https://dx.doi.org/10.1016/j.ocecoaman.2022.106386

Optimal Scheduling of Autonomous Vessel Trains in a Hub-and-Spoke Network

Xiao Yang [a], Weihua Gu [a,*], Wei Wang [b], Shuaian Wang [b]

[a] Department of Electrical Engineering, The Hong Kong Polytechnic University, Hong Kong Special Administrative Region

[b] Department of Logistics & Maritime Studies, The Hong Kong Polytechnic University, Hong Kong Special Administrative Region

* Corresponding author, Email: weihua.gu@polyu.edu.hk

Abstract

An autonomous vessel train features several autonomous vessels sailing together, piloted by a conventional, manned leader vessel. It is a promising transitional solution at the present technological level before full autonomy is realized. We develop mixed-integer programming models for jointly optimizing the autonomous vessel assignment to vessel trains and vessel train routes and schedules in a hub-and-spoke network. Solutions to these models capture the optimal tradeoff between vessel trains' added detour and delay costs and the lower sailing cost of autonomous ships. Numerical case studies are carried out for a real-world short-sea shipping network around the Bohai Bay of China. Results reveal sizeable cost savings of vessel train operations compared to the case where only conventional ships are used. Sensitivity analyses are performed to unveil how the benefit of vessel trains is affected by key operating factors, e.g., the fleet composition, the vessel train size limit, and the network topology. The results inform practitioners of suitable and profitable scenarios for implementing the vessel train strategy. This study can be viewed as the first step toward real implementation of the economically competitive and environmentally friendly autonomous freight ships via vessel trains.

Keywords: ship scheduling; autonomous ships; vessel trains; hub-and-spoke networks

1. Introduction

1.1 Background

Waterway transportation contributes to over 80% of the international trade in goods (UNCTAD, 2020). However, conventional ships operated by human crew are facing several major challenges. First, the shipping industry is facing a severe shortage of seafaring personnel (especially in Europe), partly due to the shortcomings (e.g., lacking family friendliness and isolation from social life) of seagoing professions (Brooks and Greenberg, 2022). The shortage is worsening since the shipping demand is growing and the voyage durations become longer due to the lower sailing speeds justified by environmental and economic considerations (Burmeister and Rødseth, 2016). Second, human errors are a major cause of vessel accidents (Hu et al., 2020; Xing and Zhu, 2022; Yu et al., 2021). Third, ship waste and emissions have become increasingly serious issues for waterway transportation (Romano and Yang, 2021), a significant portion of which is created by crew members' daily life (Zhang et al., 2021). Finally, crew members are also a major contributor to the huge cost of waterway transportation (Kalouptsidi, 2021; UNCTAD, 2021). Hence, the shipping industry is keen on finding innovative technologies that can overcome the above challenges (Yang et al., 2019).

An increasingly popular innovation that can reduce the need for crew and the associated problems is autonomous vessels (Munim, 2019). Examples include autonomous dry bulk ships (Burmeister and Rødseth, 2016), container ships (Kremer, 2021; Mitsui O.S.K. Lines, 2022; Tvete, 2022), ferries (Rolls-Royce, 2018; Mitsui O.S.K. Lines, 2022), and tugs (Schuler, 2021; the Maritime Executive, 2022). Compared to the conventional manned vessels, autonomous vessels have the following advantages:

(i) Autonomous vessels can largely resolve the maritime personnel shortage problem.

(ii) Thanks to the novel hull designs, increased automation, and less or no crew required, autonomous vessels have lower bunker, operation, and personnel costs (Liu et al., 2016). The cost reduction will incentivize the shift from road transport to the more environmentally friendly waterway transport mode (Wiercx et al., 2019; Rogerson et al., 2020; Hu et al., 2022a).

(iii) By minimizing human errors, autonomous vessels would be potentially safer than conventional ones (Ahvenjärvi, 2016; Liu et al., 2016).

(iv) Due to the reduced bunker consumption, autonomous vessels are more environmentally friendly (Ahvenjärvi, 2016).

