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Chung-Cheng Lu
Department of Transportation and Logistics Management, National Yang Ming Chiao Tung University, Taiwan

Hui-Chieh Li
Department of Business Administration, National Taipei University of Business, Taiwan, huichiehli@ntub.edu.tw

Hung-Yu Chen
Department of Transportation and Logistics Management, National Yang Ming Chiao Tung University, Taiwan

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RESEARCH ARTICLE

An Optimization Model for Supporting Bunkering Decisions in Bulk Shipping

Chung-Cheng Lu [a], Hui-Chieh Li [b,*], Hung-Yu Chen [a]

[a] Department of Transportation and Logistics Management, National Yang Ming Chiao Tung University, Taiwan
[b] Department of Business Administration, National Taipei University of Business, Taiwan

Abstract

This study addresses a bunkering optimization problem for bulk shipping carriers that explores route deviation to find optimal bunkering locations and amounts. A mixed integer linear programming (MILP) model is developed to determine optimal bunkering decisions that minimize total operating costs, including total daily operating costs, bunkering costs, port charges and surcharges, while observing time window constraints at loading/unloading ports. The proposed model is evaluated using instances generated from real data provided by H company with its operational headquarters in Taipei, Taiwan, which operates a fleet of handysize ships in East and South Asia. The results indicate that optimization models incorporating route deviation for bunkering purposes yield superior cost performance to those that restrict ships to bunkering at loading/unloading ports. This study provides a valuable reference point for bulk shipping companies in making bunkering decisions, and hence contributes to both the literature and the practice of bulk shipping.

Keywords: Bulk shipping, Bunkering decision, Mixed integer linear programming, Route deviation, Time window

1. Introduction

According to the United Nations Conference on Trade and Development [1], over 80 % of global trade volume is seaborne, underscoring maritime transportation's crucial role in international trade and the global economy. This dominance stems from high cargo capacity and lower pollution per unit transported. Despite global challenges, UNCTAD [2] projects maritime trade growth exceeding 2 % annually from 2024 to 2028. This growth is expected in maritime categories of both container shipping (on fixed routes and schedules) and bulk shipping (on flexible routes and schedules). The latter form, typically associated with tramp shipping, is experiencing increased demand due to expanding global trade. The bulk shipping market is estimated to grow at a compound annual growth rate (CAGR) of 4.2 % until 2027 [2].

While the growth prospects for tramp bulk shipping are promising, the sector faces the unique challenges of revenue stability and cost management. Highly volatile freight rates, as reflected in the Baltic Dry Index (BDI), along with cargo demand variability, lead to significant fluctuations in bulk shipping revenues. Consequently, effective cost management is critical to ensuring sustainable profitability for bulk shipping companies. Fleet operational costs of tramp bulk carriers consist of two major items: ship-related expenses and fuel expenditures. Bunker costs represent a significant portion of the expenses of carriers, potentially accounting for over 50 % of total operational costs, and making the price they pay for fuel a paramount issue [3,4]. Carriers' profitability depends on fuel supply strategies and ineffective fuel supply management may result in substantial financial deficits in extreme-case scenarios. Given the significant impact of fuel costs on fleet operational expenses, optimizing bunkering decisions becomes crucial for maintaining profitability in the unpredictable bulk shipping market.

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* Corresponding author.
E-mail address: huichiehli@ntub.edu.tw (H.-C. Li).

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The volatility inherent in tramp shipping poses significant operational challenges for bulk shipping companies, particularly in voyage planning and fuel supply management. Bulk shipping companies face uncertain prospects when scheduling future voyages for their fleets. Ideally, a bulk shipping company would wish to plan several voyages for a ship over the next few months in one block, or at least confirm a new voyage as the current one nears completion. But this uncertainty is also problematic for bunkering decisions, which must be made in real-time and require time-critical fuel strategy analysis to determine optimal refueling need, quantity, and bunkering port choices. Fluctuations in global crude oil prices and variations in port characteristics further complicate these decisions, because of significant port price differentials. Consequently, carriers often rely on past experience to make bunkering decisions, potentially overlooking essential variables, which negatively impacts their operational efficiency and cost-effectiveness. This situation highlights the complex interplay between voyage planning, fuel management, and profitability seen in the bulk shipping sector, underscoring the need for advanced decision support systems that can navigate these challenges and enhance carriers' strategic capabilities and improved operational outcomes.

Previous research on bunkering decision optimization has primarily focused on liner shipping; only limited attention has been paid to the unique challenges faced by tramp shipping. Besbes and Savin [5] did develop a stochastic optimization framework for maximizing individual tramp ship profitability in which bunkering decisions were included. They characterized optimal policies for scenarios with constant prices across time and ports, and constant prices across time but varying across ports. Meng et al. [6] tackled the tramp ship routing problem with port-specific bunker prices, optimizing routes, cargo allocation, and bunkering amounts to maximize profit, adopting a tailored branch-and-price solution approach. Vilhelmsen et al. [7] investigated the impact of incorporating bunker planning into the routing and scheduling process for tramp operators transporting full shiploads. Their findings demonstrate that an integrated approach can significantly enhance profitability.

Previous research on bulk shipping fuel management has predominantly focused on bunkering at vessels' predetermined loading/unloading ports. However, according to our interviews with bulk shipping carriers, deviating from predetermined routes to explore ports with better bunkering options (e.g., significantly lower fuel prices) is a recognized practice adopted to reduce total costs. Therefore, a bunkering decision-making framework for bulk shipping should incorporate route deviation. To the best of our knowledge, there is no current published research that incorporates route deviation options into bunkering decision models for bulk shipping companies. Furthermore, no existing research adequately addresses the practical complexities of managing dual fuel supply, specifically the concurrent provisioning of traditional heavy fuel oil and lighter marine gas oil. This study addresses these gaps by formulating a mixed integer linear programming (MILP) model for bulk shipping companies. The model determines the optimal bunkering ports and quantities for both heavy fuel oil and marine gas oil as it considers potential route deviations for total cost minimization. Our study contributes to the existing literature on route deviations in the bunkering problem by incorporating route deviation options, which capture the influences of fuel prices at different ports and transit times between them. Although similar approaches have been explored in previous studies (e.g., [8,9]; Vilhemsen et al., 2014), our approach offers a distinct perspective by specifically accounting for the typical use of heavy fuel oil and marine gas oil, a crucial factor in ensuring cost calculation accuracy and practical operational considerations.

The remainder of the paper is organized as follows. Section 2 summarizes the relevant literature, and is followed by model formulations in Section 3. A case study is presented in Section 4. Finally, Section 5 concludes the study.

