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ABSTRACT

The liner shipping schedules determine the container transportation time and the arrival time of ships, which has a significant influence on the shipper selection behavior and the transportation demand. This paper addresses the container liner shipping schedule optimization with shipper selection behavior considered. Our problem is formulated as a mixed-integer nonlinear programming model, where the shipper selection behavior is evaluated by a nested logit model. A particle swarm optimization (PSO) framework embedded with CPLEX solver is designed, by combining the constraint relaxations and the linearization techniques with the heuristic rules. The numerical experiments are conducted based on the Persian Gulf route of COSCO SHIPPING LINES. The results show that: the total freight demand is increased by 23% and the weekly operation revenue is increased by 31% after considering shipper selection. Besides, we find that the planned ship speed should be increased for time-preference shippers with electronic or refrigerated products, while it should be decreased for price-preference shippers with general or bulk cargoes. These conclusions can provide decision support for the operation practice of liner shipping schedule design.

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Container transportation; liner shipping schedule optimization; arrival time window; shipper selection behavior; PSO algorithm

1. Introduction

According to the latest statistical report published by Shanghai Shipping Exchange, the on-time rate of top liner shipping companies in 2021 was 26.4%, which is a sharp drop of 27.6% compared with that in 2020. Among the top liner shipping companies, Hamburg Süd had the highest on-time rate of 42.9%, while Evergreen had the lowest on-time rate of 18.5%. In addition, the on-time rates of Maersk, Wan Hai, and PIL are from 30% to 40%, and the on-time rates of HPL, COSCO, CMA CGM, MSC, and OOCL are from 20% to 30%. For a long time in the future, the lack of empty containers, the shortage of shipping space, the skipping of ports, and the rise in freight rates may further reduce the reliability of liner shipping schedules, which may lead to a sharp decline in shipper satisfaction. Therefore, the optimization for liner shipping schedules and the improvement of shipper satisfaction have become a growing concern for liner shipping companies.

In academic research and maritime practice, liner shipping companies can effectively improve schedule reliability by setting buffer times in the in-port processes and sailing processes of ships. However, buffer time leads to an increase in the number of ships and the ship rent, so the liner shipping companies are cautious about this measure. When making optimization decisions on the planned arrival time at each port and the planned ship speed on each leg, liner shipping companies

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always weigh the fixed costs of fleet, the fuel costs of ships, and the in-port costs of ships. This problem is called the container liner shipping schedule optimization problem, which has significant influences on container transportation time and shipper satisfaction. Some studies have addressed this problem, Meng et al. (2014) reviewed the route design and schedule optimization problems at strategic, tactical, and operational levels. Wang and Meng (2012a) introduced the time uncertainties in the container liner shipping schedule optimization problem. Wang and Meng (2012b) studied the robust optimization problem of the container liner shipping schedule. Song, Dong, and Paul (2015) studied the multi-objective optimization of the container liner shipping schedule. Wang, Alharbi, and Davy (2014a) introduced the constraint of port time window into the liner shipping schedule optimization problem, then Alharbi, Wang, and Davy (2015) introduced the port time window constraint into the liner shipping route network. Qi et al. (2021) made impact analysis of different container arrival patterns on ship scheduling in liner shipping. Xing and Zhong (2017) proposed a container rerouting model for container flow recovery based on a given vessel schedule. Tierney et al. (2019) introduced the restriction on the on-time rate of ship arrival, and Tan et al. (2018) considered the effects of nonidentical streamflow speed and uncertain dam transit time. Lee, Lee, and Zhang (2015) and Du et al. (2022) optimized the liner shipping schedule by utilizing the ship speed adjustment measure, which can balance the optimality and reliability of planned schedules. Mulder, Van, and Dekker (2019a) proposed a natural framework to simulate random events causing ship late arrival and ship speed adjustment, and Mulder and Dekker (2019b) formulated a stochastic discrete problem with long-term and short-term decision variables. Jiang et al. (2020a) studied the big customers' preferences on ship arrival time, and Jiang, Mao, and Zhang (2020b) jointly optimized the liner shipping routes and schedules. Zheng et al. (2022) proposed a liner ship scheduling model with time-dependent port charges. According to the reviewed literature, the liner shipping schedule optimization problem focuses on whether the planned schedules are closer to the maritime practices. For example, they introduce the on-time rate restriction, the time window constraint, the low-carbon objective, and the time uncertainties. However, all the above literature ignored the impact of planned schedules on shipper satisfaction, which cannot adapt to the maritime practices.

Similar to the liner shipping schedule optimization problem, there are timetable optimization problems in highway research and railroad research. In the literature on the bus timetable optimization problem, Ibarra-Rojas, Giesen, and Rios-Solis (2014) balanced the maximization of transfer passengers and the minimization of operation costs. Parbo, Nielsen, and Prato (2014) optimized the timetable from the perspective of minimizing the waiting time experienced by passengers when transferring either to or from a bus. Wu et al. (2016) formulated a multi-objective optimization model to make a trade-off between the total number of transfer passengers and the maximum deviation from existing timetables. Vargaa, Tettamanti, and Kulcsár (2018) presented a multi-objective control strategy-based model to reduce bus bunching and improve public transport reliability. Chu et al. (2019) proposed a mixed-integer linear programming model, for joint optimization of the bus timetable and the passenger choices of travel paths. Ma, Li, and Yu (2020) formulated a timetable optimization model for maximizing passenger volume, driven by the bus GPS data and IC card data. Zhang et al. (2021) modified an existing single-line bus timetable by slightly shifting the vehicle departure times and the holding vehicles taking into account time-dependent travel times. Tang et al. (2021) formulated a bi-objective optimization model to minimize the total waiting time of passengers and the departure times of buses. Then in the literature on the train timetable optimization problem, Yang, Li, and Gao (2009) formulated a bi-objective optimization model with minimum passenger travel time and minimum train delay time. For optimizing a passenger train timetable, Niu and Zhou (2013) provided a satisfaction evaluation method for passenger waiting time, and Zhu et al. (2015) studied the time-varying characteristics of passenger flow. Gupta, Tobin, and Pavel (2016) proposed a two-step linear optimization model to calculate energy-efficient timetables in metro railway networks, for minimizing the total energy consumed by all trains and maximizing the utilization of regenerative energy produced by braking trains. Lee et al. (2017) proposed a simulation-based approach to reduce the average delay, by adjusting the time supplement and buffer time in a given passenger railway timetable. Sander, Bešinović, and Goverde (2017) introduced the train timetable adjustment problem, and they proposed a mixed integer linear programming model for minimizing the deviation from the original timetable. Guo et al. (2017) proposed a mixed integer nonlinear programming model to tackle the train timetable optimization problem for subway networks, to enhance the performance of transfer synchronization between different rail lines. To optimize the headway, running time of sections, and dwell time at stations, Li et al. (2019) proposed a multi-objective timetable programming model to minimize the energy consumption, passenger waiting time at stations, and waiting time of transfer passengers. Kumar and Mishra (2021) proposed a multi-objective optimization model for the minimization of train delay, dwell time, timetable deviation, and operation cost.

The works on the bus and train timetable optimization problems pay attention to the improvement of passenger satisfaction, including the reduction of waiting time, the decrease in crowding level, and the conformity of selection habits. All the above literature presents numerous findings about passengers' satisfaction evaluation and behavior analysis, which can be a reference for analyzing shipper selection behavior of liner shipping transportation. Since bus and train timetable optimization problems belong to the passenger transport research, the improvement of passenger satisfaction can be the only optimization objective. However, our liner shipping schedule optimization problems belong to the freight transport research, which is always overly concerned with income increases or cost reductions. As a result, the liner shipping schedule optimization problem often ignores the shippers' satisfaction evaluation and selection behavior analysis. In fact, the liner shipping schedules determine the container transportation time between any two ports on the route, which is of great concern to shippers and has a significant influence on the shippers' satisfaction and route selection. Besides, low shipper satisfaction also leads to reductions in the demand for container transportation (Wang, Meng, and Zhang 2014b). The in-port time of ships, the port call of ships, and the number of ships will decrease with the decline in container transportation demand, which may make it difficult to maintain the effective operation of liner shipping routes. Therefore, the liner shipping schedule optimization problems need to consider the shippers' satisfaction and route selection with the goal of improving operation revenue.