Thus, researchers and practitioners have become increasingly interested in autonomous vessels over the past two decades (Naeem et al., 2008; Khare and Singh, 2012; Rødseth, 2017; Munim, 2019). Ongoing research and development projects include MUNIN (Burmeister and Rødseth, 2016), ReVolt (Tvete, 2022), Yara Birkeland (Kremer, 2021), etc. Studies have been devoted to various aspects of autonomous vessels, including technologies (Escario et al., 2012; Höyhtyä et al., 2017; Im et al., 2018), economic viability (Kretschmann et al., 2017; Ghaderi, 2019; Akbar et al., 2021), business models (Munim, 2019), law and regulatory issues (Karlis, 2018; Klein et al., 2020), and human factors (Wahlström et al., 2015; Ahvenjärvi, 2016). See Gu et al. (2020) for a comprehensive review of the literature on autonomous vessels. Most current autonomous vessels are small in size due to their better maneuverability (Liu et al., 2016). Those smaller vessels are especially fit for providing feeder services in a hub-and-spoke network, such as inland waterway, sea-river, and short-sea networks (Munim, 2019).

However, given the current technological limitations, fully autonomous vessels are feasible only in laboratory tests or small-scale operations (Gu et al., 2020). At present, autonomous vessels are not allowed to sail alone in a complicated waterway transport environment like regional hub-and-spoke networks. Thus, transitional solutions were proposed to expedite the implementation of autonomous vessels with limited autonomy levels. A promising one is vessel trains (also termed vessel platoons), each consisting of several autonomous vessels led by a manned ship (Munim, 2019); see Fig. 1 for illustration. This idea was initiated by the project NOVel Iwt and MARitime transport concepts (NOVIMAR), funded by European Union (Munim, 2019). The leader vessel of a vessel train is a fully manned, conventional ship with navigation, communication, and control equipment for piloting the entire vessel train. Follower vessels in a train are autonomous ones with less or no crew onboard. These autonomous vessels must be escorted by the leader vessel throughout their voyages. The idea is similar to the autonomous truck platoons led by manned trucks (Bhoopalam et al., 2018; van Brummelen et al., 2018).

Fig. 1. The vessel train concept of NOVIMAR.

Vessel trains can significantly improve the safety and security of autonomous vessels, allowing them to be operated under the present technology level. As a result, crew and operating costs will be reduced, and the level of automation will be promoted in waterway transportation. Thus, it is an ideal transitional solution before full autonomy of vessel operations is realized. On the other hand, optimal vessel train scheduling is a new research problem since *autonomous vessels must be piloted by a manned leader vessel*. The latter will take detours to escort every autonomous follower to its destination. Unfortunately, the literature on ship scheduling has by-and-large remained silent on this issue.

1.2 Literature review

Vessel scheduling problems have been extensively studied in the literature (e.g., Liu et al., 2022). Reviews of vessel scheduling studies can be found in Ronen (1983), Christiansen et al. (2004), Meng et al. (2014), Psaraftis (2019), and Chen et al. (2022). Most of those studies focused on conventional manned vessels.

On autonomous vessel operations, many works studied individual vessels instead of vessel trains, assuming that those vessels can sail themselves *without the help of any manned ship* (e.g., Kretschmann et al., 2017; Zhang and Wang, 2020; Akbar et al., 2021[1]). Only a few studies

[1] Akbar et al. (2021) modeled a hub-and-spoke network similar to the one studied in our paper.

are found on autonomous vessel train operations, as summarized in Table 1. Nevertheless, some of those studies still assumed fully autonomous vessels that can sail by themselves (Chen et al., 2018, 2019, 2020; Liang et al., 2021; van Pampus et al., 2021; Wu et al., 2022)[2]. Recall that conventional manned vessels are needed to lead autonomous vessels in the complicated water transport environment, given the present and forthcoming technological levels. Only two works considered platoons of partially autonomous vessels requiring conventional leaders (Colling and Hekkenberg, 2020; Meersman et al., 2020). Regrettably, they both focused on the cost-benefit analysis of vessel trains rather than the optimal scheduling problem. To our best knowledge, Chen et al. (2020) is the only study that optimized the schedules of autonomous vessel trains. However, as mentioned above, this study also assumed fully autonomous vessels are used. Note that the scheduling problem of vessel trains with partial autonomy is much more complicated because a vessel train will experience detours to ensure each autonomous vessel is escorted to its destination by a manned ship.