2. Literature review

2.1. Bunker supply management for liner shipping

Bunker supply issues have been extensively explored but specifically in the context of liner shipping. Bunkering decisions can be considered at both the tactical and operational levels and involve decisions about where to bunker, how much fuel to purchase and which fuel contracts to close in advance [10]. Lin and Leong [11] developed a stochastic model that simultaneously optimizes sailing speeds, ship deployment, and bunkering decisions. The model determines optimal bunkering ports, accounting for varying fuel prices across different ports. In the study of Yao et al. [12], bunker fuel management strategy was investigated in terms of bunkering port selection, bunkering amount determination and ship speed adjustment so as to minimize total bunker fuel-related costs. Wang and Teo [3] demonstrated interactions between liner network planning and bunker hedging, showing the benefits to be gained by integrating bunker hedging into the liner network planning process. Meng et al. [4] investigated the bunker procurement planning problem, considering the purchasing of bunker from bunker futures contracts and the spot market to hedge risk in fluctuation of bunker prices. Wang and Meng [13] examined the sailing speed of containerships and refueling of bunker in a liner shipping network, while their model was later extended in Wang et al. [14] by further considering randomization of bunker prices. As with the previously mentioned studies, Liu et al. [15] also discussed fuel management strategies, but they particularly focused on the problem of optimization under uncertain demand. They found that trade-offs between the number of deployed ships, bunker consumption, and inventory costs are significant in supporting the planning process of decision-makers. From a supply chain perspective, Yang and Lam [16] assessed both the operational and economic performance of the bunkering of ammonia, an alternative ship fuel.

2.2. Bunker supply management for tramp shipping

While previous research on tramp shipping has primarily focused on ship routing and scheduling issues [17,18], a few studies have addressed fuel management issues. Vilhelmsen et al. [7] introduced a tramp ship routing and scheduling problem with bunker optimization. The study assumed uniform fuel supply times across all ports, so placed less emphasis on time-related costs in its decision-making analysis. Instead, it focused on the impact of interport fuel price differentials and geographical locations on fuel supply decisions. Fuentes et al. [9] did explore the influence of time costs, in uncertain waiting times, together with uncertain fuel prices, in the selection of bunker fuel stops in tramp shipping. They found a trade-off between port efficiency and the economic benefit of bunkering at cheaper ports, even if voyages ended in regions with higher fuel prices. Besbes and Savin [5] developed a stochastic optimization framework to maximize the profitability of an individual tramp ship incorporating bunkering decisions. They characterized the optimal policy in cases where prices were constant through time and did not differ across ports and in others where prices were constant through time but differed across ports. Meng et al. [6] addressed the tramp ship routing problem considering port-specific bunker prices, optimizing ship routes, cargo allocation, and bunker purchase amounts to maximize total profit. Bunker detours were not considered in their model. Oh and Karimi [8] developed a MILP model to optimize multiparcel tanker operations under fuel price uncertainty. The model determined optimal voyage speeds and refueling plans to minimize expected total operating costs. It considered bunkering only at route deviation ports and used a scenario-based approach with probabilities, based on historical data, to model future fuel price fluctuations. Omholt-Jensen et al. [19] also investigated the tramp ship routing and scheduling problem with bunker optimization.

In bulk shipping, demand is influenced by charter requirements and direction, which can vary significantly between voyages. To address this variability, companies typically finalize fuel supply decisions after new voyage information is confirmed and before the vessel begins its next task. This approach helps avoid additional process fees from route adjustments. The current study sets the decision-making time point for fuel supply decisions to be before the start of the next voyage. The planning horizon considers all confirmed voyage information for the fleet, including sailing, loading, and unloading times. If a detour is arranged for fuel supply, detour and fuel supply times are also included. This study innovates by simultaneously considering both route deviation and cargo handling ports for bunkering, addressing a gap in previous research. Its comprehensive cost model includes operating costs, differentiated bunker costs, port charges, and surcharges. It accounts for the typical use of heavy fuel oil in open seas and marine gas oil in emission control areas, a crucial determinant of cost calculation accuracy and operational decision appropriateness. The optimization model evaluates trade-offs between bunkering at cargo ports versus deviating to specialized ports, considering varying fuel prices, availability, and consumption rates across different conditions, making it a more realistic representation of the bunker supply optimization problem. Table 1 presents a summary of the most relevant studies, highlighting key differences from our research.

3. Model formulation

3.1. Problem description

A bulk shipping company typically plans one or more new voyages based on cargo demand information obtained through the sales department, which is then handed to the fuel supply management department for its consideration. This department conducts calculations and analyses based on the voyage information to make fuel supply decisions for the carrier's forthcoming voyages. The aim of our study is to develop an optimization model to assist bulk shipping companies in making fuel supply

Table 1. Summary of the most relevant studies and differences from our research.

Consideration	Besbes and Savin [5]	Oh and Karimi [8]	Vilhelmsen et al. [7]	Meng et al. [6]	Omholt-Jensen et al. [19]	This paper
Number of fuel types	1	1	1	1	1	2
Spot fuel price data			✓	✓	✓	✓
Cargo handling ports with bunkering services	✓			✓		✓
Route deviation for bunkering						✓
Time window constraints at ports				✓		✓
Port charges and fuel surcharge for bunkering ports		✓				✓
Unlimited number of bunkering operations	✓			✓	✓	✓
Fuel consumption during port operations		✓	✓		✓	✓
Difference in fuel consumption between operations and bunkering		✓				✓
Differences in bunkering time at various ports		✓				✓

decisions for their fleets. The fuel supply decisions involved includes determining whether the ships need refueling for the planned voyages, how much fuel to order, and which refueling ports to use. Planned voyages refers to all new voyages set up by the sales department for the carrier's ships, which may amount to one or more independent sailings.

The fleet in the study is composed of both owned vessels and ships leased under time charter agreements. In bulk shipping, different chartering modes have distinct cost structures. For instance, under a voyage charter, the charterer pays a freight rate based on cargo quantity or a lump sum for a specific voyage, while the shipowner covers operational costs such as fuel, port charges, and crew expenses. In contrast, time charter involves charterers paying a daily or monthly hire rate for the ships' use, with responsibility for operational costs like fuel and port fees, while the shipowner covers maintenance, crew wages, and insurance. Meanwhile, bareboat charter requires charterers to bear all operational costs in exchange for a lease fee. In the study, we focus solely on cost structures related to fuel supply decisions, including fuel costs, port fees, fuel surcharges, refueling time costs, detour time costs, and detour fuel consumption costs.