For the timetable optimization problems in highway research and railroad research, most previous literature pays attention to the travel time, the transfer time, the crowding level, etc. However, due to the multinomial logit model, few works focus on the passenger selection behavior considering multiple factors. Referencing the related findings in highway research and railroad research, the logit model seems suitable for analyzing shippers' route selection behavior. Affected by the independence assumption of irrelevant alternatives (IIA property), the multinomial logit model will produce an inaccurate analysis of route selection behavior between relevant alternatives (Jing et al. 2020; Jiang et al. 2020c). Therefore, we use the advanced nested logit model instead of the traditional multinomial logit model for selection behavior analysis. This nested logit model allows the alternatives in the same layer to be correlated with each other, while the alternatives in different layers remain independent of each other. The nested logit model has been used in related fields. Veldman, Garcia-Alonso, and Vallejo-Pinto (2013) analyzed the impact of transport cost and service quality on port choice. Fan and Luo (2013) analyzed ship investment and ship choice behavior according to the collected data. Barros (2016) presented a demand analysis of Angola seaports from 1996 to 2013. Yin, Fan, and LI (2018) analyzed the influence of the second ship register on vessel registration and flag choice. Jing et al. (2020) analyzed the selection behaviors of railway shippers for freight services. Jiang et al. (2020c) evaluated the shipper selection behavior for seaports, transportation modes, and dry ports.

This paper addresses the container liner shipping schedule optimization problem considering shipper selection behavior. The main contributions include: (i) A nested logit model is proposed to analyze shippers' route selection behavior. With shipper selection considered, we formulate the liner shipping schedule optimization problem as a mixed-integer nonlinear programming model with time window constraints. (ii) To effectively solve our mixed-integer nonlinear programming model, the particle swarm optimization (PSO) framework embedded with CPLEX solver has been designed, where the constraint relaxations, the linearization techniques, and the heuristic rules are introduced. (iii) At the practical application, our model and algorithm can provide method support for the liner shipping schedule optimization problem. The container liner shipping schedule optimization with shipper selection behavior considered can improve shipper satisfaction with container liner shipping transportation.

This paper is organized as follows: Section 1 describes the liner shipping schedule optimization and the shippers' route selection behavior; Section 2 formulates a liner shipping schedule optimization model with time window constraints considering shipper selection; Section 3 elaborates the processes and steps of the particle swarm optimization (PSO) framework embedded with CPLEX solver; Section 4 carries out the numerical experiments for the Persian Gulf route of COSCO SHIPPING LINES; Section 5 summarizes the research contributions and prospects of this paper.

2. Problem description

2.1. Notations

$\Omega = \{1, \ldots, i, \ldots, N\}$ is the set of port calls on the route, and N is the total number of port calls. Port i is the ith port on the route ($1 \leq i \leq N$), and Port N+1 means that the ship returns to port 1 after the voyage completion. Leg i is the ith leg on the route ($1 \leq i \leq N$), which is the route from port i to port i+1. It should be noted that Leg N indicates the liner shipping route from port N to port 1.

Parameters:

Ω_i^p: the time window set of port operators at port i;
Ω_i^o: the time window set of container shippers at port i;
Ω^c: the set of liner shipping companies in the container transportation market;
Ω^r: the set of liner shipping routes in the container transportation market;
v^n: the minimum ship speed;
v^x: the maximum ship speed;
L_i: the sea distance of ship on leg i;
p_i: the storage cost per TEU at port i;
ρ_i: the container handling efficiency at port i;
$D_{i,j}$: the weekly transportation demand from port i to port j;
$P_{i,j}$: the transportation price per TEU from port i to port j;
$\mu_{i,j}^c$: the utility coefficient of shippers for company reputation from port i to port j;
$\mu_{i,j}^p$: the utility coefficient of shippers for transportation price from port i to port j;
$\mu_{i,j}^t$: the utility coefficient of shippers for transportation time from port i to port j;
$\mu_{i,j}^w$: the utility coefficient of shippers for arrival time window from port i to port j;
ε^c: the random utility of shippers for the selection of liner shipping company;
ε^r: the random utility of shippers for the selection of liner shipping route;
c^s: the weekly fixed cost of ship;
α_1: the calculation coefficient of in-port cost;
α_2: the calculation coefficient of fuel cost;

Variables:

v_i: the decision variable for planned ship speed on leg i;
t_i^a: the decision variable for planned arrival time at port i;
Q: the decision variable for number of ships on the route;
t_i^p: the in-port time of ship at port i;
t_i^s: the sailing time of ship on leg i;
$T_{i,j}$: the container transportation time from port i to port j;

$l_{i,j}$: a zero-one variable for judging whether the planned arrival time satisfy the time window constraint;

$\theta^{c}_{i,j}$: the shipper utility for liner shipping company c from port i to port j;

$\theta^{r,c}_{i,j}$: the shipper utility for liner shipping route r from port i to port j if company c has been selected;

$\beta^{c}_{i,j}$: the shipper selection ratio for liner shipping company c from port i to port j;

$\beta^{r,c}_{i,j}$: the shipper selection ratio for liner shipping route r from port i to port j if company c has been selected;

$\beta^{r}_{i,j}$: the shipper selection ratio for liner shipping route r from port i to port j;

c^{p}_{i}: the in-port cost of ship at port i;

c^{f}_{i}: the fuel cost of ship on leg i;

C: the weekly operation cost of liner shipping routes;

I: the weekly operation income of liner shipping routes;

R: the weekly operation revenue of liner shipping routes.

2.2. Liner shipping schedule optimization

To clearly describe the processes of liner shipping voyages, an illustration is shown in Figure 1. Arrows indicate the port rotation on the route, and ports 1–5 are the port calls on the route. A ship departs from port 1, and it arrives at port 2 after the in-port process at port 1 and the sailing process on leg 1. Then, the ship delivers containers at port 3 via the in-port process at port 2 and the sailing process on leg 2. A complete shipping voyage is completed when the ship returns to port 1. We formulate the above process as formula (1) - formula (3). Formula (1) calculates the planned arrival time (t^{a}_{i+1}) at port i+1, and formula (2) calculates the planned arrival time (t^{a}_{N+1}) when the ship returns to port 1. In formula (1) and formula (2), the in-port time depends on the transportation demand and the container handling efficiency, and the sailing time depends on the sea distance and the planned ship speed.

After determining the planned arrival time at each port, we can calculate the planned round-trip time and the number of ships on the route. The planned round-trip time is the completion time of a liner shipping voyage, and it can be calculated by $t^{a}_{N+1} - t^{a}_{1}$. Then, according to the planned round-trip time and the schedule interval (i.e. 168 hours), formula (3) calculates the required number of ships (Q) on the route. We define the set $Q \in \{1, 2, \ldots, Q^{m}\}$, where Q^{m} is the maximum number of ships. The number of ships is a positive integer that cannot exceed the maximum

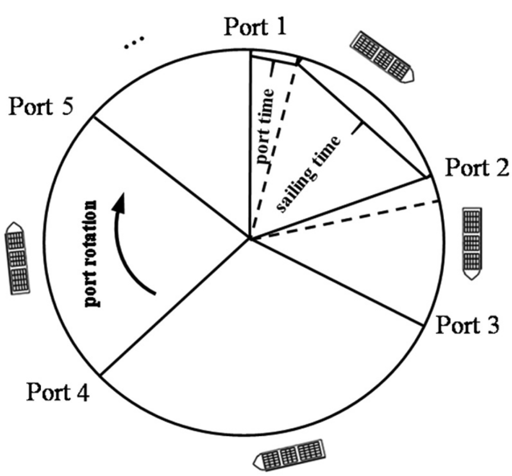

Figure 1. An illustration on liner shipping voyage.

number limit. For example, if the schedule interval is 168 h and the planned round-trip time is 820 h, we set the number of ships as 5.

$$t^a_{i+1} = t^a_i + t^p_i + t^s_i \tag{1}$$

$$t^a_{N+1} = t^a_N + t^p_N + t^s_N \tag{2}$$

$$Q = \left(t^a_{N+1} - t^a_1\right)168 \tag{3}$$

Since a port serves multiple containerships simultaneously, there may be no available berths when the ships arrive at the port (Wang, Alharbi, and Davy 2014a; Alharbi, Wang, and Davy 2015). For example, the port has available berths on Monday, Tuesday, Thursday, and Saturday, while no available berths on the other three days of the week. Then, the liner shipping company needs to set the planned arrival times for ships on Monday, Tuesday, Thursday, or Saturday, which is the constraint of arrival time windows. In addition, the port operation also leads to the constraints of the arrival time window for the following reasons. Some ports would not arrange for workers to work on holidays, and some ports prohibit ships to enter or leave at night for safety reasons. Some ports have limited water depth in port channels, so containerships need to enter or leave by the tide. To comply with operation practice, we require the arrival times of ships at each port to meet the time window constraints.