Table 1. Summary of studies on autonomous vessel train operations.

Study	Topic	Manned leader vessel	Vessel scheduling
Chen et al. (2018)	Vessel train formation control	No	No
Chen et al. (2019)	Vessel train formation control	No	No
Chen et al. (2020)	Passing time minimization	No	Yes
Colling and Hekkenberg (2020)	Economic viability	Yes	No
Meersman et al. (2020)	Economic and societal benefits	Yes	No
Liang et al. (2021)	Platoon control laws	No	No
van Pampus et al. (2021)	Vessel train formation control	No	No
Wu et al. (2022)	Vessel train formation control	No	No

On a side note, Zhen et al. (2018) optimized the assignment of barges to tugs and the departure time of tugs from a seaport. Although this cited study focused on conventional ships, the barge-to-tug assignment and scheduling problem is similar to our autonomous vessel train

[2] Chen et al. (2018), van Pampus et al. (2021), and Wu et al. (2022) focused on the vessel train formation control problem considering collision avoidance.

scheduling problem. Unfortunately, they only examined a simple shipping network, i.e., a one-dimensional river. Thus, their model cannot be applied to general hub-and-spoke networks.

In summary, no study has solved the optimal vessel assignment and scheduling problem for autonomous vessel trains led by manned ships in a hub-and-spoke network.

The autonomous vessel train scheduling problem is similar to the autonomous vehicle platoon scheduling problem (Bhoopalam et al., 2018; Zhang et al., 2020; Lesch et al., 2021; Luo and Larson, 2021). For example, both ideas benefit by reducing fuel and labor costs. Moreover, both problems entail the joint optimization of platoon formation (i.e., vessel or vehicle assignment to platoons), scheduling, and routing with detours. However, prevailing vehicle platoon scheduling models cannot be directly applied to vessel trains, mainly for the following reasons.

First, autonomous vehicle platoons can be more flexibly operated than autonomous vessel trains. An autonomous vehicle can conveniently switch between human-driving and driverless modes (e.g., a driver can sit in the cab and be ready for the switch when the vehicle is self-driving, or a vehicle can park curbside to pick up or drop off a driver for the switch). This means an autonomous vehicle can join or detach from a platoon at any time or location, and the leader vehicle of a platoon (usually operated by a human driver) will not escort all follower vehicles to their destinations. On the other hand, an autonomous vessel cannot join or leave a vessel train in the middle of its voyage since the crew cannot board or alight the ship en route (Colling and Hekkenberg, 2020). Thus, the manned leader vessel must escort every member autonomous vessel throughout the latter's voyage. This constraint renders the autonomous vessel train routing and scheduling problem more complicated than the autonomous vehicle platooning problem, given that other operating conditions are similar.

Second, the operating environments and constraints of autonomous vehicle platoons do not apply to our vessel train scheduling problem. For example, autonomous vehicle platooning problems often consider a many-to-many network (Luo and Larson, 2021; Hu et al., 2022b), while a hub-and-spoke network is usually assumed for regional waterway transportation (Huang et al., 2022). In addition, vehicle (e.g., truck) travel times are tightly constrained by the drivers' regulations on the continuous driving hours (Goel, 2010, 2014; Goel et al., 2012; Hu et al., 2022c). However, in most cases, vessels do not have this problem since the crew live on the ship and work in shifts. In short, a new mathematical program needs to be formulated for the autonomous vessel train routing and scheduling problem.

1.3 Overview of the paper

In light of the above research gap, we show the cost advantages of vessel trains by formulating novel models for jointly optimizing the formation and scheduling of vessel trains and the sequence of ports visited by each vessel train in a hub-and-spoke network. Our objective is to minimize the vessels' total sailing cost and delay penalty. We assume that autonomous ships cannot sail alone and must be piloted by conventional ships throughout their journeys. The models are suitable for planning the operations of vessels with limited autonomy during the transitional period toward full autonomy.

We model two operating scenarios: a freight distribution scenario where all the vessels travel from a hub port to a set of feeder ports and a backhaul scenario where all the vessels return from the feeder ports to the hub port. The models are linearized and solved via CPLEX.

