Optimization and Engineering
https://doi.org/10.1007/s11081-023-09803-1

RESEARCH ARTICLE

A unified operation decision model for dry bulk shipping fleet: ship scheduling, routing, and sailing speed optimization

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Received: 20 October 2022 / Revised: 10 March 2023 / Accepted: 13 April 2023

Abstract
Dry bulk shipping plays a crucial role in the global transportation of raw material across continents. As the primary player in the dry bulk shipping market, the dry bulk shipping company operates a fleet of vessels to generate revenue by meeting the transportation demands of shippers. The main challenge faced by dry bulk shipping companies is scheduling vessels, optimizing shipping routes, and determining sailing speeds to maximize operational revenue (i.e., the gap between freight revenue and operational costs). To address this problem, we develop an extended space-time network that encompasses collaborative ship scheduling, routing, and sailing speed decisions. We formulate the research problem as a mixed-integer programming model that aims at maximizing the total fleet operation revenue during the planning horizon while satisfying operational constraints. We conduct a series of numerical experiments using an illustrative example and a real-world grain transportation network to validate the effectiveness of our approach. Numerical results demonstrate that our approach is promising and can provide useful insights for dry bulk shipping operations management.

Keywords Dry bulk shipping · Vessel scheduling · Shipping route · Sailing speed

1 Introduction

The international maritime shipping industry is a critical component of global cargo transportation, which accounts for 80% of the world's cargo transportation. Among the various sectors in shipping industry, dry bulk shipping plays a pivotal role in transporting common raw materials (i.e., iron ore, grain, coal, bauxite and alumina,

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Published online: 27 April 2023

and phosphate rock) between different continents. This industry accounts for almost 50% of the world's seaborne trade due to its large capacity and low cost (Wu et al. 2021). As the primary participant in the dry bulk shipping industry, dry bulk shipping companies face several decision problems, including fleet size planning at the strategic level and ship scheduling, routing, and sailing speed decisions at the operational level. In this paper, we focus on the decision problems faced by dry bulk shipping companies at the operational level, where they operate a fleet of vessels to provide commodity transportation services for shippers with the aim of revenue maximization.

The operating revenue of a dry bulk shipping company is determined by the freight income earned by serving transportation demands, as well as the operational cost of ships. However, due to the fully competitive dry bulk shipping market, the company does not have strong bargaining power over the shippers, and the freight rate is determined by the market supply–demand conditions. This issue was more significant in the last 2 years when the dry bulk shipping capacity expansion outpaced transportation demand, leading to an oversupply condition in the market. Therefore, it is crucial for dry bulk shipping companies to optimize ship scheduling to serve more transportation demands and earn more freight revenue. On the other hand, ship operation costs, such as bunker costs, are mainly influenced by shipping routes and sailing speeds. Therefore, dry bulk shipping companies must optimize shipping routes and sailing speeds to minimize operational costs and improve the total fleet operation revenue, which is the difference between freight revenue and operational costs. To achieve this goal, efficient operational decisions must be made about ship scheduling (e.g., matching between ships and cargo), routing, and sailing speed simultaneously. In this process, the time window requirements for cargo loading and discharging play a crucial role in the bulk shipping operational decision-making.

Dry bulk shipping companies typically operate a fleet of ships to transport bulk commodities in large consignments. Since the dry bulk shipping industry operates as a type of tramp shipping without fixed routes or schedules, careful consideration must be given to ship-cargo matching and related operational constraints, such as ship capacity, and loading and discharging time window constraints, to achieve operational efficiency. Once a vessel and cargo are matched, the operator must determine the shipping route and sailing speed to complete the trip between loading and discharging ports, while ensuring that the time window requirement is met. The dry bulk shipping operator must select the ship for specific cargo transportation tasks and optimize the shipping route and sailing speed during the ship's journey to the discharging port to achieve maximum operation efficiency. However, designing an optimization approach for the collaborative ship scheduling, routing, and sailing speed decisions in the dry bulk shipping industry is challenging. In this paper, we address this problem by considering a case in which a dry bulk shipping company operates a fleet of ships to meet cargo transportation demands during the planning horizon. Our objective is to optimize ship scheduling, routing, and sailing speed to maximize operational revenue. To achieve this, we construct an extended space-time network that represents the ship operation process and includes dummy nodes to denote the origin and destination nodes of ships and cargoes during the planning horizon. This network representation method enables us to formulate the unified operational decision problem into a tight mixed-integer programming model, which can be efficiently solved with an on-shelf solver. Our numerical experiments using both synthetic and real data from a grain transportation network demonstrate that our approach is efficient and provides valuable insights for dry bulk shipping operations management.

The remainder of this paper is organized as follows: Sect. 2 provides a brief review of relevant literature. We describe the problem and network representation used in this research in Sect. 3. The mixed-integer linear programming model for the unified dry bulk shipping operation problem is presented in Sect. 4. In Sect. 5, we conduct numerical experiments using real grain transportation data. Finally, we conclude the paper in Sect. 6.

2 Literature review

The research problem addressed in this paper is closely related to two streams of topics in the literature: dry bulk shipping fleet scheduling and routing optimization. Therefore, we review these related works in this section.

2.1 Dry bulk shipping fleet scheduling problem

Research on dry bulk shipping scheduling dates back to Appelgren's work in 1969 and 1971, in which he found that tramp shipping operators tend to select cargo that maximizes profit. Following Appelgren's conclusion, subsequent research on ship scheduling has aimed to maximize fleet revenue by optimizing the matching rules between cargo and ships (Agarwal and Ergun 2008; Peng et al. 2016; Halvorsen-Weare and Fagerholt 2017; Andersson and Ivehammar 2017; Zhao and Yang 2018; Zhenfeng et al. 2019; Yu et al. 2021). For example, Yu et al. (2017) formulated the dry bulk shipping fleet scheduling problem as a linear mixed-integer programming problem and used a heuristic algorithm to maximize total fleet revenue. Some scholars have also considered the ship-cargo matching problem under different cargo types (i.e., spot cargo and contract cargo) and developed corresponding mathematical models to address this problem (Vilhelmsen et al. 2017; Li et al. 2020). However, the above works only focused on the impact of cargo selection on dry bulk shipping fleet scheduling at the macro level and could not consider micro-level influencing factors (e.g., loading and discharging time windows).

To address this problem, some works have incorporated the effects of dry bulk transportation demand, loading and discharging ports, and loading and discharging time windows on dry bulk shipping fleet scheduling (Stålhane et al. 2015; Siddiqui and Verma 2015; Wen et al. 2016). For instance, Wu et al. (2021) considered the impact of demand uncertainty on the dry fleet scheduling problem and developed a robust optimization model to maximize shipping companies' profit. Guan et al. (2017) analyzed the influence of berthing time on dry bulk shipping fleet scheduling and developed a linear programming model with opportunity constraint time windows for the problem. Additionally, some scholars have studied the dry bulk shipping fleet scheduling problem under carbon-constrained policies (Doudnikoff and Lacoste 2014; Fagerholt and Psaraftis 2015; Sheng et al. 2019). However, these works mainly focused on maximizing the freight revenue of the shipping company by optimizing the cargo-ship matching decision. They did not consider the routing and sailing speed decision when the ship sails from the loading port to the discharging port, which significantly impacts operation costs.

