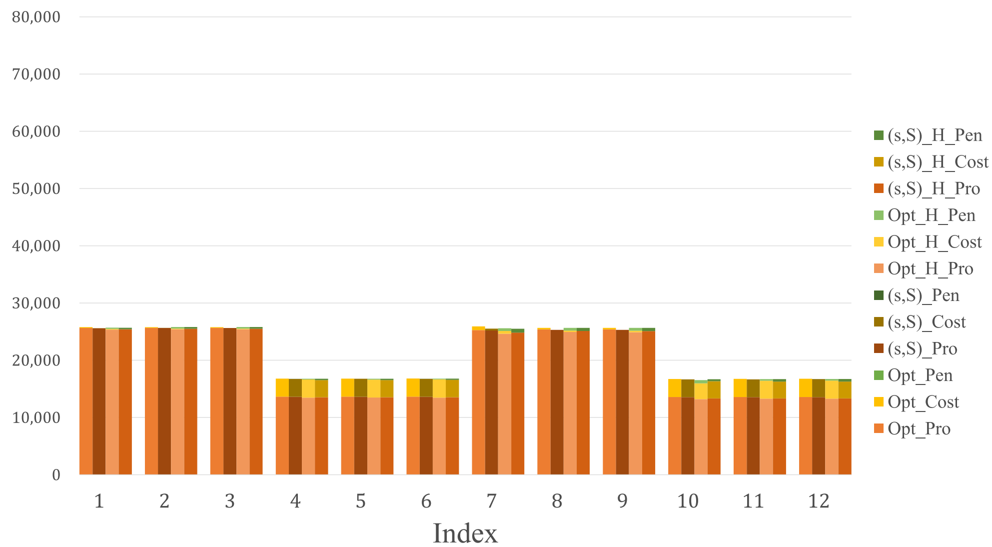

Fig. 21. Financial performances of the heuristics assuming $\phi = 3/4$; $\rho = 1$.

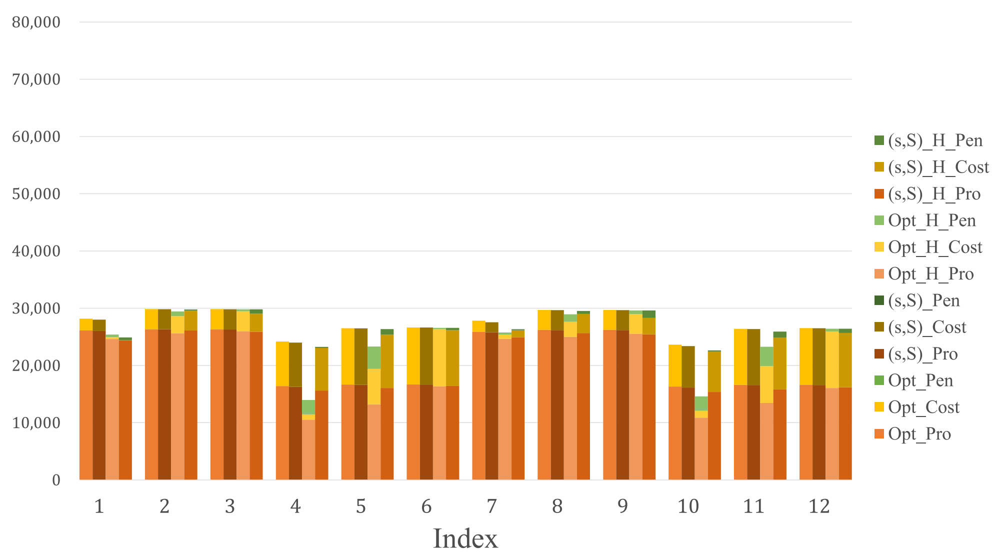

Fig. 22. Financial performances of the heuristics assuming $\phi = 1/2$; $\rho = 1$.

When ϕ is reduced to 1/2, the (s, S) heuristic maintains a profit gap of within 6.6% across all cases (Fig. 22). However, the Opt heuristic shows a gap of within 5.7% in balanced scenarios but exhibits a substantial gap of up to 36% in imbalanced scenarios, resulting in a considerable divergence from the (s, S) heuristic. Nevertheless, this gap narrows to within 3.5% when the number of containers is ample.

When ϕ decreases to 1/4, the Opt heuristic is no longer a viable option (Fig. 23). While the (s, S) heuristic maintains a profit gap of within 7.3% across all cases, the Opt heuristic exhibits a much larger gap, ranging from a minimum of 12% to a maximum of 62%. Particularly, in imbalanced scenarios, the Opt heuristic shows a gap of at least 43%, clearly demonstrating its lack of robustness. Moreover, when ϕ is less than or equal to 1/2, there are cases where the profit of the Opt heuristic even decreases.

Unlike in the cases where ρ decreases, there is a limit to the potential revenue that can be obtained when ϕ decreases. Consequently, profitability relies heavily on how efficiently ECR is performed. However, when ϕ is small, the Opt heuristic tends to generate lower revenue compared to the others while incurring lower costs but higher penalties. In other words, effective container circulation through appropriate ECR is not being achieved. The Opt heuristic performs repositioning based on some fixed quantities in each period. Accordingly, it lacks flexibility in ECR, which directly leads to a decline in performance. In contrast, the (s, S) heuristic, grounded in the (s, S) inventory management policy, allows for much more flexible repositioning, resulting in significantly higher robustness.