The following sample situations illustrate two different scenarios of interest in this study. In Scenario 1, a handysize bulk carrier has just completed unloading operations at Shanghai Port, China. The future voyage information established by the sales department is for the ship to load cargo at Kaohsiung Port, Taiwan, and then sail to Chittagong, Bangladesh. As shown in Fig. 1, the bulk shipping company needs to make fuel supply decisions before the ship departs from Shanghai Port, indicating that the departure from Shanghai is the planning starting point. The fuel inventory at the time of completion of operations in Shanghai will be considered the initial fuel stock for planning. The company needs to confirm whether fuel supply needs to be arranged during the voyage, determine at which port to supply it, and decide the supply volume to meet the fuel inventory requirements set by the shipping company at the end of the voyage. The figure shows that, along the route, in addition to the starting port (Shanghai) and cargo loading and unloading ports (Kaohsiung and Chittagong), there are also nearby ports like Hong Kong, Singapore, and Port Klang, Malaysia, where fuel supply can be arranged. At this point, the estimated total time of the newly established voyage will be viewed as the planning horizon. The total cost of arranging fuel supply at each port will be calculated based on various fuel supply cost factors, ensuring that arrangements do not exceed the time windows for loading and unloading at each port. The objective is to make the optimal fuel supply decision before starting the voyage, while ensuring that the ending point of the planning horizon —namely, the fuel inventory when the ship completes unloading at Chittagong—meets bulk shipping company requirements.

In Scenario 2, in addition to the voyage from Kaohsiung to Chittagong, the sales department also establishes a subsequent voyage for the ship to load cargo at Kakinada Port, India, after leaving Chittagong and then sail to Belawan Port, Indonesia. As shown in Fig. 2, the two voyages are confirmed before departing from Shanghai, so the planning horizon will be adjusted to start when the ship departs from Shanghai and end when it arrives at Belawan and completes unloading. Fuel supply will be arranged in such a way that it does not exceed the time windows for loading and unloading at each port, with the fuel inventory after unloading at Belawan still needing to meet the requirements of the bulk shipping company.

From these two scenarios, it can be observed that the planning horizon becomes longer with the increase in established voyages, and the options for fuel supply also increase. Although this provides greater flexibility in fuel supply for the shipping company, it also complicates the fuel supply planning. Additionally, the number of future voyages established for other ships in the fleet may vary, necessitating fuel supply planning and decision-making based on the future voyage information established for each ship.

3.2. The MILP model

The following notations are defined for presenting the proposed mathematical formulation.

Sets	
V	the set of ships
Q	the set of ports
Q^v	subset of ports where ship v conducts cargo handling operations
Indices and Parameters	
v	index for ships
i, j	indices for the ports in the network where $i = o$ denotes the first port and $i = d$ represents the final port
$\overline{C}$	deadweight tonnage
d_o^v	the departure time of ship v from the first port o
q_i^v	the cargo loading/unloading volume of ship v at port i, $q_i^v > 0$ represents cargo loading, while $q_i^v < 0$ is cargo unloading
T_{ij}	the sailing time between port i and port j
D	daily operation cost of a ship
B_h, B_l	storage tank capacities for heavy fuel oil and marine gas oil, respectively
C_h, C_l	sailing-specific consumption rates for heavy fuel oil and marine gas oil, respectively
W_h, W_l	cargo handling-specific consumption rates for heavy fuel oil and marine gas oil, respectively
K_h, K_l	bunker-specific consumption rates for heavy fuel oil and marine gas oil, respectively
$u_{i,h}$, $u_{i,l}$	the prices for heavy fuel oil and marine gas oil at port i, respectively
e_i, k_i, s_i	port-specific charges, refueling durations and associated surcharges at port i, respectively
β_i^v	binary indicator representing the cargo operation for ship v at port i
(a_i^v, b_i^v)	time window for ship v at port i
T_i^v	port call duration for ship v at port i
Decision variables	
x_{ij}^v	binary variable indicating direct voyage of ship v from port i to port j
α_i^v	binary variable indicating port i as a bunkering location for ship v
H_i^v, L_i^v	bunker quantities of heavy fuel oil and marine gas oil for ship v at port i, respectively
Auxiliary variables	
$R_{i,h}^v$, $R_{i,l}^v$	remaining (bunkered) quantities of heavy fuel oil and marine gas oil for ship v when arriving at port i, respectively
t_i^v	The arrival time (day) of ship v at port i

Denote t_d^v as the arrival time of ship v at the final port d and T_d^v the port call duration of ship v at port d. The total sailing time of ship v can be derived as $t_d^v - d_o^v + T_d^v$. Then, total daily operating cost is calculated as follows.

$$\sum_{\forall v} \left(t_d^v - d_o^v + T_d^v\right) \cdot D \tag{1}$$

Total bunkering cost is determined by multiplying the bunkering quantities of heavy fuel oil and marine gas oil by port-specific price, as follows

$$\sum_{\forall v} \sum_{\forall i} \left(u_{i,h} \cdot H_i^v + u_{i,l} \cdot L_i^v\right) \tag{2}$$

Port charges are fees paid to port authorities for the utilization of port waters, navigational channels and berthing facilities during a ship's entry, departure and stay in port. In the current study, total port cost accounts for port charges incurred due to route deviations for bunkering purposes. In particular, port charges are not levied if the bunkering location is at the predetermined loading/unloading port. Consequently, total port charges can be formulated as

$$\sum_{\forall v} \sum_{\forall i} \alpha_i^v \cdot \left(1 - \beta_i^v\right) \cdot e_i \tag{3}$$

Surcharges encompass two components: a flat fee for deploying oil containment equipment during bunkering to prevent environmental contamination, and additional barge fees imposed by the bunker supplier for fuel transfer operations. Total surcharges can be represented as

$$\sum_{\forall v} \sum_{\forall i} \alpha_i^v \cdot s_i \tag{4}$$

The problem of interest is to determine the route of the ships (x_{ij}^v), their bunkering ports (α_i^v), and the bunker fuel amounts for both heavy fuel oil (H_i^v) and marine gas oil (L_i^v) at bunkering ports, so as to minimize the sum of total daily operating cost, bunkering cost, port charges and surcharges. The MILP model of the problem is presented as follows:

$$\begin{aligned} \text{Min} \sum_{\forall v} \left(t_d^v - d_o^v + T_d^v\right) \cdot D + \sum_{\forall v} \sum_{\forall i} \left(u_{i,h} \cdot H_i^v + u_{i,l} \cdot L_i^v\right) \\ + \sum_{\forall v} \sum_{\forall i} \alpha_i^v \cdot \left(1 - \beta_i^v\right) \cdot e_i + \sum_{\forall v} \sum_{\forall i} \alpha_i^v \cdot s_i \end{aligned} \tag{5}$$

