Robust Dry Bulk Fleet Route Optimization Under Navigation Risk Consideration

JUN GAO AND JIE WANG
College of Transportation Engineering, Dalian Maritime University, Dalian 116026, China
Corresponding author: Jie Wang (dwjie@163.com)

This work was supported in part by the Major Marine Projects of the National Social Foundation of China under Grant 18VHQ005, and in part by the National Key Research and Development Program of China under Grant 2017YFC1405600.

ABSTRACT Dry bulk shipping plays an essential role in international bulk commodity transportation. The dry bulk shipping company that operates a fleet has to design an efficient and safe route for each vessel to complete the transportation task and reduce the navigation risk on the course. Considering the navigation risk is uncertain, we use the robust optimization approach to optimize the routes for a dry bulk shipping fleet. We aim to determine the shipping route that can minimize the total transportation cost and ensure that the navigation risk is no more than a certain threshold. To address this problem, this paper first develops a deterministic formulation for the dry bulk fleet route planning. Then its robust counterpart is formulated to incorporate the uncertain navigation risk, which can ensure the worst-case navigation risk shall not exceed the given threshold. At last, we carry out a series of numerical experiments using actual data to evaluate the performance of our approach. The numerical results reveal that our approach can efficiently solve the route planning problem and make the trade-off between navigation risk and total transportation cost.

INDEX TERMS Dry bulk fleet, navigation risk, robust optimization, uncertainty, route planning.

I. INTRODUCTION

International maritime transportation is an essential carrier of the world commodity trade and undertakes 80% of the global cargo transportation tasks. Specifically speaking, the dry bulk shipping industry carrying bulk cargoes (i.e., ores and grains) accounts for half of the total maritime trade [1]. In this way, dry bulk shipping occupies an important position in international shipping. The dry bulk shipping company that operates a fleet is the main participant of the dry bulk shipping industry, which provides transportation services for shippers. Once contracts give the transportation task, the dry bulk shipping company faces a challenging task to determine the shipping route for each vessel. Generally speaking, the profit-oriented shipping companies will take the lowest transportation cost as the primary goal. In this way, the dry bulk fleet’s route planning problem is the shortest path problem that aims to minimize the total transportation cost by optimizing the route for each vessel.

In recent years, the number of navigation accidents induced by natural factors (e.g., bad weather) and military factors (e.g., pirates, armed conflict) has proliferated. Statistics from the International Maritime Organization (IMO) reveal that 111 ship safety incidents occurred at critical nodes of global dry bulk shipping routes (i.e., Malacca Strait, Strait of Hormuz, and Mandalay Strait) in 2020. More importantly, some severe navigation accidents may affect the efficiency and safety of maritime transportation and have a significant impact on the global supply chain safety. For instance, the grounding accident of Ever Given (March 23, 2021) from Evergreen Marine Corporation (Taiwan) caused that nearly 450 vessels are delayed at Suez Canal for more than one week. This accident has had a severe impact on global commodity transportation. In this way, we note the navigation risk significantly affects the entire shipping industry and even the international commodity trade. Therefore, the dry bulk shipping company must incorporate the navigation risk into the shipping route design for the fleet. In this paper, we focus on designing the shipping route for each vessel in the fleet that can minimize the total transportation cost and ensure the total navigation risk of the fleet is no more than a certain threshold.

Dry bulk fleet navigation risk mainly refers to the damage and loss of vessels in the fleet and the cargo induced by lousy weather, ship accidents, and military conflicts.
In case that the factors and events affecting the dry bulk fleet navigation risk are characterized, we can estimate the nominal value of navigation risk for the vessel on each leg in the route. However, the estimated navigation risk value may exhibit significant variation due to the stochastic nature of the natural and political risk factors. As a result, the shipping route designed based on the nominal value of navigation risk may exceed the given threshold of total navigation risk. In other words, the shipping routes designed with the deterministic optimization model cannot satisfy the navigation risk constraints for the fleet. We exploit the robust optimization approach to plan the shipping route for the dry bulk fleet to address this problem. Compared with fuzzy programming and stochastic programming, which assume that the affiliation function and probability distribution are known, the robust optimization method only needs to give the range of values of uncertain parameters, which is more suitable for solving this kind of uncertainty decision problem.

We first formulate the deterministic model for the shipping route planning problem. The aim is to minimize the total transportation cost and ensure the entire navigation risk of the fleet is no less than a certain threshold. We then consider the value of navigation risk may deviate from the nominal value and develop the robust counterpart of the deterministic model. The robust model can ensure the worst-case navigation risk does not exceed the threshold. To evaluate the performance of our approach, we use a set of actual data from the Chinese gran import shipping network to carry out the case study.

The remainder of this paper is organized as follows: Section 2 briefly reviews the related works in the literature. Section 3 describes the route planning problem for dry bulk fleet, which considers navigation risk uncertainty. Section 4 presents a deterministic route planning model for the dry bulk fleet and derives its robust counterpart by considering the navigation risk uncertainty. The case study with actual data is carried out in Section 5. At last, we conclude this paper in Section 6.

II. LITERATURE REVIEW

In this section, we review two streams of works that are closely related to our research problem: dry bulk vessel route optimization and the robust optimization approach.

