Abstract: In the post-pandemic era, the complexity of the international shipping situation, such as environmental policies, port congestion, and local conflicts, poses challenges to the stability of liner shipping, which requires strict adherence to schedules. This paper addressed the issue of schedule recovery for liner ships operating under Emission Control Areas (ECAs) regulations in the face of disruptive events. It established a bi-objective nonlinear programming model based on recovery costs and delay severity and designed a bi-objective particle swarm optimization algorithm based on two traversals of voyage leg path selection and port skipping decisions of feasible solutions to solve it. The effectiveness of the algorithm was validated through a case study of a 6000 TEU liner ship, summarizing the correlation laws of operational decisions such as port skipping, voyage leg path selection, and speed adjustment, and proposing the optimal recovery strategy for liner ships under long-term ECA constraints while ensuring short-term schedule resilience. The findings demonstrate that, in compliance with emission restrictions, ships operating within ECA are required to slow down to mitigate costs. In contrast, ships operating outside of ECA regions must accelerate their pace to adhere to established shipping schedules.

Keywords: schedule recovery; ECA regulations; disruptive events; liner shipping; bi-objective programming

1. Introduction

Maritime shipping stands as the predominant mode of transportation, encompassing approximately 90% of global trade freight volume [1]. In the post-pandemic epoch, there has been a discernible augmentation in the capacity of the global commercial fleet [2]. Notably, the exigencies of liner services, integral to containerized transport, necessitate stringent adherence to scheduling stability [3]. Incidences of disruption during transit, exemplified by the Suez Canal blockade incident involving the ship “Ever Given” in March 2021, or the temporary cessation or impaired functionality of ports due to localized conflicts, natural calamities, or unforeseen events, compel numerous liner ships to recalibrate their predetermined routes. Consequently, liner companies may opt to circumvent inaccessible ports, thereby ensuring the timely delivery or reception of the bulk of cargo at alternative ports [4]. This strategic maneuver not only safeguards the interests of clients but also upholds corporate reputation to the maximum extent possible.

Simultaneously, within the framework of global warming, transportation serves as a critical component of the green supply chain [5]. Liner companies engaged in maritime transportation are actively undergoing a transition to comply with the regulations set forth by the Emission Control Areas (ECA) for ships operating under the International Maritime Organization (IMO) [6]. Liner ships have recourse to various measures such as transitioning between marine gas oil (MGO) or heavy fuel oil (HFO), installing scrubbers, or opting for full-scale liquefied natural gas (LNG) conversion [7]. Presently, approximately half of...
the operational liner ship fleet persists in utilizing the MGO/HFO fuel interchange [8]. Ships employing these measures typically navigate through ECAs by strategically selecting optimal routes and modulating speeds both within and beyond ECAs. This presents liner companies with a protracted operational planning conundrum. In the face of the current intricate and volatile international maritime milieu, liner companies are unavoidably confronted with transient disruptions stemming from unforeseen events [9]. Thus, the expeditious formulation of efficacious strategies to ensure the resilience of liner transportation assumes paramount significance.

Based on the preceding analysis, it can be inferred that the issue of schedule recovery in liner transportation when faced with disruptive events under compliance with ECA regulations constitutes an operational decision-making process. It involves integrated optimization concerning whether liner ships should “skip ports” and how to select routes and set flexible speeds within ECAs. Diverging from prior research, this paper contributes in the following ways: (1) A model is established encompassing bi-objective programming concerning both schedule recovery costs and schedule recovery time, incorporating constraints related to time, port skipping, routing path, and speed. (2) Decision sets regarding port skipping, voyage leg path selection, and speed adjustment are nested and traversed using coded algorithms, leading to the design of a bi-objective particle swarm optimization algorithm for solving the established model. (3) By utilizing an example of a 6000 TEU liner ship, the paper proposes optimal recovery strategies for liner ship operations under the constraints of long-term compliance with ECA regulations and the assurance of short-term schedule recovery.

The remainder of the paper is structured as follows: Section 2 provides a comprehensive review of the current research on liner shipping schedule recovery and liner ship operations in compliance with ECA regulations. Section 3 formulates the bi-objective minimization model addressing both total cost and delay degree. Section 4 details the encoding of the primary logical decisions within the ship scheduling recovery model and outlines the procedural steps of the bi-objective particle swarm optimization algorithm. Section 5 presents a case study designed to evaluate various scenarios, comparing the effects of initial delay durations and port skipping penalties on the outcomes of schedule recovery, followed by an analysis and synthesis of the results. Finally, Section 6 offers concluding remarks, proposes relevant management insights for the operation and administration of liner shipping companies and suggests promising avenues for future research on schedule recovery challenges.

2. Literature Review

Liner shipping management decisions primarily encompass three levels: strategic [10], tactical [11], and operational [12]. From the financial crisis of 2008 to the implementation of ECA regulations by IMO until 2015, and more recently, the impact of events such as the COVID-19 pandemic, the Russia–Ukraine conflict, and incidents in the Red Sea on the global trade system, many scholars have focused on the management issues of liner ship services based on these pivotal decisions. This section will specifically delineate the relationship between our work and the following research domains: (1) schedule recovery in liner shipping; and (2) liner ship operations under ECA regulations.

2.1. Schedule Recovery in Liner Shipping

Notteboom [13] proposed that port congestion and stoppages are the primary reasons for the unreliability of liner services. Svanberg et al. [14] evaluated the impact of disruptive events at the Port of Gothenburg from 2016 to 2017, revealing a significant decline in container throughput and ship calls in the subsequent years. Thus, it can be observed that disruptive events at ports have a considerable impact on the profitability and efficiency of liner ship operations, constituting a factor in liner transportation that cannot be overlooked [15].
Hu et al. [16] reviewed and summarized the application of disturbance management in various studies such as shipping and land transportation, suggesting that disturbance management requires systematic theoretical frameworks and efficient solution algorithms. Following the outbreak of the COVID-19 pandemic, there has been an increasing number of studies focusing on disruptions caused by port incidents affecting liner transportation. Notteboom et al. [17] compared the container port and liner transportation supply and demand during the 2020 COVID-19 outbreak with those during the 2008–2009 financial crisis, analyzing the impact of service interruptions at major ports worldwide on the global supply chain. Huang et al. [18] explored the influence of port congestion on the shipping network design in the post-COVID-19 era. Wan et al. [19] evaluated the effectiveness of different recovery strategies adopted by liner transportation in response to port service interruptions. The results indicate that decision-makers would choose different recovery strategies based on demand requirements.