subject to

$$\sum_i x_{io}^v = 1, \forall v \in V \tag{6}$$

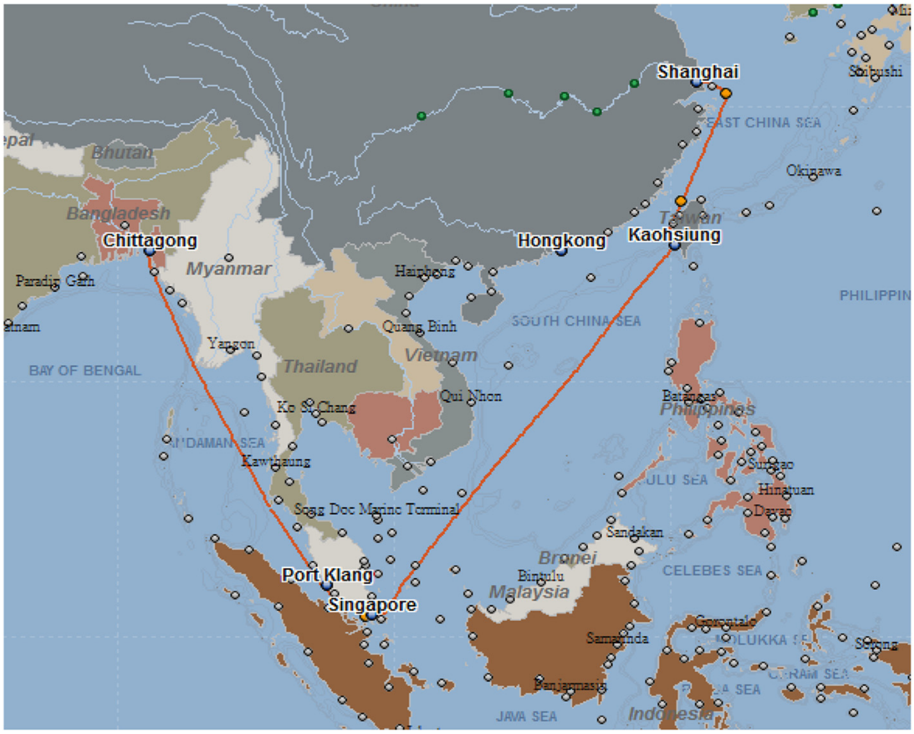

Fig. 1. Illustrative sample situation for Scenario 1.

$$\sum_i x_{io}^v = 0, \forall v \in V \tag{7}$$

$$\sum_i x_{ih}^v - \sum_{\forall j} x_{hj}^v = 0, \forall h \in Q\ \forall v \in V \tag{8}$$

$$\sum_i x_{id}^v = 1, \forall v \in V \tag{9}$$

$$\sum_i x_{dj}^v = 0, \forall v \in V \tag{10}$$

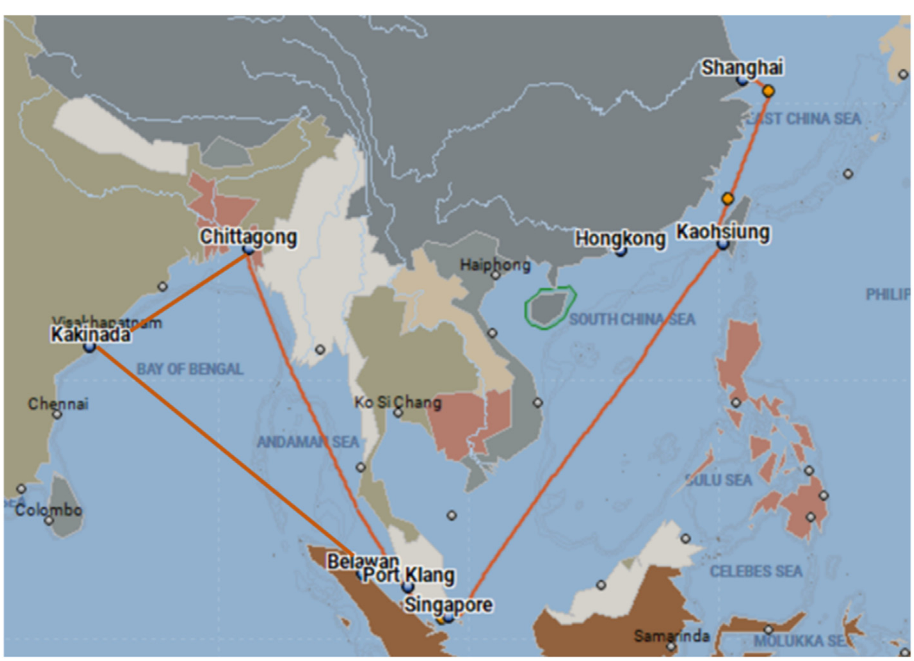

Fig. 2. Illustrative sample situation for Scenario two.

$$\sum_i x_{ij}^v = 1, \forall j \in Q^v \ \forall v \in V \tag{11}$$

$$\sum_i x_{ij}^v \leq 1, \forall v \in V \tag{12}$$

$$\sum_i x_{ij}^v \geq \alpha_j^v, \forall v \in V \tag{13}$$

$$\alpha_o^v = 0, \forall v \in V \tag{14}$$

$$0 \leq H_i^v \leq \alpha_i^v \cdot B_h, \forall v \in V \tag{15}$$

$$0 \leq L_i^v \leq \alpha_i^v \cdot B_l, \forall v \in V \tag{16}$$

$$0 \leq R_{i,h}^v + H_i^v \leq B_h, \forall v \in V \tag{17}$$

$$0 \leq R_{i,l}^v + L_i^v \leq B_l, \forall v \in V \tag{18}$$

$$0 \leq R_{i,h}^v + R_{i,l}^v + H_i^v + L_i^v \leq \overline{C} - q_i^v, \forall v \in V \tag{19}$$

$$R_{j,h}^v - M \cdot \left(1 - x_{ij}^v\right) \leq R_{i,h}^v - T_i^v \cdot W_h - T_{ij}^v \cdot C_h - \alpha_i^v \cdot \left(1 - \beta_i^v\right) \cdot k_i \cdot K_h + H_i^v, \forall v \in V \tag{20}$$

$$R_{j,l}^v - M \cdot \left(1 - x_{ij}^v\right) \leq R_{i,l}^v - T_i^v \cdot W_l - T_{ij}^v \cdot C_l - \alpha_i^v \cdot \left(1 - \beta_i^v\right) \cdot k_i \cdot K_l + L_i^v, \forall v \in V \tag{21}$$

$$t_j^v + M \cdot \left(1 - x_{ij}^v\right) \geq t_i^v + T_i^v + \alpha_i^v \cdot \left(1 - \beta_i^v\right) \cdot k_i + T_{ij}, \forall v \in V \tag{22}$$

