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How to Deploy Electric Ships for Green Shipping

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Abstract: Maritime transport plays an important role in global economic development but also inevitably faces increasing pressures from all sides, such as ship operating cost reduction and environmental protection. An ideal innovation to address these pressures is electric ships, which are more environmentally friendly than conventional manned fuel oil ships. The electric ship is in its early stages. To provide high-quality transportation services, the service network needs to be designed carefully. Therefore, this research simultaneously studies the location of charging stations, charging plans, route planning, ship scheduling, and ship deployment under service time requirements. The problem is formulated as a mixed-integer linear programming model with the objective of minimizing total cost comprised of charging cost, construction cost of charging stations, and fixed cost of ships. A case study using the data of the shipping network along the Yangtze River is conducted in order to evaluate the performance of the model. Valuable managerial insights are also derived from sensitivity analyses.

Keywords: electric ship; green shipping; charging station location; route planning; ship scheduling

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1. Introduction

Waterway transportation is the backbone of global economic development and accounted for over 80% of international trade volume in 2021 [1]. In the last two decades, the maritime industry has undergone many reforms and adopted innovations to deal with increasing pressures from all sides. For example, freight rates have increased since the second half of 2020 [1]. Inefficient shipping management has also led to a surge in costs. To make the shipping industry greener, from 1 January 2020, the International Maritime Organization (IMO) reduced the upper limit for sulfur content in ship fuel oil from 3.5% to 0.5% [2]. In June 2021, the IMO amended Annex VI of its Convention, which seeks further reductions in greenhouse gas emissions. Among shipping innovations, electric ships are believed to be both cost-effective and environmentally friendly [3]. Compared with conventional manned fuel oil ships, electric ships are more environmentally friendly [4].

Although electric ships might be the future of the shipping industry, they are currently in the early stages. Yara Birkeland, the world's first fully electric and autonomous container vessel, completed its maiden voyage in December 2020, sailing nearly seven hours from Brevik to Horten, Norway. To provide high-quality transportation services, the service network must be designed carefully, considering cargo delivery routes, ship scheduling, and ship deployment [5]. The location of charging stations and charging plans also need to be considered because of the limited sailing distance of such ships.

Since electric ships are in their early stages, a large amount of research has focused on feasibility and efficiency issues, with very limited research on operational issues. This research simultaneously optimizes the location of charging stations, the charging plan, route planning, ship scheduling, and ship deployment for electric ships and is the first quantitative study that solves combinational operational problems for electric ships. Although much research has been carried out on electric vehicles and there are similarities between electric vehicles and ships, the research cannot be applied directly. The reasons will be elaborated in Section 2 (Literature Review).

Therefore, this study simultaneously examines the location of charging stations, the charging plan, route planning, ship scheduling, and ship deployment. The problem is formulated as a mixed-integer linear programming (MILP) model with the objective of minimizing total costs, which comprise charging costs, charging station construction costs, and ships' fixed costs. The model is solved using CPLEX. To validate the method, a case study is conducted using data from the Yangtze River shipping network. Two operating scenarios are considered in the case study to evaluate the model's performance: an electric ship scenario in which all of the transportation tasks are fulfilled by electric ships and a conventional ship scenario in which all of the transportation tasks are fulfilled by fuel oil ships. This research also conducts extensive sensitivity analyses for key operating factors, including battery capacity, charging speed, volume capacity, and a service time limit of transportation tasks. These insights are useful in the application of electric ships in the future.

2. Literature Review

There is growing interest in electric vessels over the last decade. Nuchturee, Li, and Xia [6] provide comprehensive reviews on promising technologies and practices that are applicable to onboard energy systems of all-electric ships. Su et al. [7] investigates the allocation of fault current limiters in power systems to suppress fault currents and save the investment costs of high-capacity circuit breakers. Crapse et al. [8] propose metrics to assess and manage power quality in an electric ship power system.

Łebkowski and Koznowski [9] analyse the feasibility of using electric and hybrid systems to drive Small Waterplane Area Twin Hull vessels. Gao et al. [10] study the energy control strategy for hybrid electric ships to delay battery aging. Most of the research investigates energy efficiency and safety. Very limited research has explored the operational optimization of electric ships, such as the location of charging stations, the charging plan, route planning, ship scheduling, and ship deployment. Therefore, we need to refer to articles that explore the operational optimization problem for conventional ships and research that studies location of charging stations for electric vehicles.

There is a great deal of literature on operational optimization for conventional ships [11,12]. The study by Agarwal and Ergun [13] was the first to examine the imposition of regular service frequency when designing ship scheduling and cargo routing. Wang et al. [14] optimize the container path under given ship routes so that containers can be delivered on time and the transportation cost is minimal. Karsten et al. [15] examine the flow of multi commodities along shipping routes under the constraints of service time limits. This problem is extended by Balakrishnan and Karsten [16], whose study considers transshipment limits and multi-type ships. Song et al. [17] optimize ship deployment, sailing speed, and ship scheduling under uncertainties. Zhen et al. [18] simultaneously consider ship schedule, fleet deployment, and container routing, all of which are influenced by travel speed of ships. Zhen et al. [19] extend the problem by considering stochastic demand. Zhen et al. [20] optimize shipping routes and speeds under emission control policy. El Noshokaty [21] develop a forecasting system when optimizing ship routes and scheduling. Mahmoodjanloo et al. [22] optimize routing and schedule for multiple ships in the various terminals of a port considering draft limits. Wang and Wu [23] explore the effects of uncertainty in a transportation system. Due to the increasing emphasis on sustainable development, the shipping operational optimization was extended to incorporate environmental protection [24–30].

Due to the limited travel range of electric vehicles, the design of charging stations network is of great importance. Comprehensive reviews on charging station location can be found in Bilal and Rizwan [31] and Kchaou-Boujelben [32]. According to Kchaou-Boujelben [32], most of the research in this field adopts a flow-based method to formulate the problem. Wang and Lin [33] formulate the charging station location as a maximal coverage location problem with the objective to maximize the electric vehicle flow covered by charging stations. Arslan and Karaşan [34] locate charging stations in order to maximize the travel distance for both electric vehicles and plug-in hybrid electric vehicles. Bouguerra and Layeb [35] apply a set coverage model to optimize charging station location and sizing. Dong et al. [36] first predict the charging demand of electric vehicles and its spatial distribution, and then apply maximal coverage location model for charging station location. Fakhrmoosavi et al. [37] also input the predicted charging demand into location models with the objective of minimizing the total cost, comprising infrastructure investment cost and time cost for charging. Besides location, energy efficiency management is also considered [38,39].