A numerical case of the Bohai Bay port network of China is studied. Results unveil that optimally scheduled vessel trains have a great potential to reduce the overall operating cost compared to the benchmark scenario where only conventional ships are used[3]. For example, if an autonomous vessel costs 70% of a conventional one, vessel trains can save up to 18% of the cost. Extensive sensitivity analyses are conducted for key operating factors, including the autonomous ships' sailing cost rates, delay penalty rates, the numbers of leader and autonomous vessels, the tightness of sailing time windows, the size limit of vessel trains, and the waterway network topology. These unveil useful insights into the operating conditions under which the

[3] Under our problem setting, vessel trains would surely have no cost advantage if the vessels were fully autonomous, since detours can be eliminated, and vessel schedules can be more flexible if each vessel sails alone. Vessel trains are advantageous only in the transitional period when each autonomous vessel must be piloted by a conventional ship. Thus, the cost saving is derived by comparing to the scenario where all the vessels are conventional, not to the future scenario of full autonomy. We want to make sure this point is clear to the readers.

autonomous vessel trains are more competitive. The insights have implications for the future development and commercialization of autonomous vessel trains.

In summary, our paper makes the following main contributions to the literature:

(i) To our best knowledge, this is the first study that optimizes the vessel train formation, schedules, and routes considering that manned leader ships are needed to pilot vessels with limited autonomy. The results present the maximum potential economic benefits vessel trains can attain under given technological and cost levels. This complements the literature on economic viability of vessel trains (Colling and Hekkenberg, 2020; Meersman et al., 2020) that analyzed specific case studies only.

(ii) Our extensive numerical studies unveil several insights regarding how the cost benefit of vessel trains is affected by a variety of key operating parameters, including the technological parameter (vessel train size limit), cost parameters, and operating parameters (schedule time windows, fleet composition, and network topology). These findings will assist practitioners in determining the favorable conditions for vessel train implementation.

In addition, our model can be integrated with vessel train formation control models (Chen et al., 2018, 2019, 2020; van Pampus et al., 2021) to provide more detailed guidance for real-world vessel train operations.

The rest of this paper is organized as follows. Section 2 describes the problem definition, model formulations, and linearization. Numerical results of the Bohai Bay case study are presented in Section 3. Conclusions and future research directions are discussed in Section 4.

2. Problem description and formulation

Notations used in this paper are summarized in Section 2.1. Section 2.2 presents the problem setup and key assumptions. The freight distribution problem is formulated as a mixed-integer nonlinear program (MINLP) in Section 2.3, and the program is linearized in Section 2.4. Section 2.5 formulates the backhaul problem.

2.1 Notations

Sets:

P set of all the ports, $P \equiv \{0, 1, \dots, |P|\}$;

L set of all the conventional leader vessels, $L \equiv \{1,2, \cdots, |L|\}$;

F set of all the autonomous follower vessels, $F \equiv \{|L| + 1, \cdots, |L| + |F|\}$.

Indices:

i, j indices of ports, $i, j \in P$, $i = 0$ indicates the hub port;

l index of a leader vessel or a vessel train led by vessel l, $l \in L$;

f, k indices of autonomous follower vessels, $f, k \in F$.

Parameters for the vessel:

$t_{i,j}$ the direct travel time from port i to port j, $t_{i,j} = t_{j,i}$, $t_{i,i} = 0$, $i, j \in P$;

d_l, d_f the destination port of leader vessel $l \in L$ or follower vessel $f \in F$;

T_l, T_f the earliest departure time of leader vessel $l \in L$ or follower vessel $f \in F$ from the origin port (e.g., the hub port in the freight distribution problem);

T_l', T_f' the expected arrival time of leader vessel $l \in L$ or follower vessel $f \in F$ at its destination port;

c_l, c_f sailing cost rate of leader vessel $l \in L$ or follower vessel $f \in F$ per unit travel time;

p_l, p_f penalty cost rate for leader vessel $l \in L$ or follower vessel $f \in F$ per unit delay at its destination port;

u_l the maximum number of follower vessels that can be led by $l \in L$;

M a sufficiently large number.