In the field of schedule recovery, Bruer et al. [20] provided a pioneering definition of the problem, employing a two-dimensional spatiotemporal graph to map the sailing conditions of liner ships and establish a schedule recovery model. Subsequently, an increasing number of scholars have begun researching this niche area of schedule recovery. However, the literature volume remains relatively limited.

Lee et al. [21] proposed a model that considers delivery reliability, utilizing a Markov chain to predict delay times. The results emphasized that delays might necessitate increasing sailing speed to recover the schedule. Li et al. [22] categorized the uncertainties in liner transportation into regular and exceptional uncertainties, analyzing them using probability models and multi-stage stochastic control, respectively. This approach aimed to dynamically adjust recovery strategies in real-time to minimize costs and delays.

Xing and Wang [23] proposed a weighted optimization model considering service standards and recovery costs. Abioye et al. [15] considered strategies such as speed adjustment, loading and unloading rate adjustments, and port skipping decisions, establishing a schedule recovery model aimed at minimizing profit loss. Li et al. [24] studied disruptive events with advanced information availability, demonstrating that this strategy could save 17.33% of the costs in liner transportation.

2.2. Liner Ship Operations under ECA Regulations

Detailed information regarding routes and schedules related to liner ship operations is typically released in advance by liner companies. For liner ship operations, considerations include cargo booking, cargo routing, and schedule recovery issues arising from disruptive events such as port congestion, adverse weather conditions, ship breakdowns, etc. [3]. In response to ECA regulations, some studies have analyzed technical aspects such as ship fuel switching between MGO/HFO, installation of scrubbers, and adoption of LNG dual-fuel engines (Abadi and Goicoechea [25]; Fan et al. [26]; Zhao et al. [27]). For liner ships employing MGO/HFO fuel switching, the focus primarily lies on decision-making regarding fleet renewal, ship deployment, voyage leg path selection, and speed adjustment (Dulebenets [28]; Theocharis et al. [29]; Li et al. [30]).

Zhao et al. [31] integrated three technologies including fuel conversion, scrubbers, and LNG dual-fuel engines to make decisions regarding ship acquisition, retrofitting, sale/lease, deployment, and speed adjustment to address uncertainties in future transportation markets and ECA regulations. Yang and Zou [32] established an economic environmental benefit model for the annual deployment of liner ships, comparing the differences between complying with ECA regulations through MGO/HFO fuel switching and alternative fuel schemes such as LNG/methanol. Tan et al. [33] conducted simulations on ship voyage leg path selection compliance with different ECA regulations using Automatic Identification System (AIS) data, analyzing the cost-effectiveness of different operational strategies. Fagerholt and Psaraftis [34] studied the operational strategies of ships employing MGO/HFO fuel switching before and after entering ECAs, optimizing ship speeds within and outside ECAs, and crossing paths of ECA boundaries to increase daily profits.
Table 1 compares and summarizes the similarities and differences between this study and relevant literature in terms of ECA regulations, schedule recovery, port skipping, voyage leg path selection, speed adjustment, model types, etc. The research finds that there are relatively few studies that simultaneously consider both ECA regulations and schedule recovery. Therefore, further research is necessary to investigate operational strategies under the influence of these two factors.

Table 1. Summary of this study compared with the related literature.

<table>
<thead>
<tr>
<th>Author</th>
<th>ECA Regulations</th>
<th>Schedule Recovery</th>
<th>Port Skipping</th>
<th>Voyage Leg Path Selection</th>
<th>Speed Adjustment</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chen et al. [35]</td>
<td>✓</td>
<td>X</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>Discrete Choice Model (DCM)</td>
</tr>
<tr>
<td>Zhen et al. [36]</td>
<td>✓</td>
<td>X</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>Mixed Integer Programming</td>
</tr>
<tr>
<td>Zhao et al. [31]</td>
<td>✓</td>
<td>X</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>Bi-objective Programming</td>
</tr>
<tr>
<td>Zhen et al. [37]</td>
<td>✓</td>
<td>X</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>Bi-objective Mixed Integer Programming</td>
</tr>
<tr>
<td>Abioye et al. [15]</td>
<td>✘</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>Mixed Integer Nonlinear Programming</td>
</tr>
<tr>
<td>Wen et al. [38]</td>
<td>✓</td>
<td>X</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>Bi-objective Fuzzy Programming</td>
</tr>
<tr>
<td>Li et al. [24]</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>Mixed Integer Programming</td>
</tr>
<tr>
<td>Elmi et al. [39]</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>Multi-objective Programming</td>
</tr>
<tr>
<td>This paper</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>Bi-objective Programming</td>
</tr>
</tbody>
</table>

Note: “✓” represents that this study is included in the literature; “✗” represents that this study is not included in the literature.

By synthesizing the classification and focal points of current research on liner transportation optimization under ECA regulations, it is evident that, in recent years, an increasing number of studies have begun to integrate ECA constraints into problem descriptions and mathematical models. However, there is a notable paucity of research addressing ECA considerations at the operational level, indicating significant potential for exploring schedule recovery problems in conjunction with ECA regulations. Consequently, this paper incorporates ECA rules into the schedule recovery problem, considering scenarios where the liner utilizes clean fuel oil within the ECA and permits the ship to adjust its speed to manage fuel costs both inside and outside the ECA within the same voyage leg.

3. Problem Description and Modeling

3.1. Problem Description

This study focuses on the voyage process of a single ship in liner transportation, which operates on a multi-port calling route. When facing schedule delays caused by unforeseen events, the ship will take a series of actions such as port skipping, speed adjustment, and voyage leg path selection to recover the schedule. Firstly, the concepts related to liner transportation routes, port skipping operations, voyage leg path selection, and sailing time distribution are defined. Based on this foundation, the problem of schedule recovery in liner transportation, which complies with the ECA regulations, is described. This problem falls into the realm of operational optimization.

3.1.1. Liner Transportation Routes

The type of route in this study is a multi-port calling route, where the ship follows a predetermined sequence and schedule of ports as listed in the sailing schedule and visits each port exactly once. Some ports along the route are located within the ECA designated by the IMO, as indicated by the circled areas in Figure 1. The figure depicts a multi-port calling route consisting of six ports, with the liner transportation service involving the ship sequentially calling at these six ports along the direction indicated by the arrows.
The journey of the ship between two adjacent ports along the route is referred to as a voyage leg. In Figure 1, the route consists of six voyage legs, with the last voyage leg representing the ship’s journey to a virtual port. During the service, the ship maintains a constant speed on each voyage leg, but the speed may vary between different voyage legs. In other words, the speed of each voyage leg is independent of the speeds of other voyage legs.