Even though operational optimization problem and charging station location problem are usually studied separately, there are studies that simultaneously consider both problems. Schiffer and Walther [40] optimize vehicle routing and charging station location under time window constraints. Vehicles are allowed to be partially charged and to deviate from their paths to recharge. Arslan et al. [41] also optimize these two types of decisions with the objective of maximizing vehicle flow in a road network under travel range and deviation tolerance constraints. Chen et al. [42] propose a bi-level model where the upper level decides facility location and capacity and the lower level optimizes driver's behavior. Liu et al. [43] also propose a bi-level model to determine wireless charging link location and electricity price. The latter influences the routing of electric vehicles and their charging behavior. Wang et al. [44] simultaneously locate two types of charging infrastructures and route electric vehicles within the charging network. Zhang et al. [45] study the operational problems of electric buses, including scheduling, charging strategy, and fleet size. The combination problem for electric vehicles is similar to that of electric ships, but electric vehicle models cannot be applied directly to electric ships mainly for the following reasons: first, most of the research on electric vehicles is focused on private automobiles that do not have a fixed schedule, whereas ships run on a fixed schedule that determines the number of ships to be deployed. Second, electric vehicles are usually charged during blocks of idle time, such as office hours or at night, but ships can be charged at any port they visit if there is a charging station. As ships must load and unload cargo, which takes at least a few hours, the crew can decide whether to charge and how much time to spend charging at the ports they visit. Third, electric vehicles are usually used for travel within city limits and have low mileage and power consumption. An electric vehicle can operate for at least one day on a single charge, whereas ships sail long distances, requiring multiple charges along the way.

Therefore, this research develops an innovative optimization model for electric ships, which optimizes the locations of charging stations, the charging plan, route planning, ship scheduling, and ship deployment under the constraints of service time requirements. The research on electric ships is very limited. This study will be the first quantitative research that solves operational problems for electric ships.

3. Problem Formulation

In this section, we will describe the problem, summarize assumptions, and introduce the model.

3.1. Problem Description

Since this research simultaneously considers port operation and shipping routes and decisions involving these two aspects are optimized by one party, the method proposed is only applicable to specific sea areas, such as Yangtze River or Bohai Bay area, where some large shipping companies are both ship operators and port stakeholders.

We consider a liner shipping network which operates a set R of container shipping routes to serve a set $P = \{1, \ldots, |P|\}$ of ports. Each route $r \in R$ that serves $|I_r|$ ports of call and $|I_r|$ legs forms a loop, which can be described as $\left(p_{r1}, p_{r2}, \ldots, p_{r|I_r|}, p_{r1}\right)$ with $p_{r,|I_r|+1} = p_{r1}$. The voyage from port p_{ri} to port $p_{r,i+1}$ is denoted as leg i $(i = 1, \ldots, |I_r|)$. An example with three routes is illustrated in Figure 1.

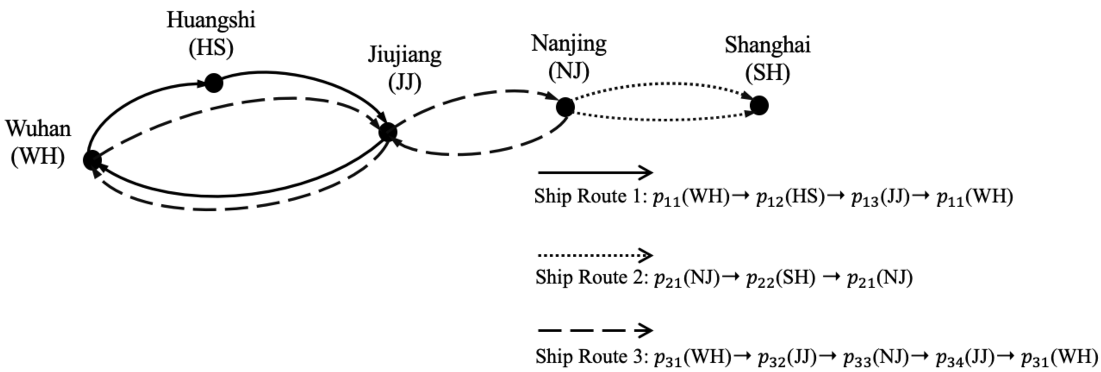

Figure 1. A liner shipping network with three ship routes.

A fleet of n_r homogenous ships that sail on route r have a limit on battery capacity Q_r and volume capacity V_r. When a ship visits port of call p_{ri}, the remaining energy is h_{ri}. A ship can decide the amount of energy charged at port p_{ri}, denoted by z_{ri}, if this port has a charging station, i.e., the variable x_m that indicates whether a charging station is constructed at port m equals 1 and the parameter K^P_{mri} that indicates whether port m is the ith port of call on route r equals 1. The charging amount satisfies $h_{ri} + z_{ri} \leq Q_r$, $0 \leq z_{ri} \leq \sum_{m \in P} Q_r K^P_{mri} x_m$, and $\frac{z_{ri}}{\alpha} \leq t^d_{ri}$, where α is battery charging speed and t^d_{ri} is ship dwelling time at the ith port of call on route r. When the ship arrives at $p_{r,i+1}$, the remaining energy $h_{r,i+1}$ equals the remaining energy when the ship departs from p_{ri} minus the energy consumption on the ith leg on route r, denoted by L_{ri}, i.e., $h_{r,i+1} = h_{ri} + z_{ri} - L_{ri}$. All ships deployed on route r ($\forall r \in R$) maintain a fixed service frequency β, i.e., the time interval (days) between two adjacent visits to the same port of call on route r. For example, if $\beta = 1$, it means each port of call on route r is visited once a day. The service frequency and the number of ships deployed on a route determine ship dwelling time at the ports of call on this route, which can be expressed as $24 \times n_r \beta = \sum_{i \in I_r} (T_{ri} + t^d_{ri})$ where T_{ri} is the given traveling time on the ith leg on route r. The ship dwelling time t^d_{ri} should be no less than operation time O_{ri} at the ith port of call on route r, which includes time for loading and unloading containers.