2.2 Dry bulk shipping fleet routing optimization

With the rapid development of the dry bulk shipping industry over the last few decades, the dry bulk shipping fleet routing problem has attracted significant research interest in the transportation community. The related works generally aim to minimize the total fleet cost or maximize the total fleet revenue by optimizing the fleet routing during the planning horizon. Ship operation cost is closely related to the technical parameters of different ships. Therefore, Ronen (1986, 1993) studied the dry bulk shipping fleet routing problem by considering the impact of route selection on the transportation cost of different ships. The most significant proportion of the dry bulk shipping fleet's daily operation cost is bunker fuel cost, which mainly depends on the ship's sailing speed. For this reason, some works have incorporated sailing speed optimization into the bulk fleet routing problem during the planning horizon. For example, Norstad et al. (2011) optimized the dry bulk shipping fleet routing by considering the optimal speed to obtain the minimal transportation cost path for the dry bulk shipping fleet during the planning horizon. The ship's sailing speed can also influence bunker fuel consumption and determine carbon emissions. Thus, some works considered the cost of fleet carbon emissions and the selection of bunkering ports in the route optimization of the dry bulk shipping fleet (Fan et al. 2019). Additionally, Meng et al. (2015) formulated the dry bulk shipping fleet routing problem with bunker fuel procurement decisions as an integer linear programming model and used a branch and bound method to solve it. Korsvik et al. (2011) studied the tramp ship routing problem under the condition of allowing cargo split loading and used a large-scale nearest neighbor search algorithm to solve it.

As the dry bulk shipping market develops and the variety of dry bulk cargo increases, the influencing factors and research objectives considered in dry bulk shipping fleet routing optimization research have become diversified (Agra et al. 2017; Dong et al. 2018). For example, Hu (2018) studied disaster relief material shipping routing problems with minimum transportation time and implemented the results to solve the distribution problem of large materials in emergencies. Fei and Hong (2020) studied the dry bulk transshipment route problem by considering port berth docking restrictions and import/export demand. Moreover, some works dynamically adjust the fleet transportation routes using AIS data of ships sailing between specific channels or ports (Shu et al. 2013; Xiao et al. 2015; Breithaupt et al. 2016; Andersson and Ivehammar 2017). However, the above works generally focused on optimizing the shipping route between given loading and discharging ports and did not incorporate the ship scheduling problem during the research horizon. To the best of our knowledge, the unified operation decision problem, including ship scheduling, routing, and sailing speed optimization, studied in this paper is new to the literature.

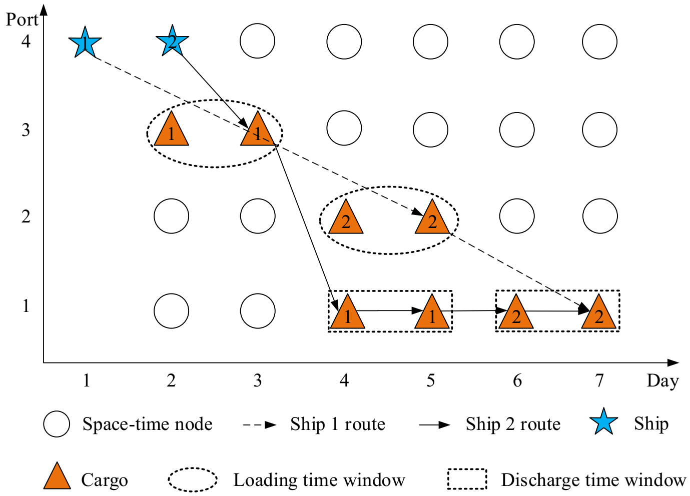


Fig. 1 Schematic diagram of the dry bulk fleet scheduling and routing

3 A unified operation decision problem for bulk shipping

3.1 Problem statement

In this paper, we investigate a unified operational decision problem faced by a tramp shipping company that operates a fleet of bulk ships indexed by the set $\mathcal{S} = \{1, 2, \ldots, s\}$. The company shall fulfill cargo transportation demands between different ports during the planning horizon T, where each cargo has a specified loading and discharging time window. The goal is to maximize the total operation profit earned by transporting cargoes from loading to discharging ports while satisfying the time window requirement. This problem involves matching ships with cargoes, which concerns the shipping scheduling problem and is influenced by several factors such as cargo volume, ship capacity, distance between ship position and loading ports, and time window requirement. Once a ship is assigned to transport a specific cargo, the shipping route and sailing speed during its journey significantly influence the operation cost and arrival time at the discharging port. Thus, the operator must simultaneously determine the shipping route and sailing speed for each ship. We present an illustrative example in Fig. 1 to provide a concrete understanding of the research problem in this paper.

We utilize a space-time network to model ship operations and cargo trajectories during the planning horizon. As shown in Fig. 1, we depict an illustrative example in which two ships are tasked with serving two candidate cargoes across four ports over a period of seven days. Although ship capacity was assumed to be sufficient to meet transportation demand, the operator also has to consider loading and discharging time window requirements for each cargo. For instance, we suppose that ship 2 requires at least four days to sail from Port 4 to Port 2, which cannot satisfy the time window requirement for cargo 2 at the loading port. As a result, the bulk operator shall assign

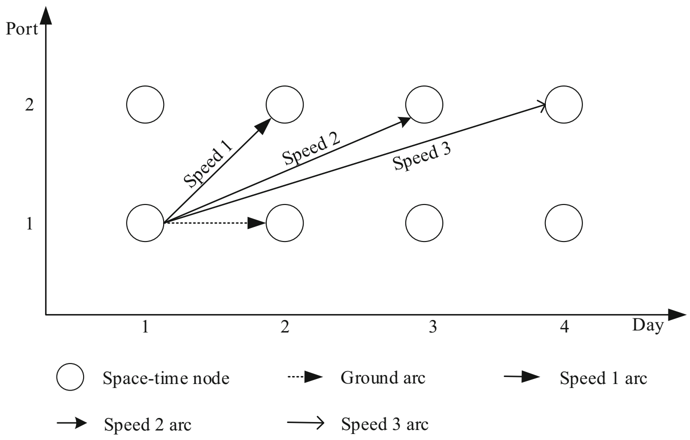


Fig. 2 Representation of ship's sailing speed in the space-time network

ship 1 to serve cargo 2 and use ship 2 to transport cargo 1. In addition to matching ships with cargoes, the operator also has to determine the optimal shipping route and sailing speed for each journey from the loading port to the discharging port.

By computing the operation cost of the ships, we can determine the routes with the lowest total operation cost of the fleet as illustrated in Fig. 1. The operation cost of a ship includes both fixed and variable costs. The fixed cost refers to the daily cost incurred during dry bulk transportation, which can be obtained through the ship's historical operation data. The variable cost mainly refers to the bunker fuel cost of the main engine, which is incurred only when the ship is sailing. It is important to note that the ship's path from the loading port to the discharging port is composed of a set of arcs in the space-time network. This path not only indicates the sequence of ports visited by the ship but also denotes the sailing speed at each shipping leg between consecutive visited ports. To elaborate on this point, we use the illustrative space-time network shown in Fig. 2. In this network, there are multiple arcs between Port 1 and Port 2, and each arc denotes a specific sailing time between the two ports under a specific sailing speed. Therefore, this paper addresses the operation decision problem of ship scheduling, route, and sailing speed, all of which are considered simultaneously using a space-time network to represent the trajectory of both the ship and cargo during their journey from the loading port to the discharging port.