The departure time at the first port is required to satisfy formula (4), and the time window constraint at port i+1 is expressed as formula (5). As the above cases happen every week, we set the arrival time windows within 168 h, i.e. from 00:00 on Monday to 24:00 on Sunday. Formula (5) determines the specific date and time in one week of the planned arrival times. For example, the arrival time 134 indicates 14:00 on Saturday, and the time window [56, 66] is the time period from 08:00 on Wednesday to 18:00 on Wednesday.

$$0 \le t^a_1 < 168 \tag{4}$$

$$\left(t^a_{i+1} \bmod 168\right) \in \Omega^p_{i+1} \tag{5}$$

We can adjust sailing times or in-port times to make the planned arrival times satisfy the arrival time constraints. Since the in-port process is complex and difficult to adjust, we focus on the sailing time adjustment by optimizing the planned ship speed on each leg. Specifically, increasing the planned ship speed can shorten the sailing time and advance the arrival time, while reducing the planned ship speed can extend the sailing time and delay the arrival time. Generally, the containership sets a specific interval of speed adjustment $[v^n, v^x]$, to ensure it will not lose power due to low speed and will not damage the engine due to high speed. Therefore, formula (6) restricts the adjustment interval of planned ship speed (v_i) on leg i, and formula (7) calculates the sailing time of ship (t^s_i) on leg i.

$$v^n \le v_i \le v^x \tag{6}$$

$$t^s_i = L_i v_i \tag{7}$$

In this paper, the operation cost C consists of the costs in the operation of liner shipping routes, including fixed costs, in-port costs, and fuel costs (Wang and Meng 2012b). The fixed costs mainly include the ship rent of fleet and the company operation cost, which depend on the weekly fixed cost of ship c^s and the number of ships Q. The in-port costs c^p_i mainly include the port charges and the container handling charges, which depend on the calculation coefficient of in-port cost α_1 and the in-port time of ship t^p_i. The fuel costs c^f_i come from the fuel consumption of ships, which depend on the calculation coefficient of fuel consumption α_2, the planned ship speed v_i, and the sailing time of ship t_i^s. The fuel consumption of the ship is directly proportional to the third power of planned ship speed (Qi and Song 2012), so the function calculating fuel cost per hour is expressed as $\alpha_2 {v_i}^3$. It is necessary for ship speed optimization to balance the impact of ship speed on sailing time and fuel consumption, since the planned speed has the exact opposite effect on these two factors. Accordingly, formula (8) calculates the in-port costs of ships (c_i^p) at port i, and formula (9) calculates the fuel costs of ships (c_i^f) on leg i; Then, formula (10) calculates the weekly operation cost (C) on the route, including the fixed costs of fleet, the in-port cost at each port, and the fuel costs on each leg.

$$c_i^p = \alpha_1 t_i^p \tag{8}$$

$$c_i^f = \alpha_2 {v_i}^3 t_i^s \tag{9}$$

$$C = c^s Q + \sum_{i=1}^{N} c_i^p + \sum_{i=1}^{N} c_i^f \tag{10}$$

2.3. Shippers' route selection behavior

Most previous literature on the liner shipping schedule optimization aims to minimize weekly operation cost, while few works focus on the operation income. The weekly operation income depends on the container transportation demands at each port, which is related to the number of port calls. Since the port calls and port rotation are known in our liner shipping schedule optimization problem, the weekly transportation demand and the weekly operation income are usually fixed. However, there is usually more than one liner shipping route between any two ports, shippers will evaluate several routes and select one from them. Even if the total transportation demand is fixed, the liner shipping schedule still determines the container transportation time and the arrival time of ships, and further affects the shipper selection ratio and the carried transportation demand (Wang, Meng, and Zhang 2014b). Thus, the weekly operation income (I) of liner shipping routes can be calculated by formula (11), based on the weekly transportation demand ($D_{i,j}$), the shipper selection ratio ($\beta_{i,j}^r$), and the transportation price per TEU ($P_{i,j}$). Furthermore, formula (12) calculates the weekly operation revenue of liner shipping routes, and then the maximization of operation revenue is set as the optimization objective of our problem.

$$I = \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} \left(P_{i,j} D_{i,j} \beta_{i,j}^r \right) \tag{11}$$

$$R = I - C \tag{12}$$

According to previous findings, the shipper selection behavior is mainly influenced by the price factor and the time factor, e.g. the transportation price $P_{i,j}$, the storage cost p_i, the transportation time $T_{i,j}$, and the storage time (Cheng and Wang 2021; Wang, Wang, and Meng 2015), and also affected by the cargo attributes, the transportation convenience, the transportation safety, and the operation reliability (Zeng et al. 2020; Zhang and Zhu 2019; Shibasakia et al. 2017; Mesa-Arango and Ukkusuri 2014). The storage cost and storage time of containers are produced in the in-port process, which reflects the impact of the schedule interval on the shipper selection behavior. The average storage time is generally equal to the half of schedule interval (Wang, Meng, and Zhang 2014b), thus, we set it as 84 h in this paper. Based on the planned arrival times t_i^a and t_j^a, formula (13) calculates the container transportation time ($T_{i,j}$) from port i to port j.

In addition to the above factors, the related constraint of the arrival time window is introduced, for reflecting the convenience of container collection and distribution. For example, due to the difficulties in formalities handling and car dispatching on holidays or weekends, some shippers hope that ships can arrive at port on weekdays; due to the transshipment operation of main lines to feeder lines, some shippers hope that mainline ships can arrive at port before feeder schedules starting. Accordingly, we can verify whether the planned arrival times t_i^a and t_j^a satisfy the shippers' time window constraint based on formula (14), where $l_{i,j}$ is a binary variable that takes one if the time window constraint is satisfied.

$$T_{i,j} = t_j^a - t_i^a \tag{13}$$

$$l_{i,j} = \begin{cases} 1, \text{if} \left(t_i^a \bmod 168\right) \in \Omega_i^o \cap \left(t_j^a \bmod 168\right) \in \Omega_j^o \\ 0, \text{if} \left(t_i^a \bmod 168\right) \notin \Omega_i^o \cup \left(t_j^a \bmod 168\right) \notin \Omega_j^o \end{cases} \tag{14}$$

The reputation of a liner shipping company also affects the shippers' route selection behavior; however, it is often ignored by previous literature. When selecting the liner shipping routes, shippers firstly pay attention to the reputation of liner shipping company, including the brand value, the transportation safety (safety factor), and the on-time rate (reliability factor); Secondly, shippers can compare the transportation price, transportation time, and arrival time of different routes, in the liner shipping companies with good reputation. Therefore, we will utilize the advanced nested logit model instead of the traditional multinomial logit model for selection behavior analysis, to distinguish the company reputation with the transportation price, transportation time, and arrival time. The nested logit model overcomes the IIA property, and it makes the alternatives in the same layer remain related while the alternatives in different layers remain independent (Jing et al. 2020; Jiang et al. 2020c). The tree structure of the nested logit model is shown in Figure 2 to explain shipper's route selection behavior. The first layer selects the liner shipping companies, and the second layer gives the liner shipping routes of the specific company. In this model, all liner shipping companies and corresponding liner shipping routes are evaluated in turn. Finally, the liner shipping routes with good reputations, short transportation times, low transportation prices, and suitable arrival times are more likely selected, which is in line with maritime practice.

The utility value is usually used to evaluate the shipper satisfaction when selecting specific company and route (Wang, Wang, and Meng 2015; Cheng and Wang 2021; Liu, Zhao, and Huang 2022). When the utility value is high, the shippers' satisfaction and selection ratio are relatively high. To evaluate the utility value and the selection ratio, a nested logit model is formulated as formula (15) - formula (19). Formula (15) calculates the shipper utility ($\theta_{i,j}^c$) for liner shipping company c from port i to port j. Formula (16) calculates the shipper selection ratio ($\beta_{i,j}^c$) for liner shipping company c from port i to port j. Formula (17) calculates the shipper utility ($\beta_{i,j}^{r,c}$) for liner shipping route r from port i to port j, if

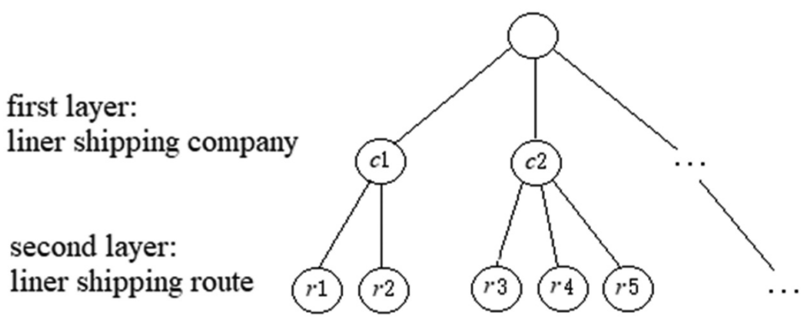

Figure 2. Tree structure of nested logit model.

company c is selected. Formula (18) calculates the shipper selection ratio ($\beta^{r,c}_{i,j}$) for liner shipping route r from port i to port j, if company c is selected. Formula (19) calculates the shipper selection ratio ($\beta^{r}_{i,j}$) for liner shipping route r from port i to port j, based on the results of formula (16) and formula (18).