$$a_i^v \leq t_i^v \leq b_i^v, \forall i \in Q^v, \forall v \in V \tag{23}$$

$$x_{ij}^v \in \{0,1\}, \forall i,j \in Q, \forall v \in V \tag{24}$$

$$\alpha_i^v \in \{0,1\}, \forall i \in Q, \forall v \in V \tag{25}$$

$$F_i^v \in \mathbb{R}^+ \cup \{0\}, \forall i \in Q, \forall v \in V \tag{26}$$

$$L_i^v \in \mathbb{R}^+ \cup \{0\}, \forall i \in Q, \forall v \in V \tag{27}$$

$$R_{i,h}^v \in \mathbb{R}^+ \cup \{0\}, \forall i \in Q, \forall v \in V \tag{28}$$

$$R_{i,l}^v \in \mathbb{R}^+ \cup \{0\}, \forall i \in Q, \forall v \in V \tag{29}$$

$$t_i^v \in \mathbb{R}^+ \cup \{0\}, \forall i \in Q, \forall v \in V \tag{30}$$

$$t_d^v \in \mathbb{R}^+ \cup \{0\}, \forall v \in V \tag{31}$$

Eq. (5) represents the objective function computing the sum of total operating cost, total bunker cost, total port cost and total surcharges which is to be minimized. Eqs. (6) and (7) ensure that each ship departs from its origin port and does not return to that port. Eq. (8) represents the flow conservation constraint for intermediate ports, excluding the origin and destination ports. Eqs. (9) and (10) constrain that each ship must stop at the final port. Eqs. (11) and (12) state that each ship is required to berth at its designated ports (Q^v) for cargo operations, with the condition that each port be visited no more than once. Eqs. (13) and (14) specify that a ship can only refuel at a port if it visits that port, while prohibiting refueling at the first port. Eqs. (15)–(18) are the constraints ensuring that the sum of the remaining fuel volume upon port arrival and the quantity of fuel bunkered at said port does not exceed the ship's storage tank capacity. Eq. (19) guarantees that the volume of fuel obtained during bunkering does not affect the cargo capacity available for loading at the port. Eqs. (20) and (21) determine remaining bunkered quantities of heavy fuel oil and marine gas oil for ship v when arriving at port i, respectively Eq. (22) calculates the arrival time of ship v at port i (α_i^v). Eq. (23) expresses the time window constraints. Eqs. (24) and (25) define the binary decision variables. Eqs. (26)–(31) define the non-negative real variables for bunker quantities of heavy fuel oil and marine gas oil for ship v at port i, remaining bunkered quantities of heavy fuel oil and marine gas oil for ship v when arriving at port i and the arrival time of ship v at port i and at the final port d, respectively.

4. Numerical example results and analyses

The proposed model was evaluated using instances generated from real data provided by H company with its operational headquarters in Taipei, Taiwan, which operates a fleet of handysize ships in East and South Asia. The problem instances of the proposed model were solved using Gurobi, a state-of-the-art optimization solver, implemented in the Python programming language. The key parameters' values presented in Table 2 are suggested by the case study company.

4.1. Solution results for one ship

To investigate and validate the benefits of route deviation, the first problem instance focused on optimizing bunkering supply for a single ship from the fleet. Three different scenarios were examined: single-voyage bunkering optimization without route deviation, single-voyage bunkering optimization incorporating route deviation and multi-voyage bunkering optimization incorporating route deviation.

Table 2. Key ship parameter values.

Parameters	Description	Value
$\overline{C}$	Deadweight tonnage (tons)	19395
D	Daily operation cost (US$/day)	7000
B_h	Storage tank capacity for heavy fuel oil (tons)	850.48
B_l	Storage tank capacity for marine gas oil (tons)	114.82
C_h	Sailing-specific consumption rate for heavy fuel oil (ton/day)	14.60
C_l	Sailing-specific consumption rate for marine gas oil (ton/day)	0.10
W_h	Cargo handling-specific consumption rate for heavy fuel oil (ton/day)	3.50
W_l	Cargo handling-specific consumption rates for marine gas oil (ton/day)	0.10
K_h	Bunker-specific consumption rates for heavy fuel oil (ton/day)	2.50
K_l	Bunker-specific consumption rates for marine gas oil (ton/day)	0.10

The first scenario, without route deviation during the voyage, involved a single voyage by a handysize bulk ship from Shanghai to Chittagong via Kaohsiung. The ship, departing from Shanghai, was scheduled to load cargo in Kaohsiung before proceeding to its final destination in Bangladesh. The corresponding model was characterized by 25 variables subject to 60 constraints. Table 3 shows the results from the solution for this first scenario.

As can be seen from Table 3, the total planning horizon was 21 days. At the Port of Kaohsiung, 317.51 tons of heavy fuel oil and 12.10 tons of marine gas oil were bunkered.

The second scenario mirrored the first scenario but allowed route deviation during the voyage, with bunkering options at the Port of Hong Kong, Singapore, and Port Klang (Malaysia). The corresponding model had 67 variables and 165 constraints. Table 4 shows the results for the second scenario.

In the proposed model, the binary decision variable, α_i^v, indicates port i as a bunkering location for ship v if $\alpha_i^v = 1$ in the optimal solution. The decision variables, H_i^v and L_i^v, represent bunker quantities of heavy fuel oil and marine gas oil for ship v at port i, respectively. For instance, in Table 4, the optimal bunkering location is Port Klang, and the corresponding bunkering quantities are 319.06 and 12.14 for heavy fuel and marine gas, respectively. Table 4 shows that following the completion of loading operations at Kaohsiung Port, the ship was directed to proceed to Port Klang for bunkering before continuing its journey. Notably, despite an extended planning horizon of 22 days, one day longer than that in the first scenario, the model yielded a reduction in total cost, due to not bunkering in Kaohsiung. This result indicates that incorporating route deviation for bunkering purposes into the planning process yields superior cost performance.

Extending the second scenario, the third scenario incorporated a second voyage. Specifically, upon completion of unloading operations at Chittagong Port, the ship was directed to proceed to Kakinada Port, India, for cargo loading. Subsequently, it sailed to Belawan Port, Indonesia, for its final unloading operation. Table 5 presents the time windows at the ports. The corresponding model comprised 105 variables subject to 265 constraints. Fig. 3 and Table 6 show the results.

As shown in Fig. 3 and Table 6, even with the addition of two more loading/unloading ports for the ship, the optimal decision was still to bunker at Port Klang after loading cargo at Kaohsiung Port. Due to the greater number of ports to be visited and the longer planning horizon of 38 days, the bunkering quantities of both heavy fuel oil and marine gas oil significantly increased over those in Scenario 2. Table 6 shows that the model generated the optimal bunkering decision with a minimized total cost of US$ 554,582.61, in a computational time of 0.11 s.

4.2. Multiple ship optimization results

The study generated a larger problem instance to further evaluate the fitness of the proposed model. There were two ships in this numerical example, labeled Scenario 4, with the voyage assignment for

Table 3. Results of single-ship single voyage without route deviation.