3.1.2. Port Skipping Operations

Liner transportation operates with a strong degree of regularity, where ships typically follow a predetermined sailing schedule and visit each port along the planned route. However, in cases of schedule delays caused by special events in specific areas or severe port congestion, ships may consider temporarily skipping a port on subsequent voyage legs to recover the schedule. For example, if a ship decides to skip the port, it will proceed directly from port $i-1$ to port $i+1$, as illustrated in Figure 2. In the figure, dashed nodes represent ports that are skipped, resulting in the cancellation of the corresponding voyage legs before and after. Additionally, a new voyage leg is added from the port $i-1$ to the port $i+1$.

During this process, the cargo originally scheduled for loading or unloading at port $i$ will be affected. Since the ship canceled its plan to call at port $i$, these cargoes need to be handled at other ports to mitigate the impact. In the industry, a common approach for handling cargoes affected by temporary port skips is known as “unload before loading”. This means that the cargo originally intended for unloading at port $i$ will be unloaded in advance at port $i-1$, awaiting transportation by the next ship or alternative mode. Similarly, cargoes intended for loading at port $i$ will be held at port $i$, awaiting loading onto the next scheduled ship. As shown in Figure 2, red-colored cargoes represent those

Figure 1. Schematic diagram of liner shipping routes.

Figure 2. Schematic diagram of skip port operation.
originally intended for unloading at port $i$, while green-colored cargoes represent those originally intended for loading at port $i$. The “unload before loading” operation requires considering the costs associated with temporary storage and subsequent transportation of these cargoes detained at two ports. Currently, with the frequent occurrence of global port congestion, many international ports have begun imposing higher demurrage fees on cargoes detained at their facilities.

3.1.3. Voyage Leg Path Selection

Without considering emission restrictions, ships typically choose the shortest sailing route to save operational time and fuel consumption. However, when the sailing route passes through an ECA, ships need to consider whether to detour around the ECA because entering or leaving the ECA boundary requires fuel switching. Sometimes ships opt for sailing perpendicular to the ECA boundary, i.e., departing from or entering the ECA at the shortest distance. When both the departure and arrival ports of a voyage leg are located within the ECA, ships may also choose to first sail out of the ECA, navigate outside the ECA to near the destination port, and then enter the ECA boundary perpendicular to it for port call.

Therefore, the selection of voyage leg paths for ships can be classified into four categories based on whether the departure and arrival ports of the leg are within the ECA. Both ports at the ends of the voyage leg are within the ECA, but the distance between them is considerable, with a significant portion of the voyage leg’s route lying outside the ECA, as shown in Figure 3a. Both ports at the ends of the voyage leg are within the ECA, and the distance between them is relatively short, with the direct sailing path entirely within the ECA, as shown in Figure 3b. The departure and arrival ports at the ends of the voyage leg are located in and out of the ECA, respectively, as shown in Figure 3c. Both ports at the ends of the voyage leg are outside the ECA, as shown in Figure 3d. In the first three cases, ships need to select the sailing route and adjust the speeds within the ECA and non-ECA portions of the voyage leg when passing through the ECA.

![Figure 3. Schematic diagram of voyage leg path selection (a–d).](image)

3.1.4. Sailing Time Distribution

During the sailing of a ship in any given voyage leg, besides the time spent at sea, there are also durations associated with port operations, including loading and unloading times at ports, as well as waiting times in queues. To facilitate the description of the problem, we divide the total time required for a ship to complete a voyage into four components: time spent navigating within an ECA, time spent navigating outside an ECA, queue time at ports, and loading/unloading time at ports.

The time spent navigating within and outside an ECA refers to the duration a ship spends at sea within or outside designated ECA zones, respectively. Queue time at ports indicates the duration ships need to wait in the vicinity of a port due to a high number of ships docking within a short period or due to low loading/unloading efficiency at the port. Port loading/unloading time refers to the duration ships spend on cargo loading
and unloading operations when docked at a port. The relationship among these four components is illustrated in Figure 4. After completing loading and unloading operations at port \( i = 1 \), the ship proceeds towards port \( i \). In this voyage leg, there are both ECA and non-ECA routes. Upon nearing port \( i \), the ship may need to queue before docking for cargo operations.

![Figure 4. The sailing time distribution of a ship in a voyage leg.](image)

Below, we provide definitions and descriptions of the diverse parameters and variables encompassed in this issue, utilizing the appropriate mathematical symbols.

In liner shipping, ships are required to execute tasks along predetermined routes according to scheduled ship arrivals. Along these routes, there exists a set of port collections \( N \), where ships are sequentially required to call at ports \( 1, 2, \ldots, n \). The sailing schedule includes the scheduled arrival times \( T_{i}^{\text{Arrive}} \) of ships at each port. In the event of tardiness, late penalties \( C_{i}^{\text{Late}} \) will be incurred. During sailing, ships must engage in cargo loading and unloading operations between different ports. Therefore, there exists a cargo loading and unloading matrix, denoted as \( PD \), which describes the cargo handling relationships between each pair of ports. Additionally, ships must switch between fuels to ensure compliance along the route, with MGO being required within ECAs and VLSFO being permissible outside ECAs. The prices of these two fuels are represented as \( P_{\text{MGO}} \) and \( P_{\text{VLSFO}} \). The approximate power-law relationship between fuel consumption rate and ship speed has been adjusted by numerous experiments. We adopt the expression \( F(v) = F(v_0)(v/v_0)^\theta \) for the fuel consumption rate as a function of speed \( v \) proposed by Brouer et al. [40], where \( F(v_0) \) represents the fuel consumption rate at the ship at the design speed \( v_0 \). In this paper, we set the power exponent \( \theta = 3 \).

On each voyage leg, there exists a set of sailing paths denoted as \( M \). Based on the distribution of ECAs at the terminals of the voyage leg, ships determine their sailing path from paths \( 1, 2, \ldots, m \). In other words, when the ship selects sailing path \( j \) on voyage leg \( i \), \( z_{ij} \) is set to 1. Additionally, it is necessary to determine the ship’s sailing speeds inside \( v_{ij}^{\text{ECA}} \) and outside \( v_{ij}^{\text{NECA}} \) the ECA. The total sailing time of the ship on voyage leg \( i \) along path \( j \) is divided into four parts: the sailing time inside and outside the ECA, denoted as \( L_{ij}^{\text{ECA}}/v_{ij}^{\text{ECA}} \) and \( L_{ij}^{\text{NECA}}/v_{ij}^{\text{NECA}} \), respectively, the queue time at the port \( T_{i}^{\text{Wait}} \), and the loading/unloading time at the port \( T_{i}^{\text{Load}} \).