3.2 Network representation

As previously mentioned, we have access to information about the available time and position of each ship at the beginning of the research horizon. However, due to differences in the cargo carried, each ship will arrive at a different port by the end of the planning horizon. Furthermore, each dry bulk cargo has several possible loading and discharging nodes, which are subject to loading and discharging time windows, making it challenging to track the path of cargoes during the planning horizon. Developing a tractable model that simultaneously incorporates ship scheduling, routing, and speed optimization is challenging because there are multiple origin and destination nodes for each ship and cargo. To tackle this challenge, we adopt the convention used in network flow models, which associates one origin and destination node for each commodity. To simplify the problem and facilitate model formulation, we introduce a dummy terminal node for each ship, as well as a dummy origin and destination node for each cargo, in this paper. To be more precise, we introduce a dummy terminal node $\mathcal{D}_s$ for all ships in the dry bulk shipping fleet at the end of the planning horizon, which reduces complexity and enables us to track ships' movements more efficiently. We also create dummy loading and discharging nodes for each dry bulk cargo, following the same approach used for ship paths. As a result, our network representation approach ensures that each cargo and ship has only one origin and destination node during the planning horizon. This simplification allows us to develop a network flow-related model that accurately captures the unified operation decision problem presented in this paper.

Based on the aforementioned approach, we can represent the space-time network of dry bulk transportation as a directed network denoted by $\mathcal{G} = (\mathcal{N}, \mathcal{E})$. The set of nodes $\mathcal{N}$ includes actual nodes such as ports, straits, and canals that ships will pass during their journey, as well as dummy nodes added to facilitate model formulation. The planning horizon is divided into consecutive T days, sorted by Day 1, Day 2,..., Day T. In other words, each node can be represented by its coordinate, which is an ordered pair of (Day, Position). In this paper, we define $\mathcal{O} = \{O_1, O_2, \ldots, O_s\}$ as the set of initial positions for each ship in the fleet at the start of the planning horizon, where O_s represents the initial position of ship s. As mentioned earlier, we use the dummy node D to denote the final position of all ships in the fleet. Therefore, the unified operation decision for ship s during the planning horizon can be represented by the path from its initial position node $\mathcal{O}_s$ to the dummy terminal node D. Similarly, we define $\widetilde{\mathcal{O}} = \{\widetilde{O}_1, \widetilde{O}_2, \ldots, \widetilde{O}_k\}$ and $\widetilde{\mathcal{D}} = \{\widetilde{D}_1, \widetilde{D}_2, \ldots, \widetilde{D}_k\}$ as the sets of dummy origin and destination nodes for cargoes during the planning horizon.

Under this network representation method, each cargo k begins its journey at the fixed dummy node $\widetilde{O}_k$ and terminates at the dummy node $\widetilde{D}_k$. This network representation simplifies the model formulation for the research problem significantly. To illustrate this method, we use Fig. 3 to represent the space-time network diagram of dry bulk transportation with dummy nodes. We can observe that $\widetilde{O}_1$ and $\widetilde{O}_2$ are the dummy loading nodes for cargo 1 and cargo 2, respectively. Additionally, $\widetilde{D}_1$ and $\widetilde{D}_2$ are the dummy discharging nodes for cargo 1 and cargo 2, respectively. Lastly, D represents the dummy terminal node for the ships in the dry bulk shipping fleet at the end of the planning horizon. In this way, we can simultaneously incorporate the ship scheduling, routing and speed optimization problem by determining the path of ships and cargoes from their single origin node to the terminal node.

4 Model formulation

This section begins by outlining the assumptions used in this research. We then introduce the notations used in the model formulation and formulate the unified decision problem as a mixed-integer programming model.

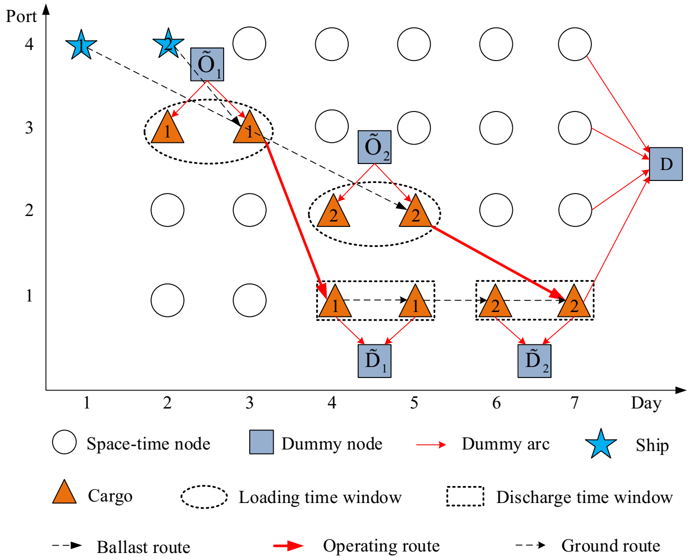


Fig. 3 Space-time network diagram of dry bulk transportation

4.1 Assumptions

The assumptions used in this research can be listed as follows.

1. Dry bulk ships are able to commence loading and discharging operations immediately upon arriving at the loading and discharging port. In other words, we do not consider the ship waiting berth time at the loading and discharging port.
2. The cargo transportation must comply with the time window requirement at the loading and discharging ports; otherwise, the cargo transportation demand will not be met.
3. For the sake of simplicity, we exclude the cargo loading and discharging time from the model formulation, and do not consider the impact of cargo handling operations at the loading and discharging ports on the ship and cargo trajectories.
4. The variable cost of the dry bulk ship is solely determined by the ship's speed and shipping route during the planning horizon, and does not take into account the impact of cargo weight on the ship's operation cost.
5. In the space-time network, dry bulk cargo cannot be transported through the same arc, and two ships are also prohibited from traveling through the same arc.

4.2 Notations

To construct the unified operation decision model for the dry bulk shipping fleet, we begin by listing the parameters and variables used in the model in Table 1.