In the nested logit model, the selection ratio $\beta^{r}_{i,j}$ for liner shipping route is obtained by shippers' selection behavior analysis, and it is used to forecast the container transportation demand. We consider that shippers always prefer low transportation prices and short transportation times in formula (17) (Jiang et al. 2020c). In addition, the utility value $\mu^{w}_{i,j}$ can be obtained only if both of the arrival times at port i and port j satisfy the time window constraint. The utility coefficient ($\mu^{c}_{i,j}$) for company reputation, the utility coefficient ($\mu^{p}_{i,j}$) for transportation price, the utility coefficient ($\mu^{t}_{i,j}$) for transportation time, and the utility coefficient ($\mu^{w}_{i,j}$) for arrival time window are known parameters that are calibrated through RP/SP survey (Jing et al. 2020; Jiang et al. 2020c; Zeng et al. 2020; Zhang and Zhu 2019; Shibasakia et al. 2017), or valued referencing to liner shipping market (Wang, Wang, and Meng 2015; Du, Zhao, and Ji 2017; Tan, Zeng, and Meng 2022). Parameters ε^{c} and ε^{r} are the random utility of shippers, representing the influence of unknown factors on the shipper selection behavior. These two random utilities follow the double exponential distribution (Jiang et al. 2020c).

$$\theta^{c}_{i,j} = \mu^{c}_{i,j} + \varepsilon^{c} \tag{15}$$

$$\beta^{c}_{i,j} = \frac{\exp\left(\theta^{c}_{i,j}\right)}{\sum_{c} exp\left(\theta^{c}_{i,j}\right)} \tag{16}$$

$$\theta^{r,c}_{i,j} = \frac{\mu^{p}_{i,j}}{\left(P_{i,j} + p_{i}\right)} + \frac{\mu^{t}_{i,j}}{\left(T_{i,j} + 84\right)} + \mu^{w}_{i,j} l_{i,j} + \varepsilon^{r} \tag{17}$$

$$\beta^{r,c}_{i,j} = \frac{\exp\left(\theta^{r,c}_{i,j}\right)}{\sum_{r} exp\left(\theta^{r,c}_{i,j}\right)} \tag{18}$$

$$\beta^{r}_{i,j} = \beta^{c}_{i,j}\beta^{r,c}_{i,j} \tag{19}$$

With the given transportation prices between any two ports and the schedule interval on the route, we can try to shorten the transportation times between two ports for attracting shippers. However, shortening transportation time leads to improving the planned ship speed, as well as increasing the fuel consumption of ships. As a result, the fuel cost and the operation cost will increase significantly. Therefore, it is necessary to balance the operation income and the operation cost, for optimizing the planned arrival time and the planned ship speed. Furthermore, we also consider the differences in shipper utility functions at each port due to different cargo attributes. For example, shippers may prefer the route with lower transportation prices for transporting low-value general and bulk cargoes, while they pay more attention to shorter transportation times when considering high-value electronic products and refrigerated products. Thus, different shipper utility functions (cargo attribute factor) on each leg should be considered when optimizing the planned arrival time and the planned ship speed. Improving or reducing the planned ship speed on each leg uniformly may not increase the shipper selection ratio.

3. Liner shipping schedule optimization model considering shipper selection behavior

3.1. Assumptions

To formulate the complex liner shipping schedule optimization model, the following assumptions are considered:

(1) The liner shipping schedule optimization is carried out for a single liner shipping route, namely, we will not study the container transhipments.
(2) The port calls and port rotation are known and fixed during the planning period.
(3) The service frequency of our liner shipping route is set as once a week, then the schedule interval is 168 h.
(4) The ships allocated for the liner shipping service are the same type with the known parameters of ship speed and fuel consumption.
(5) The total transportation demands per week between any two ports are known and fixed during the planning period.
(6) The container capacity meets the volume of cargo transported, and the cargo rejection is not considered in this paper.
(7) The ships can berth as soon as they arrive at port, if the arrival time window is satisfied.
(8) Shippers are rational, namely, they always select the liner shipping company and liner shipping route with high utility value.
(9) The shipper utility coefficients for company reputation, transportation time, transportation price, and arrival time window are known in this paper.

3.2. Model formulation

With the fixed port calls, port rotation and schedule interval, and the constraints of arrival time window and speed adjustment interval, the liner shipping schedule optimization problem aims to maximize the weekly operation revenue. Considering the influence of shippers' route selection behavior on the weekly container transportation demand, our proposed model is formulated as [M1]. Due to the continuous decision variables (i.e. planned ship speed) and integer decision variables (i.e. planned arrival time and number of ships), [M1] is a mixed integer programming model. Besides, a nonlinear nested logit model (i.e. formula (28) - formula (34)) is introduced to [M1] for selecting the liner shipping companies and liner shipping routes. Then, [M1] belongs to a mixed integer nonlinear programming model.

[M1]

$$\text{Max } R = I - C \tag{20}$$

Subject to

$$0 \le t_1^a < 168 \tag{21}$$

$$t_i^p = \frac{\left(\sum_{j=1, j\neq i}^{N} D_{i,j}\beta_{i,j}^r + \sum_{j=1, j\neq i}^{N} D_{j,i}\beta_{j,i}^r\right)}{\rho_i}, 1 \le i \le N \tag{22}$$

$$t_i^s = L_i v_i, 1 \le i \le N \tag{23}$$

$$v^n \le v_i \le v^x, 1 \le i \le N \tag{24}$$

$$t_{i+1}^{a} = t_i^{a} + t_i^{p} + t_i^{s}, 1 \le i \le N \tag{25}$$

$$\left(t_i^{a} \bmod 168\right) \in \Omega_i^{p}, 1 \le i \le N{+}1 \tag{26}$$

$$Q = \left(t_{N+1}^{a} - t_1^{a}\right)168 \tag{27}$$

$$\theta_{i,j}^{c} = \mu_{i,j}^{c} + \varepsilon^{c}, 1 \le i \le N, 1 \le j \le N, j \ne i \tag{28}$$

$$\beta_{i,j}^{c} = \frac{\exp\left(\theta_{i,j}^{c}\right)}{\sum_{c} exp\left(\theta_{i,j}^{c}\right)}, 1 \le i \le N, 1 \le j \le N, j \ne i \tag{29}$$

$$T_{i,j} = t_j^{a} - t_i^{a}, 1 \le i \le N, 1 \le j \le N, j \ne i \tag{30}$$

$$l_{i,j} = \begin{cases} 1,\text{if}\left(t_i^{a} \bmod 168\right) \in \Omega_i^{o} \cap \left(t_j^{a} \bmod 168\right) \in \Omega_j^{o} \\ 0,\text{if}\left(t_i^{a} \bmod 168\right) \notin \Omega_i^{o} \cup \left(t_j^{a} \bmod 168\right) \notin \Omega_j^{o} \end{cases}, 1 \le i \le N, 1 \le j \le N, j \ne i \tag{31}$$

$$\theta_{i,j}^{r,c} = \frac{\mu_{i,j}^{p}}{\left(P_{i,j} + p_i\right)} + \frac{\mu_{i,j}^{t}}{\left(T_{i,j} + 84\right)} + \mu_{i,j}^{w} l_{i,j} + \varepsilon^{r}, 1 \le i \le N, 1 \le j \le N, j \ne i \tag{32}$$

$$\beta_{i,j}^{r,c} = \frac{\exp\left(\theta_{i,j}^{r,c}\right)}{\sum_{r} exp\left(\theta_{i,j}^{r,c}\right)}, 1 \le i \le N, 1 \le j \le N, j \ne i \tag{33}$$

$$\beta_{i,j}^{r} = \beta_{i,j}^{c}\beta_{i,j}^{r,c}, 1 \le i \le N, 1 \le j \le N, j \ne i \tag{34}$$

$$I = \sum_{i=1}^{N} \sum_{j=1, j \ne i}^{N} \left(P_{i,j} D_{i,j} \beta_{i,j}^{r}\right) \tag{35}$$

$$c_i^{p} = \alpha_1 t_i^{p}, 1 \le i \le N \tag{36}$$

$$c_i^{f} = \alpha_2 {v_i}^{3} t_i^{s}, 1 \le i \le N \tag{37}$$

$$C = Qc^{s} + \sum_{i=1}^{N} c_i^{p} + \sum_{i=1}^{N} c_i^{f} \tag{38}$$

$$t_i^{a} \ge 0 \text{ and integer}, 1 \le i \le N{+}1 \tag{39}$$

$$Q > 0 \text{ and integer} \tag{40}$$

Formula (20) is the objective function of this model, for maximizing the weekly operation revenue on the route. Formula (21) is the time window constraint of port operators for the departure time at the first port. Formula (22) calculates the in-port time of ships at each port, including the unloading and loading times. Formula (23) calculates the sailing time of ships on each leg. Formula (24) is the constraint of the ship speed adjustment interval. Formula (25) calculates the planned arrival time at each port. Formula (26) is the time window constraint of port operators for the planned arrival time at each port. Formula (27) calculates the number of ships required on the route. Formula (28) calculates the shipper utility for the liner shipping companies between any two ports. Formula (29) calculates the shipper selection ratio for the liner shipping companies between any two ports. Formula (30) calculates the container transportation times between any two ports. Formula (31) can determine whether the planned arrival times at any two ports satisfy the time window constraint of shippers. Formula (32) calculates the shipper utility for the liner shipping routes of a specific company between any two ports. Formula (33) calculates the shipper selection ratio for the liner shipping routes of a specific company between any two ports. Formula (34) calculates the shipper selection ratio for the specific liner shipping routes between any two ports. Formula (35) calculates the weekly operation income on the route. Formula (36) calculates the in-port cost of ships at any port. Formula (37) calculates the fuel cost of ships on each leg. Formula (38) calculates the weekly operation cost on the route. Formula (39) constrains that the planned arrival times are non-negative integers. Formula (40) constrains that the number of ships is a positive integer.