Decision variables:

$\phi_{l,f}$ a binary variable that equals one if $l \in L$ is the leader of $f \in F$, and zero otherwise;

$\beta_{k,f}^{l}$ a binary variable that equals one if autonomous vessel $f \in F$ is successive to autonomous vessel $k \in F$ in vessel train $l \in L$ (i.e., f will be dropped off right after k by the same vessel train in the freight distribution problem), and zero otherwise;

τ_l the actual departure time of leader vessel $l \in L$ from the origin port;

τ_f the actual departure time of follower vessel $f \in F$ from the origin port;

$\lambda_l,\ \lambda_f$ the actual travel time of leader vessel $l \in L$ or follower vessel $f \in F$.

Auxiliary variables:

$\theta_l,\ \theta_f$ delay of leader vessel $l \in L$ or follower vessel $f \in F$.

2.2 Problem setup

Consider a regional waterway transportation network represented by a set of ports $P \equiv \{0, 1, \dots, |P|\}$, including a hub port numbered 0 and feeder ports $i \in P\backslash\{0\}$. We first investigate a freight distribution problem where the cargoes are loaded to the vessels (conventional or autonomous) at the hub port and transported to the feeder ports. A backhaul problem, i.e., the freight collection problem where vessels (carrying cargoes or not) travel from the feeder ports to the hub port, will be discussed in Section 2.5. Denote $L \equiv \{1, 2, \dots, |L|\}$ the set of conventional manned ships that can serve as leader vessels of vessel trains, and $F \equiv \{|L| + 1, \dots, |L| + |F|\}$ the set of autonomous vessels. Each vessel train consists of one leader vessel, denoted by $l \in L$, and n_l autonomous follower vessels. We specify that $0 \le n_l \le u_l$ where u_l denotes the maximum number of follower vessels led by l. The leader vessel sails solo if $n_l = 0$. With a slight abuse of notation, we also use l to indicate the vessel train led by l.

The destination port of leader vessel $l \in L$ is denoted by d_l and that of autonomous follower vessel $f \in F$ is denoted by d_f, $d_l, d_f \in P\backslash\{0\}$. Vessel train l may call several ports to drop off the follower ships before arriving at the leader's destination d_l; see Fig. 2 for the illustration of a typical vessel train's voyage. Denote T_l and T_f the earliest departure times of $l \in L$ and $f \in F$ from the hub port, and T_l' and T_f' their expected arrival times at the destination ports, respectively. A penalty will be imposed on a ship that arrives later than the expected arrival time. This penalty will be calculated by the delay multiplied by a predefined penalty cost rate, denoted by p_l for $l \in L$ and p_f for $f \in F$. We assume that the sailing time from port $i \in P$ to port $j \in P$, denoted by $t_{i,j}$, is identical for all the vessels and vessel trains. Further assume that the sailing cost, including the fuel, operating, crew, and vessel renting costs, is proportional to the travel time. Denote c_l and c_f the sailing cost per unit of travel time for $l \in L$ and $f \in F$, respectively.

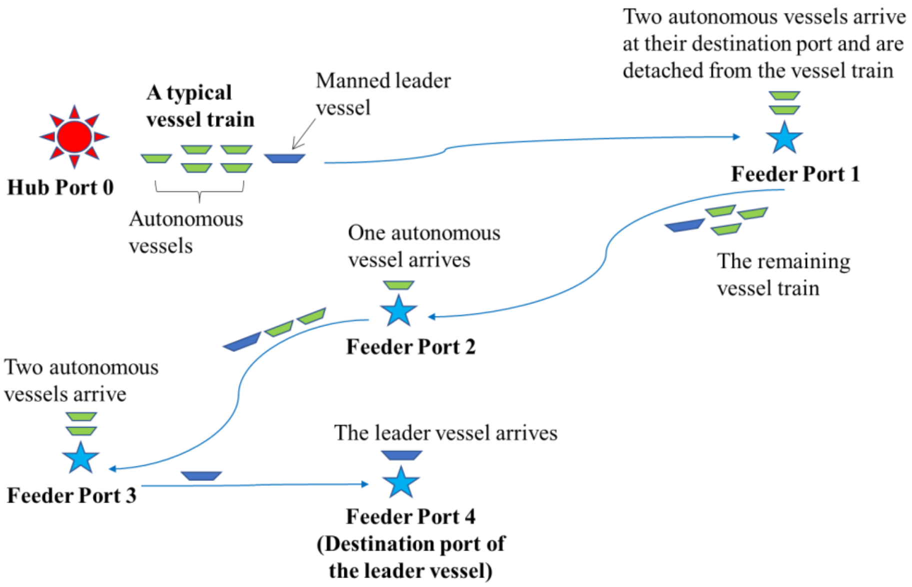


Fig. 2. Voyage of a typical vessel train for freight distribution in a hub-and-spoke network.