Table 1 Parameters and variables used in the model

	Descriptions
Sets	
$\mathcal{N}$	Set of nodes in the space-time network, $i \in \mathcal{N}$
$\mathcal{A}$	Set of arcs between nodes in the space-time network, $(i, j) \in \mathcal{A}$
$\mathcal{S}$	Set of dry bulk ships in the fleet, $s \in \mathcal{S}$
$\mathcal{K}$	Set of dry bulk transportation demand, $k \in \mathcal{K}$
$\mathcal{O}$	Set of initial position of dry bulk ships
$\widetilde{\mathcal{O}}, \widetilde{\mathcal{D}}$	Set of dummy loading and discharging nodes of dry bulk cargo
Parameters	
D	Dummy terminal node for dry bulk ships
P^k	Dry bulk cargo k's freight rate
Q^k	Dry bulk cargo k's transportation demand
W^s	The capacity of ship s
c^s_{ij}	Transportation cost of dry bulk ship s from node i to j
λ	[0, 1], proportion of overflow penalty to the fright rate of dry bulk demand
Decision variables	
x^s_{ij}	{0, 1}, 1 if ship s passes through the arc (i, j), and 0 otherwise
y^k_{ij}	{0, 1}, 1 if dry bulk cargo k is transported through the arc (i, j), and 0 otherwise
z^k_{ij}	The volume of dry bulk cargo k that travels across arc (i, j)
F^k	Dry bulk cargo k's unsatisfied demand

4.3 Model formulation

Based on the problem description and network represented outlined in Sect. 3, we can develop a model formulation for the unified operation decision problem for the dry bulk shipping fleet. Consider a bulk shipping company that operates a vessel fleet $\mathcal{S}$ to fulfill the set of cargo transportation demands $\mathcal{K}$ during the planning horizon. The company can earn freight revenue P^k by transporting one unit of cargo k, while the penalty for unsatisfied demand is λP^k (where $\lambda \in [0, 1]$ denotes the proportion of overflow penalty to the freight rate). Additionally, each ship s will incur an operation cost c^s_{ij} if it travels across arc (i, j) in the time-space network. The objective of the operator is to maximize the net revenue (i.e., the total freight rate minus operation cost and overflow penalty) during the planning horizon. This requires the operator to determine the path for each cargo from the loading port to the discharging port. Therefore, the research problem can be formulated as a network flow-related model.

$$\max \quad \sum_{k\in\mathcal{K}} P^k(Q^k - F^k) - \sum_{s\in\mathcal{S}} \sum_{(i,j)\in\mathcal{A}} c^s_{ij}\, x^s_{ij} - \sum_{k\in\mathcal{K}} \lambda P^k F^k \tag{P}$$

$$\text{s.t.} \quad \sum_{j|(i,j)\in\mathcal{A}} x_{ij}^s - \sum_{j|(j,i)\in\mathcal{A}} x_{ji}^s = \begin{cases} 1 & \forall s \in \mathcal{S}, i = O_s \\ 0 & \forall s \in \mathcal{S}, i \neq O_s, D \\ -1 & \forall s \in \mathcal{S}, i = D \end{cases} \tag{1}$$

$$\sum_{j|(i,j)\in\mathcal{A}} y_{ij}^k - \sum_{j|(j,i)\in\mathcal{A}} y_{ji}^k = \begin{cases} 1 & \forall k \in \mathcal{K}, i = \widetilde{O}_k \\ 0 & \forall k \in \mathcal{K}, i \neq \widetilde{O}_k, \widetilde{D}_k \\ -1 & \forall k \in \mathcal{K}, i = \widetilde{D}_k \end{cases} \tag{2}$$

$$\sum_{i|(i,j)\in\mathcal{A}} z_{ij}^k + F^k = Q^k \quad \forall k \in \mathcal{K}, i = \widetilde{O}_k \tag{3}$$

$$\sum_{i|(i,j)\in\mathcal{A}} z_{ij}^k + F^k = Q^k \quad \forall k \in \mathcal{K}, j = \widetilde{D}_k \tag{4}$$

$$\sum_{i|(i,j)\in\mathcal{A}} z_{ij}^k - \sum_{i|(j,i)\in\mathcal{A}} z_{ji}^k = 0 \quad \forall k \in \mathcal{K}, j \neq \widetilde{O}_k, \widetilde{D}_k \tag{5}$$

$$\sum_{s\in\mathcal{S}} \sum_{i|(i,j)\in\mathcal{A}} x_{ij}^s \leq 1 \quad j \neq D \tag{6}$$

$$z_{ij}^k \leq M y_{ij}^k \quad \forall k \in \mathcal{K}, (i, j) \in \mathcal{A} \tag{7}$$

$$\sum_{k\in\mathcal{K}} z_{ij}^k \leq \sum_{s\in\mathcal{S}} x_{ij}^s W^s \quad \forall (i, j) \in \mathcal{A} \tag{8}$$

$$z_{ij}^k \geq 0 \quad \forall k \in \mathcal{K}, (i, j) \in \mathcal{A} \tag{9}$$

$$F^k \geq 0 \quad \forall k \in \mathcal{K} \tag{10}$$

$$x_{ij}^s \in \{0, 1\} \quad \forall s \in \mathcal{S}, (i, j) \in \mathcal{A} \tag{11}$$

$$y_{ij}^k \in \{0, 1\} \quad \forall k \in \mathcal{K}, (i, j) \in \mathcal{A} \tag{12}$$

In model (P), the objective function aims to maximize the operating revenue of the dry bulk shipping fleet. Specifically, the first term represents the revenue earned by the fleet for transporting dry bulk cargo during the planning horizon, while the second term denotes the operation cost of the fleet when ferrying cargoes from loading ports to discharging ports. The third term reflects the penalty for overflow in dry bulk transportation demand that remains unsatisfied during the planning horizon. Constraint (1) enforces the flow conservation constraint for each ship at the source, sink, and other nodes, ensuring that each dry bulk ship can traverse a complete path through the selected segments during the planning horizon. Meanwhile, constraint (2) enforces the flow conservation constraint for each dry bulk cargo transportation at the loading, discharging, and other nodes, which guarantees that the segment selected for cargo transportation within the planning horizon can form a complete path from the loading port to the discharging port. Constraint (3) ensures that the sum of cargo volume transported from the dummy loading node and the demand overflow (unsatisfied demand) equals the transportation demand of each cargo $k \in \mathcal{K}$. Similarly, Constraint (4) ensures that the dry bulk cargo carried by the dry bulk shipping fleet terminates its journey at the dummy discharging node, and the sum of this cargo volume and demand overflow equals the total transportation demand of each cargo $k \in \mathcal{K}$. The conservation constraint of cargo volume at other nodes is imposed by Constraint (5).

Table 2 Dry bulk shipping fleet information

No.	Available time	Available position	Capacity (Ton)	Economic speed (kn)	Daily variable cost (USD)	Daily fixed cost (USD)
1	1	1	39,000	14	19,200	5200
2	2	3	44,000	14	21,300	5300

Constraint (6) ensures that each arc in the space-time network can only be visited by a single ship at a time, which is due to berthing limitations at ports. This constraint also guarantees that each cargo can only be transported by a single ship. Constraint (7) imposes the route selection constraint for each cargo k, ensuring that the volume of cargo k that travels across arc (i, j) is zero unless this arc is on cargo k's route from the loading port to the discharging port. The capacity constraint on each arc (i, j) is imposed by Constraint (8), which ensures that the total volume of cargoes on arc (i, j) does not exceed the ship capacity on this arc. Finally, the feasible domain of the decision variables is defined in Constraints (9)–(12).

We note that model (P) is a linear mixed-integer programming model that follows the style of network flow-related models. One of the model's compelling features is its tight and compact formulation, and our numerical results in the following sections demonstrate that the objective gap between model (P) and its linear relaxation is minimal. As a result, the model imposes a lower computational burden and can be solved by off-the-shelf solvers within a reasonable time.

5 Case study

In this section, we provide an illustrative example and a real grain transportation network to demonstrate the feasibility and applicability of our unified operation decision model for the dry bulk shipping fleet operations management. We use data from the illustrative network and the real grain transportation network to determine the optimal ship scheduling, routing, and sailing speed for the dry bulk shipping fleet, and analyze the impact of parameter on the revenue performance. We simulate the dry bulk shipping fleet environment using the Python programming language and solve the optimization problem with the Gurobi (9.5.1) solver. All experiments are conducted on a Windows PC with a 3.9 GHz i9 CPU and 128 G RAM.