In summary, the Opt heuristic demonstrates competitive performance under ordinary conditions, but its effectiveness declines sharply in extreme situations, such as when $\rho \leq 1/2$ or $\phi \leq 1/2$. In contrast, the (s, S) heuristic maintains robust performance even as ϕ decreases; however, its performance also deteriorates significantly when ρ decreases. Although decreasing ρ leads to an increasing gap between the heuristics and the optimal profit, the overall profits still increase. From this perspective, reducing ρ is beneficial if feasible. However, in practice, it is challenging to decrease ρ. While strategies such as marketing or gentrification may enhance customer loyalty, it is practically impossible to dramatically reduce ρ in the short term. Accordingly, a scenario in which ρ decreases to 1/2 or even 1/4 is unrealistic, and the severe gap from the optimal profit under these conditions may not be a critical concern in practice.

On the other hand, interestingly, there is a realistic approach to reducing ϕ to as low as 1/4. Foldable containers, introduced in Section 2.1, can reduce transportation costs to approximately one-fourth of those associated with standard containers. Therefore, launching an OCRS that exclusively

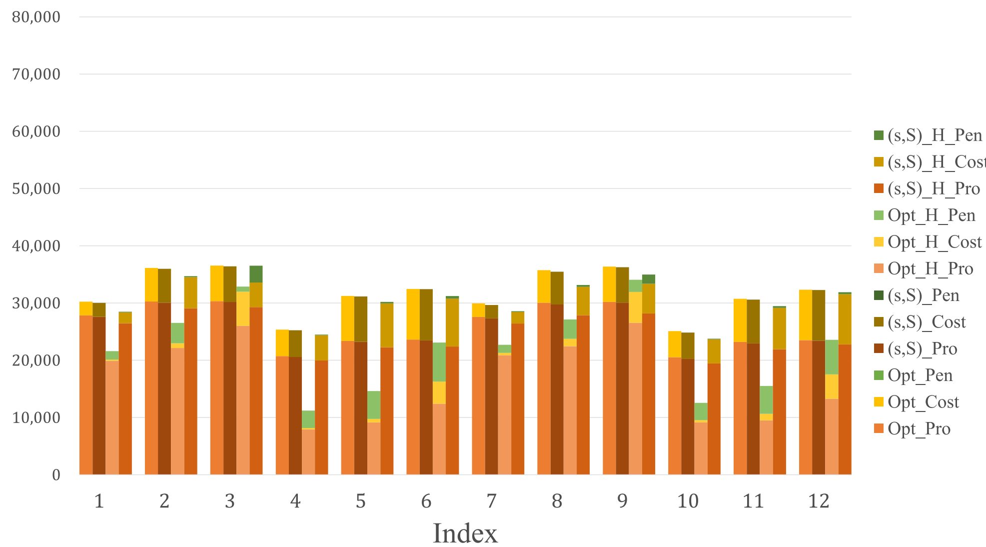

Fig. 23. Financial performances of the heuristics assuming $\phi = 1/4$; $\rho = 1$.

handles foldable containers could reduce ϕ to as low as 1/4. From this perspective, the (s, S) heuristic, which demonstrates robust performance even in scenarios with low ϕ, offers significant practical value. The observed results of the heuristics can be further summarized as follows, closely aligning with the findings in Section 5.2.

1. An excessive number of containers is not necessary.
2. The balance between continents significantly affects the results.
3. The volatility of demand does not have a significant impact.
4. Decreasing ECR costs (ϕ) makes a tremendous difference in imbalanced situations, which are highly likely to occur in practice.
5. The (s, S) heuristic demonstrates robust performance, except in extreme scenarios where ρ is severely reduced.

5.4. Managerial insights and practical challenges

By confirming the robust performance of the (s, S) heuristic, we have demonstrated that the optimal prices and parameters obtained from the mathematical models, based on historical data, can be effectively implemented in practice to ensure robust decision-making. In particular, the proposed mathematical models and heuristics serve complementary roles. Building on these findings, we not only verified the potential of the OCRS but also proposed a highly practical strategy that can be implemented when launching the actual service. Furthermore, based on the experimental results, we suggest the following priorities for the launch of a new service.

1. Start with a small number of containers.
2. Adopt the rental and ECR policies aligned with the (s, S) heuristic.
3. Strive to maintain the balance of demands between continents.
4. Make efforts to lower customers' price sensitivity (ρ) and ECR costs (ϕ).
5. Iteratively increase the number of containers and secure additional demand.

Nevertheless, there are numerous additional factors that should be considered when implementing the OCRS in practice. Among them, several key challenges are summarized as follows.

• Since the OCRS relies on economies of scale to efficiently perform ECR, a minimum level of demand is a prerequisite. Due to the current severe imbalance in intercontinental trade volumes, offering reasonable pricing is likely to attract sufficient demand on routes such as Asia to North America. More importantly, securing demand in the opposite direction (i.e., alleviating the imbalance) significantly improves profitability, which highlights the need for strategic focus. However, regular demand in these routes is presumed to be effectively managed by shipping companies; therefore, it is necessary to consider proactive strategies for capturing irregular or ad-hoc demand.