All transportation tasks that have to be fulfilled by ships on route set R are denoted by E, a set of OD pairs. Each transportation task e has a given number of N_e (TEUs) containers every β day to be transported and a specified service time limit T_e (days), i.e., the time interval between departure time at the original port and arrival time at destination port. A set B_e of transportation plans, i.e., feasible paths between the OD pair associated with a transportation task e, can be adopted to fulfill the transportation task e. For example, two transportation plans exist for a transportation task from Wuhan to Nanjing, which are shown in Table 1. The routing decision is to distribute N_e containers among B_e transportation plans, i.e., $\sum_{b \in B_e} y_b = N_e$ where y_b is number of containers to be shipped on transportation plan $b \in B_e$. All transportation plans fulfilled by the same ship cannot exceed volume capacity, i.e., $\sum_{e \in \mathrm{E}} \sum_{b \in B_e} K^B_{bri} y_b \leq V_r$, where $K^B_{bri} \in \{0, 1\}$ indicates whether transportation plan b uses the ith leg on route r. As each transportation plan has a predetermined service time limit, the total time l_b (hours) of the transportation plan b selected to fulfill transportation task e, including ship sailing time, dwelling time at ports, and transshipment time, cannot exceed time limit, i.e., $\frac{l_b}{24} \leq T_e$. Ship navigation time is the total sailing time on legs where the plan travels. Dwelling time at ports is the total time spent on all ports of call that the plan visits. Transshipment means that containers are moved from a ship on one route to a ship on another route when both ships visit the same port. For example, a transshipment (r, i, s, j) means containers are moved from a ship on ith port of call on ship route r to a ship on jth port of call on ship route s. The time spent on transshipment (r, i, s, j) is the minimum time interval (hours) from arrival of a ship on ith port of call on ship route r, denoted by a_{ri}, to departure of a ship on jth port of call on ship route s, denoted by $a_{sj} + t^d_{sj}$. The transshipment time of a transportation plan is the total time spent on transshipping containers in order to fulfill the plan.

Table 1. Feasible transportation plans from Wuhan to Nanjing.

No.	Transportation Plan
1	p_{11}(WH)→p_{12}(HS)→p_{13}(JJ)→p_{33}(NJ)
2	p_{31}(WH)→p_{32}(JJ)→p_{33}(NJ)

Since for shipping companies, cost is an important consideration for adopting a new technology. The objective of this research is to fulfill all transportation tasks within the required service time limit with minimal cost that is composed of charging cost, the construction cost of charging station, and the fixed cost of ships.

3.2. Summary of Assumptions

Before formulating the mathematical model, we make following assumptions:

(1) The shipping network, including routes and ports, is already determined, because shipping network design usually belongs to the strategic planning of a shipping company, which takes some time and involves benefits of multiple parties.
(2) The ships deployed on each route are homogenous with the same predetermined battery capacity and volume capacity. Because in the early stages, for cost and regulation reasons, a shipping company will adopt the same-size ships on each route. However, this assumption can be easily relaxed in our model.
(3) All transportation tasks are known in advance in terms of origin, destination, the number of containers, and required service time, because a cargo owner will usually book a shipping service and sign a contract with the shipping company in advance.
(4) Transportation plans for each transportation task are already known. Since the shipping network is already known, the transportation plans are usually determined in advance for the convenience of customers.
(5) The charging rate is a constant. This assumption can be easily relaxed, and we will discuss the impact of charging rate in Section 4.
(6) The ship sailing speed is a constant. Ship sailing speed usually changes for various reasons. For simplicity, we made this assumption.

Remark: some of these assumptions can be relaxed with a subtle modification of our model, while relaxation of others requires significant modification of the model. For example, the second assumption can be relaxed by adding a dimension to parameters and variables to represent ship type. The last two assumptions can be relaxed by formulating a function for charging amount and ship sailing time, respectively. The relaxation of other assumptions may formulate the problem as a stochastic programming model.

3.3. Model Formulation

The problem is formulated as a mixed-integer programming model. All notations are listed in Table 2. For convenience and easy understanding the model, we use lowercase English letters for decision variables and indices, uppercase English letters for input parameters and sets, and Greek letters for constant parameters. The model is given as follows:

$$[\text{M1}]\ \text{Min}\ \sum_{r\in R}\sum_{i\in I_r} C^R_{ri} z_{ri} + \sum_{m\in P} C^C_m x_m + \sum_{r\in R} C^S_r n_r \quad (1)$$

subject to

$$h_{r,i+1} = h_{ri} + z_{ri} - L_{ri},\ \forall r\in R,\ i\in I_r \quad (2)$$

$$h_{ri} + z_{ri} \le Q_r,\ \forall r\in R,\ i\in I_r \quad (3)$$

$$0 \le z_{ri} \le \sum_{m\in P} Q_r K^P_{mri} x_m,\ \forall r\in R,\ i\in I_r \quad (4)$$

$$\frac{z_{ri}}{\alpha} \le t^d_{ri},\ \forall r \in R,\ i \in I_r \tag{5}$$

$$24 \times n_r \beta = \sum\nolimits_{i \in I_r} (T_{ri} + t^d_{ri}),\ \forall r \in R \tag{6}$$

$$t^d_{ri} \ge O_{ri},\ \forall r \in R,\ i \in I_r \tag{7}$$

$$\sum\nolimits_{b \in B_e} y_b = N_e,\ \forall e \in \mathrm{E} \tag{8}$$

$$\sum_{e \in \mathrm{E}} \sum\nolimits_{b \in B_e} K^B_{bri} y_b \le V_r,\ \forall r \in R,\ i \in I_r \tag{9}$$

$$l_b = \sum\nolimits_{r \in \mathrm{R}} \sum\nolimits_{i \in I_r} K^B_{bri} T_{ri} + \sum\nolimits_{r \in \mathrm{R}} \sum\nolimits_{i \in I^D_{br}} K^B_{bri} t^d_{ri} + \sum\nolimits_{(r,i,s,j)} \in S K^{trans}_{brisj} g_{risj},\ \forall b \in B_e,\ e \in \mathrm{E} \tag{10}$$

$$a_{r,i+1} = a_{ri} + t^d_{ri} + T_{ri},\ \forall r \in R,\ i \in I_r \tag{11}$$

$$0 \le a_{r1} \le 24\beta,\ \forall r \in R \tag{12}$$

$$g_{risj} = a_{sj} + t^d_{sj} - a_{ri} + 24\beta u_{risj},\ \forall (r,i,s,j) \in S \tag{13}$$