Day	Port	Loading/unloading volume (tons)	Residual fuel volume upon arrival (tons)		Bunker quantity (tons)	
			Heavy fuel	Marine gas	Heavy fuel	Marine gas
0	Shanghai	–	500	80	0	0
3	Kaohsiung	15000	467.44	79.78	317.51	12.10
17	Chittagong	−15000	614	90.40	0	0
21	Chittagong	–	600	90	–	–
Total cost (US$)		362671.98				
CPU time (s)		0.02				

Table 4. Results of single-ship single voyage with route deviation.

Day	Port	Loading/unloading volume (tons)	Residual fuel volume upon arrival (tons)		Bunker quantity (tons)	
			Heavy fuel	Marine gas	Heavy fuel	Marine gas
0	Shanghai	–	500	80	–	–
3	Kaohsiung	15,000	467.44	79.78	0	0
13	**Port Klang**	0	361.61	78.75	**319.06**	**12.14**
18	Chittagong	−15,000	614	90.40	0	0
22	Chittagong	0	600	90	–	–
Total cost (US$)		356,149.14				
CPU time (s)		0.07				

The bold represents the optimal bunking port.

the first ship being identical to that described in Scenario 3. For the other ship, a further voyage had been assigned on completion of its previous mission at Belawan Port, with this next voyage involving cargo loading at the Port of Palembang, Indonesia, and subsequent unloading at Qinzhou Port, China. The available bunkering options included both the ship's scheduled loading/unloading ports and the detour ports of Hong Kong, Singapore and Port Klang. Table 7 presents the time window constraints at the ports. The model comprised 302 variables subject to 778 constraints. Fig. 4 and Table 8 show the results from the solution for this scenario.

As can be seen in Table 8, the optimization model determined the most cost-effective bunkering strategy in a longer computational time of 2.6 s, for a minimized total cost of US$ 915,082.87 and cumulative voyage durations of 38 and 15 days for the first and second ships, respectively. Fig. 4 shows that, although the voyage paths were different, both ships visited Port Klang. The two ships opted to replenish both their heavy fuel oil and marine gas oil supplies at Port Klang. This bunkering decision highlights Port Klang's growing importance as a refueling hub in the region, with its offering of competitive prices for both fuel types. The highlighted numbers in the tables (Tables 4, 6 and 8) indicate the optimal bunkering ports and the corresponding fuel quantities. It can be noted that Port Klang is consistently identified as a cost-effective bunkering location across multiple scenarios due to its competitive fuel prices.

4.3. Complex large example optimization results

To further evaluate the applicability of the model in large real cases, we considered a complex large

Table 5. Time windows at ports in Scenario 3.

	Kaohsiung	Chittagong	Kakinada	Belawan
Lower bound, a_i^v	2	5	19	26
Upper bound, b_i^v	5	19	26	35

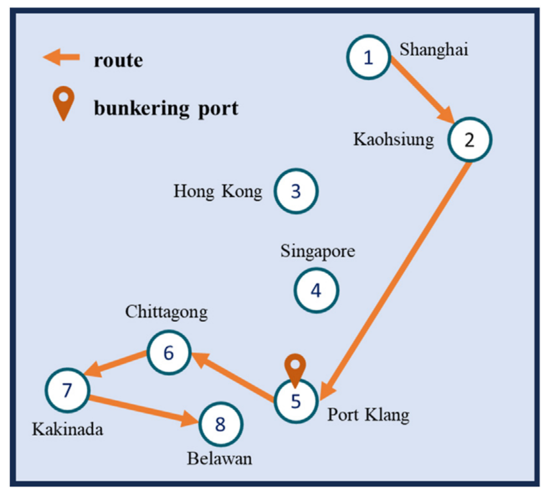

Fig. 3. Optimal shipping route in Scenario 3.

example in which three ships which had just completed their voyage assignments within a similar time frame were subsequently tasked with executing scheduled tramp services in East and South Asia. For the sake of simplification, the ports were assigned alphanumeric codes and encompassed a total of 14 locations. Among these, port #6 and port #8 represented the same physical port, since the second ship performed both unloading and loading operations at this location. Ports # 4 and #9 merely served as available bunkering locations for route deviation purposes. The voyages for the three ships were as follows. Ship #1 designated port #11 as its origin port, and cargo loading was performed at port #12, followed by unloading at port #13. Ship #2 sailed first port #10, and executed two voyages in succession: the first voyage involved loading cargo at port #11 and discharging it at port #6; the second voyage entailed loading at port #8 and unloading at port #14. Ship #3, operating from port #2, also performed two voyages: the first, loading at port #3 and unloading at port #5, and the second, loading at port #7 and unloading at port #1. Table 9 presents the time window constraints in the complex sample situation. The model comprised 801

Table 6. Results of the single-ship multi-voyage with route deviation.

Day	Port	Loading/unloading volume (tons)	Residual fuel volume upon arrival (tons)		Bunker quantity (tons)	
			Heavy fuel	Marine gas	Heavy fuel	Marine gas
0	Shanghai	–	500	80	0	0
3	Kaohsiung	15,000	467.44	79.78	0	0
13	**Port Klang**	0	361.61	78.75	**450.57**	**13.80**
18	Chittagong	−15,000	745.51	92.06	0	0
24	Chittagong	16,000	699.09	91.44	0	0
33	Kakinada	−16,000	617.50	90.50	0	0
38	Belawan	–	600	90	–	–
Total cost (US$)		554,582.61				
CPU time (s)		0.11				

The bold represents the optimal bunking port.

Table 7. Time windows at ports in Scenario 4.

	Ship #1			
	Kaohsiung	Chittagong	Kakinada	Belawan
Lower bound, a_i^v	2	5	19	26
Upper bound, b_i^v	5	19	26	35
	Ship #2			
	Palembang		Qinzhou	
Lower bound, a_i^v	1		7	
Upper bound, b_i^v	7		20	

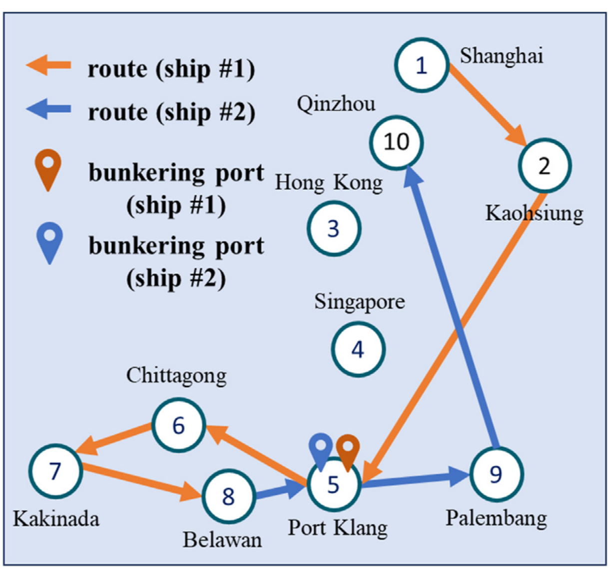

Fig. 4. Optimal shipping routes in Scenario 4.

variables subject to 2127 constraints. Fig. 5 and Table 10 show the optimization results.