Due to some uncontrollable factors, the ship departed from the departure port of voyage leg \( i \) later than the scheduled time by \( \xi \) hours. This will require the ship to make efforts to regain lost time during subsequent voyages to restore the sailing schedule and avoid the amplification of delays. Therefore, the ship can adopt the following strategies to recover the sailing schedule: skip one of the subsequent ports or increase the sailing speed on voyage leg \( i \). Among these, the decision variable \( y_{i} \) for skipping a port is a binary variable \( (0,1) \), where \( y_{i} \) takes the value of 0 if port \( i \) is skipped, otherwise it is 1.

For each port, the port usage fee at port \( i \) is \( C_{i}^{\text{Port}} \), the cost of skipping port \( i \) is \( C_{i}^{\text{Skip}} \), and the unit cargo loading/unloading cost at port \( i \) is \( C_{i}^{\text{Load}} \). If the ship chooses to skip port \( i \), and the cargo originally scheduled for loading/unloading at port \( i \) cannot be transported as planned, then at port \( i - 1 \), the cargo that should have been unloaded at port \( i \) needs to be unloaded, incurring cargo loading/unloading costs and demurrage fees. The unit cargo...
demurrage fee at port \(i - 1\) is \(c_{i-1}^{\text{Demurrage}}\). Since no cargo is loaded at port \(i\), a penalty fee is charged. The penalty fee for uncollected cargo at port \(i\) is \(c_i^{\text{Penalty}}\). The penalty fee refers to the demurrancy charge of the container waiting at the port for one week.

Therefore, when a ship encounters uncontrollable delays in its sailing schedule, the required course of action includes determining whether the ship should skip a port and if so, which port to skip. Additionally, the ship needs to adjust its sailing path and speed for subsequent voyage legs.

3.2. Modeling

To comprehensively quantify the potential impacts of sailing schedule recovery, this model sets bi-objective functions: one for recovery costs and another based on the degree of time-based delay.

\[
\begin{align*}
\min \quad & \left[ p_{\text{MGO}} \sum_{i \in N} \sum_{j \in M} F(v_0) \left( \frac{c_{ij}^{\text{ECA}}}{v_0} \right)^{t_{ij}^{\text{ECA}}} + p_{\text{VLSFO}} \sum_{i \in N} \sum_{j \in M} F(v_0) \left( \frac{c_{ij}^{\text{NECA}}}{v_0} \right)^{t_{ij}^{\text{NECA}}} \right] z_{ij} \\
& + \text{COPEX}_v + \text{COPEX}_y \sum_{i \in N} \sum_{j \in M} \left( \frac{c_{ij}^{\text{ECA}}}{v_{ij}} + \frac{c_{ij}^{\text{NECA}}}{v_{ij}} \right) z_{ij} + \text{COPEX} \left( t_{i}^{\text{Wait}} + t_{i}^{\text{Load}} \right) y_i \\
& + c_{\text{Port}} y_i + \sum_{i \in N} c_{\text{Load}} \left( Q_i^+ + Q_i^- \right) y_i + \sum_{i \in N} c_{\text{Late}} \left( t_{i}^{\text{Arrive}} - t_{i}^{\text{Arrive}} \right) y_i \\
& + \left[ \left( c_{\text{Demurrage}} + c_{\text{Load}} \right) Q_i + c_{\text{Penalty}} Q_i^+ \right] (1 - y_i) + \sum_{i \in N} c_{\text{Skip}} (1 - y_i)
\end{align*}
\]

\[
\min \frac{\sum_{i \in N} \left( Q_i^+ + Q_i^- \right) \left( t_{i}^{\text{Arrive}} - t_{i}^{\text{Arrive}} \right)}{\sum_{i \in N} \left( Q_i^+ + Q_i^- \right)}
\]

Subject to

\[
t_{i}^{\text{Arrive}} = t_{i-1}^{\text{Arrive}} + t_{i-1}^{\text{Load}} + \sum_{j \in M} \left( \frac{c_{ij}^{\text{ECA}}}{v_{ij}} + \frac{c_{ij}^{\text{NECA}}}{v_{ij}} \right) z_{ij} + t_{i}^{\text{Wait}}, \quad \forall i \in N
\]

\[
0 \leq \sum_{i \in N} y_i \leq n - 2,
\]

\[
\sum_{j \in N} z_{ij} = 1, \quad \forall i \in N,
\]

\[
v_{ij}^{\text{Min}} \leq v_{ij}^{\text{NECA}} \leq v_{ij}^{\text{Max}}, \quad \forall i \in N, \forall j \in M
\]

\[
v_{ij}^{\text{Min}} \leq v_{ij}^{\text{ECA}} \leq v_{ij}^{\text{Max}}, \quad \forall i \in N, \forall j \in M
\]

\[
y_i, z_{ij} \in \{0,1\}.
\]

The objective Function (1) minimizes the sailing schedule recovery cost, which encompasses the ship’s fuel consumption cost, operational cost (time-dependent, with an hourly operational fee \(\text{COPEX}\)), port fees, cargo loading/unloading costs, late penalty costs, and skip port costs. The objective Function (2) minimizes the time-based delay severity, representing the weighted sum of delay severity at each port along the route. Although the delay time varies at each port, it does not fully represent the delay severity. Therefore, weights are assigned to each port based on cargo volume to measure the overall delay severity. According to the sequence of port calls, there exists a constraint (3) relating the arrival times at adjacent ports, where the arrival time at port \(i\) equals the arrival time at port \(i - 1\) plus the loading/unloading time at port \(i - 1\), the sailing time within and outside the ECA between the two ports, and the queue time at port \(i\). The skip port operation must adhere to constraint (4), which imposes restrictions on the number of times a ship can skip ports along the route, with the starting and ending ports not allowed to be skipped.
Constraint (5) indicates that only one sailing path can be chosen among the \( j \) paths in each voyage leg \( i \). Constraints (6) to (8) define the domain of decision variables.

4. Solution Algorithm

The model (1)–(8) constitutes a bi-objective nonlinear programming problem, and its decision variables cannot be directly solved using existing commercial solvers. Therefore, this paper first obtains feasible solutions through traversing based on voyage leg path decisions and port skipping decisions. Then, a bi-objective particle swarm optimization algorithm is employed to solve the model and obtain the Pareto optimal frontier. The bi-objective particle swarm optimization algorithm designed is programmed using MATLAB R2022a.

