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Optimal reefer slot conversion for container freight transportation

ABSTRACT

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

KEYWORDS

Ship slots; fleet deployment planning; sequence of ships; strings; uncertainty.

1. INTRODUCTION

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

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

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

In maritime studies, a great deal of research effort has been devoted to container ship fleet deployment problems. This effort is mainly focused on determining the ship type for a given shipping service route (Gelareh and Meng, 2010; Meng et al., 2012; Song and Dong, 2013; Ng, 2014). In such studies, it is assumed that the container ships are categorized into different types. Moreover, all the ships belonging to a particular category are homogenous, i.e. they have the same capacity. In addition, the ship fleet deployed for a given route only consists of one type of ship. However, the ships in a fleet may not all have the same capacity (Lin and Liu, 2011; Du et al., 2017). For instance, consider the example listed in Table 1 (relating to the China–USA Yangtze Service route operated by France's CMA CGM Group, the third largest shipping liner in the world). The table lists the six ships deployed in the fleet which consists of four different ship types, each with a different capacity (CMA CGM, 2016).

Table 1. The capacities of the ships in the fleet used for the Yangtze Service route.

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

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

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

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

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

2. ESTIMATING THE PROFIT FOR A GIVEN STRING

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

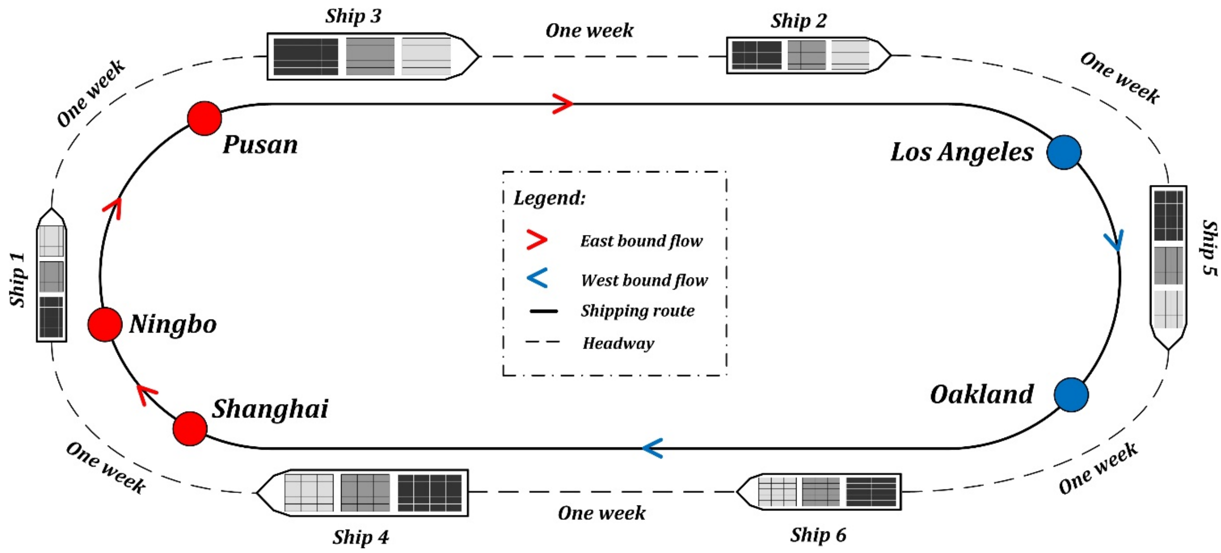

Fig. 1. A sequence of container ships in a string.

2.1. Decision variables and parameters

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

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

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

Decision variables:

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

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

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

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

Input parameters:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

2.2. Container delay and rejection rules

Suppose that the V ships are in the sequence given by the string $1 \to 2 \cdots v \cdots \to V$. The dry (reefer) container capacity of the ship v is E_v^d (E_v^r). In a particular week, when ship v arrives at its destination port, the number of dry (reefer) containers that are at the port because they were delayed from the previous week is D_{v-1}^d (D_{v-1}^r). Moreover, the new dry (reefer) container demand in the current week is ω^d (ω^r), which is the realization of $\tilde{\omega}^d$ ($\tilde{\omega}^r$). Based on the values of D_{v-1}^d and D_{v-1}^r (which were determined one week ago) and the values of ω^d and ω^r (which are just observed), the shipping line needs to determine the number of dry (reefer) containers to postpone. Denote this quantity by D_v^d (D_v^r) and the number they need to reject by R_v^d (R_v^r). We analyze the decisions as follows:

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

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

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

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

2.3. Calculation of the weekly profit

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

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

$$g^d\left(q^d - \overline{R}^d\right) + g^r\left(q^r - \overline{R}^r\right). \tag{1}$$

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

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

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

Consequently, the expected profit per week is

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

Note that the first term in the right-hand side of Eq. (3) is a constant and is independent of the sequence of the ships in the string.