$$0 \le g_{risj} \le 24\beta,\ \forall (r,i,s,j) \in S \tag{14}$$

$$0 \le \frac{l_b}{24} \le T_e,\ \forall b \in B_e,\ e \in \mathrm{E} \tag{15}$$

$$x_p \in \{0,1\},\ \forall p \in P \tag{16}$$

$$y_b \ge 0,\ \forall b \in B_e,\ e \in \mathrm{E} \tag{17}$$

$$h_{ri} \ge 0,\ \forall r \in R,\ i \in I_r \tag{18}$$

$$n_r \in \mathbb{Z}_+,\ \forall r \in R \tag{19}$$

$$a_{ri} \ge 0,\ \forall r \in R,\ i \in I_r \tag{20}$$

$$u_{risj} \in \{0,1\},\ \forall (r,i,s,j) \in S \tag{21}$$

The objective function (1) minimizes total cost. Equation (2) are the relation of remaining energy between two consecutive ports of call. Constraints (3)–(5) set limits for charging amount at a port of call. Constraints (3) require that energy of a ship after charging cannot exceed battery capacity. Constraints (4) state that a ship can only recharge at the port of call where a charging station is constructed and the charging amount cannot exceed battery capacity. Constraints (5) stipulate that charging time cannot exceed ship dwelling time at a port of call. Constraints (6) are the relationships between the number of deployed ships, service frequency, and time spent on route where the time consumed on each route is the sum of sailing and dwelling time on this route. Constraints (7) stipulate that ship dwelling time at a port of call is no less than a fixed operation time that is used for loading and unloading containers. Constraints (8) distribute the containers of transportation tasks to a set of transportation plans. Constraints (9) require that shipping containers cannot exceed ship volume capacity. Constraints (10)–(15) require transportation plans to be fulfilled within the service time limit. Constraints (10) are expressions of the time consumption of transportation plans. Constraints (11) are arrival times at ports of call, and the arrival time at the first port of call at each route is restricted by Constraints (12). Constraints (13) and (14) are transshipment time and its range. Constraints (16)–(21) are the domains of decision variables and auxiliary variables.

Table 2. Notations used in this research.

Indices and Sets	
R	Set of container shipping routes
r	Index of a shipping route, $r \in R$
P	Set of all ports on shipping routes
m	Index of a port, $m \in P$
I_r	Set of the port of calls (or legs) on ship route r
i	Index of port of call or leg $(i, i+1)$ on a ship route, $i \in I_r$
p_{ri}	The ith port of call on ship route r, $p_{ri} \in P$
E	Set of OD pairs
e	Index of an OD pair, $e \in E$
B_e	Set of transportation plans to fulfill transportation task of an OD pair e
b	Index of a transportation plan, $b \in B_e$
I_{br}^D	Set of the ports of call on ship route r that do not require transshipment when transportation plan b visits, e.g., p_{12}(HS) in Table 1
S	Set of transshipment
(r, i, s, j)	Index of a transshipment from the ith port of call on ship route r to the jth port of call on ship route s, $r, s \in R$, $i \in I_r$, $j \in I_s$, $(r, i, s, j) \in S$. (r, i, s, j) means the ith port of call on ship route r and the jth port of call on ship route s correspond to the same port, i.e., $p_{ri} = p_{sj}$, e.g., $(1, 3, 3, 2)$ in Table 1
$\mathbb{Z}_+$	Set of non-negative integers
Parameters	
C_{ri}^R	The unit charging cost (RMB/kWh) at port p_{ri}
C_m^C	The construction cost (RMB/β days) of a charging station at port m
C_r^S	The fixed cost (RMB/β days) of a ship deployed on route r, including purchasing cost of a ship, labor cost, insurance, etc.
L_{ri}	The energy consumption (kWh) on ith leg on route r
Q_r	The battery capacity (kWh) of ship on route r
α	Energy charging speed (kWh/h)
β	The fixed ship service frequency (days), i.e., time interval between two adjacent visits to the same port on the same route
N_e	The number of containers to be transported for OD pair e
K_{mri}^P	1 if the ith port of call on route r is port m, 0 otherwise
K_{bri}^B	1 if transportation plan b uses the ith leg on route r, 0 otherwise
K_{brisj}^{trans}	1 if transportation plan b uses transshipment (r, i, s, j), 0 otherwise
V_r	Volume capacity (TEUs) of each ship deployed on ship route r
T_{ri}	Ship sailing time (hours) on ith leg on route r
O_{ri}	Ship operation time (hours), including loading and unloading, at the ith port of call on route r
T_e	Service time limit (days) to fulfill transportation task of an OD pair e
Decision variables	
x_m	Binary variable, =1 if a charging station is constructed at port m; =0 otherwise
y_b	The number of containers to be shipped on transportation plan b
z_{ri}	The energy charging amount (kWh) at port of call p_{ri}
h_{ri}	The remaining energy (kWh) when a ship visits the ith port of call on route r
n_r	The number of ships deployed on route r
a_{ri}	Arrival time of a ship visiting ith port of call on route r
t_{ri}^d	Ship dwelling time (hours) at the ith port of call on route r
g_{risj}	Transshipment time of (r, i, s, j), i.e., minimum time interval (hours) from arrival of a ship on ith port of call on ship route r to departure of a ship on jth port of call on ship route s such that containers can be transshipped from the former ship to the latter
l_b	Time (hours) consumed by transportation plan b
Auxiliary variables	
u_{risj}	A binary variable used to transfer g_{risj} to be non-negative

Theorem 1. *The problem that simultaneously considers charging station location, charging plan, route planning, ship scheduling, and ship deployment is NP-hard.*

Proof. The set cover problem is NP-hard. We show the NP hardness of the shipping problem by reducing the set cover problem into the shipping problem in polynomial time. The set cover problem is defined as follows: Given a universe U, a family S of subsets of U, and an integer k, there is a subfamily $C \subseteq S$ of sets whose union is U and the size is k or less. Suppose $C^R_{ri} = 0$, $C^S_r = 0$, $\alpha = \infty$, and $Q_r = \infty$, the shipping problem is equivalent to optimize the location of charging stations such that each route has at least one charging station. Suppose there is a universal route set U where each route $u \in U$ is composed of a sequence of ports to be visited. There are $|P|$ ports, and for each port $p \in \{1, 2, \ldots, |P|\}$, there is a set S_p comprising the routes that travel through the port p. A set $S = \left\{S_1, S_2, \ldots, S_{|P|}\right\}$ is a family of set S_p. The shipping problem is to identify a subfamily $C \subseteq S$ of sets whose union is U and the size is k or less, which is equivalent to the set cover problem. Thus, the set cover problem can be solved by solving shipping problem in polynomial time.