4.1. The Solution to the Voyage Leg Path Decision

For a liner shipping route with six ports, there are five voyage legs to analyze. If four of these ports are within an ECA, each voyage leg will contain sailing paths with ECA restrictions at one or both ends. As shown in Figure 5, there are various sailing paths available for the voyage legs connecting the ports. For instance, there are two sailing paths from the first port to the second port, two paths from the second port to the third port, and so on. Considering all possible combinations of sailing paths along this route, there are a total of 32 options.

![Figure 5. The optional voyage leg paths of a ship.](image)

Each voyage leg’s different sailing paths have varying distances within and outside the ECA, resulting in differences in costs and time. Therefore, we created a matrix representing the sailing path collection, allowing for the traversal of each sailing path through matrix data. Storing the data in matrix form enables handling large-scale problems and solving situations where multiple paths exist on each voyage leg. Table 2 presents the nested traversal code steps for voyage leg path selection.

<table>
<thead>
<tr>
<th>Nested Traversal for Voyage Leg Path Decision.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1: Create the sailing path distance matrix PD to store all path distance data for ( n ) voyage legs.</td>
</tr>
<tr>
<td>Step 2: Use nested loops to traverse all paths for each voyage leg. Traverse and select each path for voyage leg 1, selecting the corresponding row and column data in the matrix PD.</td>
</tr>
<tr>
<td>Traverse and select each path for voyage leg 2, selecting the corresponding row and column data in the matrix PD.</td>
</tr>
<tr>
<td>Traverse and select each path for voyage leg ( n ), selecting the corresponding row and column data in the matrix PD.</td>
</tr>
<tr>
<td>Step 3: Use the traversed sailing path schemes as inputs for traversing port skipping operations.</td>
</tr>
</tbody>
</table>

4.2. The Solution to the Port Skipping Decision

After nested traversal of all possible sailing path schemes, we proceed to traverse all port skipping operations that the ship may undertake based on each feasible combination of sailing paths. Here, it is possible to limit the number of port-skipping occurrences. In reality, if a ship experiences excessive delays during a single voyage along the entire route,
the shipping company may consider canceling service on that route. Table 3 presents the Nested traversal steps of port skipping decision.

Table 3. Nested traversal steps of port skipping decision.

<table>
<thead>
<tr>
<th>Nested Traversal of Port Skipping Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1: Take a feasible scheme selected through nested traversal of sailing paths as input.</td>
</tr>
<tr>
<td>Step 2: Traverse each intermediate port to skip along the route (excluding the starting port 1 and the ending port n).</td>
</tr>
<tr>
<td>Skip the port 2</td>
</tr>
<tr>
<td>Skip the port 3</td>
</tr>
<tr>
<td>...</td>
</tr>
<tr>
<td>Skip the port n – 1</td>
</tr>
<tr>
<td>Step 3: Use nested for loops to traverse all feasible combinations of sailing paths as feasible solutions to calculate the objective function values.</td>
</tr>
</tbody>
</table>

4.3. Bi-Objective Particle Swarm Optimization Algorithm

After the two-level traversal of voyage leg path decisions and port skipping decisions, all feasible solutions of the model are preliminarily generated. By substituting these feasible solutions into objective Functions (1) and (2), the recovery costs and delay severity corresponding to all feasible solutions can be determined.

Using a bi-objective particle swarm optimization algorithm, it is possible to move the particle swarm towards the Pareto frontier direction in a two-dimensional bi-objective coordinate system in each iteration. Eventually, after completing the iteration cycles, the latest non-dominated solution set forms the Pareto optimal solution set.

The following are the steps of the bi-objective particle swarm optimization algorithm iteration process:

Step 1: Randomly generate an initial particle swarm and calculate the fitness values corresponding to the particle positions. Use the initial positions of each particle as the initial individual best positions \( p_{best} \).

Step 2: Find the global best position. Compare and select non-dominated solutions from the initial particle swarm and store them in a \( rep \) set as the initial \( rep \) set. The selection of non-dominated solutions in the \( rep \) set uses the \( \text{DetermineDomination} \) function. When both fitness values of particle A are better than those of particle B, particle A is said to dominate particle B. After the comparison of the initial particle swarm is completed, the non-dominated solutions are stored in the \( rep \) set.

Step 3: Based on the original positions of particles, use learning factors to guide particles to learn individual and global best positions, enabling the particle swarm to iterate toward better directions. Update the positions of all particles. The formula for particle movement speed is the same as that in the single-objective particle swarm algorithm.

Step 4: Calculate new fitness values based on the new positions of the particle swarm. Determine individual best positions and update the \( rep \) set. Select new global best positions \( g_{best} \) as the reference for the next iteration.

Step 5: Check if the current \( rep \) set is full. If it is full, divide the solutions within the grid of the adaptive grid into grids and select the grid with the highest density. Remove one solution from that grid and add a new non-dominated solution.

Step 6: Check if the iteration limit has been reached. If not, return to step 2 to start a new iteration. Repeat this process until the iteration limit is reached. Finally, output the particle iteration trajectory and the Pareto optimal solution set.

5. Case Study

This paper selects a 6000 TEU liner ship operated by COSCO on the Far East–Northwest Europe route as the research subject. The ship departs from Shanghai Port and sequentially calls at the ports of Ningbo, Xiamen, Yantian, Singapore, and Felixstowe. A complete
voyage takes 33 days. The parameters related to port operations and container terminal handling are detailed in Tables 4 and 5. This paper considers a scenario where the ship’s actual departure time from the initial port is delayed by 24 h due to unforeseen factors. The specific demurrage charges of the ports are listed in Table 6. The computational experiments were conducted on a computer running Windows 11 (64-bit) with a 12th Gen Intel(R) Core (TM) i7-12700H 2.30 GHz processor (Intel, Santa Clara, CA, USA). It takes 320 s to run the optimization software for a typical case.

Table 4. Relevant parameters of port operation.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECA fuel price (MGO) [a]</td>
<td>1280</td>
<td>USD/ton</td>
</tr>
<tr>
<td>Non-ECA fuel price [a]</td>
<td>700</td>
<td>USD/ton</td>
</tr>
<tr>
<td>Ship rental fee [a]</td>
<td>35,500</td>
<td>USD/day</td>
</tr>
<tr>
<td>Port loading fee [b]</td>
<td>42</td>
<td>USD/20 TEU</td>
</tr>
<tr>
<td>Port unloading fee [b]</td>
<td>42</td>
<td>USD/20 TEU</td>
</tr>
<tr>
<td>Port waiting fee per week [c]</td>
<td>250–300</td>
<td>USD/20 TEU</td>
</tr>
<tr>
<td>Pilotage and port fees [b]</td>
<td>2250</td>
<td>USD</td>
</tr>
<tr>
<td>Initial delay parameter</td>
<td>24</td>
<td>Hour</td>
</tr>
<tr>
<td>Speed range parameter [a]</td>
<td>15–25</td>
<td>Knots</td>
</tr>
<tr>
<td>Port late penalties [24]</td>
<td>300–500</td>
<td>USD/hour</td>
</tr>
</tbody>
</table>

Note: (1) 1 knot = 1 NM (nautical mile) per hour; (2) fuel consumption rate per hour = 0.012 × v^3/24, where v is the speed in knots, unit: tons/NM (nautical mile). Data Source: authors’ compilation based on date [a] https://www.clarksons.net/n/#/portal, accessed on 3 June 2023; [b] http://studyofnet.com/710550253.html, accessed on 8 June 2023; [c] https://www.jd-link.com/articles/encyclopedias/834, accessed on 21 June 2023.