As shown in Fig. 5 and Table 10, port #13 was the optimal bunkering location for ships #1 and #2, while ship #3 refueled at port #5 with heavy fuel oil, followed by marine gas oil at port #1. Specifically, the first ship, after loading cargo at port #12, proceeded to port # 13 for unloading and, at the same time, refueling, completing its 13-day voyage. Ship #2 had a 27-day itinerary, initiated with cargo loading at port #8, followed by a detour to port #13 for bunkering, and concluding with cargo unloading at port #14. Finally, ship #3 completed two voyages with separate heavy fuel oil and marine gas oil bunkering over 36 days. The total cost for the fleet was US$1,126,706.69. This complex problem instance could be solved in 1637.92 s (or 27.3 min), which is acceptable, making it a usable practical application. These results for this complex large example demonstrate the applicability of the proposed model to large real-world problem instances.

To determine the impact of incorporating route deviation for fuel supply purposes, the same problem instance was solved a second time with no route deviations allowed.

Significantly, the routes of ship #1 and #3 remained unaltered in the two solutions obtained with and without detours. This can be attributed to the inclusion of ports with favorable fuel supply conditions already in their predetermined cargo loading and unloading itineraries. Consequently, the imposition of non-deviation constraints did not necessitate modifications to their routes. Fig. 6 and Table 11 show the optimization results for the third ship, ship #2 when route deviation was not allowed.

Ship #2's route with deviations was the same as that of the ship in Scenario 3, shown in Fig. 3. With route deviation allowed, it detoured to port #13 for bunkering after completing its second cargo loading operation at port #8, before proceeding to port #14 for unloading. However, as shown in Fig. 6, because of the no-deviation constraint, fuel supply was arranged concurrently with the second cargo loading operation at port #8, after which the ship sailed directly to port #14 for unloading. The total cost in the no-deviation case increased from US$1,126,707 to US$1,170,481, i.e., an approximately 4 % increase in total costs. This is evidence that incorporating route deviation fuel supply options indeed yields cost-effective results.

Table 8. Results of the multi-ship multi-voyage scenario.

Day	Port	Loading/unloading volume (tons)	Residual fuel volume upon arrival (tons)		Bunker quantity (tons)	
			Heavy fuel	Marine gas	Heavy fuel	Marine gas
Ship #1						
0	Shanghai	–	500	80	0	0
3	Kaohsiung	15,000	467.44	79.78	0	0
13	**Port Klang**	0	361.61	78.75	**450.57**	**13.80**
18	Chittagong	−15,000	745.51	92.06	0	0
24	Chittagong	16,000	699.09	91.44	0	0
33	Kakinada	−16,000	617.50	90.50	0	0
38	Belawan	–	600	90	–	–
Ship #2						
0	Belawan	0	300	50	0	0
1	Port Klang	0	291.24	49.94	384.83	31.41
3	Palembang	13,000	648.67	81.13	0	0
12	Qinzhou	−13,000	560.50	80.30	0	0
15	Qinzhou	0	550	80	–	–
Total cost (US$)		915,082.87				
CPU time (s)		2.6				

The bold represents the optimal bunking port.

Table 9. Time windows at ports in the complex large example.

Ship #1				
	Port #12		Port #13	
Lower bound, a_i^v	1		5	
Upper bound, b_i^v	5		10	
Ship #2				
	Port #6	Port #8	Port #11	Port #14
Lower bound, a_i^v	4	11	0	19
Upper bound, b_i^v	11	19	4	30
Ship #3				
	Port #1	Port #3	Port #5	Port #7
Lower bound, a_i^v	19	2	17	7
Upper bound, b_i^v	35	7	19	35

4.4. Managerial implications

This paper represents a systematic attempt to model the bulk carrier routing problem that facilitates bunkering decision-making by bulk shipping companies. In particular, the study underlines the importance of considering multiple factors (i.e., fuel prices, operational costs, and port charges) in determining optimal refueling decisions, and understanding that bulk shipping companies have to adopt a comprehensive cost analysis approach in decision-making, rather than focus on a single factor. The results also show that deviating from original routes for bunkering purposes brings cost

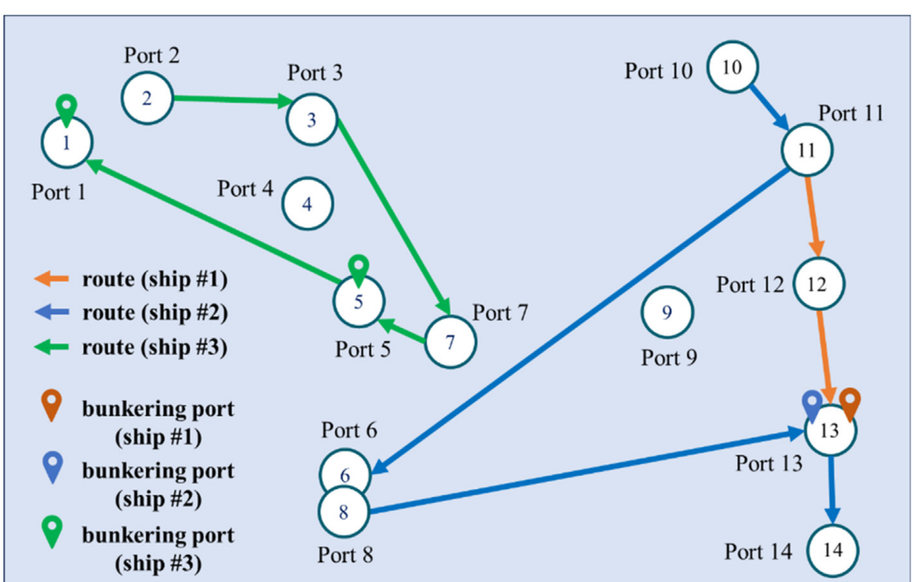

Fig. 5. Optimal shipping routes in the complex sample situation.

Table 10. Optimization results in the complex sample situation.