The shipping problem is formulated as an MILP model, which can be solved easily by an MILP solver, such as CPLEX. The MILP solver uses branch-and-cut method to solve MILP. The basic idea is to construct a search tree consisting of nodes and apply branches and cuts to active nodes until either no more active nodes are available or some limit has been reached. Every node is a linear subproblem whose integrality has to be checked. A branch is the creation of two new nodes from a parent node. A cut is a constraint added to the model to limit the size of the solution domain. The MILP solver starts by processing the root node. If the solution violates any cuts, the MILP solver may add some cuts until no more violated cuts are detected. Otherwise, the MILP solver will check the integrality of the solution. If the integrality constraints are satisfied and the objective value is better than that of the current incumbent, the solution of the node-problem is used as the new incumbent. If not, branching will occur. The procedure iterates until the objective value of node problem and current incumbent converge or some limit has been reached. □

4. Case Study

In this section, a case study using real-world data was conducted to evaluate the model performance. Through sensitive analyses, valuable managerial insights were obtained to guide practical operations. All the experiments were carried out on a Dell XPS 15 9500 laptop with i7-10750H CPU, 2.60 GHz processing speed, and 16 GB of memory. The model was implemented in C++ programming and solved by CPLEX 12.10 [46].

4.1. Parameter Setting

This research considers a shipping network with 13 ports along the Yangtze River, as shown in Figure 2. A total of 14 routes, shown in Table 3, with service frequency set to 1 day, are serviced by these ports. The electric ships deployed on each route are assumed to be homogenous in terms of ship size, volume capacity, battery capacity, sailing range, sailing speed, and charging speed. The data of the ships is based on the construction plan of electric containerships ordered by COSCO Shipping Development that plans to achieve zero emission in key domestic waters, such as Yangtze River. The unit charging cost is the average industry electricity price. The construction cost of a charging station is estimated according to Tang et al. [47]. All parameter values are shown in Table 4. Port operation in Table 5 is obtained from Tan et al. [48]. Real distances between ports are shown in Table 6. A total of 65 OD pairs are generated, including the number of containers to be transported and the service time limit.

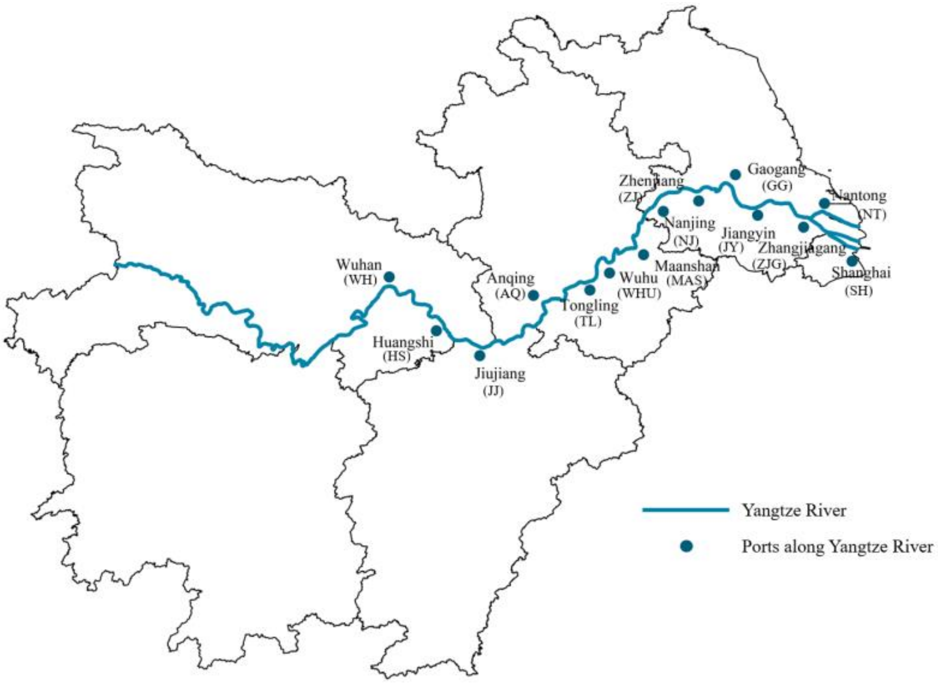

Figure 2. A shipping network along the Yangtze River.

Table 3. Shipping routes along the Yangtze River.

No.	Route
1	WH→HS→JJ→NJ→TC→SH→TC→NJ→JJ→HS→WH
2	WH→HS→AQ→NJ→AQ→HS→WH
3	WH→AQ→WH
4	HS→JJ→WHU→SH→WHU→JJ→HS
5	AQ→TL→TC→SH→TC→TL→AQ
6	WHU→NJ→SH→NJ→WHU
7	NJ→SH→NJ
8	ZJ→ZJG→TC→ZJG→ZJ
9	ZJ→TC→SH→TC→ZJ
10	JY→ZJG→TC→SH→TC→ZJG→JY
11	JY→TC→SH→TC→JY
12	ZJG→NT→TC→SH→TC→NT→ZJG
13	ZJG→NT→SH→NT→ZJG
14	TC→SH→TC

Table 4. Parameter values.

Parameters	Values	Units
Ship size (length × beam)	119.8 × 23.6	meter
Volume capacity	700	TEU
Battery capacity	57,600	kWh
Traveling range	315	nautical miles
Traveling speed	10.5	knots
Charging speed	7200	kWh/hour
Unit charging cost	0.6	RMB/kWh
Construction cost	34,149	RMB/day
Fixed cost of a ship	6356	RMB/day

Table 5. Port operation time.

Index	Port	Operation Time (Hours)
1	WH	4.09
2	HS	5.23
3	JJ	4.95
4	AQ	2.74
5	TL	2.20
6	WHU	5.21
7	NJ	2.68
8	ZJ	3.20
9	JY	2.51
10	ZJG	1.28
11	NT	3.70
12	TC	7.32
13	SH	7.35

Table 6. Distances between ports (nautical miles).