• Since container lessors generally do not own vessels, they are unable to perform ECR independently. In other words, it is similar to the situation where shippers with shipper-owned containers need to secure vessel capacity by entering into contracts with carriers. However, suppose a customer of the OCRS rents containers for the route from Asia to North America. In that case, a corresponding amount of vessel capacity is generally expected to be available (though not necessarily) on the return leg from North America to Asia. Therefore, while a lack of vessel capacity is unlikely to be an issue, utilizing this capacity at minimal cost is crucial. According to Zhao (2007), this can be achieved at a relatively low cost, and actively leveraging the spot market is one potential strategy.

• From a highly practical perspective, there are several considerations that must be addressed. First, a reliable platform is required to provide stable services across multiple countries (Xu et al., 2021, 2022, 2023b). Through this platform, customers can access information on rental prices and the availability of containers, and, depending on the regulatory frameworks of each country, they may be able to make immediate payments and arrange for container pickup. In such cases, technologies like blockchain should be employed to ensure the protection of customer data and the security of transactions (Liu et al., 2023b,c; Xu et al., 2023a; Lam and Lee, 2024). Furthermore, unlike in long-term container leasing, a single container in this service is highly likely to be utilized by multiple customers, similar to MSSs. Therefore, the service provider must place particular emphasis on tracking and maintenance of containers, potentially by adopting technologies such as the Internet of Things (Lee et al., 2025). In addition, it is essential to ensure that the service complies with the legal requirements of all countries where it is intended to be offered. Although the proposed service is fundamentally equivalent to the existing one-way leasing practices, and container leasing is already conducted globally, launching a new service may require meeting additional regulatory standards. Consequently, thorough legal review and verification processes are indispensable.

• This study has certain limitations in its consideration of port authority policies (Dong et al., 2023; Yi et al., 2023). The policies most relevant to the proposed OCRS are related to free time allowances and storage charges. Port authorities generally grant shipping lines a free time period ranging from three to seven days (depending on the port, type of cargo, volume, and season), after which storage fees are imposed if containers are not cleared. These charges may arise due to delays in customer pickup, but they can also result from the lack of efficient container circulation, leading to containers being left idle at the terminal. Although such storage costs were not explicitly considered in the initial analysis, they turned out to be negligible under the proposed OCRS, where containers are continuously circulated. However, when launching the service in practice, it is necessary to explicitly account for these factors. Furthermore, demurrage and detention charges resulting from uncertainties in customer behavior should also be carefully considered (Yu et al., 2018; Jeong et al., 2025).

6. Concluding remarks

In this paper, we studied the pricing and ECR strategy for the OCRS and demonstrated the effectiveness of this service. A rational OCRS was proposed to alleviate intercontinental container imbalances and to ease the burden on shipping companies. We aimed to reduce logistics waste by optimizing deadheading container transportation and to lay the groundwork for establishing resilient and eco-friendly maritime logistics networks. Considering that shipping companies are potential customers of this service, the expected competitors are also those carriers performing ECR on their own. Consequently, the service is designed to be price-competitive and rational by guaranteeing lower prices than the price of retrieving an empty container by themselves. We analyzed the profitability of the proposed service and found that it is sufficiently profitable even in such limited circumstances. In addition, we demonstrated the robustness of a practically applicable strategy. Specifically, the heuristic based on the (s, S) inventory management policy demonstrated solid performance. Based on computational experiments with various directions, we presented the priorities when launching the service. Furthermore, we provided guidelines on appropriate pricing for various situations. Through these considerations, we focused on ensuring that the proposed service is practically acceptable.

With the recent advancement of digital platforms and growing interest in the efficient utilization of resources, attention to the sharing economy has also increased. In particular, sharing services that blur the boundaries between traditional rental and leasing services have gained worldwide popularity. Although containers, unlike cars, bicycles, or scooters, are typically managed within B2B industries and are thus less accessible to the general public, we have made an effort to incorporate the concept of the sharing economy into this domain. Due to the lack of research integrating container leasing with one-way leasing contracts or the sharing economy, we hope that this study might encourage a surge in related research activities. Such expansion could prevent logistical crises, like those aroused during the COVID-19 pandemic, by resolving intercontinental container imbalances and by easing the burden on shipping companies, thereby promoting growth in the container spot market (Shi et al., 2023; Feng et al., 2024).

To conclude, we aim to highlight three possibilities for extending this research. First, as previously mentioned, this study aimed to lay the groundwork for establishing resilient maritime logistics networks. However, this research did not extend to a detailed examination of how and to what extent the proposed OCRS contributes to the formation of such resilient maritime logistics networks (Liu et al., 2023a; Song et al., 2024; Zhang et al., 2024b; Gu and Liu, 2025). A quantitative analysis in this regard is expected to further highlight the potential and value of the OCRS. Second, we focused on the main east–west route, where imbalances are most severe, and specifically analyzed five major ports lying on this route. However, in practice, other routes also experience significant imbalances. Increasing the number of ports could introduce greater complexity but also could enable the construction of larger circulation systems, potentially leading to more intriguing analyses.