4. Particle swarm optimization (PSO) framework embedded with CPLEX solver

Due to nonlinear objective functions and constraint conditions, our proposed model [M1] cannot be directly solved by the state-of-the-art MILP solvers such as CPLEX. To facilitate solving, we try to divide the model [M1] into two main parts, including a liner shipping schedule optimization model with time window constraint and a nested logit model for shipper selection analysis. There are some difficulties in the liner shipping schedule optimization model: (i) The linearization for the reciprocal of ship speed ($t_i^s = L_i v_i$); (ii) The linearization for the nonlinear function "mod" ($\mathrm{t_i^a} \bmod 168$); (iii) The linearization for the fuel cost function with the third power of ship speed ($\mathrm{c_i^f} = \alpha_2 \mathrm{v_i}^3 \mathrm{t_i^s}$); (iv) The linearization for the arrival time windows of ships ($\mathrm{l_{i,j}}=1, \mathrm{if} \left(\mathrm{t_i^a} \bmod 168\right) \in \Omega_\mathrm{i}^\mathrm{o} \cap \left(\mathrm{t_j^a} \bmod 168\right) \in \Omega_\mathrm{j}^\mathrm{o}$). Referencing to Wang, Alharbi, and Davy (2014a), Alharbi, Wang, and Davy (2015), and Jiang, Mao, and Zhang (2020b), we linearize the above nonlinear functions. Due to no effective method for solving the nested logit model, it is difficult to obtain the exact solution. The enumeration method is applied to solve small-scale cases, but cannot solve large-scale cases in limited calculation time (Song et al. 2016; Jiang et al. 2020c). Later, heuristic algorithms are proven to solve the nested logit model efficiently in various scales (Cheng and Wang 2021; Liu, Zhao, and Huang 2022). Following previous findings, we proposed a hybrid algorithm combined CPLEX solver with heuristic rules, where the CPLEX solver is used to solve the linearized model [M3] and heuristic rules deal with the nested logit model. It has to be noted that the hybrid algorithm is a heuristic method that can only find the satisfactory results in limited calculation time. Some numerical experiments are conducted to prove the validity of our hybrid algorithm in the following subsection 5.2.

To balance the solving efficiency and accuracy for our mixed integer nonlinear programming model, a particle swarm optimization (PSO) framework embedded with CPLEX solver is proposed. We show the algorithm flow chart in Figure 3, where the PSO framework constructs and improves the solution schemes, and the CPLEX solver deals with the relaxed model and evaluates the solution schemes. Firstly, we relax the selection behavior analysis, and linearize the fuel consumption function and time window constraint in the relaxed model. As a result, a mixed integer nonlinear programming model becomes a linear model that can be solved via CPLEX solver to obtain the optimal solution. Secondly, the solution schemes are evaluated and improved continuously to achieve an intelligent search for the optimal scheme in a large-range solution space. In the PSO

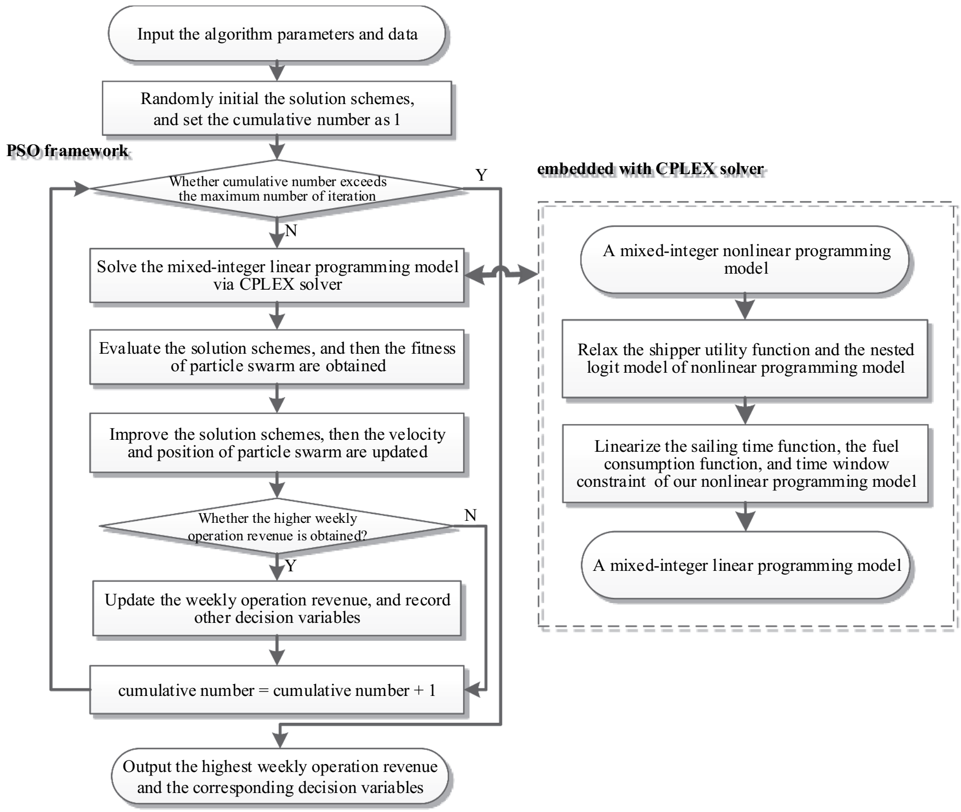

Figure 3. Algorithm flow chart.

framework, the shipper selection ratio is coded as the particle position, and the CPLEX result is seen as the particle fitness. This particle fitness shows the individual optimal position and the group optimal position, which is used to update the velocity and position of particle swarms.

4.1. Model relaxation and linearization

[M1] is a mixed-integer nonlinear programming model for container liner shipping schedule optimization considering shipper selection behavior. To facilitate the model linearization, the shipper utility function and the nested logit model are relaxed, namely, formula (28) - formula (34) needs to be removed from [M1]. In addition, the relaxation processes of our model also include:

(i) Add the formula $\beta_{i,j}=a_{i,j}, 1 \leq i \leq N, 1 \leq j \leq N, j \neq i$, which means that the shippers' route selection ratios between any two ports need to be given in advance. In the formula, $a_{i,j}$ is the parameter of the relaxed model, which comes from the solution scheme of PSO algorithm.

(ii) Add the formula $t_j^a - t_i^a = T_{i,j}, 1 \leq i \leq N, 1 \leq j \leq N, j \neq i$, which means that the transportation time is used to limit the planned arrival times at two ports. Then, based on the shipper selection ratio $a_{i,j}$, we can use the nested logit model to calculate the transportation time $T_{i,j}$.

(iii) Formula (26) is modified as $\left(t_{i+1}^a \bmod 168\right) \in \Omega_{i+1}^p \cup \Omega_{i+1}^o, 1 \leq i \leq N+1$, which means that the time window constraints need to be added to the planned arrival time at each port. In the formula, the symbol $\cup$ means that the planned arrival time at each port should satisfy the time window constraints of container shippers and port operators.

Then, the shipper selection analysis in model [M1] has been completely relaxed after the above processes. The liner shipping schedule optimization model without shipper selection is shown as following [M2].

[M2]

$$Max\ R = I - C \tag{41}$$

Subject to formulas (21)-(27) and (35)-(40).

$$\beta_{\mathrm{i,j}} = \mathrm{a_{i,j}}, 1 \leq \mathrm{i} \leq \mathrm{N}, 1 \leq \mathrm{j} \leq \mathrm{N}, \mathrm{j} \neq \mathrm{i} \tag{42}$$

$$\mathrm{t_j^a} - \mathrm{t_i^a} = \mathrm{T_{i,j}}, 1 \leq \mathrm{i} \leq \mathrm{N}, 1 \leq \mathrm{j} \leq \mathrm{N}, \mathrm{j} \neq \mathrm{i} \tag{43}$$

$$\left(\mathrm{t_i^a} \bmod 168\right) \in \Omega_{\mathrm{i}}^{p} \cup \Omega_{\mathrm{i}}^{\mathrm{o}}, 1 \leq \mathrm{i} \leq \mathrm{N+1} \tag{44}$$

However, [M2] is still a mixed-integer nonlinear programming model. We linearize [M2] by referring to previous literature (Wang, Alharbi, and Davy 2014a). The main steps are as follows:

(i) The reciprocal function v_i in formula (23) - formula (24) is linearized via formula (46) - formula (47). Specifically, we set $\mu_i = v_i, 1 \leq i \leq N$. Then, $L_i v_i$ is linearized as $\mathrm{L_i}\mu_{\mathrm{i}}$ and $\mathrm{v}^n \leq \mathrm{v_i}$ is linearized as $\mu_i \leq v^n$.