A. DRY BULK VESSEL ROUTE OPTIMIZATION

As a critical part of maritime transportation, the operations and management of dry bulk shipping have attracted lots of research interest in recent years. In particular, there are also some works on shipping route planning and path selection. For instance, some works focus on identifying the best route for dry bulk shipping by incorporating the speed, ship cargo capacity, and transportation demand so that the shipping company can maximize the total profit [2]–[4]. Moreover, Hu [5] studied the planning of shipping routes to carry the disaster relief materials to minimize the total travel time. In addition, some works exploited the vessel AIS data to estimate the cost of different paths and studied the dynamic route planning problem [6]–[9]. Fei and Hong [10] investigated a dry bulk hub port transshipment network by considering port berth docking restrictions and import/export demand and found that the benefits of adopting a hub port transshipment mode outperform traditional direct transportation.

The transportation community has developed some new methods to address the planning of shipping routes for the dry bulk fleet in recent years. Some works developed mixed integer linear programming models to optimize the selection of vessel routes and the allocation of vessels for each course [11], [12]. De et al. [13] introduced the loading and unloading constraints and ship capacity constraints into the problem and developed a mixed-integer nonlinear programming model that satisfies actual route planning requirements. Other researchers considered the uncertainties of ship schedules and weather conditions and developed stochastic programming models to optimize ship transportation routes [14]–[16]. With the rapid development of intelligent computation, heuristic algorithms have been gradually applied to solve dry bulk fleet routing problems. Yamashita et al. [17] proposed a heuristic algorithm by considering the biased scheduling rules, insertion, and exchange steps to solve the actual large-scale vessel route planning problem. Pinto et al. [18] proposed a heuristic algorithm with a variable neighborhood search strategy to solve the vessel route selection and scheduling problem with cargo capacity restrictions and loading constraints. In addition, heuristic algorithms based on adaptive large-neighborhood search have been established to plan the transportation routes of the dry bulk fleet with ship scheduling and allocation consideration [19], [20].

The last few years have witnessed the rapid process in the planning of dry bulk fleet routes. The current works have considered many factors (i.e., ship speed, cargo transport volume, capacity) in the fleet routing problem and developed many models and algorithms to address this problem. However, the navigation risk has not been considered in the dry bulk fleet routing problem to the best of our knowledge. As a result, the shipping routes determined by the current works may face severe navigation risks. To address this problem, this paper incorporates the navigation risk into the dry bulk fleet routing problem. We develop the model formulation to minimize the total transportation cost and require that the entire navigation risk does not exceed a certain threshold. Moreover, we also develop a robust optimization counterpart of the deterministic model to incorporate the uncertainty of navigation risk.

B. ROBUST OPTIMIZATION APPROACH

Robust optimization is an appealing approach to address the problem with uncertain parameters that are only known to belong to some uncertain set [21]–[23]. Its objective is to optimize the worst-case objective function [24]–[28]. Robust optimization can obtain a “robust” solution to protect the decision-maker against adverse realizations of
uncertainty [29]. Therefore, the robust optimization approach has attracted considerable attention in the academic community [30]. For example, Chung et al. introduced the robust optimization approach to the NDP model for the optimal DTA of a single-stage system under demand uncertainty. On this basis, they further presented a robust dynamic pricing model and a distributional robust chance-constrained optimization model [31]–[33]. As most of the solutions obtained with the robust optimization framework seem overly conservative, extensive research has focused on constructing an uncertainty set for which potential parameter uncertainty and decision-maker preferences can be obtained and employed to construct a feasible optimization model [34]. Linear robust optimization problems must construct them as standard mathematical programming models through the uncertainty set structure [35]. There are four main types of uncertainty sets include interval, budgeted, polyhedral, and ellipsoidal uncertainties [24], [25], [27]. Given its unique advantages for solving problems with parameter uncertainty, the robust approach has been applied in many research areas such as vehicle path planning [36], [37], shipping transportation service design [38], and transit network design [39], [40] et al. [41]–[44].

In this paper, we exploit the robust optimization approach to address the dry bulk routing problem with uncertain navigation risk. Few articles study the dry bulk fleet routing problem from this perspective to the best of our knowledge. We first develop the deterministic model with nominal navigation risk, then develop its robust counterpart by assuming the cumulative deviation of navigation risk is no more than a certain value. Moreover, we also carry out a case study with actual shipping data to elaborate on the performance of our approach.

III. ROBUST DRY BULK FLEET ROUTE OPTIMIZATION PROBLEM

A. PROBLEM STATEMENT

We consider the case that a dry bulk shipping company operates a fleet denoted as K and needs to design a shipping route for each vessel to perform the transportation task with pre-determined origin and destination. Each ship performs one voyage in the decision horizon, and the corresponding shipping network is represented by a directed network denoted as $G = (N, A)$ (c.f.Figure 1). In the shipping network, $N = \{1, 2, \ldots, n\}$ is the set of nodes which can be ports, straits, and canals that dry bulk vessels must pass through to transport their cargo from the origin to the destination port. $A = \{a_1, a_2, \ldots, a_m\}$ is the set of the network arcs. Moreover, $OD = \{od_1, od_2, \ldots, od_k\}$ is the set of corresponding voyages (e.g., origin and destination port) of vessels in the fleet. In detail, $O = \{o_1, o_2, \ldots, o_k\}$ is the set of origin ports of the vessels in the fleet, $D = \{d_1, d_2, \ldots, d_k\}$ is the set of destination ports of vessels in the fleet. Each network arc $a = (i, j)$ has a corresponding weight vector $W_{ij} = (c_{ij}, r_{ij})$, $c_{ij}$ is the transportation cost incurred by the carrier from nodes $i$ to $j$, and the $r_{ij}$ is the uncertain navigation risk of each vessel from nodes $i$ to $j$.