The objective is to minimize the sum of the sailing cost and the penalty for all the vessels. The optimal decision is concerned with: (i) how the autonomous vessels are assigned to the leader vessels to form vessel trains; and (ii) when each vessel train departs from the hub port and in what order it calls each member ship's destination port.

2.3 Mathematical formulation of the freight distribution problem

[M0]

$$\min \sum_{l \in L}[c_l \lambda_l + p_l(\tau_l + \lambda_l - T_l')^+] + \sum_{f \in F}\left[c_f \lambda_f + p_f\left(\tau_f + \lambda_f - T_f'\right)^+\right] \quad (1)$$

subject to

$$\sum_{l \in L} \phi_{l,f} = 1, \ \forall f \in F \quad (2)$$

$$\sum_{f \in F} \phi_{l,f} \le u_l, \ \forall l \in L \quad (3)$$

$$\tau_f \geq T_f,\ \forall f \in F \tag{4}$$

$$\tau_f \geq \tau_l - M\left(1 - \phi_{l,f}\right),\ \forall l \in L, \forall f \in F \tag{5}$$

$$\tau_l \geq T_l,\ \forall l \in L \tag{6}$$

$$\tau_l \geq \phi_{l,f} T_f,\ \forall l \in L,\ \forall f \in F \tag{7}$$

$$\lambda_f \geq t_{0,d_f},\ \forall f \in F \tag{8}$$

$$\lambda_f \geq \lambda_k + t_{d_k,d_f} - M\left(1 - \beta_{k,f}^{l}\right),\ \forall l \in L,\ \forall f, k \in F, f \neq k \tag{9}$$

$$\sum_{k\in F} \sum_{f\in F, f\neq k} \beta_{k,f}^{l} \geq \sum_{f\in F} \phi_{l,f} - 1,\ \forall l \in L \tag{10}$$

$$\sum_{f\in F, f\neq k} \beta_{k,f}^{l} \leq 1,\ \forall l \in L, \forall k \in F \tag{11}$$

$$\lambda_l \geq t_{0,d_l},\ \forall l \in L \tag{12}$$

$$\lambda_l \geq \lambda_f + t_{d_f,d_l} - M\left(1 - \phi_{l,f}\right),\ \forall l \in L,\ \forall f \in F \tag{13}$$

$$\tau_f \geq 0,\ \forall f \in F \tag{14}$$

$$\tau_l \geq 0,\ \forall l \in L \tag{15}$$

$$\lambda_f \geq 0,\ \forall f \in F \tag{16}$$

$$\lambda_l \geq 0,\ \forall l \in L \tag{17}$$

$$\phi_{l,f} \in \{0,1\},\ \forall l \in L,\ \forall f \in F \tag{18}$$

$$\beta_{k,f}^{l} \in \{0,1\},\ \forall l \in L,\ \forall f, k \in F, f \neq k. \tag{19}$$

The two terms of objective (1) are the total costs for manned leaders and autonomous followers, respectively, where decision variables τ_l and τ_f denote the actual departure times of leader vessel $l \in L$ and autonomous vessel $f \in F$ from the hub port, respectively; λ_l and λ_f denote the sailing times of vessel l and f from the hub port to their destination ports, respectively; and function $(\cdot)^+$ returns the maximum of 0 and the argument.

Constraint (2) guarantees that each autonomous vessel is led by one leader vessel, where binary decision variable $\phi_{l,f}$ indicates whether autonomous vessel f is assigned to vessel train l. Constraint (3) specifies the capacity of each vessel train. Constraints (4) and (5) indicate that an autonomous vessel's departure time from the hub port is not earlier than its earliest departure time and the departure time of its leader, where M is a sufficiently large number.