Finally, as the third possibility, if the proposed service were to be implemented, the key determinant of its success would ultimately be whether there actually is sufficient demand. Consequently, future research could also be linked to operational optimization studies that consider the OCRS from the perspective of carriers. Specifically, regarding customers (i.e., carriers), it is crucial to analyze whether adding one-way container rental as a new option is genuinely advantageous and how containers should be deployed to maximize the effectiveness of the OCRS. By investigating the impacts of reducing the number of owned containers on liquidity securement and ancillary cost reduction, such research can demonstrate the superiority of the new service, contributing to cost alleviation for shipping companies, to enhancing logistics efficiency, and to fostering the development of maritime logistics markets. Even further, this line of research could be extended to examine the potential impacts on existing alliances that were originally formed to reduce costs. We hope that these extensions could form critical branches of future research.

CRediT authorship contribution statement

Junseok Park: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Data curation, Conceptualization. **Ilkyeong Moon:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

See Tables A.14–A.20.

Table A.14
Detailed optimal prices assuming $\rho = 1$; $\phi = 1$.

Origin	Destination	1	2	3	4	5	6	7	8	9	10	11	12
NB	NB	–	–	–	–	–	–	–	–	–	–	–	–
	SH	0.5025	0.4970	0.4960	0.5030	0.5056	0.5028	0.5111	0.4960	0.4966	0.4990	0.5020	0.5012
	BS	0.4093	0.4052	0.4054	0.4065	0.4085	0.4073	0.4148	0.4016	0.4069	0.4062	0.4053	0.4055
	VC	1.5955	1.5740	1.5721	1.7951	1.7950	1.7957	1.6071	1.5728	1.5707	1.7959	1.7945	1.8002
	LA	1.5894	1.5726	1.5735	1.7966	1.7933	1.7963	1.5900	1.5710	1.5719	1.7958	1.7957	1.7915
SH	NB	0.5070	0.5002	0.5024	0.4958	0.4946	0.5000	0.5184	0.5035	0.5047	0.4997	0.4978	0.4984
	SH	–	–	–	–	–	–	–	–	–	–	–	–
	BS	0.4067	0.4060	0.4060	0.4045	0.4031	0.4017	0.4141	0.4050	0.4055	0.4055	0.4098	0.4011
	VC	1.5974	1.5743	1.5751	1.7945	1.7961	1.7925	1.6086	1.5765	1.5747	1.7960	1.7930	1.7979
	LA	1.5882	1.5758	1.5752	1.7922	1.7923	1.7925	1.5943	1.5753	1.5747	1.7950	1.7956	1.7965
BS	NB	0.5968	0.5937	0.5914	0.5950	0.5913	0.5932	0.5986	0.5966	0.5991	0.5948	0.5949	0.5949
	SH	0.5955	0.5946	0.5971	0.5960	0.5954	0.5945	0.5968	0.5946	0.5914	0.5954	0.5905	0.5966
	BS	–	–	–	–	–	–	–	–	–	–	–	–
	VC	1.6875	1.6686	1.6691	1.8939	1.8913	1.8966	1.6746	1.6697	1.6713	1.8924	1.8892	1.8855
	LA	1.6647	1.6676	1.6673	1.8880	1.8934	1.8890	1.6588	1.6681	1.6703	1.8932	1.9017	1.8953
VC	NB	0.5135	0.4275	0.4258	0.2033	0.2033	0.2048	0.5515	0.4302	0.4268	0.2058	0.2036	0.2004
	SH	0.5076	0.4248	0.4254	0.2067	0.2091	0.2057	0.5448	0.4265	0.4228	0.2042	0.2026	0.2039
	BS	0.4088	0.3309	0.3316	0.1073	0.1061	0.1082	0.4334	0.3323	0.3333	0.1103	0.1130	0.1029
	VC	–	–	–	–	–	–	–	–	–	–	–	–
	LA	0.5360	0.4997	0.5001	0.4998	0.5000	0.5000	0.5229	0.5001	0.4999	0.5001	0.4997	0.5000
LA	NB	0.4912	0.4263	0.4271	0.2025	0.2010	0.2032	0.5308	0.4274	0.4272	0.2050	0.2038	0.2016
	SH	0.4830	0.4276	0.4259	0.2064	0.2079	0.2076	0.5286	0.4260	0.4272	0.2026	0.2056	0.2034
	BS	0.3846	0.3317	0.3322	0.1128	0.1085	0.1096	0.4241	0.3281	0.3329	0.1100	0.1121	0.1040
	VC	0.5324	0.5001	0.5000	0.5003	0.5001	0.5000	0.5404	0.4999	0.5001	0.4999	0.5001	0.5000
	LA	–	–	–	–	–	–	–	–	–	–	–	–

Table A.15
Detailed optimal prices assuming $\rho = 3/4$; $\phi = 1$.