Dry bulk fleet route planning seeks to minimize the total transportation cost of the fleet. At the same time, the navigation risk of the dry bulk fleet should not exceed a threshold $R$. In general, studies on the planning of dry bulk fleet transportation routes assume that the navigation risk is deterministic. However, the practical navigation risk of dry bulk carriers exhibits significant volatility and uncertainty. It may be induced by the direct or indirect influence of multiple factors such as natural, political, and military factors. In this situation, the dry bulk fleet transportation route determined according to the nominal value of navigation risk may not be optimal and may even violate navigation risk constraints. This work investigates the problem of dry bulk fleet route planning based on robust optimization to address this problem. In this way, we can satisfy the navigation risk constraint in the worst-case and optimize the corresponding transportation cost. We assume the uncertainty set of the navigation risk of the dry bulk vessel as follows: the cumulative variation of the navigation risk for all arcs does not exceed the threshold $\Gamma$. As a result, we can reformulate the deterministic route planning problem into a robust optimization model. To solve this robust model efficiently, we exploit the duality theory of linear programming to derive a tractable equivalent model.

B. ASSUMPTIONS

Given the navigation risk uncertainty, the dry bulk fleet route planning problem is essentially a cost-minimization path planning problem. Before formulating the model, we first describe the assumptions in this research:

(1) During the decision horizon, each dry bulk vessel in the fleet performs one voyage, i.e., the ship transports the cargo from the origin to the destination port to complete the transportation task.

(2) Transportation cost considers the fuel cost during the voyage.

(3) The ships are sailing at economical speed during the entire voyage. As the fuel cost is determined by speed, the transportation cost on different paths can be determined when the sailing distance between the nodes is determined [3].

(4) We consider the total transportation cost and entire navigation risk of a fleet with multiple vessel types.
IV. MODEL FORMULATION

A. NOTATIONS

The notations used in this paper are shown in the following Table 1.

| Parameters | Descriptions |
|------------|--------------|
| $K$        | Set of dry bulk vessels in the fleet |
| $O_k$      | Set of origin ports of the dry bulk vessels |
| $D_k$      | Set of destination ports of the dry bulk vessels |
| $R$        | Entire acceptable navigation risk of the fleet |
| $c_{ij}^k$ | Transportation cost of the dry bulk vessel $k$ from nodes $i$ to $j$ |
| $\bar{r}_{ij}^k$ | Navigation risk of the dry bulk vessel $k$ from nodes $i$ to $j$ |
| $\tilde{r}_{ij}^k$ | The average value of the navigation risk of the dry bulk vessel $k$ from nodes $i$ to $j$ |
| Decision Variables | $x_{ij}^k \in \{0, 1\}$, 1 if the dry bulk vessel $k$ passes through the segment from nodes $i$ to $j$, and 0 otherwise |

B. DETERMINED FORMULATION OF DRY BULK FLEET ROUTE PLANNING

We first assumed that the navigation risk is fixed and known in the deterministic dry bulk fleet route planning formulation. Then, we focus on minimizing the total fleet transportation cost and ensure the entire navigation risk of the fleet does not exceed the threshold $R$.

We assume that the transportation cost incurred by the dry bulk carrier $k$ passing through the network arc $(i, j)$ is $c_{ij}^k$, and the navigation risk is $\tilde{r}_{ij}^k$. The transportation cost mainly refers to the fuel cost incurred by the dry bulk vessel during transportation. The transportation risk refers to the possibility of causing the loss or destruction of the dry bulk vessel and the cargo it carries. As a result, the deterministic formulation can be formulated as the following model.

\[
\begin{align*}
\min \quad & \sum_{k \in K} \sum_{(i,j) \in A} c_{ij}^k x_{ij}^k \quad \text{(P1)} \\
\text{s.t.} \quad & \sum_{j \mid (i,j) \in A} x_{ij}^k - \sum_{j \mid (j,i) \in A} x_{ji}^k = 1, \quad \forall k \in K, \ i = O_k \\
& \sum_{j \mid (i,j) \in A} x_{ij}^k - \sum_{j \mid (j,i) \in A} x_{ji}^k = 0, \quad \forall k \in K, \ i \neq O_k, D_k \\
& \sum_{j \mid (i,j) \in A} x_{ij}^k - \sum_{j \mid (j,i) \in A} x_{ji}^k = -1, \quad \forall k \in K, \ i = D_k \\
& \sum_{k \in K} \tilde{r}_{ij}^k x_{ij}^k \leq R \quad \text{(4)}
\end{align*}
\]

In the deterministic dry bulk fleet route planning formulation (P1), the objective function is to minimize the total transportation cost for all ships in the fleet. Constraints (1)–(3) are flow balance constraints and ensure that each dry bulk vessel can form a complete path through the selected segments between the origin and the destination port. Constraint (1) guarantees that the dry bulk vessel $k$ departs from the origin port. Constraint (2) ensures the continuity of the transportation route chosen by the dry bulk vessel $k$. Constraint (3) guarantees that the dry bulk vessel $k$ eventually sails to the destination port. Constraint (4) ensures that the entire navigation risk of the whole fleet does not exceed the threshold $R$.