5.1 An illustrative case

5.1.1 Data description

We begin by applying our approach to an illustrative dry bulk transportation network consisting of 7 ports and a planning horizon of 10 days. Throughout this period, there are two ships available in the dry bulk shipping fleet, and their initial positions, available time, and operation costs are outlined in Table 2.

Table 3 Dry bulk cargo information

No.	Transportation demand (Ton)	Freight rate (USD)	Loading port	Discharging port	Loading time window	Discharging time window
1	35,000	69	1	4	[1, 3]	[4, 6]
2	31,000	75	3	5	[2, 4]	[7, 9]
3	30,000	48	4	7	[5, 6]	[9, 10]

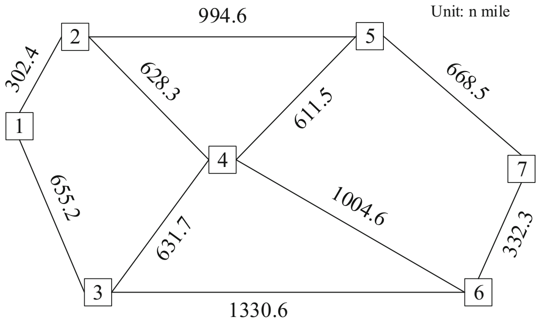
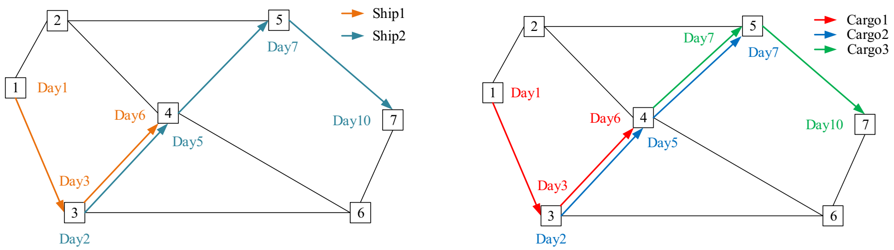


Fig. 4 Schematic diagram of the connectivity between ports



(a) Ship route (b) Cargo route

Fig. 5 Ship routing and cargo transportation route

There are three dry bulk transportation demands during the planning horizon, each with known loading and discharging ports, loading and discharging time windows, transportation volumes, and other cargo information, as presented in Table 3. Additionally, the connectivity and sailing distances between different ports are illustrated in Fig. 4.

5.1.2 Results and analysis

To start, we calculate the operation costs of each ship for each leg of the dry bulk shipping fleet and input them as parameters into the model. Next, we obtain the route for each ship in the dry bulk shipping fleet and the transportation route for each cargo, as presented in Fig. 5. Ship 1 loads cargo 1 at Port 1 on Day 1, arrives at Port 4 on Day 6 to discharge the cargo, and then remains at Port 4 until the end of the planning horizon. Ship 2 loads cargo 2 at Port 3 on Day 2, arrives at Port 4 on Day 5 to load cargo 3, and then arrives at Port 5 on Day 7 to discharge cargo 2. Finally, it arrives at

Table 4 The preliminary optimization results

Gross profit (USD)	Sailing cost (USD)		Maximum revenue (USD)
	Ship1	Ship2	
5,364,000	73,600	211,000	5,079,400

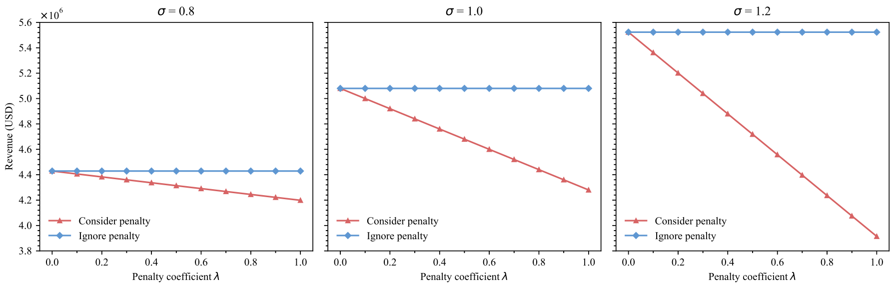


Fig. 6 Total fleet operation revenue variations under different penalty

Port 7 on Day 10 to discharge cargo 3. Table 4 presents the sailing costs incurred by each ship and the maximum revenue that the transportation company can achieve.

The aim of this study is to examine the effect of the penalty coefficient (λ) on the total fleet operation revenue under different transportation demands. We introduce a parameter, σ, to represent the proportion of transportation demand (market thickness), with $\sigma = 0.8$ resulting in a reduction of the demand for each OD pair to 80% of its original value. In addition, we also analyze the scenario where there is no overflow penalty. The results are presented in Fig. 6.

Figure 6 illustrates the relationship between the penalty coefficient λ and the total fleet operation revenue obtained from our unified operation decision model under varying transportation demands. First of all, the total revenue without overflow penalty would increase when the value of σ rise from 0.8 to 1.2. This is because that the operator could improve its revenue by serving cargoes with higher freight rate. Secondly, the operation revenue under all value of σ would linearly decrease when the overflow penalty coefficient increases from 0.0 to 1.0. Moreover, the total operation revenue decreases linearly by approximately 0.5%, 1.7%, and 3.5% for every 10% increase in the penalty coefficient λ, when the value of σ is 0.8, 1.0, and 1.2, respectively. This suggests that the total operation revenue is more sensitive to overflow penalty under heavy demand conditions.

We can further investigate the influence of transportation demand variation on the total revenue performance of our constructed model. By adjusting the transportation demand in the interval between −20% and +20%, we can analyze the total revenue under different penalty coefficient values λ (e.g., 0.2, 0.4, and 0.6). The results are presented in Fig. 7.

We can obtain the following insights from the results in Fig. 7. Firstly, the total revenue increases linearly with transportation demand up to a growth rate of 10%. Specifically, for each 5% increase in transportation demand, the total operating revenue of the dry bulk shipping fleet increases by approximately 3%, 2.4%, and 1.7%,

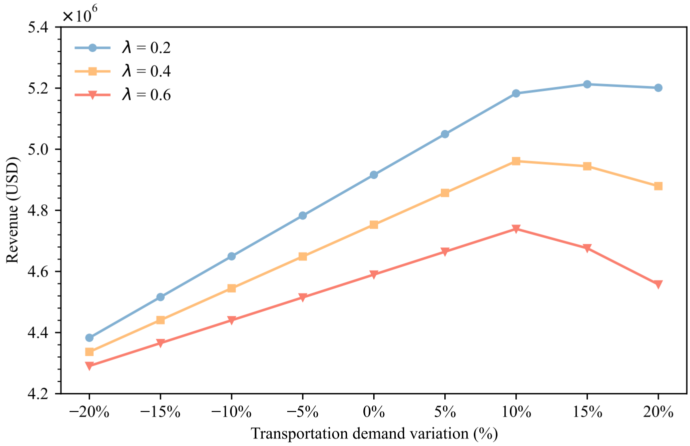


Fig. 7 Total fleet operation revenue variation under different transportation demand