(ii) The nonlinear function 'mod' in formula (44) is linearized via formula (48) - formula (50). Specifically, the variable $\mathrm{k_{i+1}}$ is used to determine how many 168 h are contained in the planned arrival time, and the variable $\mathrm{t_{i+1}^{a}}$ is used to determine the specific date and time in one week of the planned arrival time.

(iii) The fuel cost function $\alpha_2 \mathrm{v_i}^3 \mathrm{t_i^s}$ in formula (37) is linearized as $\mathrm{L_i}\alpha_2\mu_{\mathrm{i}}{}^{-2}$. Then, the nonlinear function $\mu_{\mathrm{i}}{}^{-2}$ can be linearized by referring to Wang, Alharbi, and Davy (2014a) and Jiang, Mao, and Zhang (2020b). We first find the most approximate value ($\mu_{\mathrm{i}}^{\mathrm{z_i}}$) of variable μ_{i}, and estimate the nonlinear function $\mu_{\mathrm{i}}{}^{-2}$ based on the tangent slope $\left[(\mu_i)^{-2} - (\mu_i^{z_i})^{-2}\right](\mu_i - \mu_i^{z_i}) = -2(\mu_i^{z_i})^{-3}$. Formula (55) defines the value range $\mu_{\mathrm{i}}^{\mathrm{z_i}}$, $\mathrm{z_i} \in \{1, 2, \ldots, 168\mathrm{Q^m}\}$ of variable μ_{i}, formula (56) describes the approximation condition $\mu_{\mathrm{i}}^{\mathrm{z_i}-1} \leq \mu_{\mathrm{i}} \leq \mu_{\mathrm{i}}^{\mathrm{z_i}}$ of variable μ_{i}, and formula (57) uses the above tangent slope to estimate the fuel cost $\mathrm{L_i}\alpha_2\mu_{\mathrm{i}}{}^{-2}$.

(iv) The arrival time window $\Omega_{\mathrm{i}}^{p} \cup \Omega_{\mathrm{i}}^{o}$ in formula (44) is linearized via formula (51) - formula (54). Firstly, the arrival time window Ω_{i}^{p} of port operators and the arrival time window Ω_{i}^{o} of shippers are combined into the set of arrival time windows $\Omega_{\mathrm{i}}^{\mathrm{x}}$. Then, the same time windows are removed from the set $\Omega_{\mathrm{i}}^{\mathrm{x}}$, while the different time windows are retained. In the set $\Omega_{\mathrm{i}}^{\mathrm{x}}$, each time window x, $\mathrm{x} = 1, 2\ldots, \mathrm{X}$ can be expressed as $\left[\mathrm{T}_{\mathrm{i,x}}^{n}, \mathrm{T}_{\mathrm{i,x}}^{x}\right] \in \Omega_{\mathrm{i}}^{\mathrm{x}}, \mathrm{x} = 1, 2\ldots, \mathrm{X}$, including the earliest arrival time and the latest arrival time. We define M as an infinite number and the variable $\mathrm{y_{i,x}}$ as a binary variable to evaluate whether the xth arrival time window is satisfied. Formula (51) constrains that the planned arrival time is not earlier than the earliest arrival time, and formula (52) constrains that the planned arrival time is not later than the latest arrival time. Formula (53) constrains that only one arrival time window can be satisfied, and formula (54) requests $\mathrm{y_{i,x}}$ as a binary variable.

Then, the mixed-integer nonlinear programming model [M2] is relaxed and linearized into the mixed-integer linear programming model [M3] that can be effectively solved via CPLEX solver.

[M3]

$$Max\ R = I - C \tag{45}$$

Subject to formulas (22), (25), (27), (35)-(36), (38)-(40), and (42)-(43).

$$t_i^s = L_i \mu_i, 1 \le i \le N \tag{46}$$

$$vx \le \mu_i \le v^n, 1 \le i \le N \tag{47}$$

$$\bar{t}_i^a = t_i^a - 168k_i, 1 \le i \le N+1 \tag{48}$$

$$0 \le \bar{t}_i^a < 168, 1 \le i \le N+1 \tag{49}$$

$$k_i \in \{0, 1, 2, \ldots, Q^m - 1\}, 1 \le i \le N+1 \tag{50}$$

$$\bar{t}_i^a \ge T_{i,x}^n - M(1 - y_{i,x}), 1 \le i \le N+1, 1 \le x \le X \tag{51}$$

$$\bar{t}_i^a \le T_{i,x}^x + M(1 - y_{i,x}), 1 \le i \le N+1, 1 \le x \le X \tag{52}$$

$$\sum_{x=1}^{X} y_{i,x} = 1, 1 \le i \le N+1 \tag{53}$$

$$y_{i,x} \in \{0, 1\}, 1 \le i \le N+1, 1 \le x \le X \tag{54}$$

$$\mu_i^{z_i} = z_i L_i, 1 \le i \le N, z_i \in \{1, 2, , 168Q^m\} \tag{55}$$

$$\mu_i^{z_i - 1} \le \mu_i \le \mu_i^{z_i}, 1 \le i \le N, z_i \in \{1, 2, \ldots, 168Q^m\} \tag{56}$$

$$c_i^f = L_i \alpha_2 \left[3(\mu_i^{z_i})^{-2} - 2(\mu_i^{z_i})^{-3} \mu_i \right], 1 \le i \le N, z_i \in \{1, 2, \ldots, 168Q^m\} \tag{57}$$

4.2. Particle swarm optimization framework

Step 1 Solution construction

Based on the parameters and data input into the PSO algorithm, we initialize the set of solution schemes. Aimed at the solution scheme (particle swarm), the values of shipper selection ratios between two consecutive ports are assigned randomly, while the values of shipper selection ratios

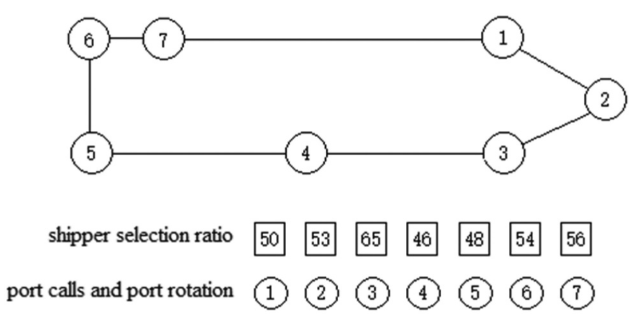

Figure 4. Example of solution coding.

between non-consecutive ports are not assigned. An example of solution coding is shown in Figure 4, where the values of shipper selection ratios between two consecutive ports from port 1 to port 7 are 50%, 53%, 65%, 46%, 48%, 54%, and 56%.

Step 2 Solution evaluation

Step 2.1 Based on formula (28) - formula (34) and the shipper selection ratio ($\beta_{i,i+1}$) in one solution scheme, the container transportation time ($T_{i,i+1}$) between two consecutive ports can be calculated. Furthermore, we calculate the container transportation time ($T_{i,j}$) between two non-consecutive ports and the corresponding shipper selection ratio ($\beta_{i,j}$) between any two ports.

Step 2.2 According to parameters $T_{i,j}$ and $\beta_{i,j}$, we solve the mixed-integer linear programming model [M3] via CPLEX solver. If the model fails for solving due to the time window constraint not being satisfied, the weekly operation revenue is assigned to negative infinity. We calculate the weekly operation revenue if the time window constraint can be satisfied.

Step 2.3 Based on decision variables obtained, i.e. μ_i, k_i and $\bar{t}_i^a$ of [M3], we calculate decision variables v_i and t_i^a to obtain the planned arrival time at each port and the planned ship speed on each leg.

Step 3 Solution improvement

Step 3.1 The set of solution schemes can be regarded as a complete particle swarm, where a solution scheme is an individual particle. It should be noted that the shipper selection ratio in each solution scheme indicates the spatial position of an individual particle. According to the particle fitness (evaluation value) obtained from the set of solution schemes, we can determine the historical optimal position of an individual particle. Then, the historical optimal position of the particle swarm can be found based on the historical optimal positions of all individual particles.

Step 3.2 In the algorithm iteration, the historical optimal position of the particle swarm is P_g, the historical optimal position of the kth particle is P_k, and the position and velocity of the kth particle in the dth iteration are respectively X_k^d and V_k^d. According to the historical optimal position (P_k) of an individual particle and the historical optimal position (P_g) of the particle swarm, the position and velocity of the kth particle can be updated via formula (58) - formula (59). In formula (58), r_1, r_2 are the random number in the range of [0,1], ρ is the inertia factor of particles moving at their original velocity, and ω_1, ω_2 are the learning factor of particles moving to the historical optimal position. These parameters, i.e. ρ, ω_1, ω_2, control the updated velocity of particles to correct movement direction and step size.

$$V_k^{d+1} = \rho V_k^d + \omega_1 r_1 (P_k^d - X_k^d) + \omega_2 r_2 (P_g^d - X_k^d) \tag{58}$$

$$X_k^{d+1} = X_k^d + V_k^{d+1} \tag{59}$$

Step 3.3 Judge whether the cumulative number reaches the maximum number, if so, enter step4, else, take the particle swarm with updated position and velocity into step2.