Table 5. Container terminal handling charges.

<table>
<thead>
<tr>
<th>Ports</th>
<th>Container Types</th>
<th>20 TEU</th>
<th>40 TEU</th>
<th>45 TEU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shanghai</td>
<td>Dry Cargo Container</td>
<td>76</td>
<td>116</td>
<td>143</td>
</tr>
<tr>
<td></td>
<td>Dangerous Goods Container</td>
<td>98</td>
<td>152</td>
<td>186</td>
</tr>
<tr>
<td></td>
<td>Refrigerated Container</td>
<td>113</td>
<td>173</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dry Cargo Container</td>
<td>77</td>
<td>120</td>
<td>174</td>
</tr>
<tr>
<td>Ningbo</td>
<td>Dangerous Goods Container</td>
<td>145</td>
<td>225</td>
<td>331</td>
</tr>
<tr>
<td></td>
<td>Refrigerated Container</td>
<td>114</td>
<td>187</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dry Cargo Container</td>
<td>109</td>
<td>170</td>
<td>221</td>
</tr>
<tr>
<td>Guangdong</td>
<td>Dangerous Goods Container</td>
<td>148</td>
<td>257</td>
<td>325</td>
</tr>
<tr>
<td></td>
<td>Refrigerated Container</td>
<td>194</td>
<td>300</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dry Cargo Container</td>
<td>74</td>
<td>116</td>
<td>141</td>
</tr>
<tr>
<td>Fujian</td>
<td>Dangerous Goods Container</td>
<td>99</td>
<td>153</td>
<td>187</td>
</tr>
<tr>
<td></td>
<td>Refrigerated Container</td>
<td>81</td>
<td>125</td>
<td></td>
</tr>
</tbody>
</table>


Table 6. Demurrage charges of ports.

<table>
<thead>
<tr>
<th>Port</th>
<th>Average Demurrage Fee per Standard Container after a Week (USD/TEU)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Singapore</td>
<td>240</td>
</tr>
<tr>
<td>Cai Mep</td>
<td>240</td>
</tr>
<tr>
<td>Hongkong</td>
<td>350</td>
</tr>
<tr>
<td>Shekou</td>
<td>350</td>
</tr>
<tr>
<td>Ningbo</td>
<td>600</td>
</tr>
<tr>
<td>Shanghai</td>
<td>800</td>
</tr>
<tr>
<td>Busan</td>
<td>240</td>
</tr>
<tr>
<td>Panama Canal</td>
<td>240</td>
</tr>
</tbody>
</table>

Data Source: authors’ compilation based on date https://www.jd-link.com/articles/encyclopedias/834/, accessed on 15 June 2023.
5.1. Bi-Objective Function Value

The movement trajectories of the particles and the Pareto front during the algorithm’s iterations are shown in Figure 6. The black particles represent the particle iteration trajectory, while the red particles represent the final Pareto front. From the iterative trajectories of the particles, the bi-objective particle swarm optimization algorithm moves towards the origin, as both objectives, recovery cost, and delay degree, aim to be minimized. Additionally, the density of the particles’ trajectories increases as they approach the Pareto front, indicating that the direction of the particles’ iterations is correct. Therefore, the bi-objective particle swarm optimization algorithm demonstrates good performance and effectiveness in solving the research problem in this paper.

![Iterative trajectory diagram of particles. Note: The red circles refer to the final Pareto front optimal solution set.](image)

Through the designed solution algorithm, the latest non-dominated solution set, or Pareto front, was output. We found that due to capacity constraints, the number of solutions was limited. This is because when the capacity is exceeded, the rep set will evaluate and randomly delete the excess non-dominated solutions based on the solution density in the adaptive grid. However, in the resulting output, we aim to obtain the Pareto front from all iterations to obtain as many optimal solutions as possible. Therefore, after the solution algorithm completes its run, we add the frontier part that captures the optimal solutions to obtain the final Pareto front optimal solution set. As shown in Figure 6, the vertical axis represents the recovery cost, and the horizontal axis represents the delay degree, which refers to the average number of hours of delay per container. There are solutions in the Pareto front with a delay degree exceeding 24 h, whereas the initial delay time is 24 h. Hence, we eliminate the invalid solutions exceeding 24 h. There are 95 valid solutions with a delay degree within 24 h.

Table 7 lists the extreme values of the two objective functions among the 95 valid Pareto front solutions, which represent the value range of this set of Pareto solutions. From the perspective of the two objective function values, the extreme value difference in recovery cost in the Pareto front optimal solution set is USD 360,000, and the extreme value difference in delay degree is 16.23 h. This means that in this case, an increase of 10.75% in recovery cost can compensate for 67.63% of the delay degree.
Table 7. Extremum of Pareto frontier effective solution.

<table>
<thead>
<tr>
<th>Pareto Solution Number</th>
<th>Objective Function 1: Total Cost (Million USD)</th>
<th>Objective Function 2: Delay Degree (Hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.70</td>
<td>7.68</td>
</tr>
<tr>
<td>95</td>
<td>3.35</td>
<td>23.91</td>
</tr>
</tbody>
</table>

In this instance, the initial delay time is 24 h. From the perspective of the delay degree in the Pareto front optimal solution set, the 95 non-dominated solutions have reduced the delay duration to varying degrees, to some extent achieving the recovery of the shipping schedule. According to the segmented statistics of the delay degree, as shown in Figure 7, it can be observed that 50.5% of the non-dominated solutions have achieved a delay degree within 16 h, meaning they have reduced the delay by at least 8 h.

Figure 7. Distribution of the optimal solution set on the Pareto frontier.

5.2. Shipping Schedule Recovery Decision-Making

The decisions to be made for the 6000 TEU liner ship in this model include the voyage leg path, port skipping, and its speeds within and outside ECA waters. The Pareto front optimal solution set reveals some interesting patterns.