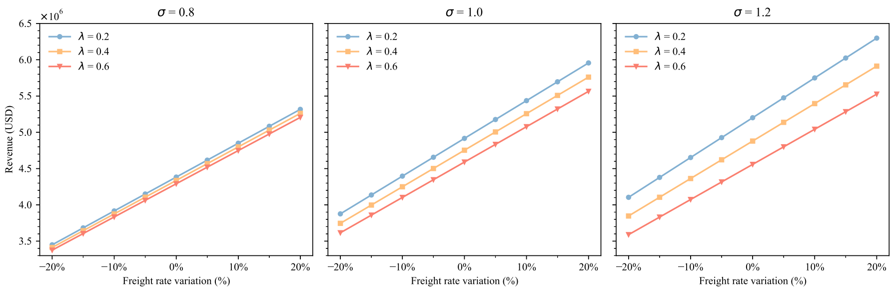


Fig. 8 Total fleet operation revenue violation under different freight rates

respectively, when the penalty coefficient λ is set at 0.2, 0.4, and 0.6. However, the total revenue decreases when the transportation demand growth rate exceeds 10%, due to the rising overflow penalty that adversely impacts the total revenue. Secondly, the total revenue decreases with the increase of the transportation demand overflow penalty coefficient λ, for each demand increase rate. This decrease can be attributed to the insufficient ship capacity that cannot accommodate all demand during the planning horizon, leading to an increase in the overflow penalty under larger values of λ. Finally, the maximum total fleet operation revenue is estimated to decrease by approximately 4.6% for every 20% increase in the penalty coefficient λ.

The variation of the total fleet operation revenue with different dry bulk freight rates is depicted in Fig. 8, where the penalty coefficient λ is set at 0.2, 0.4, and 0.6. The results reveal several insights. Firstly, the total fleet operation revenue linearly increases with the rise of dry bulk freight rate under the same transportation demand. Additionally, under each freight rate variation, the total fleet operation revenue decreases under larger penalty coefficient λ. Secondly, the difference between the revenue obtained under different penalty coefficients λ increases with the increase of the freight rate and dry bulk transportation demand. Finally, the total revenue of the fleet increases with the rise of dry bulk transportation demand under the same penalty coefficient λ

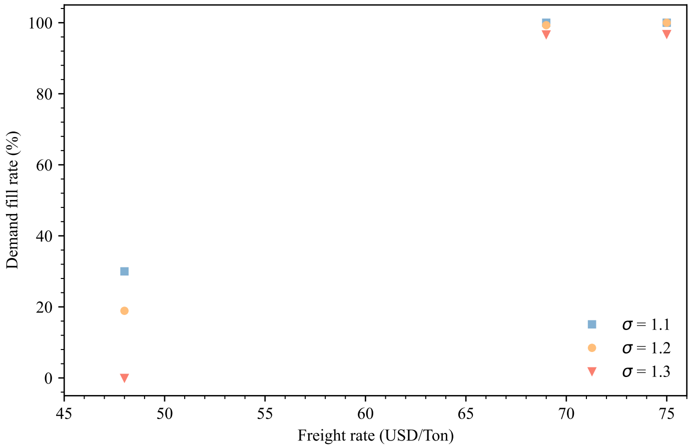


Fig. 9 Transportation demand fill rate versus freight rate

and freight rate. For instance, when the penalty coefficient λ is 0.2 and the freight rate increases by 20%, the total operating revenue of the dry bulk shipping fleet increases from about 5.3 million USD to 6.3 million USD, as the value of the proportion of transportation demand σ changes from 0.8 to 1.2.

Lastly, we examine the fill rate, i.e., the proportion of satisfied demand to the total transportation demand, for cargoes with different freight rates in Fig. 9. The results show that the fill rate for the cargo with a freight rate of 48 USD/Ton varies significantly under different demand increase rates. For example, as the transportation demand increases from 10% to 30% (i.e., the value of σ changes from 1.1 to 1.3), the fill rate for the cargo with a freight rate of 48 USD/Ton decreases from 30% to 0. Conversely, the fill rate for cargoes with high freight rates (e.g., 69 USD/Ton and 75 USD/Ton) remains nearly constant under varying demand increase rates. This observation suggests that the operator favors serving cargoes with higher freight rates under heavy demand conditions.

5.2 A dry bulk shipping fleet for grain transportation

5.2.1 Basic data

In this subsection, we demonstrate the practicality of our approach using realistic data from a grain shipping company's dry bulk shipping fleet. The fleet comprises of four Handysize bulk carriers with different technical specifications, as detailed in Table 5, which provides information about the capacity, daily operation cost, available time, and position of each ship. Additionally, there are 11 dry bulk cargoes that can be transported during a planning horizon of 120 days. Table 6presents details about the dry bulk transportation demand, loading and discharging ports, loading and discharging time windows, and other relevant information for each cargo.

Table 5 Dry bulk shipping fleet information

No.	Available time	Available position	Capacity (Ton)	Economic speed (kn)	Daily variable cost (USD)	Daily fixed cost (USD)
1	12	Sydney	31,760	13.5	21,500	5200
2	4	Belém	32,800	14	22,300	5300
3	1	New Orleans	31,770	13.9	21,500	5300
4	7	Rotterdam	34,650	14.2	23,400	5400

Table 6 Dry bulk cargo information

No.	Transportation demand (Ton)	Freight rate (USD)	Loading port	Discharging port	Loading time window	Discharging time window
1	27,050	45.4	Sydney	Ho Chi Minh	[13, 17]	[31, 34]
2	24,728	60.8	Rotterdam	Fujairah	[7, 10]	[31, 35]
3	34,814	107.6	Belém	Qingdao	[4, 6]	[47, 50]
4	29,304	47.5	New Orleans	Le Havre	[1, 5]	[22, 24]
5	30,576	46.2	Vancouver	Dalian	[63, 65]	[82, 84]
6	34,939	48.3	Vancouver	Guangzhou	[78, 80]	[98, 100]
7	31,733	70.1	Dunkerque	Port Klang	[8, 11]	[36, 39]
8	29,862	44.8	Seattle	Tokyo	[100, 102]	[116, 119]
9	30,616	65.6	Sydney	Fujairah	[14, 17]	[40, 44]
10	28,879	47.5	Vancouver	Ningbo	[64, 66]	[81, 83]
11	35,341	59.7	Seattle	Guangzhou	[98, 101]	[118, 120]

Table 7 The preliminary optimization results

Ship no	Cargo no	Sailing cost (USD)	Revenue (USD)
1	1, 9	1,077,600	8,541,253.2
2	3, 10, 11	2,867,100	
3	4, 5, 8	2,637,700	
4	2, 7, 6	2,137,600	