Day	Port	Loading/unloading volume (tons)	Residual fuel volume upon arrival (tons)		Bunkered quantity (tons)	
			Heavy fuel	Marine gas	Heavy fuel	Marine gas
Ship #1						
0	#11	0	260	45	0	0
2	#12	16,000	237.22	44.84	0	0
9	**#13**	−16,000	175.04	44.11	**223.96**	**1.29**
13	#13	–	385	45	–	–
Ship #2						
0	#10	0	315	40	0	0
2	#11	13,800	298.21	39.89	0	0
10	#6	−13,800	235.74	39.08	0	0
13	#8	12,000	225.24	38.78	0	0
18	**#13**	0	189.63	38.23	**294.24**	**32.62**
22	#14	−12,000	437.50	70.50	0	0
27	#14	–	420	70	–	–
Ship #3						
0	#2	0	200	30	0	0
3	#3	14,000	158.1	29.71	0	0
14	#7	−14,000	59.13	28.66	0	0
18	**#5**	17,500	39.87	28.22	**339.23**	0
31	**#1**	−17,500	237.50	26.95	0	**3.55**
36	#1	–	220	30	–	–
Total cost (US$)		1,126,706.69				
CPU time (s)		1637.92				

The bold represents the optimal bunking port.

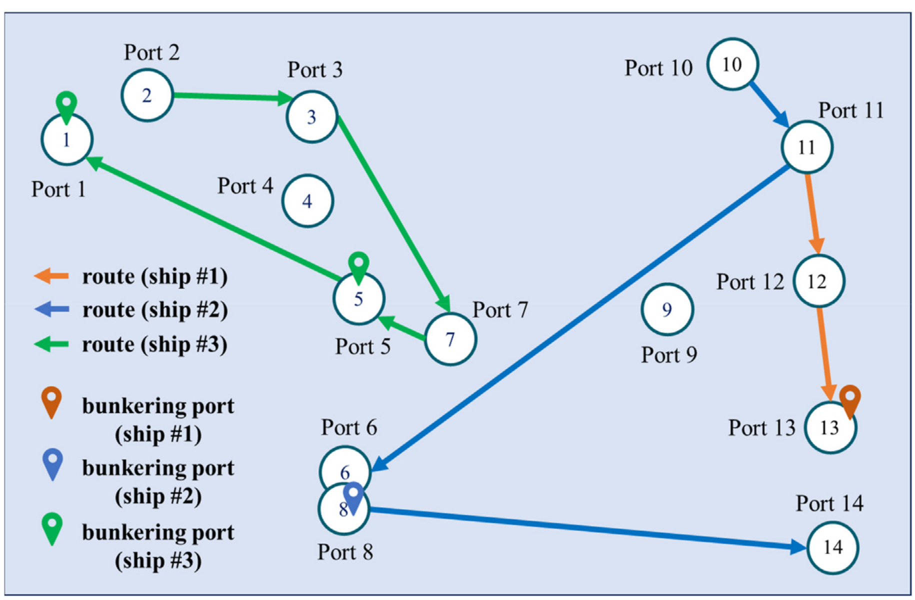

Fig. 6. Optimal complex sample situation shipping routes without route deviation.

Table 11. Optimization results for ship #2 without route deviation.

Day	Port	Loading/unloading volume (ton)	Residual fuel volume upon arrival (ton)		Bunker quantity (ton)	
			Heavy fuel	Marine gas	Heavy fuel	Marine gas
0	#10	0	315	40	0	0
2	#11	13800	298.21	39.89	0	0
10	#6	−13800	235.74	39.08	0	0
13	#8	12000	225.24	38.78	292.83	32.58
21	#14	−12000	437.50	70.50	0	0
26	#14	–	420	70	–	–

benefits, indicating that bulk shipping companies need to flexibly consider the possibility of route deviation for bunkering purposes and not rigidly adhere to shortest-distance routes. The study mentions that some ports have fuel price advantages, reminding that shipping companies need to closely monitor fuel price differences at different ports. Moreover, the strategy of separate bunkering of heavy fuel oil and marine gas oil at different ports suggests additional possibilities for optimizing fuel management and cost control.

5. Conclusions

This study proposes a mixed integer linear programming (MILP) model to address a bunkering optimization problem for bulk shipping carriers that explores route deviation to find optimal bunkering locations and amounts. The proposed decision support model is designed to accommodate ship-specific parameters for different vessel types and remains applicable across various bulk shipping scenarios, as cargo weight parameters are unaffected by cargo type variations. Moreover, the selection of cost components in the model were based on the cost structure in bulk shipping operations. We focused on key cost components which are crucial in optimizing bunkering decisions, as they directly impact the profitability of bulk shipping companies. The model allows for route deviation by the fleet to minimize total operating costs while satisfying time-window constraints at loading/unloading ports.

The study presents a systematic approach to modeling the bulk carrier routing problem, focusing on supporting bunkering decisions for bulk shipping companies. The model identifies cost-effective refueling locations, determines optimal fuel quantities, and considers factors such as fuel prices, transit times, and operational costs. The scenario analysis presented in Section 4.3 showed that allowing route deviations for refueling reduced total costs by approximately 4 % compared to a no-deviation constraint. This demonstrates that incorporating route deviation options can significantly enhance cost efficiency in bunkering decisions.

This result indicates that the reduction in fuel-related costs achieved through bunkering at mid-voyage ports outweighs the incremental time-related costs associated with detours. This trade-off provides the basis for the economic viability of incorporating route flexibility in fuel management in bulk shipping. Reaching this result, the model incorporated two types of fuels (i.e., heavy fuel oil and marine gas oil) and allowed fleets to make independent decisions about bunkering of the two types, respecting their distinct consumption patterns and price structures. The results indicate that when planning for total cost minimization, ships should not always opt to replenish both fuel types concurrently at a single port. In addition, we found that a complex instance could be solved in a reasonable amount of time, demonstrating the applicability of the model in real-world bulk carrier route decision-making.

A limitation of our study is the fact that it used a case of a bulk shipping company with several shipping routes, which might not represent the entire bulk shipping industry. To gain a comprehensive understanding of the model's applicability, it would be beneficial to evaluate the bunkering decision-support model using diverse characteristics of different bulk shipping companies. The study employed hard time window constraints that reflect contractual cargo loading schedules. However, weather-related delays and the other uncertainties inherent in bulk shipping operations in practice often lead to early or late port arrivals. Future studies could relax these hard constraints in favor of soft time windows that incorporate penalty functions for schedule deviations. This approach would allow for a more nuanced analysis of the trade-offs between adherence to schedules and the potential benefits of route deviations.

The proposed model is deterministic, limiting decision-making processes to a single strategic choice at the beginning of the planning horizon, which restricts its ability to adapt to time-related changes and fluctuations in market conditions, fuel prices, and operational uncertainty. Furthermore, as indicated in the previous literature (e.g., [8,9]), market dynamics also influence vessel speed, impacting bunker inventory management. Future studies could explore the integration of dynamic or stochastic programming techniques, alongside more sophisticated modeling approaches, to provide a more realistic framework that captures operational variability and enhances model applicability.

Ethics information

Ethical approval was not required for the study as it did not involve any human or animal subject.

Conflict of interest

The authors declare that they have no conflict of interest.

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