5.2.1. Speed Adjustment inside and outside ECA

According to the distribution of the Pareto front optimal solution set, five solutions are selected from the 95 non-dominated solutions, focusing on the perspectives of recovery cost and delay degree. Solutions 91–95 are the five solutions with the minimum recovery cost, while solutions 1–5 are the five solutions with the minimum delay degree. Table 8 lists the sailing speed results inside and outside ECA for these ten Pareto solutions.

Because all Pareto solutions choose route 2 for voyage leg 1, which is a straight path entirely within the ECA due to the short distance between the two ports, the sailing speed outside the ECA for voyage leg 1 is 0. Additionally, by observing the average sailing speeds inside and outside the ECA for the same voyage leg among these ten Pareto solutions, it is evident that the speed inside the ECA is lower than outside the ECA. This is caused by the more expensive fuel used within the ECA area. Therefore, reducing the speed inside the ECA can save fuel consumption costs.
To achieve the recovery of liner transportation schedules, besides increasing sailing speed, it is also possible to optimize the voyage leg paths and decide which ports to skip. To clarify whether the ship circumvented the ECA or chose to skip ports in these 10 Pareto solutions, we visualize the decisions regarding voyage leg paths and port skipping as shown in Figure 8.

![Route of the Pareto solution and decision results of port skipping](image)

**Figure 8.** Route of the Pareto solution and decision results of port skipping (a–c). Note: Numbers represent the visiting sequence of different ports.

In Figure 8, (a) represents Pareto Solution 1, (b) represents Pareto Solution 2, and (c) represents the voyage leg path selection and skipped ports for Pareto Solutions 3–5 and 91–95. By examining the results of recovery cost, delay degree, and skipped ports for these ten Pareto solutions from Table 9, although the voyage leg path selection and skipped ports are consistent for Pareto Solutions 3–5 and 91–95 in (c), they achieve a balance between recovery cost and delay degree by choosing a suitable sailing speed for their situation. Combining the sailing speed results inside and outside the ECA for all voyage legs in Table 8, we can deduce that when inclined to save recovery costs, the ship under Pareto Solutions 91–95 will reduce its speed, but this will increase the delay degree; similarly, when inclined to reduce the delay degree, the ship under Pareto Solutions 3–4 will increase its speed, but this will correspondingly increase the recovery cost. Further observation of (a) and (b) shows that the ships are striving to reduce the delay degree to the minimum to recover the shipping schedule. Under Pareto Solution 2, the ship in (b) reduces the delay duration by choosing a shorter straight path for voyage leg 2, while under Pareto Solution 1, the ship in (a) recovers the shipping schedule by skipping the port of Xiamen. Of course,
the increase in recovery cost due to port skipping is evident, but for adverse impacts highly focused on reducing the delay degree, such as losing customers, ships must choose this aggressive strategy.

Table 9. Port skipping decision results of Pareto solution.

<table>
<thead>
<tr>
<th>Pareto Solution Number</th>
<th>Delay Degree (Hours)</th>
<th>Recovery Cost (Million USD)</th>
<th>Skipped Ports</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7.68</td>
<td>3.71</td>
<td>Xiamen</td>
</tr>
<tr>
<td>2</td>
<td>7.82</td>
<td>3.61</td>
<td>No</td>
</tr>
<tr>
<td>3</td>
<td>8.36</td>
<td>3.60</td>
<td>No</td>
</tr>
<tr>
<td>4</td>
<td>8.51</td>
<td>3.58</td>
<td>No</td>
</tr>
<tr>
<td>5</td>
<td>8.57</td>
<td>3.57</td>
<td>No</td>
</tr>
<tr>
<td>91</td>
<td>23.45</td>
<td>3.35</td>
<td>No</td>
</tr>
<tr>
<td>92</td>
<td>23.56</td>
<td>3.35</td>
<td>No</td>
</tr>
<tr>
<td>93</td>
<td>23.68</td>
<td>3.35</td>
<td>No</td>
</tr>
<tr>
<td>94</td>
<td>23.91</td>
<td>3.35</td>
<td>No</td>
</tr>
<tr>
<td>95</td>
<td>23.91</td>
<td>3.35</td>
<td>No</td>
</tr>
</tbody>
</table>

5.3. Results Impact for Different Scenarios

The following is an expansion of possible scenarios in this case study, focusing on the impact of initial delay time and penalties for port skipping on the ship’s final decisions regarding shipping schedule recovery. It analyzes the corresponding effects on recovery costs and delay degrees.

5.3.1. Impact of Initial Delay Time

By setting three different initial delay times, analyze the ship’s recovery cost and recoverable delay degree for the remaining voyage needed for schedule recovery when facing delays of different durations. Keeping other parameters constant, the model’s initial delay time parameters are set to 12 h, 24 h, and 36 h, respectively. The Pareto front optimal solution sets for the three scenarios are shown in Figure 9, and the corresponding resulting data are shown in Table 10.

Figure 9. Pareto optimal solution under different initial delay times. Note: The red circled part is the solution for choosing to skip the port.
Combining Figure 9 and Table 10, two conclusions related to recovery cost can be drawn. Firstly, the recovery cost of the shipping schedule is positively correlated with the initial delay time. For scenarios requiring recovery to the same delay degree, the longer the initial delay time, the higher the recovery cost required. Secondly, from the left side of the Pareto front, it can be observed that there is a limit to the recovery of delay degree. This is related to the maximum sailing speed, the distribution of ECA along the route, and the distance of the voyage. After compensating for the delay degree to a certain extent, increasing the recovery cost further will not achieve better results.

Additionally, there is a certain pattern in the ship’s decision to skip ports. The red circles in Figure 9 represent solutions that choose to skip ports, while the other Pareto solutions do not. The tendency of ships to skip ports is positively correlated with the initial delay time. That is, the longer the initial delay time, the more likely the ship will choose to skip ports. When the initial delay time is short, ships mainly recover the shipping schedule through voyage leg path selection and increasing sailing speed, as the recovery cost of these conventional operational decisions is far lower than the penalty for skipping a port.

5.3.2. Impact of Port Skipping Penalty

Port skipping is a relatively rare occurrence in ship operations because it can lead to an implicit loss of goodwill and customer satisfaction and additional costs for handling the skipped cargo. We set three different penalties for port skipping. Keeping the initial delay time at 24 h and other parameters constant, the model’s penalty parameter for skipping a port is set to USD 140 per standard container, USD 175 per standard container, and USD 210 per standard container, respectively. The port-skipping operations in the Pareto front optimal solution sets for the three scenarios are shown in Figure 10.