C. ROBUST COUNTERPART FOR DRY BULK FLEET ROUTE PLANNING

Based on the deterministic model constructed above, we consider the navigation risk of the dry bulk vessel between nodes as an uncertainty parameter. Moreover, dry bulk vessel transportation routes are planned to minimize the total fleet transportation cost by the robust optimization method with the maximum entire fleet navigation risk within the uncertainty set [45].

Let $\bar{r}_{ij}^k, (i,j) \in A$ be the estimated average value of the dry bulk vessel navigation risk between the nodes. Then the uncertainty set of the ship’s navigation risk between the nodes is defined as follows:

\[
\mathcal{U} = \left\{ \bar{r} \in A \mid \sum_{k \in K} \sum_{(i,j) \in A} |\tilde{r}_{ij}^k - \bar{r}_{ij}^k| \leq \Gamma \right\} \quad \text{(5)}
\]

The uncertainty set (5) indicates that the cumulative variation of transportation risk between nodes on the routes for all dry bulk vessels should not exceed a threshold $\Gamma$. Let $T_{ij}^k$ be the absolute value of the variation of navigation risk. For a given $x$ value, the maximum value of the entire navigation risk of the fleet can be obtained by the following mathematical model.

\[
\begin{align*}
\max \quad & \sum_{k \in K} \sum_{(i,j) \in A} T_{ij}^k x_{ij}^k \quad \text{(P2)} \\
\text{s.t.} \quad & \sum_{k \in K} \sum_{(i,j) \in A} T_{ij}^k \leq \Gamma \quad \text{(6)} \\
& \tilde{r}_{ij}^k - \bar{r}_{ij}^k \leq T_{ij}^k, \quad \forall k \in K, \forall (i,j) \in A \\
& \bar{r}_{ij}^k - \tilde{r}_{ij}^k \leq T_{ij}^k, \quad \forall k \in K, \forall (i,j) \in A 
\end{align*}
\]

In the above formulation (P2), the navigation risk of the dry bulk vessel between nodes is considered a decision variable, and its objective is to maximize the entire navigation risk of the fleet according to the decision maker’s planning of the routes. The constraints satisfy the transportation risk uncertainty set $\mathcal{U}$. Let $\alpha, \beta_{ij}^k, \gamma_{ij}^k$ be the dual variables corresponding to the above Constraints (6), (7), and (8), respectively. Then, the dual problem of the above formula (P2) can be described as follows:

\[
\begin{align*}
\min \quad & \alpha + \sum_{k \in K} \sum_{(i,j) \in A} \tilde{r}_{ij}^k (\beta_{ij}^k - \gamma_{ij}^k) + \alpha \Gamma \quad \text{(P3)} \\
\text{s.t.} \quad & \alpha - \beta_{ij}^k + \gamma_{ij}^k \geq 0, \quad \forall k \in K, \forall (i,j) \in A \\
& \beta_{ij}^k - \gamma_{ij}^k \geq x_{ij}^k, \quad \forall k \in K, \forall (i,j) \in A \\
& \beta_{ij}^k \geq 0, \quad \beta_{ij}^k \leq 0, \quad \gamma_{ij}^k \geq 0.
\end{align*}
\]
We can obtain a robust counterpart of the deterministic dry bulk fleet route planning formulation according to the above analysis. In detail, Constraint (4) in the model (P1) is replaced by the corresponding dual problem described above and can be described as follows:

\[
\min \sum_{k \in K} \sum_{(i,j) \in A} c_{ij}^k x_{ij}^k
\]

s.t. \[
\sum_{j \mid (i,j) \in A} x_{ij}^k - \sum_{j \mid (j,i) \in A} x_{ji}^k = 1, \quad \forall k \in K, \quad i = O_k
\] (12)

\[
\sum_{j \mid (i,j) \in A} x_{ij}^k - \sum_{j \mid (j,i) \in A} x_{ji}^k = 0, \quad \forall k \in K, \quad i \neq O_k, \quad D_k
\] (13)

\[
\sum_{k \in K} \sum_{(i,j) \in A} \bar{r}_{ij}^k (\beta_{ij}^k - \gamma_{ij}^k) + \alpha \Gamma \leq R
\] (15)

\[
\alpha - \beta_{ij}^k - \gamma_{ij}^k \geq 0, \quad \forall k \in K, \quad \forall (i,j) \in A
\] (16)

\[
\beta_{ij}^k - \gamma_{ij}^k \geq x_{ij}^k, \quad \forall k \in K, \quad \forall (i,j) \in A
\] (17)

\[
\beta_{ij}^k \geq 0, \quad \beta_{ij}^k \geq 0, \quad \gamma_{ij}^k \geq 0
\] (18)

The model is a robust optimization model eventually obtained by rewriting model (P2) into the corresponding feasibility problem by introducing dual variables. Therefore, the robust counterpart (P4) still falls under linear programming.

V. CASE STUDY
A. DATA DESCRIPTION
To demonstrate the feasibility of our robust approach for dry bulk fleet route planning, we select the Chinese grain import transportation routes to conduct a case study of the grain transportation route planning.