Origin	Destination	1	2	3	4	5	6	7	8	9	10	11	12
NB	NB	–	–	–	–	–	–	–	–	–	–	–	–
	SH	0.7017	0.6981	0.6993	0.9666	1.0000	1.0000	0.7053	0.6594	0.6610	0.9328	1.0000	1.0000
	BS	0.6786	0.6252	0.6250	0.9666	1.0000	1.0000	0.6569	0.6375	0.6378	0.9683	1.0000	1.0000
	VC	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	LA	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
SH	NB	0.7106	0.7007	0.7009	0.9666	1.0000	1.0000	0.7084	0.6717	0.6736	0.9399	1.0000	1.0000
	SH	–	–	–	–	–	–	–	–	–	–	–	–
	BS	0.6823	0.6623	0.6610	0.9666	1.0000	1.0000	0.6550	0.6443	0.6453	0.9372	1.0000	1.0000
	VC	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	LA	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
BS	NB	0.7193	0.7197	0.7193	0.9667	1.0000	1.0000	0.7478	0.6956	0.6964	0.9585	1.0000	1.0000
	SH	0.7236	0.7206	0.7195	0.9664	1.0000	1.0000	0.7471	0.6903	0.6896	0.9500	1.0000	1.0000
	BS	–	–	–	–	–	–	–	–	–	–	–	–
	VC	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	LA	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
VC	NB	0.4650	0.3200	0.3206	0.0333	0.0000	0.0000	0.4990	0.3656	0.3634	0.0370	0.0000	0.0000
	SH	0.4658	0.3191	0.3190	0.0333	0.0000	0.0000	0.4815	0.3594	0.3566	0.0361	0.0000	0.0000
	BS	0.4571	0.3000	0.2999	0.0333	0.0000	0.0000	0.4621	0.3363	0.3332	0.0356	0.0000	0.0000
	VC	–	–	–	–	–	–	–	–	–	–	–	–
	LA	0.6661	0.7008	0.7005	0.9667	1.0000	1.0000	0.6741	0.6693	0.6660	0.9395	1.0000	1.0000
LA	NB	0.4722	0.3191	0.3189	0.0333	0.0000	0.0000	0.4944	0.3631	0.3633	0.0366	0.0000	0.0000
	SH	0.4643	0.3193	0.3190	0.0333	0.0000	0.0000	0.4793	0.3579	0.3566	0.0361	0.0000	0.0000
	BS	0.4656	0.3000	0.2999	0.0333	0.0000	0.0000	0.4588	0.3332	0.3332	0.0352	0.0000	0.0000
	VC	0.6693	0.7002	0.7004	0.9668	1.0000	1.0000	0.6674	0.6662	0.6668	0.9343	1.0000	1.0000
	LA	–	–	–	–	–	–	–	–	–	–	–	–

Table A.16
Detailed optimal prices assuming $\rho = 1/2$; $\phi = 1$.

Origin	Destination	1	2	3	4	5	6	7	8	9	10	11	12
NB	NB	–	–	–	–	–	–	–	–	–	–	–	–
	SH	1.0000	1.0000	0.9963	1.0000	1.0000	0.9958	1.0000	1.0000	0.9989	1.0000	0.9998	0.9957
	BS	1.0000	1.0000	0.9975	0.9876	0.9877	0.9951	0.9998	1.0000	0.9957	0.9910	0.9901	0.9964
	VC	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	LA	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
SH	NB	1.0000	1.0000	0.9966	1.0000	1.0000	0.9946	1.0000	1.0000	0.9918	1.0000	1.0000	0.9987
	SH	–	–	–	–	–	–	–	–	–	–	–	–
	BS	1.0000	1.0000	0.9945	0.9871	0.9898	0.9951	0.9994	0.9996	0.9951	0.9936	0.9912	0.9950
	VC	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	LA	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
BS	NB	1.0000	1.0000	0.9979	1.0000	1.0000	0.9972	1.0000	1.0000	0.9963	1.0000	1.0000	0.9989
	SH	1.0000	1.0000	0.9968	1.0000	1.0000	0.9976	1.0000	0.9995	0.9970	1.0000	0.9997	0.9992
	BS	–	–	–	–	–	–	–	–	–	–	–	–
	VC	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	LA	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
VC	NB	1.0980	1.0999	1.0013	1.0981	1.0974	0.9946	1.0974	1.0999	0.9972	1.0971	1.0984	1.0017
	SH	1.1034	1.1009	0.9998	1.0977	1.1013	1.0025	1.0892	1.0880	0.9991	1.0828	1.0850	0.9988
	BS	1.0994	1.0998	0.9974	0.9974	1.0007	0.9975	1.0822	1.0850	0.9956	1.0013	1.0014	0.9998
	VC	–	–	–	–	–	–	–	–	–	–	–	–
	LA	0.9621	0.9780	0.9770	0.9910	0.9761	0.9812	0.9800	0.9829	0.9925	0.9830	0.9909	0.9880
LA	NB	1.1035	1.1015	1.0009	1.0984	1.1004	1.0038	1.0941	1.0982	1.0001	1.0917	1.0923	0.9999
	SH	1.1003	1.0998	0.9968	1.1009	1.1013	1.0017	1.0872	1.0878	0.9994	1.0882	1.0890	1.0006
	BS	1.0992	1.0999	0.9991	1.0007	0.9979	0.9960	1.0826	1.0878	1.0009	0.9962	1.0009	1.0005
	VC	0.9955	0.9915	0.9872	0.9871	0.9949	0.9853	0.9841	0.9897	0.9906	0.9970	0.9869	0.9915
	LA	–	–	–	–	–	–	–	–	–	–	–	–

Table A.17
Detailed optimal prices assuming $\rho = 1/4$; $\phi = 1$.

Origin	Destination	1	2	3	4	5	6	7	8	9	10	11	12
NB	NB	–	–	–	–	–	–	–	–	–	–	–	–
	SH	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	BS	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	VC	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	LA	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
SH	NB	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	SH	–	–	–	–	–	–	–	–	–	–	–	–
	BS	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	VC	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	LA	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
BS	NB	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	SH	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	BS	–	–	–	–	–	–	–	–	–	–	–	–
	VC	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	LA	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
VC	NB	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	SH	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	BS	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	VC	–	–	–	–	–	–	–	–	–	–	–	–
	LA	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
LA	NB	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	SH	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	BS	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000	2.0000
	VC	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	LA	–	–	–	–	–	–	–	–	–	–	–	–

Table A.18
Detailed optimal prices assuming $\phi = 3/4$; $\rho = 1$.