5.2.2 Results and analysis

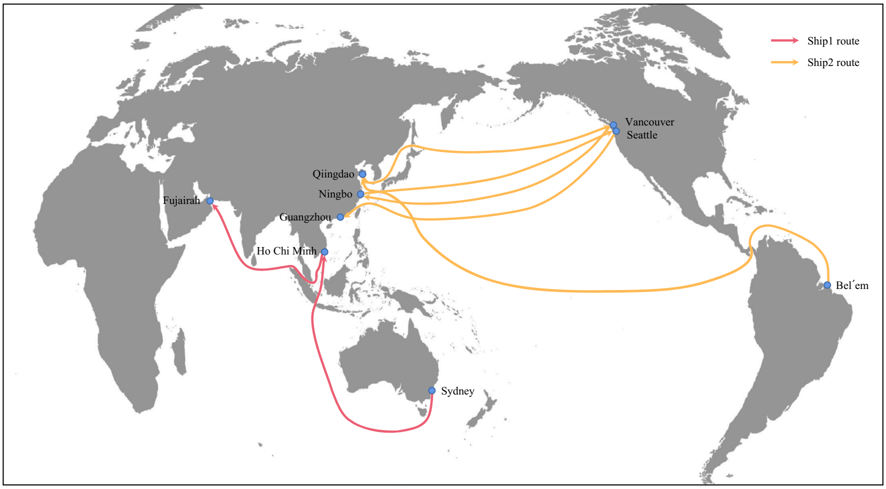
Initially, we preprocess the raw data and feed it into the model for computation. The preliminary optimization outcomes, comprising the dry bulk shipping fleet scheduling scheme, the sailing costs incurred by each ship, and the revenue that the transportation company can generate, are shown in Table 7. Additionally, we derive the routes of the ships in the dry bulk shipping fleet during the research horizon, as illustrated in Fig. 10.

Subsequently, we investigate the changes in the total fleet operation revenue by varying the value of the penalty coefficient λ under different proportions of transportation demand σ. We also compare these results with those obtained from the model without a penalty term, and depict the results in Fig. 11.

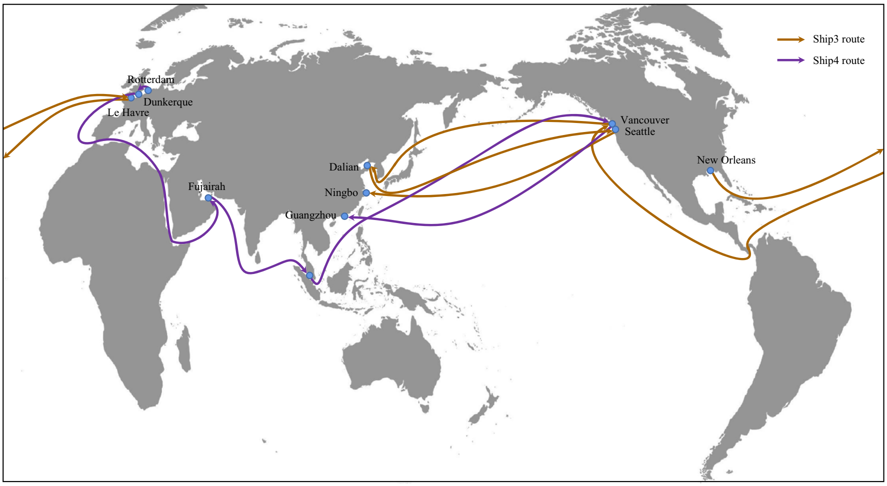
As depicted in Fig. 11, the total fleet operation revenue obtained from our model decreases as the penalty coefficient λ value rises from 0 to 1. The revenue decline rate increases with the growth of dry bulk transportation demand. Specifically, the total operating revenue of the dry bulk shipping fleet will decrease by approximately 3.1%, 3.7%, and 5.4% for each 10% increase in the penalty coefficient λ when the value of σ is 0.8, 1.0, and 1.2, respectively. These outcomes validate the practical relevance and effectiveness of our unified operation decision model in optimizing the dry bulk shipping fleet scheduling, routing, and sailing speed.

We examine the variation of the total fleet operation revenue with a dry bulk transportation demand variation of $\pm 20\%$ by setting the value of the penalty coefficient λ as 0.2, 0.4, and 0.6. As shown in Fig. 12, we observe that the total revenue linearly increases with the rise of transportation demand when the increase rate is small. However, it subsequently decreases as the transportation demand increase rate surpasses a certain threshold. Additionally, under each demand increase rate, the total revenue decreases with the rise of the demand overflow penalty coefficient λ. The reason is that when the total transportation demand is large, the ship capacity is insufficient to serve all the demands, and the overflow penalty would increase with larger values of λ, thus deteriorating the total operation revenue. Furthermore, we estimate that the maximum total fleet operation revenue decreases by about 7.2% for each 20% increase in the penalty coefficient λ.

We also analyze the variation of the total fleet operation revenue with different dry bulk freight rates when the penalty coefficient λ is 0.2, 0.4, and 0.6, as presented in Fig. 13. The results illustrate that the total fleet operation revenue displays a proportional relationship with the dry bulk freight rate, i.e., it linearly increases with the



(a) Route for Ship 1 and Ship 2



(b) Route for Ship 3 and Ship 4

Fig. 10 Schematic diagram of the dry bulk shipping fleet routing

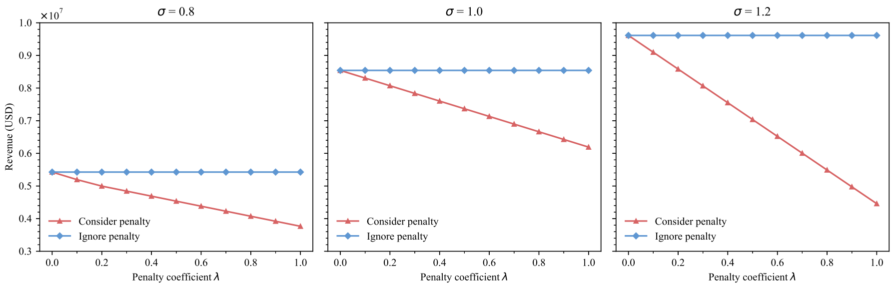


Fig. 11 Total fleet operation revenue variations under different penalty

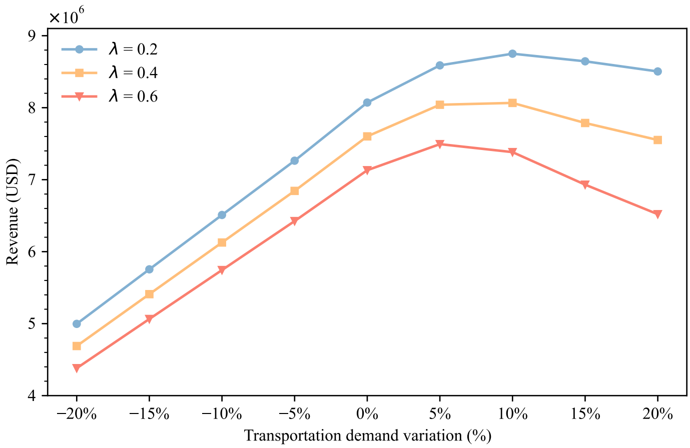


Fig. 12 Total fleet operation revenue variation under different transportation demand

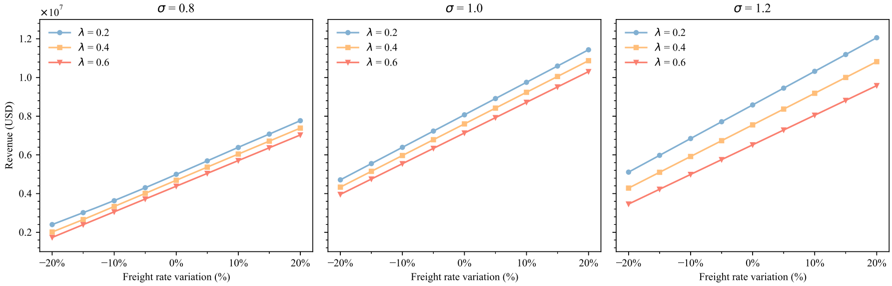


Fig. 13 Total fleet operation revenue violation under different freight rates

rise of the dry bulk freight rate at the same transportation demand. Furthermore, the total fleet operation revenue decreases with the increase of the penalty coefficient λ. Additionally, the difference between the revenue under different penalty coefficients λ increases with the rise of the freight rate and dry bulk transportation demand. Finally, the total revenue of the fleet also increases with the rise of the dry bulk transportation demand for the same variation in the penalty coefficient λ and freight rate.