The selected Chinese grain import route network consists of 40 nodes and 107 arcs. The names and numbers of each node are shown in Table 2. In Table 2, nodes 1–16 are loading ports, nodes 17–33 are the straits and canals to be crossed, and nodes 34–40 are discharge ports. The dry bulk vessel type of the studied grain transportation fleet contains two types: Panamax and Handysize. The fleet has 6 Panamax ships and 10 Handysize ships. The specific information of each transport vessel type, economical speed, origin port, and destination port in the fleet is shown in Table 3.

For the navigation risk of dry bulk vessels on each segment of the voyages, this study uses the Global Integrated Shipping Information System (GISIS) database as the data source to count the severity of ship safety incidents, including ship collision, grounding, and sinking and their probability of occurrence. The database was established and is maintained by the International Maritime Organization (IMO) and has 15 modules, including Maritime Security, Piracy and Armed Robbery, and Maritime Casualties and Incidents. This work mainly uses the module on Maritime Casualties and Incidents for data statistics. To ensure the timeliness and completeness of the statistics, we extract and count the ship safety accidents recorded in the GISIS database during 2016–2020 as the base data and calculate the average value of navigation risk for each arc.

B. TRANSPORTATION COST
According to assumption (2), the transportation cost of dry bulk vessel \( k \) during the transportation from nodes \( i \) to \( j \) is the fuel price and fuel consumption product. Fuel consumption is the product of sailing time and dry bulk vessel’s hourly fuel consumption. The said fuel consumption is approximately proportional to the third power of the dry bulk carrier’s speed [46], so the transportation cost of dry bulk vessel \( k \) during the transportation from nodes \( i \) to \( j \) can be expressed as follows:

\[
\bar{c}_{ij}^k = \delta^k p L_{ij}^k v^2_k
\] (19)

In the formula, \( p \) is the fuel price, \( \delta^k \) is the scale factor between fuel consumption and the speed of dry bulk vessel \( k \), \( L_{ij}^k \) is the sailing distance from nodes \( i \) to \( j \), and \( v_k \) is the economical speed of dry bulk vessel \( k \).

C. TRANSPORTATION RISK
In the Formal Safety Assessment (FSA) guidance issued by the IMO, a risk is defined as a combination of the probability of a ship safety incident and the severity of the consequences arising from the ship safety incident. In IMO’s GISIS, the severity of a ship safety incident is classified into three levels: very serious, serious, and less serious. Therefore, we define the dry bulk vessel navigation risk as to the sum of the product of the probability of the occurrence of dry bulk vessel safety incidents of different severity levels and the severity of the results of those incidents. Then, the average estimate of the dry bulk vessel navigation risk between the nodes can be expressed as follows:

\[
\bar{r}_{ij}^k = \frac{e_{ij}^k m_{ij}^0 + e_{ij}^k m_{ij}^1 + e_{ij}^k m_{ij}^2}{N}
\] (20)
In the formula, $e_{ij}^v$, $e_{ij}^s$, $e_{ij}^l$ denote the probability of a very serious, serious, and not serious ship safety incident, respectively. $m_{ij}^v$, $m_{ij}^s$, $m_{ij}^l$ denote the corresponding severities of the related ship safety incident. $N$ is the years of statistical data.

### D. RESULTS AND ANALYSIS

We simulate the dry bulk fleet routing problem using Python programming language and solve the optimization problem by Gurobi (9.1.0) solver. All the experiments are performed on a 2.8GHz i5 CPU Windows PC with 8G RAM. Then, we estimate the corresponding parameters, input the calculated average transportation cost and navigation risk of each dry bulk carrier in the fleet on each arc into the solver.

Firstly, it is assumed that the navigation risk variation of each arc is zero, i.e., $\Gamma = 0$. At this time, the model is a dry bulk fleet route planning model with deterministic navigation risk. The transportation cost and navigation risk data of each arc are substituted into the model for calculation. The variation of total fleet transportation cost is studied by adjusting the value of $R$, i.e., by considering the risk preference of decision-makers. The relationship between the total fleet transportation cost and the navigation risk threshold $R$ is shown in Figure 2.

As shown in Figure 2, when the constraint value $R$ is 274.4, each dry bulk carrier in the fleet can operate normally on the route, and the total fleet transportation cost is $44.156$ million. As the constraint value $R$ increases continuously, the total fleet transportation cost continues to decrease. When the constraint value $R$ increases from 274.4 to 277.1, i.e., the constraint value $R$ increases by 1%, the total fleet transportation cost decreases from $44.156$ million to $42.027$ million, which is a decrease of 4.8%. Subsequently, whenever the constraint value $R$ increases by 1%, the total fleet transportation cost decreases until the total fleet transportation cost reaches the lowest $37.759$ million when the constraint value $R$ is 356.7. At this time, the optimal solution of the robust counterpart is equal to the optimal solution obtained in the navigation risk determination model. This result reveals that our robust counterpart reduces to the deterministic formulation when robust counterpart parameters $\Gamma = 0$. When navigation risk is determined during the planning of dry bulk vessel routes, the total fleet transportation cost is inversely proportional to the decision maker’s risk tolerance with an increasing proportionality coefficient. The higher the decision maker’s risk tolerance, the lower the total fleet transportation cost; conversely, the lower the decision maker’s risk tolerance, the higher the total fleet transportation cost.