Origin	Destination	1	2	3	4	5	6	7	8	9	10	11	12
NB	NB	–	–	–	–	–	–	–	–	–	–	–	–
	SH	0.5134	0.4986	0.4983	0.4996	0.5004	0.4997	0.5143	0.4979	0.4935	0.4994	0.4996	0.5010
	BS	0.4206	0.4051	0.4043	0.4993	0.4998	0.5000	0.4133	0.3985	0.4032	0.4988	0.4990	0.4992
	VC	1.5946	1.5739	1.5729	1.7503	1.7501	1.7511	1.5927	1.5735	1.5735	1.7495	1.7494	1.7493
	LA	1.5904	1.5733	1.5733	1.7499	1.7506	1.7501	1.5790	1.5708	1.5701	1.7496	1.7489	1.7491
SH	NB	0.5121	0.5029	0.5012	0.4995	0.4997	0.4995	0.5144	0.5035	0.5048	0.5001	0.5003	0.4995
	SH	–	–	–	–	–	–	–	–	–	–	–	–
	BS	0.4110	0.4055	0.4054	0.4994	0.4997	0.4996	0.4110	0.4040	0.4055	0.4998	0.4994	0.4981
	VC	1.5854	1.5740	1.5756	1.7498	1.7506	1.7497	1.5918	1.5758	1.5737	1.7494	1.7494	1.7492
	LA	1.5792	1.5752	1.5746	1.7498	1.7504	1.7495	1.5795	1.5748	1.5749	1.7497	1.7497	1.7496
BS	NB	0.5985	0.5955	0.5947	0.4998	0.5000	0.5007	0.6187	0.5963	0.5970	0.5014	0.5015	0.5008
	SH	0.5892	0.5938	0.5937	0.4998	0.5003	0.5004	0.6102	0.5937	0.5928	0.5007	0.5008	0.5013
	BS	–	–	–	–	–	–	–	–	–	–	–	–
	VC	1.6758	1.6666	1.6672	1.7590	1.7502	1.7535	1.6841	1.6692	1.6689	1.7575	1.7555	1.7509
	LA	1.6675	1.6685	1.6678	1.7503	1.7559	1.7503	1.6770	1.6684	1.6706	1.7512	1.7510	1.7526
VC	NB	0.4624	0.4271	0.4266	0.2513	0.2498	0.2505	0.4609	0.4280	0.4277	0.2504	0.2520	0.2521
	SH	0.4632	0.4262	0.4260	0.2510	0.2507	0.2503	0.4591	0.4260	0.4240	0.2509	0.2502	0.2514
	BS	0.3724	0.3327	0.3309	0.2482	0.2498	0.2510	0.3819	0.3302	0.3322	0.2498	0.2497	0.2493
	VC	–	–	–	–	–	–	–	–	–	–	–	–
	LA	0.5154	0.5003	0.5000	0.4996	0.5000	0.4997	0.5396	0.4983	0.4991	0.5001	0.5001	0.5001
LA	NB	0.4667	0.4279	0.4266	0.2517	0.2499	0.2530	0.4738	0.4307	0.4285	0.2494	0.2516	0.2529
	SH	0.4564	0.4250	0.4266	0.2518	0.2505	0.2521	0.4627	0.4260	0.4246	0.2493	0.2505	0.2520
	BS	0.3653	0.3325	0.3315	0.2504	0.2504	0.2515	0.3824	0.3313	0.3302	0.2493	0.2494	0.2502
	VC	0.5263	0.5000	0.4998	0.5002	0.5000	0.5008	0.5329	0.5034	0.5001	0.4999	0.4998	0.4999
	LA	–	–	–	–	–	–	–	–	–	–	–	–

Table A.19
Detailed optimal prices assuming $\phi = 1/2$; $\rho = 1$.