3. OPTIMIZING THE SEQUENCE OF SHIPS IN A STRING

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

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

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

Given the capacities of the ships in the fleet and demand probability mass function, we design a simulation-based approach for the optimization process. Given V ships, any two of which have different capacity, there will be $S=(V-1)!$ different possible ship sequences (as the sequence forms a loop, it does not matter which ship is chosen to be the first one). Let the sequence be denoted by s $(=1,2,\cdots,S)$ and the corresponding weekly profit be $P(s)$, as determined by Eq. (3). (With the obvious notation that $\overline{D}^d(s)$, $\overline{D}^r(s)$, $\overline{R}^d(s)$, and $\overline{R}^r(s)$ are used in place of $\overline{D}^d$, $\overline{D}^r$, $\overline{R}^d$, and $\overline{R}^r$, respectively.) Mathematically, therefore, the weekly profit of sequence s, $P(s)$, is given by:

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

We use Monte-Carlo simulations to calculate $\overline{D}^d(s)$, $\overline{D}^r(s)$, $\overline{R}^d(s)$, and $\overline{R}^r(s)$ in Eq. (4). The essence of the approach is as follows. (i) Define the number of weeks T we wish to simulate (e.g. $T=100,000$ weeks). (ii) Randomly generate the demand for each week using the probability mass function. The demand for dry (reefer) containers in week t is denoted by ω_t^d (ω_t^r). (iii) Simulate the decision-making process from weeks 1 to T. For each week t, record the number of dry (reefer) containers postponed $D_t^d(s)$ ($D_t^r(s)$) and rejected $R_t^d(s)$ ($R_t^r(s)$). (iv) The quantities $\overline{D}^d(s)$, $\overline{D}^r(s)$, $\overline{R}^d(s)$, and $\overline{R}^r(s)$ can be subsequently estimated using

$$\overline{D}^d(s) = \frac{1}{T}\sum_{t=1}^{T} D_t^d(s), \overline{D}^r(s) = \frac{1}{T}\sum_{t=1}^{T} D_t^r(s), \overline{R}^d(s) = \frac{1}{T}\sum_{t=1}^{T} R_t^d(s), \overline{R}^r(s) = \frac{1}{T}\sum_{t=1}^{T} R_t^r(s)\,. \tag{5}$$

By substituting the results from Eq. (5) into Eq. (4), we can calculate $P(s)$, and therefore choose the sequence with the maximum profit:

$$s^* = \arg\max_{s=1,2\cdots S} P(s)\,. \tag{6}$$

3.1. A two-stage simulation approach

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

Two-stage simulation algorithm

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

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

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

$$\bar{P}_{UV}(s)^{(1)} = \frac{1}{T_1}\sum_{l=1}^{T_1} P_{UV,l}(s), \tag{7}$$

where the superscript '(1)' means the first stage, and sample variance

$$\mathrm{Var}\left(\tilde{P}_{UV}(s)\right) = \frac{1}{T_1 - 1}\sum_{l=1}^{T_1}\left[P_{UV,l}(s) - \bar{P}_{UV}(s)^{(1)}\right]^2. \tag{8}$$

Step 3: Define a value θ by

$$\theta := t_{(1-\alpha_0)^{1/(S-1)}, T_1 - 1} \tag{9}$$

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

$$W_{s,s'} := \theta \cdot \left[\frac{1}{T_1}\mathrm{Var}\left(\tilde{P}_{UV}(s)\right) + \frac{1}{T_1}\mathrm{Var}\left(\tilde{P}_{UV}(s')\right)\right]^{\frac{1}{2}}, \quad s = 1,2,\cdots,S, \quad s' = 1,2,\cdots,S, \quad s \neq s'. \tag{10}$$

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

$$\bar{P}_{UV}(s')^{(1)} \leq \bar{P}_{UV}(s)^{(1)} - \max\left\{0, W_{s,s'} - \delta\right\}. \tag{11}$$

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

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

$$T_{2s} = \max\left\{T_1, \left\lceil \left(\frac{h}{\delta}\right)^2 \mathrm{Var}\left(\tilde{P}_{UV}(s)\right)\right\rceil\right\} \tag{12}$$