On this basis, we consider the navigation risk as an uncertain variable and use the developed robust formulation to plan the routes of dry bulk vessels in the fleet. Then we compare and analyze the total fleet transportation cost variation with the risk constraint value $R$ under the variation of parameter $\Gamma$. $\Gamma$ denotes the cumulative variation of the navigation risk, which can be estimated as the variation of the risk multiplied by the total navigation risk. For example, if the total navigation risk value is 10 and the risk variation is set as 0.1, the parameter $\Gamma$ is 1.0. Therefore, we can obtain the relationship between navigation risk variation and the total fleet transportation cost. We increase the navigation...
risk variation from 0 to 0.03 to examine the total fleet transportation cost fluctuations with the total fleet navigation risk under the condition of uncertain navigation risk. The result is shown in Figure 3.

As shown in Figure 3, the entire fleet navigation risk increases with the rise of the cumulative variation of the navigation risk, i.e., the entire fleet navigation risk is an increasing function of the navigation risk variation. Moreover, the variation of the total fleet transportation cost with the entire fleet navigation risk is the same as the variation in the case of navigation risk determination, and both indicate that the total fleet transportation cost decreases with the rise of entire fleet navigation risk.

To further investigate the impact of navigation risk variation on the entire fleet navigation risk, this work analyzes the entire fleet navigation risk when the total fleet transportation cost is minimized under different navigation risk variations, as shown in Figure 4.

When the navigation risk variation is 0.01, the entire fleet navigation risk that reaches the lowest total fleet transportation cost is 450.1. The entire fleet navigation risk increases with the rise of navigation risk variation. When the navigation risk variation is 0.1, the entire fleet navigation risk that reaches the lowest total fleet transportation cost is 1354.5. Relative to the deterministic case, i.e., when $\Gamma = 0$, the entire fleet navigation risk increases by approximately 29.2% for each 1% rise in the navigation risk variation. Therefore, when the total fleet transportation cost reaches the lowest value, the entire fleet navigation risk is approximately proportional to the navigation risk variation.

In addition, based on the constructed deterministic model to obtain the lowest total fleet transportation cost, we can estimate the total fleet transportation risk in the worst case by solving the pairwise problem (P3). This approach results in the worst-case value of the left-hand term $\sum_{k \in K} \sum_{(i,j) \in A} \tilde{r}_{ij} k \lambda_{ij}^k - R$ of the total fleet navigation risk constraint (4) for different cumulative variations of navigation risk, as shown in Figure 5.

As shown in Figure 5, the left-hand term of the total fleet navigation risk constraint is larger than zero when the navigation risk variation is larger than zero. The value of the constraint increases with the rise of navigation risk variation. Therefore, the robust counterpart will be infeasible when planning the dry bulk fleet transportation route determined by the nominal value.

Finally, we can also obtain the running time of solving the robust counterpart under different navigation risk variations in Figure 6.
As shown in Figure 6, with the increase of navigation risk variation, the running time of the established robust optimization formulation to solve the optimal solution fluctuates between 0.13 and 0.19 s, thereby showing a gradual decrease trend. The running time of the robust optimization formulation gradually decreases with the rise of navigation risk variation. Thus, the constructed robust optimization model has high computational efficiency in solving this kind of problem and can meet computational efficiency requirements in practice.

VI. CONCLUSION
This study develops a robust approach for planning dry bulk fleet routes, aiming to minimize the total transportation cost and ensure the navigation risk does not exceed a certain threshold. The robust counterpart for the dry bulk fleet route planning is presented to incorporate navigation risk uncertainty. Then, we select a grain transportation fleet of a shipping company operating on the Chinese grain import route network for a case study. The numerical results suggest the following practical observations. (1) The total fleet transportation cost is inversely related to the decision maker’s risk tolerance with an increasing proportional coefficient. (2) When the total fleet transportation cost reaches the minimum, the total fleet navigation risk increases with the rise of the cumulative variation of the navigation risk in an approximately proportional relationship. (3) Through the violation of the entire fleet navigation risk under different navigation risk variations and running times of the model to identify the optimal solution, the constructed robust optimization model is proven to effectively solve the dry bulk fleet route planning problem with uncertain navigation risk. Thus provides a reference basis for decision-makers.

Some limitations of this paper lie in that we model the dry bulk fleet route planning in a static environment without considering the dynamic environment. Then the impact of the navigation risk in the time-space network cannot be identified in our model. A promising direction of future research is to optimize the dry bulk fleet routes considering uncertain navigation risk in a time-space network. Moreover, some recent advances in the robust approach can be utilized to incorporate the navigation risk uncertainty in a time-space network to improve the applicability of this method.