Origin	Destination	1	2	3	4	5	6	7	8	9	10	11	12
NB	NB	–	–	–	–	–	–	–	–	–	–	–	–
	SH	0.5213	0.4995	0.5002	0.5338	0.4985	0.4994	0.5398	0.4997	0.4987	0.5272	0.5005	0.5008
	BS	0.5058	0.4983	0.5003	0.5362	0.4969	0.5002	0.4979	0.5000	0.5004	0.5304	0.4955	0.5007
	VC	1.5522	1.5003	1.4986	1.5760	1.5002	1.5002	1.5570	1.5025	1.5004	1.5867	1.4999	1.5006
	LA	1.5498	1.5009	1.4998	1.5785	1.5000	1.5008	1.5647	1.5019	1.5007	1.5871	1.5013	1.4996
SH	NB	0.5356	0.5009	0.5004	0.5383	0.5009	0.5009	0.5494	0.5006	0.5005	0.5434	0.5002	0.5005
	SH	–	–	–	–	–	–	–	–	–	–	–	–
	BS	0.5123	0.4994	0.5004	0.5354	0.4951	0.5007	0.4988	0.5007	0.4995	0.5445	0.4954	0.5003
	VC	1.5536	1.4998	1.5012	1.5746	1.5014	1.5004	1.5582	1.4999	1.4997	1.5985	1.5004	1.4996
	LA	1.5534	1.5012	1.5004	1.5760	1.5006	1.4998	1.5603	1.5014	1.5012	1.5964	1.5002	1.5004
BS	NB	0.5629	0.4998	0.4997	0.5391	0.5164	0.5000	0.5793	0.5000	0.5004	0.5384	0.5153	0.4998
	SH	0.5554	0.4997	0.5003	0.5417	0.5153	0.4997	0.5751	0.5003	0.4999	0.5391	0.5166	0.5000
	BS	–	–	–	–	–	–	–	–	–	–	–	–
	VC	1.5848	1.4999	1.5005	1.5805	1.5169	1.4993	1.5905	1.4997	1.5005	1.5954	1.5169	1.5001
	LA	1.5776	1.4999	1.5003	1.5878	1.5178	1.5008	1.5898	1.4999	1.5004	1.5930	1.5163	1.5010
VC	NB	0.5424	0.4999	0.5022	0.5144	0.4996	0.4986	0.5673	0.5014	0.4987	0.5148	0.5006	0.4970
	SH	0.5360	0.5012	0.5005	0.5139	0.4996	0.4994	0.5556	0.4996	0.5006	0.5137	0.5017	0.5022
	BS	0.5100	0.4997	0.5000	0.5145	0.5017	0.4984	0.5154	0.5016	0.4987	0.5146	0.5005	0.4980
	VC	–	–	–	–	–	–	–	–	–	–	–	–
	LA	0.5181	0.4999	0.4998	0.5183	0.4999	0.4999	0.5246	0.4999	0.4995	0.5283	0.4999	0.5000
LA	NB	0.5413	0.5018	0.4992	0.5129	0.5051	0.5009	0.5646	0.5005	0.5008	0.5146	0.5013	0.4998
	SH	0.5327	0.5002	0.4993	0.5136	0.5008	0.4984	0.5566	0.5009	0.5001	0.5141	0.5024	0.5025
	BS	0.5115	0.4975	0.5018	0.5141	0.4987	0.4974	0.5177	0.4981	0.4969	0.5121	0.5035	0.4983
	VC	0.5182	0.5002	0.4999	0.5174	0.4996	0.4999	0.5258	0.5002	0.5003	0.5252	0.5001	0.5002
	LA	–	–	–	–	–	–	–	–	–	–	–	–

Table A.20
Detailed optimal prices assuming $\phi = 1/4$; $\rho = 1$.

Origin	Destination	1	2	3	4	5	6	7	8	9	10	11	12
NB	NB	–	–	–	–	–	–	–	–	–	–	–	–
	SH	0.5955	0.5137	0.4994	0.6050	0.5351	0.4999	0.5935	0.5134	0.4981	0.5868	0.5277	0.4985
	BS	0.5952	0.5108	0.4990	0.6010	0.5318	0.4953	0.5835	0.5149	0.4999	0.5941	0.5300	0.4974
	VC	1.5268	1.2706	1.2501	1.5553	1.3243	1.2498	1.5201	1.2838	1.2499	1.5481	1.3458	1.2502
	LA	1.5310	1.2712	1.2506	1.5584	1.3242	1.2497	1.5279	1.2864	1.2505	1.5533	1.3398	1.2500
SH	NB	0.5918	0.5172	0.4997	0.6019	0.5316	0.4990	0.5874	0.5105	0.4991	0.5963	0.5335	0.5009
	SH	–	–	–	–	–	–	–	–	–	–	–	–
	BS	0.5898	0.5149	0.4998	0.5986	0.5247	0.4972	0.5803	0.5117	0.4991	0.5947	0.5342	0.5000
	VC	1.5212	1.2726	1.2494	1.5484	1.3215	1.2492	1.5178	1.2821	1.2490	1.5509	1.3459	1.2522
	LA	1.5258	1.2762	1.2504	1.5526	1.3215	1.2508	1.5267	1.2862	1.2502	1.5503	1.3426	1.2520
BS	NB	0.5993	0.5235	0.5006	0.6121	0.5339	0.5123	0.5869	0.5180	0.5007	0.6021	0.5354	0.5088
	SH	0.5972	0.5221	0.4997	0.6108	0.5313	0.5120	0.5951	0.5181	0.5000	0.5935	0.5335	0.5095
	BS	–	–	–	–	–	–	–	–	–	–	–	–
	VC	1.5185	1.2778	1.2490	1.5393	1.3256	1.2623	1.5159	1.2852	1.2486	1.5514	1.3361	1.2586
	LA	1.5279	1.2810	1.2484	1.5541	1.3255	1.2617	1.5204	1.2865	1.2495	1.5482	1.3438	1.2586
VC	NB	0.8010	0.7498	0.7497	0.8021	0.7565	0.7492	0.8018	0.7539	0.7503	0.7994	0.7644	0.7505
	SH	0.8015	0.7503	0.7506	0.8023	0.7581	0.7522	0.8029	0.7536	0.7515	0.8044	0.7635	0.7525
	BS	0.8010	0.7523	0.7511	0.8031	0.7576	0.7506	0.8015	0.7537	0.7525	0.8034	0.7646	0.7495
	VC	–	–	–	–	–	–	–	–	–	–	–	–
	LA	0.5780	0.5014	0.4998	0.6007	0.5158	0.4998	0.5838	0.5058	0.4981	0.5937	0.5273	0.5003
LA	NB	0.8018	0.7505	0.7514	0.8036	0.7573	0.7492	0.8024	0.7545	0.7507	0.8067	0.7645	0.7485
	SH	0.8013	0.7506	0.7500	0.8031	0.7583	0.7517	0.8041	0.7532	0.7495	0.8028	0.7636	0.7482
	BS	0.8015	0.7510	0.7510	0.8042	0.7580	0.7516	0.8011	0.7519	0.7521	0.8035	0.7630	0.7481
	VC	0.5733	0.5014	0.5001	0.6011	0.5155	0.4995	0.5836	0.5047	0.4997	0.5906	0.5247	0.5000
	LA	–	–	–	–	–	–	–	–	–	–	–	–