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

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

$$\bar{P}_{UV}(s)^{(2)} = \frac{1}{T_{2s}} \sum_{l=1}^{T_{2s}} P_{UV,l}(s), \quad s \in I \tag{13}$$

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

Our exploratory experiments show that the above algorithm is time-consuming and not able to find the optimal sequence using a 'reasonable' amount of computation time. (All experiments in this study were conducted using MATLAB R2016b installed on a standard PC built around an Intel Core i5 processor running at 2.83GHz and with 8GB of RAM.) The problem can be attributed to the fact that T_{2s} (in Step 4) is extremely large, ranging from 1×10^8 to 3×10^8 using the baseline settings given above. Thus, in the second stage, simulating the process for each remaining sequence for other $(T_{2s} - T_1)UV$ weeks takes a considerable amount of computation time. Essentially, based on Eqs. (8) and (12), the order of magnitude of T_{2s} is determined by $\mathrm{Var}\left(\tilde{P}_{UV}(s)\right)$, whose order of magnitude is, in turn, determined by $P_{UV,l}(s)$ (i.e. the weekly profit). Using some real-world input parameters (*vide infra*), the weekly profits $P_{UV,l}(s)$ are of the order of a few million dollars, and this is the primary cause of the problem.

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

$$P_{UV,l}(s) \mapsto \frac{1}{\beta} P_{UV,l}(s) . \tag{14}$$

For instance, if $P_{UV,l}(s)$ is 5,343,000 US\$ and $\beta = 1000$, the weekly profit becomes 5,343 where the units used are 1,000 US\$. Such a step allows us to deal with the above problem and accelerate the algorithm. Table 2 shows the computation times required for different values of β.

Table 2. Comparison of computation times for different values of the parameter β.

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

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

As can be seen from Table 2, increasing the value of β accelerates the algorithm. However, we cannot freely increase β to simply accelerate the algorithm, as there are repercussions. When $\beta = 1000$, we can only claim that the selected sequence is the optimal one to an accuracy of one unit, i.e. 1,000 US$. However, this will not necessarily be the optimal sequence to the desirable accuracy of 1 US$. As shown in the table, different β values lead to different sequences being selected. Therefore, we need to make a comprise between speed and accuracy. In this study, we select $\beta = 10$. This should be sufficiently close to the desirable accuracy (so we can be confident we have selected the correct sequence) and allow us to obtain the solution in a reasonable amount of time. In the following sections, we refer to the algorithm wherein $\beta = 10$ is used for scale reduction (i.e. via Eq. (14)) as the 'revised two-stage simulation algorithm'.

3.2. Case studies

In this section, we use the revised two-stage simulation algorithm to optimize the sequence of a string of some particular cases of interest. First of all, according to EPRI (2010) and Ting and Tzing (2004), we have to fine-tune the input parameters required. To this end, the cost coefficients which we shall use were collated and are presented in Table 3. Here, we take $c^{d,3}\left(c^{r,3}\right)$, the storage cost incurred to keep a dry (reefer) container in the yard for one week, as an example of how we fine-tuned the costs. According to EPRI (2010), the storage space in a yard is charged at a rate of US$0.21 per square foot per day. Thus, a 20-foot standard container corresponds to a weekly storage cost of US$30.

Table 3. The relevant input costs used in the case studies.