REFERENCES
[1] L. Wu, S. Wang, and G. Laporte, “The robust bulk ship routing problem with batched cargo selection,” Transp. Res. B, Methodol., vol. 143, pp. 124–159, Jan. 2021.
[2] M. Stålhane, H. Andersson, and M. Christiansen, “A branch-and-price method for a ship routing and scheduling problem with cargo coupling and synchronization constraints,” EURO J. Transp. Logistics, vol. 4, no. 4, pp. 421–443, Dec. 2015.
[3] A. W. Siddiqui and M. Verma, “A bi-objective approach to routing and scheduling maritime transportation of crude oil,” Transp. Res. D, Transp. Environ., vol. 37, pp. 65–78, Jun. 2015.
[4] M. Wen, S. Ropke, H. L. Petersen, R. Larsen, and O. B. G. Madsen, “Full-shipload tramp ship routing and scheduling with variable speeds,” Comput. Oper. Res., vol. 70, pp. 1–8, Jan. 2016.
[5] Z. Hu, “Model and algorithm for the large material distribution problem in maritime transportation,” J. Coastal Res., vol. 82, no. 1, pp. 294–306, Sep. 2018.
[6] Y. Shu, W. Daamen, H. Ligteringen, and S. Hoogendoorn, “Vessel speed, course, and path analysis in the Botlek area of the Port of Rotterdam, Netherlands,” Transp. Res. Rec., J. Transp. Res. Board, vol. 2330, no. 1, pp. 63–72, Jan. 2013.
[7] F. Xiao, H. Ligteringen, C. van Gulijk, and B. Ale, “Comparison study on AIS data of ship traffic behavior,” Ocean Eng., vol. 95, pp. 84–93, Feb. 2015.
[8] S. A. Breithaupt, A. Copping, J. Tagedast, and J. Whiting, “Maritime route delineation using AIS data from the Atlantic coast of the U.S.” J. Navigat., vol. 70, no. 2, pp. 84–93, Sep. 2016.
[9] P. Andersson and P. Ivezic, “Dynamic route planning in the Baltic sea region—A cost-benefit analysis based on AIS data,” Maritime Econ. Logistics, vol. 19, no. 4, pp. 631–649, Dec. 2017.
[10] F. Shao and H. Zhen, “An optimization method of bulk carriers transshipping network and pooling operation based quasi-liner mode,” J. Transp. Syst. Eng. Inf. Technol., vol. 20, no. 4, pp. 21–27, 2020.
[11] J. G. Rakke, H. Andersson, M. Christiansen, and G. Desaulniers, “A new formulation based on customer delivery patterns for a maritime inventory routing problem,” Transp. Sci., vol. 49, no. 2, pp. 384–401, May 2015.
[12] F. Li, D. Yang, S. Wang, and J. Weng, “Ship routing and scheduling problem for steel plants cluster alongside the Yangtze river,” Transp. Res. E, Logistics Transp. Rev., vol. 122, pp. 198–210, Feb. 2019.
[13] A. De, S. K. Kumar, A. Gunasekaran, and K. M. Tiwari, “Sustainable maritime inventory routing problem with time window constraints,” Eng. Appl. Artif. Intell., vol. 61, pp. 77–95, May 2017.
[14] A. Agra, M. Christiansen, A. Delgado, and L. M. Hvattum, “A maritime inventory routing problem with stochastic sailing and port times,” Comput. Oper. Res., vol. 61, pp. 18–30, Sep. 2015.
[15] R. Shibasaki, T. Azuma, and T. Yoshida, “Route choice of container ship on a global scale and model development: Focusing on the Suez Canal,” Rivista Internazionale Di Economia Dei Trasporti, vol. 43, no. 3, pp. 265–290, 2016.
[16] H. M. Soroush and S. M. Al-Yakoob, “A maritime scheduling transportation-inventory problem with normally distributed demands and fully loaded/unloaded vessels,” Appl. Math. Model., vol. 53, pp. 540–566, Jan. 2018.
[17] D. Yamashita, B. J. V. da Silva, R. Morabito, and P. C. Ribas, “A multi-start heuristic for the ship routing and scheduling of an oil company,” Comput. Ind. Eng., vol. 136, pp. 464–476, Oct. 2019.
[18] T. Pinto, C. Alves, and J. V. de Carvalho, “Column generation based primal heuristics for routing and loading problems,” Electron. Notes Discrete Math., vol. 64, pp. 135–144, Feb. 2018.
[19] J. Lee and B.-I. Kim, “Industrial ship routing problem with split delivery and two types of vessels,” Expert Syst. Appl., vol. 42, no. 22, pp. 9012–9023, Dec. 2015.
[20] A. Hemmati, L. M. Hvattum, M. Christiansen, and G. Laporte, “An iterative two-phase hybrid matheuristic for a multi-product short sea inventory-routing problem,” Eur. J. Oper. Res., vol. 252, no. 3, pp. 755–788, Aug. 2016.
[21] F. Zhao, H. Sun, F. Zhao, H. Zhang, and T. Li, “A globalized robust optimization approach of dynamic network design problem with demand uncertainty,” IEEE Access, vol. 7, pp. 115734–115748, 2019.
[22] Z. Lianq, Q. Alsafof, and W. Su, “Proactive resilient scheduling for networked microgrids with extreme events,” IEEE Access, vol. 7, pp. 112639–112652, 2019.
[23] H. Shahmoradi-Moghadam, N. Safaei, and S. J. Sadjadi, “Robust maintenance scheduling of aircraft fleet: A hybrid simulation-optimization approach,” IEEE Access, vol. 9, pp. 17854–17865, 2021.
[24] A. Ben-Tal and A. Nemirovski, “Robust convex optimization,” Math. Oper. Res., vol. 23, no. 4, pp. 769–805, 1998.
[25] A. Ben-Tal and A. Nemirovski, “Robust solutions of uncertain linear programs,” Oper. Res. Lett., vol. 25, no. 1, pp. 1–13, 1999.
[26] D. Bertsimas and M. Sim, “Robust discrete optimization and network flows,” Math. Program. B, vol. 98, pp. 49–71, May 2003.
[27] D. Bertsimas and M. Sim, “The price of robustness,” Oper. Res., vol. 52, no. 1, pp. 35–53, Jan. 2004.
[28] E. Delage and Y. Ye, “Distributionally robust optimization under moment uncertainty with application to data-driven problems,” Oper. Res., vol. 58, no. 3, pp. 955–962, 2010.
[29] V. Gabrel, M. Lacroix, C. Murat, and N. Remli, “Robust location transportation problems under uncertain demands,” *Discrete Appl. Math.*, vol. 164, no. 1, pp. 100–111, 2014.