Step 4 Optimal solution

According to the historical optimal position of the particle swarm, we can calculate the optimal solution scheme with the planned arrival time at each port, the planned ship speed on each leg, and the round-trip time and number of ships on the route. Then, the weekly operation income, the weekly operation cost, and the weekly operation revenue can be calculated as the final outputs of our algorithm.

Table 1. Set of arrival time window at each port.

Port	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Port 1	day/night	day/night	day/night	day/night	day/night	day/night	day/night
Port 2	day/night	day/night	day/night	daytime	daytime	daytime	daytime
Port 3	day/night	day/night	day/night	day/night	day/night		
Port 4		day/night	day/night	daytime	daytime	daytime	
Port 5	daytime	daytime	daytime	daytime	daytime		
Port 6		day/night	day/night	daytime	daytime	daytime	
Port 7	day/night	day/night	day/night	day/night	day/night		

Table 2. Container transportation parameters between any two ports.

Demand (TEU) /Price (RMB)	Port 1	Port 2	Port 3	Port 4	Port 5	Port 6	Port 7	Port 8
Port 1	-	420/300	400/360	340/480	510/1185			
Port 2		-	410/300	250/390	380/1080			
Port 3			-	240/300	400/990			
Port 4				-	470/690			
Port 5					-	310/660	460/990	520/1290
Port 6						-	230/330	450/730
Port 7							-	250/400

5. Numerical experiments

5.1. Experiments parameters

We select the important ports on the Persian Gulf route of COSCO SHIPPING LINES for numerical experiments, to verify the effectiveness of our model and algorithm. The port calls and port rotation on the route is Shanghai Port (1) - Taipei Port (2) - Shekou Port (3) - Tanjung Pelepas Port (4) - Jebel Ali Port (5) - Klang Port (6) - Hong Kong Port (7) - Shanghai Port (8). Based on the Netpas software, the sailing distance between consecutive ports is 452 nm (nautical mile), 472 nm, 1496 nm, 3461 nm, 3287 nm, 1638 nm, and 864 nm. According to the research results for the liner shipping market, the containership is 3500 TEU, the minimum ship speed is 12 kn, and the maximum ship speed is 22 kn. The daily rent is 22,500 RMB/day, the in-port cost coefficient is 13,000 RMB/day, and the fuel cost coefficient is 0.2 RMB/(ton·nm). On the computer with Windows 10, 2.50 GHz, and 8.0 GB RAM, we will use MATLAB to encode the particle swarm optimization (PSO) framework, and then use YALMIP toolbox to call CPLEX solver. The algorithm parameters are set as follows: The size of particle swarm is 200, the maximum number of algorithm iteration is 200, and $\rho = 0.2$, $\omega_1 = 0.4$, $\omega_2 = 0.6$.

The set of arrival time windows at each port is listed in Table 1. For example, if there are available berths during the daytime on Thursdays, then we need to set one arrival time window [72,84]. According to the information from liner shipping companies, the transportation demand and transportation price between any two ports are listed in Table 2. The container handling efficiency at each port is 75 TEU/hour, and the container storage cost at each port is 120 RMB/(TEU·day). Referring to the calibration results from previous literature and the market parameters of container transportation, the utility coefficients of shippers' time preference for company reputation, transportation time, and transportation price are set as 3/550/750, and the utility coefficients of shippers' price preference are set as 3/275/1250. We demonstrate the superiority of our algorithm and the effectiveness of our model in subsections 5.2 and 5.3, respectively. The sensitivity analysis is conducted in subsection 5.4 to explore the impact of utility coefficients on shipper selection ratios and liner shipping schedules.

5.2. Algorithm validation

Here, we conduct comparison experiments between our hybrid algorithm and the enumeration method. Since the CPLEX solver hardly solves our model with the nested logit model directly, we use the enumeration method to calculate the exact solution. Previous studies have shown that the CPLEX solver can solve the liner shipping schedule optimization problem with time window constraints (Wang, Alharbi, and Davy 2014a; Alharbi, Wang, and Davy 2015; Jiang, Mao, and Zhang 2020b). The numerical results of our PSO framework show that the single calculation time of CPLEX solver is less than one second, which indicates that the solving efficiency of CPLEX solver is acceptable. Furthermore, considering that the genetic algorithm (GA) is the most commonly used heuristic rule, we compare the particle swarm optimization (PSO) framework and the genetic algorithm (GA) framework with the enumeration method. To show the differences between GA framework and PSO framework more intuitively, we also introduce the CPLEX solver in the GA framework. The comparison experiments are conducted for different numbers of port calls, different sizes of particle swarms, and different maximum numbers of iterations. Then, the calculation time, maximum fitness, and average fitness of these three algorithms are listed in Table 3. The maximum fitness equals to the objective value obtained by heuristics, and the average fitness is the mean value of fitness for all particle swarms/chromosomes. The port number indicates the number of port calls reflecting the calculation scale. The iteration scale of 50×100 means that the size of particle swarms/chromosomes is 50 and the maximum number of iterations is 100.

Comparison between enumeration method and heuristic algorithms shows that: (i) For the case with four ports, the problems can be solved by enumeration method and heuristic algorithms (i.e. GA and PSO) in the limited time. While for the case with eight ports, the calculation time of the enumeration method exceeds 86,400 s (one day), the maximum fitness cannot be found in the limited time. Since the enumeration method cannot solve large-scale problems in an acceptable time, this method is unsuitable for operation practice. (ii) For the cases with four or six ports, the maximum fitness of heuristic algorithms with the maximum iteration and the objective value of the enumeration method are almost the same. The optimality gaps between enumeration method and heuristic algorithms (GA and PSO) are both less than 1%, which is acceptable in practice. Therefore, the effectiveness of the heuristic algorithm is verified.

Comparison between GA framework and PSO framework shows that: (i) The calculation times of PSO framework and GA framework are similar at different iteration scales. The calculation time of PSO framework at the maximum iteration scale is 2100 s, which is acceptable for the liner shipping schedule optimization problem with 3-month time span. (ii) When the iteration scale is relatively small, the maximum fitness of GA framework is larger than that of PSO framework; When the iteration scale is relatively large, PSO framework is similar to that of GA framework. Because the iteration scale of intelligent heuristic algorithm is generally large, it can be assumed that the PSO framework and the GA framework have similar optimization ability. (iii) With the increase in iteration scale, the average finesses of PSO framework and GA framework improve or reduce sometimes, but they will improve in general. However, the average fitness of PSO framework is significantly better than that of GA framework, regardless of the small or large iteration scale. The fitness curves of PSO framework and GA framework at the maximum iteration can be seen in Figure 5. In this figure, the average fitness of PSO framework is significantly better.

Therefore, the PSO framework has better optimization ability, compared with the GA framework and the enumeration method. The effectiveness of PSO framework embedded with CPLEX solver is verified.

5.3. Model validation

We obtain the results of our liner shipping schedule optimization model by using the PSO framework. In the results, the weekly operation income is 2.78×10^6 RMB, the weekly operation cost is

Table 3. Effect comparison between enumeration method, GA framework and PSO framework.

	Enumeration method		Genetic algorithm (GA) framework				Particle swarm optimization (PSO) framework			
Port number	Calculation time (s)	Objective value ($\times 10^5$ RMB)	Iteration scale	Calculation time (s)	Maximum fitness ($\times 10^5$ RMB)	Average fitness ($\times 10^5$ RMB)	Iteration scale	Calculation time (s)	Maximum fitness ($\times 10^5$ RMB)	Average fitness ($\times 10^5$ RMB)
4	2086	5.12	50×50	79	4.52	1.23	50×50	80	4.50	2.23
			50×100	123	4.56	1.31	50×100	128	4.53	2.26
			200×100	577	4.89	1.40	200×100	569	4.92	2.35
			200×200	1070	5.09	1.53	200×200	1058	5.11	2.37
6	21045	7.93	50×50	117	7.79	3.52	50×50	112	7.81	5.46
			50×100	184	7.84	3.61	50×100	191	7.83	5.51
			200×100	882	7.88	3.81	200×100	876	7.88	5.70
			200×200	1605	7.91	3.98	200×200	1590	7.93	5.73
8	>86400	-	50×50	155	9.81	5.02	50×50	150	9.60	8.92
			50×100	245	9.95	5.22	50×100	255	9.75	9.01
			200×100	1135	10.4	5.61	200×100	1125	10.4	9.40
			200×200	2140	10.6	6.10	200×200	2100	10.7	9.45

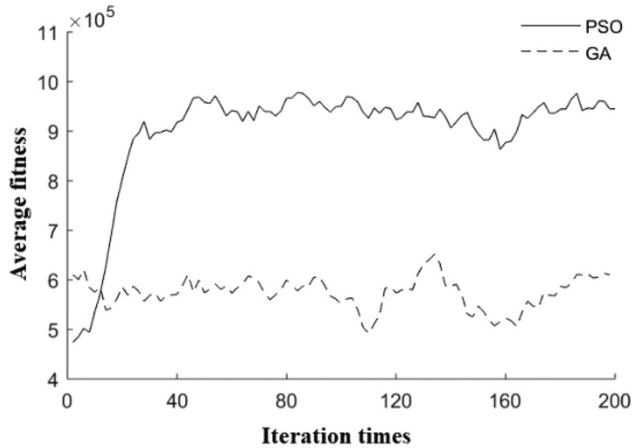

Figure 5. Fitness curve of PSO and GA.