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

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

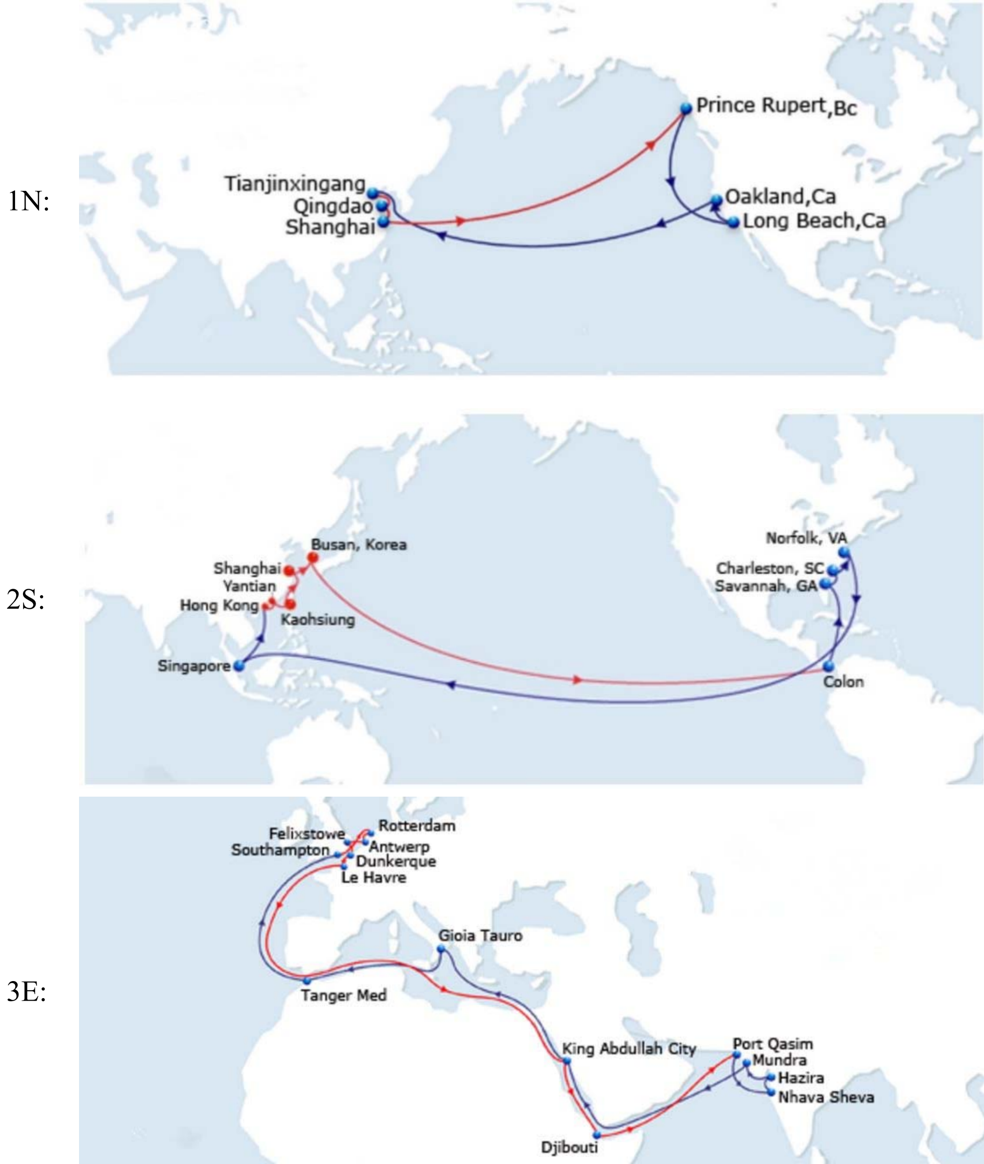

Fig. 2. The shipping routes involved in the three case studies.

Some key information about the shipping routes and ships deployed are given in Table 4 — further details can be found by referring to CMA CGM (2017). During string optimization, the number of ships deployed is another key element that can affect the scale of the problem. This is because the number of ships determines the number of possible sequences to consider. Therefore, we chose three shipping routes that deploy different numbers of ships (determined by the rotation time, considering the weekly service frequency). We assume that the dry- and reefer-container demands follow a uniform distribution with their ranges as given in Table 4. The last column in this table shows the variance of the total container demand for both dry and reefer containers.

Table 4. Information on the shipping routes and ships deployed.

Route	Name	Ship number	Rotation time (days)	Container demand (TEUs)		Total demand variance
				Dry	Reefer	
1N	Northwest Express	6	42	[7800, 9220]	[0, 800]	4.11×10^5
2S	South Atlantic Express	7	49	[4500, 6100]	[50, 900]	5.00×10^5
3E	Europe Pakistan India Consortium 1	8	56	[7250, 9100]	[100, 1300]	7.75×10^5

Table 5. Ships deployed in the three shipping routes.

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

To facilitate discussion of the experiment results, we list in Table 5 some important information about the ships deployed in each of the three shipping routes. As can be seen, in each shipping route, the deployed ships have various capacities which help address the importance of string optimization.

Based on the information presented on the shipping routes, we implemented the revised two-stage simulation algorithm to find the optimal sequence to employ. The results are shown in Table 6. The table shows that the string optimization process changes all of the original sequences used in the shipping routes. The last column shows the difference or gap in profit between the original and optimized sequences (which are all positive). As tactical-level decisions, these increases in profit can be claimed to be significant considering that the string optimization procedure is inexpensive, i.e. the approach is cost effective. The results prove the effectiveness of using the proposed algorithm for string optimization. One remarkable feature of the table is that the string optimization procedure produced a much larger profit increase for shipping route 3E than for 1N and 2S. This can be attributed to the fact that 3E involves more ships and a greater demand variance than the other two shipping routes. Therefore, it is apparent that string optimization becomes more significant when the size of the deployed fleet is large and there is a greater variance in demand.