Algorithm 1 The Opt heuristic

Initialization: y_{ij}^t and z_{ij}^t for $t \leq 0$ and IL_j^0
for $t \in \mathcal{T}$ **do**
  for $j \in J$ **do**
    $IL_j^t \leftarrow IL_j^{t-1} + \sum_{i \in J} \left(y_{ij}^{t-r_i-r_j-R_{ij}} + z_{ij}^{t-R_{ij}} \right)$
    for $i \in J \setminus \{j\}$ **do**
      if $t = 1$ **then**
        $y_{ij}^t \leftarrow \min\{Y_{ij}, d_{ij}^t, IL_j^t\}$
      else
        $y_{ij}^t \leftarrow \min\{Y_{ij} \times t - \sum_{\tau=1}^{t-1} y_{ij}^t, d_{ij}^t, IL_j^t\}$
      end
    end
  end
  for $j \in J$ **do**
    if $\sum_{k \in J} y_{jk}^t > IL_j^t$ **then**
      for $k \in J$ **do**
        $y_{jk}^t \leftarrow y_{jk}^t \times IL_j^t / \sum_{k \in J} y_{jk}^t$
      end
    end
    $IL_j^t \leftarrow IL_j^t - \sum_{k \in J} y_{jk}^t$
    for $i \in J \setminus \{j\}$ **do**
      $z_{ij}^t \leftarrow \min\{Z_{ij}, IL_j^t\}$
    end
  end
  for $j \in J$ **do**
    if $\sum_{k \in J} z_{jk}^t > IL_j^t$ **then**
      for $k \in J$ **do**
        $z_{jk}^t \leftarrow z_{jk}^t \times IL_j^t / \sum_{k \in J} z_{jk}^t$
      end
    end
    $IL_j^t \leftarrow IL_j^t - \sum_{k \in J} z_{jk}^t$
  end
end

Algorithm 2 The (s, S) heuristic

Initialization: y_{ij}^t and z_{ij}^t for $t \le 0$ and IL_j^0
for $t \in \mathcal{T}$ **do**
  for $j \in J$ **do**
    $IL_j^t \leftarrow IL_j^{t-1} + \sum_{i \in J} \left(y_{ij}^{t-r_i-r_j-R_{ij}} + z_{ij}^{t-R_{ij}} \right)$
    for $i \in J \setminus \{j\}$ **do**
      if $t = 1$ **then**
        $y_{ij}^t \leftarrow \min\{Y_{ij}, d_{ij}^t, IL_j^t\}$
      else
        $y_{ij}^t \leftarrow \min\{Y_{ij} \times t - \sum_{\tau=1}^{t-1} y_{ij}^t, d_{ij}^t, IL_j^t\}$
      end
    end
  end
  for $j \in J$ **do**
    if $\sum_{k \in J} y_{jk}^t > IL_j^t$ **then**
      for $k \in J$ **do**
        $y_{jk}^t \leftarrow y_{jk}^t \times IL_j^t / \sum_{k \in J} y_{jk}^t$
      end
    end
    $IL_j^t \leftarrow IL_j^t - \sum_{k \in J} y_{jk}^t$
    $IP_j^t \leftarrow IL_j^t + \sum_{i \in J} \left(\sum_{\tau=0}^{r_i+r_j+R_{ij}-1} y_{ij}^{t-\tau} + \sum_{\tau=0}^{R_{ij}-1} z_{ij}^{t-\tau} \right)$
  end
  for $j \in \{BS, SH, NB\}$ **do**
    if $IP_j^t < s_j$ **then**
      if $IL_{LA}^t \ge S_j - IP_j^t$ **then**
        $z_{LA,j}^t \leftarrow S_j - IP_j^t$
        $IL_{LA}^t \leftarrow IL_{LA}^t - z_{LA,j}^t$
      else
        $z_{LA,j}^t \leftarrow IL_{LA}^t$
        $IL_{LA}^t \leftarrow 0$
        if $IL_{VC}^t \ge S_j - IP_j^t - z_{LA,j}^t$ **then**
          $z_{VC,j}^t \leftarrow S_j - IP_j^t - z_{LA,j}^t$
          $IL_{VC}^t \leftarrow IL_{VC}^t - z_{VC,j}^t$
        else
          $z_{VC,j}^t \leftarrow IL_{VC}^t$
          $IL_{VC}^t \leftarrow 0$
        end
      end
    end
  end
end

Data availability

The authors do not have permission to share data.

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