Figure 14 displays the impact of transportation demand increase on the dry bulk transportation volume and demand fill rate. The figure shows that the dry bulk transportation volume increases almost linearly with the rise of dry bulk transportation demand when the increase rate is below 20%. At this point, the fleet prioritizes transporting higher freight rate dry bulk cargoes by decreasing the transportation volume of lower freight rate dry bulk cargoes due to the limitation of ship capacity and dry bulk transportation requirements. However, when the transportation demand increase rate exceeds 20%, it surpasses the total transportation capacity of the fleet. Consequently, the increased dry bulk transportation demand overflows, leading to a decrease in the transportation demand fill rate. Therefore, when the dry bulk transportation demand rises, the operator prefers to schedule the shipping fleet to transport dry bulk with relatively high freight rates. However, when the dry bulk transportation demand exceeds

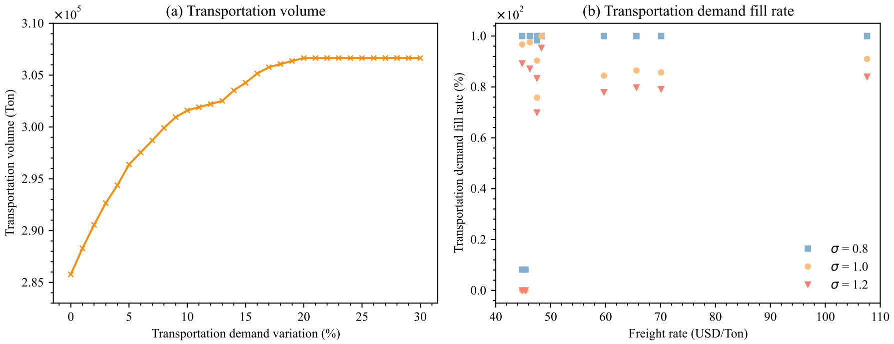


Fig. 14 Transportation volume and demand fill rate variation

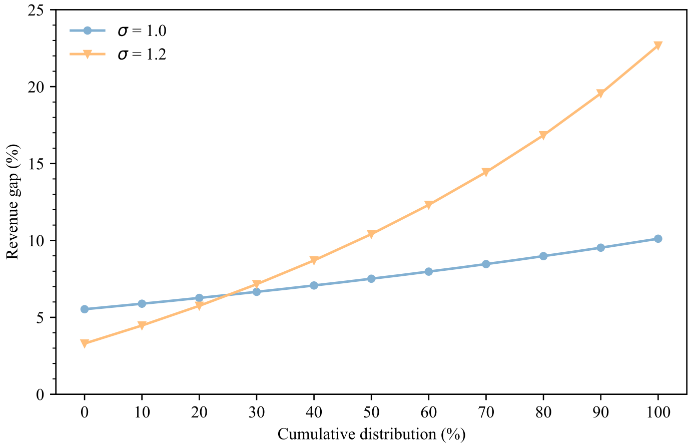


Fig. 15 The revenue performance gap between two models

the fleet's capacity, the dry bulk shipping fleet operators are unable to satisfy the demand by scheduling the fleet.

In addition, we also evaluate the performance of our mixed-integer programming model (P) and its linear relaxation, as well as the running time of model (P). We solve both the model (P) and its linear relaxation under various transportation demand and overflow penalty parameters and plot the cumulative distribution function (CDF) of the objective gap and running time in Figs. 15and 16, respectively. The X-axis represents the value of the cumulative distribution, while the Y-axis represents the percentage of revenue performance gap and running time, respectively.

From Fig. 15, we can see that the largest revenue performance gap between our model (P) and its corresponding linear relaxation across the penalty coefficient λ value range of [0, 1] is 10.1% and 22.6% when the value of σ is 1.0 and 1.2. Over 90% of the penalty coefficient λ values, the gap is no more than 9.5% and 19.5% when the value of σ is set as 1.0 and 1.2. Meanwhile, the results in Fig. 16 show that the running time of our model across the penalty coefficient λ value range of [0, 1] is no more than 3327.3 s and 710.6 s when the value of σ is 1.0 and 1.2, respectively. Over

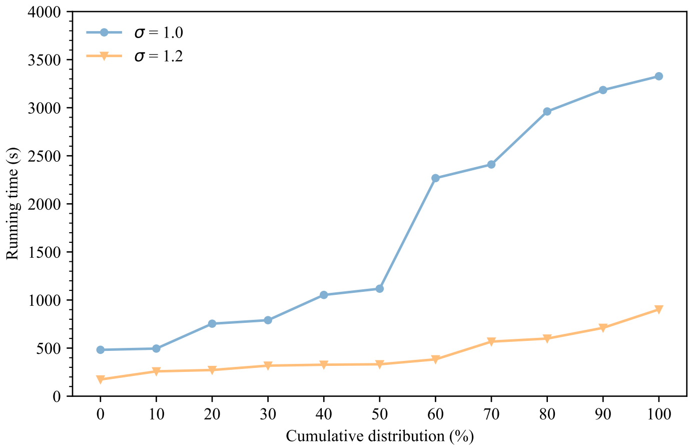


Fig. 16 Running time of the mixed-integer programming model

80% of the penalty coefficient λ values, the running time is no more than 2961.1 s and 567.4 s when the value of σ is set as 1.0 and 1.2. These results demonstrate that our unified operation decision model is very tight and can be solved in a reasonable amount of time.

6 Conclusion

In this paper, we address the challenging problem of unified operation decision for dry bulk shipping companies, which involves optimizing routing, shipping routes, and sailing speed for dry bulk shipping fleets while adhering to various complex operational constraints. To tackle this problem, we propose an extended space-time network that effectively represents the operational decisions required during the planning horizon and develop a mixed-integer linear programming model to optimize these decisions. Our experimental results demonstrate the efficacy of our approach, with the proposed model providing valuable insights for dry bulk shipping operations management. One potential avenue for future research is to incorporate demand uncertainty into our model and employ stochastic optimization techniques to address this issue.

Acknowledgements This work is jointly supported the Major Marine Projects of the National Social Foundation of China [Grant No. 18VHQ005] and the National Natural Foundation Science of China [Grant No. 72101042], the Fundamental Research Funds for the Central Universities [Grant No. 3132022171] and the National Key Research and Development Program of China [Grant No. 2017YFC1405600].

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