Table 6. Results of the string optimization process.

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

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

4. OPTIMIZING REEFER SLOT CONVERSION

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

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

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

Slot conversion algorithm

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

4.1. Slot conversion case study

String optimization is the first step carried out in our research problem. We now want to use the slot conversion algorithm (which embeds the revised two-stage optimization algorithm to optimize strings) to conduct a further investigation of the three case studies given in Section 3.2 (i.e. using the shipping routes and information given in Tables 4 and 5).

Using the same input parameters, we ran the slot conversion algorithm to obtain the number of reefer slots to convert. The results are shown in Table 7. As can be seen, all the ships involved have some dry slots that are converted to reefer slots, apart from one (namely, the CMA CGM URUGUAY in shipping route 3E which already has the maximum number of reefer slots permitted in the conversion algorithm). This verifies that the benefits gained by the greater flexibility of reefer slots outweigh the conversion costs incurred to change the existing slot configurations of the ships.

Table 7. Reefer slot conversion results for the three shipping routes.

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

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

The last column in Table 7 shows the 'optimal increment' that the optimal change in a number of reefer slots represents. This quantity corresponds to the ratio of the optimal number of converted slots to the ship's capacity (in TEU) expressed as a percentage. It is important to note that the mean optimal increments for the shipping routes, as a whole, increase from 1N to 2S to 3E. This reflects the higher significance of slot conversion for those shipping routes with larger shipping fleets and higher demand variances (as is the case for the shipping route 3E).

Overall, we have to emphasize the importance of having greater numbers of reefer slots. This is not just based on the Hamburg Süd and Hanjin cases mentioned in the Introduction in the context of competitiveness, but also because of the experimental results shown in Table 7.

Table 8. Sequence re-optimization and slot conversion.

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

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

The slot conversion algorithm is an iterative algorithm. When some dry slots have been converted to reefer slots, the previous optimal sequence may no longer be optimal as the number of reefer slots has changed. Thus, the slot conversion algorithm will not terminate until both the slot conversion and sequence rearrangement processes can no longer be further optimized. For the current examples, Table 8 illustrates the resulting sequences produced as a result of re-optimization during slot conversion. From the table, we can see that the optimal sequence after slot conversion is different to that obtained by just implementing string optimization. The 'gap' column in Table 8 corresponds to the loss of profit suffered if we insist on maintaining the previous optimal sequence. The numbers suggest that string optimization and slot conversion should always be carried out at the same time as an integrated optimization approach, exactly like our slot conversion algorithm does. Combining the gaps or differences given in Tables 8 and 6, we can say that the optimal sequence with slot conversion significantly outperforms the original sequence with the current slot configuration (as the weekly profit increases substantially).

4.2. Shipping routes with large fleets

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

The two routes selected are the French Asia Line 1 and Columbus JAX (both belonging to CMA CGM) which involve 12 and 17 ships, respectively. CMA CGM (2017) gives detailed information on the two shipping routes but some of the basic information of interest is shown in Table 5. Compared with the previously considered routes (Table 4), these routes have many more ships involved and their variance in demand is much larger.

Table 9. Basic information on the two shipping routes.

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

We first calculated the weekly profits of the original sequences used in the shipping routes (Table 10). Then, we used the slot conversion algorithm (with string optimization) to optimize the sequence of ships and convert some dry slots to reefer slots. Note that the slot conversion limit was increased to 2,500 in these two case studies as the deployed ships have larger capacities. Table 10 shows the effectiveness of the proposed approach. Compared to the original sequences, the weekly profits of the optimized fleets were improved by 9.06% (French Asia Line 1) and 7.90% (Columbus JAX). These profit increases are very significant considering the cost-efficiency of the methods used. Note also that the two routes have larger dry-to-reefer conversion rates (8.63% and 7.12%) compared to those found in the three previous cases. This result verifies the previous finding that slot conversion is more critical for shipping routes with large fleets of ships and high demand variances.

Table 10. Results obtained using string optimization and slot conversion.

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

5. CONCLUSIONS

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

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

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

(ii) The use of power packs as a method of supplying electricity could be incorporated into the analysis. (A self-contained power pack in a standard 20- or 40-foot container could act as a power source for multiple reefer boxes.) They are currently used to serve as a standby or prime power source for intermodal applications including rail, port, ship, and barge.

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