[30] Y. Lou, Y. Yin, and S. Lawphongpanich, “Robust approach to discrete network designs with demand uncertainty,” *Transp. Res. Rec.*, vol. 2009, no. 2009, pp. 86–94, Jan. 2009.

[31] B. D. Chung, T. Yao, C. Xie, and A. Thorsen, “Robust optimization model for a dynamic network design problem under demand uncertainty,” *Netw. Spatial Econ.*, vol. 11, no. 2, pp. 371–389, Jun. 2011.

[32] B. D. Chung, T. Yao, and B. Zhang, “Dynamic traffic assignment under uncertainty: A distributional robust chance-constrained approach,” *Netw. Spatial Econ.*, vol. 12, no. 1, pp. 167–181, 2012.

[33] B. D. Chung, T. Yao, C. Xie, and H. Liu, “Dynamic congestion pricing with demand uncertainty: A robust optimization approach,” *Transp. Res. B, Methodol.*, vol. 46, no. 10, pp. 1504–1518, 2012.

[34] J. C. Smith and S. Ahmed, *Introduction to Robust Optimization*. Hoboken, NJ, USA: Wiley, 2011.

[35] J. Liang, J. Wu, Y. Qu, H. Yin, X. Qu, and Z. Gao, “Robust bus bridging service design under rail transit system disruptions,” *Transp. Res. E, Logistics Transp. Res.*, vol. 132, pp. 97–116, Dec. 2019.

[36] I. Sungur, *The Robust Vehicle Routing Problem*. Los Angeles, CA, USA: Univ. Southern California, 2007.

[37] I. Sungur, F. Ordóñez, and M. Dessouky, “A robust optimization approach for the capacitated vehicle routing problem with demand uncertainty,” *IIE Trans.*, vol. 40, no. 5, pp. 509–523, Mar. 2008.

[38] N. Remli and M. Rekik, “A robust winner determination problem for combinatorial transportation auctions under uncertain shipment volumes,” *Transp. Res. C, Emerg. Technol.*, vol. 35, pp. 204–217, Oct. 2013.

[39] K. An and H. K. Lo, “Robust transit network design with stochastic demand considering development density,” *Transp. Res. Proc.*, vol. 7, pp. 300–319, Nov. 2015.

[40] M. Ng and H. K. Lo, “Robust models for transportation service network design,” *Transp. Res. B, Methodol.*, vol. 94, pp. 378–386, Dec. 2016.

[41] M. G. Villarreal-Cervantes, A. Rodriguez-Molina, C.-V. Garcia-Mendoza, O. Penalosa-Mejia, and G. Sepulveda-Cervantes, “Multi-objective on-line optimization approach for the DC motor controller tuning using differential evolution,” *IEEE Access*, vol. 5, pp. 20393–20407, 2017.

[42] J. C. Yu and Suprayitno, “Evolutionary reliable regional Kriging surrogate and soft outer array for robust engineering optimization,” *IEEE Access*, vol. 5, pp. 16520–16531, 2017.

[43] E. Jafarnejad, A. Makui, A. Hafezalkotob, and D. Mohammaditabar, “A robust approach for cooperation and cooption of bio-refineries under government interventions by considering sustainability factors,” *IEEE Access*, vol. 8, pp. 155873–155890, 2020.

[44] M. Vidan, F. D’Andreagiovanni, and H. Pandzic, “Individual thermal generator and battery storage bidding strategies based on robust optimization,” *IEEE Access*, vol. 9, pp. 66829–66838, 2021.

[45] A. Ben-Tal and A. Nemirovski, “Robust solutions of linear programming problems contaminated with uncertain data,” *Math. Program.*, vol. 88, no. 3, pp. 411–424, 2000.

[46] X. L. Jiao, X. L. Liu, R. X. Wang, and Y. P. Zhao, “Optimization model and ACO of ship assignment for international liner transportation,” *Adv. Sci. Technol. Water Resour.*, vol. 76, nos. 4–6, pp. 169–174, 2013.

**JUN GAO** was born in Dalian, Liaoning, China, in 1991. He received the B.S. degree in navigation technology from the Navigation College, Dalian Maritime University, in 2014, and the M.S. degree in business management from the School of Business Administration, Lanzhou University of Finance and Economics, in 2018. He is currently pursuing the Ph.D. degree with the College of Transportation Engineering, Dalian Maritime University.

His research interests include transportation planning and management.

**JIE WANG** received the Ph.D. degree in transportation planning and management from Dalian Maritime University, Dalian, China, in 2007.

He is currently a Professor with the College of Transportation Engineering, Dalian Maritime University. He is also the Director of the Institute of Shipping Human Resources, Dalian Maritime University, a soft Science Consulting Expert of the Ministry of Communications, and a member of Expert Group for qualification examination of Chinese tallyman. His research interests include the fields of port and shipping economy, investment decision-making and sustainable development of port and shipping enterprises, transportation development strategy and strategy, and shipping networks.