	WH	HS	JJ	AQ	TL	WHU	NJ	ZJ	JY	ZJG	NT	TC	SH
WH	0.00	77.21	145.25	233.80	285.64	343.95	395.79	442.76	505.94	515.66	538.34	579.81	607.45
HS	77.21	0.00	68.03	156.59	208.42	266.74	318.57	365.55	428.73	438.44	461.12	502.59	530.24
JJ	145.25	68.03	0.00	88.55	140.39	198.70	250.54	297.52	360.69	370.41	393.09	434.56	462.20
AQ	233.80	156.59	88.55	0.00	51.84	110.15	161.99	208.96	272.14	281.86	304.54	346.01	373.65
TL	285.64	208.42	140.39	51.84	0.00	58.32	110.15	157.13	220.30	230.02	252.70	294.17	321.81
WHU	343.95	266.74	198.70	110.15	58.32	0.00	51.84	98.81	161.99	171.71	194.38	235.85	263.50
NJ	395.79	318.57	250.54	161.99	110.15	51.84	0.00	46.98	110.15	119.87	142.55	184.02	211.66
ZJ	442.76	365.55	297.52	208.96	157.13	98.81	46.98	0.00	63.17	72.89	95.57	137.04	164.69
JY	505.94	428.73	360.69	272.14	220.30	161.99	110.15	63.17	0.00	9.72	32.40	73.87	101.51
ZJG	515.66	438.44	370.41	281.86	230.02	171.71	119.87	72.89	9.72	0.00	22.68	64.15	91.79
NT	538.34	461.12	393.09	304.54	252.70	194.38	142.55	95.57	32.40	22.68	0.00	41.47	69.11
TC	579.81	502.59	434.56	346.01	294.17	235.85	184.02	137.04	73.87	64.15	41.47	0.00	27.64
SH	607.45	530.24	462.20	373.65	321.81	263.50	211.66	164.69	101.51	91.79	69.11	27.64	0.00

4.2. Computational Performance

In this section, the results of the model were compared with those of a scenario where all ships use fuel oil. When fuel oil ships are used to deliver cargo, there is no need to consider energy recharge and location of charging station. Therefore, the objective was set to minimize total cost comprising bunkering cost and the deployment cost of conventional ships. The charging cost is a linear function of the fuel consumption with a rate of 6 RMB/liter according to the fuel oil price in China. To calculate the fuel consumption, this research first calculated electricity consumption on all routes based on information in Section 4.1, and then transformed it to fuel consumption according to fuel consumption rate, which was set to 0.4 L/kWh [48]. Since the unit charging cost and the distance of each route is given, the charging cost is a constant and can thus be deleted from model for fuel oil ships. Therefore, the optimization model for fuel oil ships is shown as follows:

$$[\text{M2}]\ \text{Min} \sum\nolimits_{r \in R} C_r^S n_r \tag{22}$$

subject to Constraints (6)–(15), (17), and (19)–(21).

The objective function (22) minimizes the total deployment cost of conventional ships. The notation C_r^S represents the fixed cost (RMB/β days) of a ship deployed on route r, including the purchasing cost of a ship, labor cost, insurance, etc., where β represents the fixed ship service frequency (days), i.e., time interval between two adjacent visits to the same port on the same route. The decision variable n_r is the number of ships deployed on route r.

All the parameters of conventional ships are the same as those of electric ships, except that the fixed cost of a conventional ship was assumed to be half of an electric ship. The comparison of the total cost of these two scenarios is shown in Figure 3. The total cost of using electric ships is only 42.8% of using conventional ships. This is because the total fuel oil cost is far more than total electricity cost. Even though we need extra cost to build charging stations and purchasing electric ships, the energy cost savings can easily make up for the extra expenses.

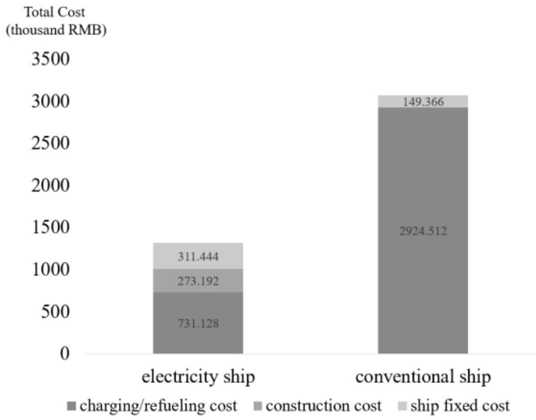

Figure 3. The comparison of total cost of scenarios using electric ships and conventional ships.

The emissions from these two scenarios were also examined. The emission factors shown in Table 7 were obtained from Wang, Mao, and Rutherford [49]. They represent the emissions intensity (g/kWh) of power stations in Hong Kong in 2020. Hong Kong's power generation mix was dominated by coal, representing 53% of total electricity, followed by nuclear (23%) and natural gas (22%). Oil and renewables constituted the remaining 2% of the generation mix. The generation mix may be different in mainland China, but the emission intensity will not be very different, because the largest emission contributor, i.e., coal, already accounted for more than half in the calculation of emissions intensity. Thus, it is believed that the data is applicable to the case study. The total energy consumption by electric ships and conventional ships were obtained from model [M1] and the description above model [M2], respectively. Then the emissions from electric and conventional ships were calculated separately by multiplying total energy consumption by emission factor. The comparison of emissions is shown in Table 8. Results show that using electric ships can reduce 80% SO_x, 93.47% NO_x, 89.47% PM, and 42.62% CO_2, which will make a great contribution to green shipping.

Table 7. Emission factors of electricity and conventional ships (gram/kWh).

	Electric Ships	Conventional Ships
SO_x	0.42	2.10
NO_x	0.64	9.80
PM	0.04	0.38
CO_2	350	610

Table 8. The emission of electric and conventional ships (thousand gram).

	Electric Ships	Conventional Ships	Reduction Rate
SO_x	511.79	2558.95	80.00%
NO_x	779.87	11,941.76	93.47%
PM	48.74	463.05	89.47%
CO_2	426,491.33	743,313.47	42.62%

However, as electric ship has travel range limit, it needs recharge at least once during the whole journey, which will extend the cargo delivery time. The total time to fulfill all the transportation tasks for electric ships is 1946.34 h, while that for conventional ships is 1893.65 h, consuming 2.78% more time.