Table 4. Arrival port time at each port and planned ship speed on each leg.

Calculation results	Port 1	Port 2	Port 3	Port 4	Port 5	Port 6	Port 7	Port 8
Ship speed (kn)	20.9	21.2	18.9	19.6	17.0	19.6	20.2	-
Sailing time (hours)	21.7	22.3	79.3	176.7	193.2	83.4	42.8	-
Handling demand (TEU)	798	269	551	541	1155	185	442	-
Arrival time (hours)	2	32	61	147	329	542	628	673

Table 5. Container transportation time and shipper selection proportion between any two ports.

Time (hour)/ Ratio (%)	Port 1	Port 2	Port 3	Port 4	Port 5	Port 6	Port 7	Port 8
Port 1	-	21.7/64	43.9/68	123.3/65	299.9/65			
Port 2		-	22.3/68	101.5/65	278.2/65			
Port 3			-	79.3/65	256.0/65			
Port 4				-	176.7/67			
Port 5					-	193.2/60	276.6/62	319.4/62
Port 6						-	83.4/68	126.2/66
Port 7							-	42.8/71

1.71×10^6 RMB, and the weekly operation revenue is 1.07×10^6 RMB. The round-trip time is 673 h and the number of ships is 4 under the schedule interval of 168 h. The planned ship speed on each leg and the planned arrival time at each port are listed in Table 4, then the transportation time and the shipper selection ratio between any two ports are listed in Table 5. In Table 4, the planned ship speed on each leg meets the constraint of ship speed adjustment interval, while the planned arrival time at each port meets the constraint of arrival time windows. This shows that our model is valid and can be applied in maritime practice.

To analyze the impact of shipper selection behavior, we design comparative experiments where shipper selection behavior is not considered. In comparative experiments, the planned ship speed is set as 12 kn on each leg, which does not change varying with utility coefficient. In the results without shipper selection behavior considered, the weekly operation cost is reduced by 18%, with the decrease in fuel cost produced by the reduction of speed. However, the shipper selection ratio is reduced by 15%, and the total freight demand is reduced by 23%. As a result, the weekly operation income and operation revenue decreased by 23% and 31%, respectively. With the fixed transportation price, the attractiveness to time-preference shippers is significantly weakened, since it cannot

Table 6. Optimal designed schedule under different time utility coefficient.

Utility coefficient	Planned ship speed (kn)	Shipper selection ratio (%)	Weekly operation cost (10^6 RMB)	Weekly operation income (10^6 RMB)	Weekly operation revenue (10^6 RMB)
$0.5\times\mu_{i,j}^{t}$	13.9	56	1.62	2.37	0.75
$0.7\times\mu_{i,j}^{t}$	16.5	61	1.67	2.51	0.84
$1.0\times\mu_{i,j}^{t}$	18.8	65	1.71	2.78	1.07
$1.2\times\mu_{i,j}^{t}$	20.1	68	1.85	2.94	1.09
$1.5\times\mu_{i,j}^{t}$	21.6	71	1.92	3.02	1.10

shorten transportation time by increasing ship speed. Therefore, it has significant implication to consider shipper selection behavior in our liner shipping schedule optimization model.

5.4. Sensitivity analysis

Since the previous literature has conducted the sensitivity analyses on the ship rent (Jiang et al. 2020a), the fuel price (Wang, Alharbi, and Davy 2014a; Alharbi, Wang, and Davy 2015; Jiang et al. 2020a), the handling efficiency (Wang, Alharbi, and Davy 2014a; Alharbi, Wang, and Davy 2015), and the arrival time window (Wang, Alharbi, and Davy 2014a; Alharbi, Wang, and Davy 2015; Jiang et al. 2020a), this paper focus on the shipper utility coefficient influencing route selection behavior. Furthermore, since the port rotation and transportation price are fixed in the liner shipping schedule optimization problem, we design sensitivity experiments to analyze the time utility coefficient $\mu_{i,j}^{t}$ that is most relevant to the decision variables of planned ship speed and planned arrival time. Based on the planned ship speed, shipper selection ratio, and weekly operation revenue under different time utility coefficients, we analyze the influence of shipper selection behavior on the optimal liner shipping schedule.

In the sensitivity experiment, the time utility coefficient is increased continuously, and the optimal liner shipping schedules under different utility coefficients are listed in Table 6. With the gradual increase in time utility coefficient, the average value of planned ship speeds is increased, and the container transportation time between any two ports is shortened correspondingly. Since the transportation price and transportation time of existing liner shipping routes are fixed, speeding up makes the transportation time of our liner shipping routes more advantageous, which increases the shipper selection ratio and weekly transportation demand. Note that the average ship speed and shipper selection ratio will not increase indefinitely due to the ship speed adjustment interval. In addition, although the weekly operation cost rises with the increase in fuel cost, the weekly operation income and the weekly operation revenue also increase rapidly. Therefore, the planned ship speed should be increased as the time utility coefficient is higher, conversely, it should be decreased. We can also find that it is not necessary to maintain a high ship speed when the price utility coefficient is high, while the planned ship speed should be decreased for the reduction of fuel costs. These conclusions can provide decision support for the operation practice of liner shipping schedule design.

6. Conclusion

In this paper, the shipper selection behavior has been introduced into the container liner shipping schedule optimization problem. We formulate a mixed-integer nonlinear programming model for our problem, where the nested logit model is conducted to evaluate shippers' satisfaction and selection behavior. To balance the rapidity and accuracy of model solving, the particle swarm optimization (PSO) framework embedded with CPLEX solver is proposed. In this algorithm, the PSO framework constructs and improves the solution schemes, and the CPLEX solver deals with the relaxed model and evaluates the solution schemes. Numerical experiments are conducted for the Persian Gulf route of COSCO SHIPPING LINES, the results show that: (i) Compared with the GA framework, the PSO framework has better average fitness under similar calculation time and maximum fitness. The single calculation time of CPLEX solver is less than one second, so the particle swarm optimization (PSO) framework embedded with CPLEX solvers is effective. (ii) The calculation results of our model meet the ship speed adjustment interval and the arrival time window constraint, which can be applied to the operation practice. The results of the comparison experiment on the shipper selection behavior showed that it has significant implication to consider shipper selection behavior in our liner shipping schedule optimization model.

The application values and management insights are demonstrated as follows: (i) The availability of berths has to be considered for liner shipping companies and port operators when designing liner shipping schedules. Our model with time window constraints can provide method support for the operation practice, and make the designed schedule apply in practice with minimum revisions. (ii) The calculation results demonstrate the necessity of considering shipper selection behavior for container liner shipping schedule design, which provides one advanced thought in decision-making. Specifically, the transportation time, the transportation price, the arrival time of ships, and the company reputation should be considered when designing liner shipping schedules. These findings can provide the decision reference for the shipper's selection behavior analysis, and help to improve shipper satisfaction with container liner shipping transportation. (iii) According to the sensitivity analysis on the shipper utility coefficient, it can be inferred that: the planned ship speed should be increased for time-preference shippers with electronic or refrigerated products, while it should be decreased for price-preference shippers with general or bulk cargoes. These conclusions can provide decision support for the operation practice of schedule design.

There are some works we will investigate in the future: (i) The shipper utility is influenced by the port rotation, the transportation price, and the transportation time. The first two factors are known parameters in the liner shipping schedule optimization problem, so it is difficult to comprehensively analyze shippers' route selection behavior. In the future, we will address the joint optimization for schedule plans, route design, and pricing problems, and carry out optimization decisions and impact analyses on the port rotation, transportation price, and transportation time. (ii) Previous schedule optimization researches focus on the single liner shipping route, but they ignore the influence of other routes on liner shipping schedules. When one pair of ports are called by multi-routes, the liner shipping schedules of different routes should not be concentrated in the same period, otherwise, it will lead to longer time interval. In the future, we will study the liner shipping schedule optimization problem in the whole route network, by referring to the findings of passenger transfer behavior in highway research and railroad research.

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