Table 10. Recovery results of shipping schedules under different initial delay times.

<table>
<thead>
<tr>
<th>Initial Delay Time (Hours)</th>
<th>Delay Degree (Hours)</th>
<th>Recovery Cost (Million USD)</th>
<th>Number of Pareto Effective Solutions</th>
<th>Number of Solutions Port Skipping</th>
<th>Percentage of Solutions Port Skipping</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>3.06–11.92</td>
<td>3.36–3.49</td>
<td>42</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>24</td>
<td>7.68–23.91</td>
<td>3.35–3.71</td>
<td>95</td>
<td>1</td>
<td>1%</td>
</tr>
<tr>
<td>36</td>
<td>7.16–35.90</td>
<td>3.36–3.84</td>
<td>74</td>
<td>9</td>
<td>12%</td>
</tr>
</tbody>
</table>

Figure 10. Port skipping operation under different skip port penalties.

In Figure 10, the vertical axis represents the decision preference, with 0 indicating the decision to skip the port and 1 indicating the opposite. The Pareto solutions from left to right represent different decision preferences, with the leftmost solution having the smallest
delay degree and the rightmost solution having the lowest recovery cost. Combining
the shipping schedule recovery results under different penalties for port skipping from
Table 11, it can be observed that as the penalty for port skipping increases, the percentage
of solutions choosing to skip ports in the Pareto front optimal solution set decreases. When
the penalty for port skipping reaches a certain threshold, the increase in recovery cost
due to port skipping becomes significantly higher than the strategies of voyage leg path
selection and increasing sailing speed.

Table 11. The result of the recovery of shipment schedule under different port skipping penalties.

<table>
<thead>
<tr>
<th>Port skipping Penalty (USD per Standard Container)</th>
<th>Delay Degree (Hours)</th>
<th>Recovery Cost (Million USD)</th>
<th>Number of Pareto Effective Solutions</th>
<th>Number of Solutions Port Skipping</th>
<th>Percentage of Solutions Port Skipping</th>
</tr>
</thead>
<tbody>
<tr>
<td>140</td>
<td>7.16–23.94</td>
<td>3.40–3.49</td>
<td>47</td>
<td>41</td>
<td>87%</td>
</tr>
<tr>
<td>175</td>
<td>7.16–23.67</td>
<td>3.44–3.66</td>
<td>31</td>
<td>14</td>
<td>45%</td>
</tr>
<tr>
<td>210</td>
<td>7.68–23.91</td>
<td>3.35–3.71</td>
<td>95</td>
<td>1</td>
<td>1%</td>
</tr>
</tbody>
</table>

6. Conclusions

In recent years, changes in the international economic situation, coupled with the
imbalance in trade, and instability in certain regions, have created numerous uncertainties
for liner shipping. Disruptive events such as route deviations and port congestion occur
frequently, leading to varying degrees of delays in liner ship operations. Additionally, ships
are required to navigate through the ECA established by the IMO. This paper defines the
shipping schedule recovery problem for liner shipping to comply with ECA regulations.
To address this problem, a bi-objective nonlinear programming model based on recovery
cost and delay degree is established. A bi-objective particle swarm optimization algorithm
based on two traversals of voyage leg path selection and port skipping decision of feasible
solutions is designed to solve the model.

The case study of a 6000 TEU ship operated by COSCO on the Far East to Northwest
Europe route shows that: (1) A series of operations such as port skipping, speed adjustment,
and voyage leg path selection have an impact on shipping schedule recovery, achieving
results in terms of recovery cost and delay degree. However, the effectiveness depends
on the decision maker’s preferences. (2) Strategies such as voyage leg path selection and
increasing sailing speed are more common than port skipping unless the decision maker
places a high priority on recovering the schedule in terms of delay degree. (3) Factors
such as initial delay time and the port skipping penalty can influence shipping schedule
recovery strategies. Generally, when the initial delay time is longer and the penalty for port
skipping is lower, port skipping is more likely to be chosen as an option. (4) To recover
the shipping schedule, ships typically reduce their speed when passing through ECAs
compared to sailing outside ECAs. Additionally, they may choose direct routes to reduce
delay duration under disruptive events.

Based on our research findings, we offer the following suggestions for shipping
schedule recovery strategies: (1) When faced with delays of varying lengths, ships should
balance decision preferences based on the subsequent voyage tasks and quickly make
corresponding recovery strategies. Shipping companies need to determine whether they
prioritize schedule punctuality to avoid the risk of customer loss or focus on cost savings
for the current voyage. The decision maker’s preferences have a crucial impact on the
overall results, and the Pareto front optimal solution set calculated by our algorithm can
provide a comprehensive decision set for selection. (2) The optimal recovery strategy for
ships should be a combination of operations such as port skipping, speed adjustment,
and voyage leg path selection, rather than a binary decision. From the research results,
when delay duration is not critical, cost-effective strategies like increasing sailing speed
and choosing direct routes can be employed to recover the schedule, resulting in relatively
lower recovery costs. However, when delays are significant, ships need to skip ports
and combine this with strategies like speed adjustment, and voyage leg path selection to achieve schedule recovery. (3) Shipping companies should prepare contingency plans for unforeseen disruptive events and consider the recovery capability of the schedule when designing the shipping schedule. From the scenario analysis, delays caused by unforeseen disruptive events may not necessarily be fully recovered to the original level, as there is a limit to the degree of recovery. Ships cannot easily cancel port calls in actual operations, and the potential loss from port skipping is difficult to estimate. Therefore, in the face of significant schedule delays, it may be advisable to consider adding buffer time at the outset of schedule design to mitigate delay risks.

This paper examines the problem of ship schedule recovery in conjunction with ECA emission limits. The current model, however, exhibits certain limitations: Firstly, while the model incorporates port congestion waiting times, it does not employ a corresponding function to predict these congestion durations. Future research could enhance the model by integrating a congestion time prediction function within the port waiting time parameter or by leveraging shipping big data to estimate congestion times. Large-scale numerical simulations and realistic scenarios could then be employed to generate more precise results. Secondly, this study does not account for uncertainties encountered during actual navigation, such as fluctuations in transportation demand, adverse weather conditions, or varying emission reduction requirements. These uncertainties would further complicate the research problem, necessitating the development of specialized algorithms to address them. Additionally, future research could extend the ship schedule recovery problem in liner shipping to include disruptions affecting multi-route transportation networks. This would entail addressing large-scale challenges, which would require the design of targeted solution algorithms. The model proposed in this paper is a post-strategy approach; future research could enrich the methodologies for ship schedule recovery in liner shipping by developing pre-strategies and mid-strategies.

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