4.3. Impact of Battery Capacity

Battery capacity is one of the most important factors in electric ship design. In this section, the battery capacity was increased from 1.5 to 5 times the base capacity to explore its impact on system performance. As the other parameters remained the same, the time to fully charge the battery increased correspondingly. The results are shown in Table 9. *Capacity* represents the magnification coefficient of battery capacity and *Station* represents the index of the ports that have a charging station. When battery capacity is increased, the overall construction cost for charging stations decreases because a larger battery capacity allows ships to travel longer without recharging, significantly reducing the number of charging stations needed. It is also found that the charging cost remains the same regardless of battery capacity because it is a component of the total cost that is to be minimized. Therefore, the charging amount always equals the energy consumption along a route under optimal conditions. An interesting phenomenon is that ships' deployment cost does not change in the same direction. The number of ships deployed on a route is primarily influenced by the dwelling time at ports of call along the route, which in turn, is partially determined by operation and charging times. As the charging amount is the same under each scenario, the total charging time is regarded as a constant that is unevenly allocated at each charging station. In the case of a sufficient number of charging stations, there may be some stations where the charging time is longer than the operation time, thus requiring additional dwelling time and increasing the travel time of the route. When there is only one charging station on each route, the entire charging time is spent at this station, undoubtedly resulting in a considerable dwelling time. Both of these scenarios increase the number of ships deployed. In the first row of Table 9, eight stations are constructed, some of which have short operation times. When the charging time is longer than the operation time, additional dwelling time is required and the number of ships deployed is not minimal. With increased battery capacity, the number of stations decreases to five and four. Thus, the dwelling time at each station is sufficient for the charging time, so no additional time is required and fewer ships are needed. When battery capacity is quadrupled, each route needs only one charging station, so the entire charging time is spent at this station, and thus more ships are deployed. Considering the trade-off between charging station construction cost and ship cost, total cost gradually decreases with increases in battery capacity. When battery capacity increases to a certain level, all of the components in Table 9 remain unchanged. As each route must build at least one charging station for ships to recharge at a low battery level, a minimum number of stations must be provided. As there is a lower bound for route travel time—the sum of travel time between the ports of call—the number of ships deployed on each route should be no less than a certain number. Table 9 shows that if there are fewer charging stations, ships must be equipped with a large-capacity battery. This study does not consider the side effects of large battery capacity, such as increased energy consumption and reduced container space. If these side effects are considered, the results might be different. Furthermore, battery capacity influences the number of ships deployed on each route. If there is a budget for ship deployment, it is important to equip the ship with a battery that fits the budget and minimizes total cost.

Further comparison between the objective values of electric and conventional ships under different battery capacities is shown in Figure 4. The vertical axis represents the ratio between the total costs of electric and conventional ships, denoted by Ra. The horizontal axis represents the magnification coefficient of battery capacity, denoted by γ. The results show that increasing battery capacity makes electric ships more cost-effective.

Table 9. The impact of battery capacity.

Capacity	Total Cost (Thousand RMB)	Charging Cost (Thousand RMB)	Charging Amount (Thousand kWh)	Construction Cost (Thousand RMB)	Station	Ship Fixed Cost (Thousand RMB)	Ship Number
1	1315.76	731.13	1218.55	273.19	1,3,4,5,6,7,12,13	311.44	49
1.5	1206.96	731.13	1218.55	170.75	3,4,7,12,13	305.09	48
2	1172.81	731.13	1218.55	136.60	3,4,12,13	305.09	48
2.5	1172.81	731.13	1218.55	136.60	3,4,12,13	305.09	48
3	1172.81	731.13	1218.55	136.60	3,4,12,13	305.09	48
3.5	1172.81	731.13	1218.55	136.60	3,4,12,13	305.09	48
4	1151.38	731.13	1218.55	102.45	4,12,13	317.80	50
4.5	1151.38	731.13	1218.55	102.45	4,12,13	317.80	50
5	1151.38	731.13	1218.55	102.45	4,12,13	317.80	50

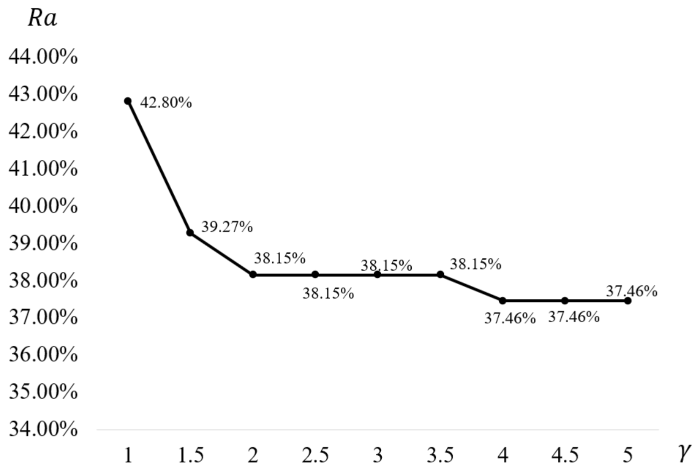

Figure 4. The ratio between the total costs of electric ships and conventional ships under different magnification coefficients of battery capacity.

The above experiments show that there is a threshold for battery capacity. When ships are equipped with batteries with this threshold capacity, the total cost and charging station construction cost will be minimal and electric ships are most cost-efficient when compared to conventional ones. However, the ship deployment cost will reach minimum with a smaller battery capacity. Therefore, if a shipping company wants to reduce total cost, producing electric ships with a larger capacity is suggested.

4.4. Impact of Charging Speed

Charging speed influences the amount of energy charged at unit time. This section explores the impact of charging speed on system performances. The charging speed is increased from 2 to 24 times. Since the other parameters remain the same, the charging time spent to charge to certain amount is shortened accordingly. Results are shown in Table 10 and Figure 5. Speed represents the magnification coefficient of the charging speed. Table 10 reveals that charging speed does not affect charging amount and location of charging station but will influence the schedule of ships on each route. Increasing charging speed will shorten charging time and therefore dwelling time, reducing the travel time along routes. Thus, the deployed ships are reduced. As charging time is shortened, ship schedule can be better optimized, resulting in a downward trend in Figure 5 for total delivery time. When charging speed is increased to eight times, charging time has little effect on ship schedule. Therefore, the total delivery time remains unchanged as the charging speed increases.

The above experiments reveal that charging speed influences ship deployment, scheduling, and choice of transportation plan. There exists a threshold for charging speed at which all aspects are the best. Therefore, it is recommended to establish charging stations with the charging speed as threshold.

Table 10. The impact of charging speed.

Speed	Total Cost (Thousand RMB)	Charging Cost (Thousand RMB)	Construction Cost (Thousand RMB)	Ship Fixed Cost (Thousand RMB)	Charging Amount (Thousand kWh)	Total Charging Time (Hour)
1	1361.13	731.13	273.19	311.44	1218.55	169.2
2	1354.77	731.13	273.19	305.09	1218.55	84.6
4	1354.77	731.13	273.19	305.09	1218.55	42.3
8	1348.42	731.13	273.19	298.73	1218.55	21.2
16	1348.42	731.13	273.19	298.73	1218.55	10.6
24	1348.42	731.13	273.19	298.73	1218.55	7.1

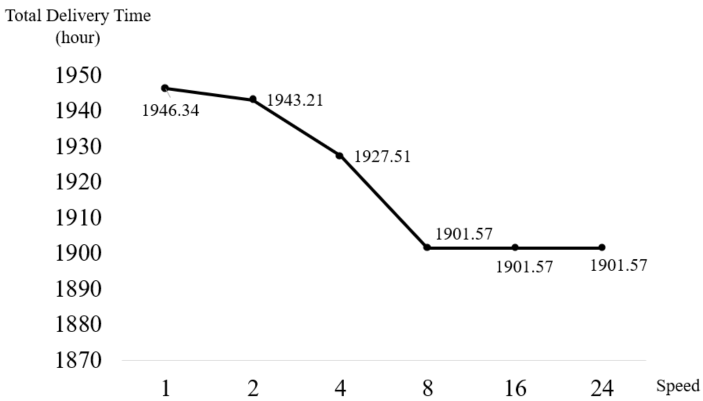

Figure 5. Total delivery time (hours) under different charging speed.

4.5. Impact of Volume Capacity

The volume capacity determines how many containers can be delivered by a ship, the influence of which is shown in Table 11. The first column is the magnification factor of the ship volume capacity. When the ship volume capacity increases, charging cost and construction cost remain unchanged, while ship cost and total delivery time decrease, because volume capacity impacts routing choice and, thus, ship schedule. All transportation tasks can be fulfilled by two types of transportation plans: direct and indirect transportation plans. The former means there is no transshipment and containers can be delivered from origin port to destination port along the same route. It is the fastest in terms of time. The latter means that containers have to be transshipped at least once before arriving at a destination port, resulting in longer delivery times. All transportation tasks prefer direct transportation plans if such plans exist and the ship volume capacity is sufficient. Therefore, when ship volume capacity increases, more transportation tasks can be fulfilled through direct transportation plans. The dwelling time at ports of call decreases because of reduced transshipment. As a result, the number of deployed ships and total delivery time decrease. When volume capacity increases to certain level, i.e., by four times in this research, all transportation tasks are completed using the shortest time plan, leaving no room for the improvement of each component. Table 11 suggests that an optimal volume capacity exists, at which all costs and total delivery time are lowest. Therefore, it is suggested that ships with the optimal volume capacity to maximize efficiency should be produced.

Table 11. Impact of volume capacity.

Volume	Total Cost (Thousand RMB)	Charging Cost (Thousand RMB)	Construction Cost (Thousand RMB)	Ship Fixed Cost (Thousand RMB)	Charging Amount (Thousand kWh)	Total Delivery Time (Hour)
1	1361.13	731.13	273.19	311.44	1218.55	1946.3
2	1361.13	731.13	273.19	311.44	1218.55	1913.5
4	1354.77	731.13	273.19	305.09	1218.55	1880
6	1354.77	731.13	273.19	305.09	1218.55	1880
8	1354.77	731.13	273.19	305.09	1218.55	1880
Infinity	1354.77	731.13	273.19	305.09	1218.55	1880

4.6. Impact of Service Time Limit of Transportation Task

Service time limit is a constraint in our model that requires that all transportation tasks be fulfilled within this time limit. In this section, service time constraints were relaxed to see what effect this would have. Results are shown in Table 12, where the first row is the result of the model with unchanged parameters, while the second row is the result of the model with relaxed service time limit. It can be seen that with the release of the service time, ship cost decreases while total delivery time increases, because there is no need to worry about the time difference between routes when designing ship schedules and there is no additional time for each route. Therefore, the travel time along each route is mainly determined by time spent on each edge, port operation time, and charging time. As a result, the number of deployed ships decreases. However, when time difference between routes is ignored, the transshipment time can be large, resulting in a large delivery time for each transportation task.

Table 12. Impact of service time limit of transportation task.

	Total Cost (Thousand RMB)	Charging Cost (Thousand RMB)	Construction Cost (Thousand RMB)	Ship Fixed Cost (Thousand RMB)	Charging Amount (Thousand kWh)	Total Delivery Time (Hour)
Origin	1361.13	731.13	273.19	311.44	1218.55	1946.3
Relaxed	1354.77	731.13	273.19	305.09	1218.55	2032.6

Table 12 demonstrates that service time limits influence ship schedule and ship cost. With larger service times, while customer satisfaction is reduced, the company saves money. Therefore, shipping companies could provide differentiated services based on customer's sensitivity to time.

5. Conclusions

This research designs a cost-efficient and environmentally friendly service network for electric ships, including the location of charging stations, charging plans, route planning, ship scheduling, and ship deployment. The problem is formulated as a MILP model with the objective of minimizing total cost comprising charging cost, the construction cost of charging stations, and the fixed cost of ships. A case study using the data of the shipping network along the Yangtze River was conducted in order to evaluate the performance of the model. Two operating scenarios were used: an electric ship scenario where all the transportation tasks are fulfilled by electric ships and a conventional ship scenario where all the transportation tasks are fulfilled by fuel oil ships. Results unveil that the total cost of using electric ships is only 42.8% of using conventional ships. Using electric ships can reduce 80% SO_x, 93.47% NO_x, 89.47% PM, and 42.62% CO_2, but consumes 2.78% more time to fulfill all the transportation tasks. Extensive sensitivity analyses are also conducted for key operating factors, including battery capacity, charging speed, volume capacity, and the service time limit of transportation tasks. Implications from the results are as follows: (1) it is necessary to equip the ship with a large capacity battery when the number of charging stations is low; (2) battery capacity will influence the number of ships deployed on each route; (3) increasing battery capacity will make electric ship more cost-effective; (4) charging speed does not affect charging amount and the location of the charging station but influences the schedule of ships on each route; (5) an optimal volume capacity exists, where all costs and total delivery time are lowest; and (6) the service time limit influences ship schedule and ship cost.

One limitation of this research is the assumptions utilized to simplify the problem. For example, sailing speed is assumed to be a constant. The relationship between energy consumption and travel distance is assumed to be linear. The electricity cost is also assumed to be a constant. In reality, sailing speed is adjusted according to schedule and the state of a ship. The changing speed will also influence energy consumption and the choice of transportation plan. The electricity cost changes throughout the day. For example, at night, the demand for electricity decreases, resulting in lower electricity prices. These issues will be addressed in future research. Additionally, we can incorporate data driven models [50,51] in the research or consider penalties or warranties when the systems allow partial satisfaction [52,53].

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