Constraints (6) and (7) indicate that a vessel train's departure time from the hub port is not earlier than each member vessel's earliest departure time. Constraint (8) guarantees that the sailing time of the first autonomous ship dropped off by vessel train l is not less than the direct sailing time from the hub port to its destination port. Constraint (9) ensures that any successive autonomous ship f's sailing time is not less than the sailing time of its preceding ship in the same vessel train plus the direct sailing time between the two ships' destination ports. The binary decision variable $\beta_{k,f}^{l}$ denotes the drop-off sequence of autonomous vessels by each vessel train. It is equal to one if vessel f is successive to vessel k in vessel train l (i.e., f is dropped off right after k) and zero otherwise. Constraint (10) indicates that the sum of $\beta_{k,f}^{l}$ for a specific vessel train l is not less than the number of follower ships assigned to that vessel train minus 1. Constraint (11) ensures that each autonomous ship k has at most one successive ship in a vessel train. Constraints (12) and (13) specify that leader l's sailing time must be not less than: (i) the direct sailing time from the hub port to its destination; and (ii) the sailing time of any follower f led by l plus the direct sailing time between the two ships' destination ports. Constraints (14)–(19) define the bounds of continuous decision variables τ_l, τ_f, λ_l, λ_f and binary variables $\phi_{l,f}$ and $\beta_{k,f}^{l}$.

By scrutinizing (4)–(7), (9), and (13), we find that the following value of M is sufficiently large to use:

$$M = \max\left\{\max_{l \in L} T_l\,, \max_{f \in F} T_f\,, (|F| + 1) \cdot \max_{i,j \in P} t_{i,j}\right\}. \tag{20}$$

Any value greater than (20) can also be used. However, using a larger M would increase the solution time.

2.4 Linearization of [M0]

The nonlinear operator $(\cdot)^{+}$ in objective (1) can be simply linearized by introducing auxiliary variables θ_l and θ_f denoting the tardiness of ship $l \in L$ and $f \in F$, respectively. The linearized program is presented as follows:

[M1]

$$\min \sum_{l\in L}[c_l\lambda_l + p_l\theta_l] + \sum_{f\in F}\left[c_f\lambda_f + p_f\theta_f\right] \tag{21}$$

subject to

Constraints (2)–(19)

$$\theta_l \geq \tau_l + \lambda_l - T_l',\ \forall l \in L \tag{22}$$

$$\theta_f \geq \tau_f + \lambda_f - T_f',\ \forall f \in F \tag{23}$$

$$\theta_l \geq 0,\ \forall l \in L \tag{24}$$

$$\theta_f \geq 0,\ \forall f \in F. \tag{25}$$

2.5 The backhaul problem

For long-term vessel train operations, the leader and follower ships distributed to the feeder ports must return to the hub port (with or without cargo) to serve future distribution trips. The autonomous ships still need to form vessel trains led by manned ships when they return. This backhaul problem is the reverse of the above freight distribution problem.

Similarly, we assume that each backhaul ship is associated with the earliest departure time from its origin feeder port and the expected arrival time at the hub port. The other parameters and variables are nearly identical to those defined for the freight distribution problem. Thus, we use the same notations listed in Section 2.1 for the backhaul problem. Only trivial changes need to be noted. For example, d_l and d_f now represent the origin ports of the ships, and $\beta_{k,f}^{l}$ now indicates whether autonomous ship f is picked up by leader l preceding ship k or not. If a backhaul ship carries no load, its expected arrival time can be set to a large value, and its cost and penalty rates can be set to a low value or zero.

Formulation **[M1]** can be applied to the backhaul problem with only two changes. First, constraint (5) should be replaced with $\tau_f + \lambda_f \geq \tau_l + \lambda_l - M(1 - \phi_{l,f}), \forall l \in L, \forall f \in F$. This indicates that an autonomous ship assigned to vessel train l cannot arrive at the hub port earlier than its leader. Second, constraint (7) should be replaced with $\tau_l + \lambda_l \geq T_f + \lambda_f -$

$M(1-\phi_{l,f}), \forall l \in L, \forall f \in F$, which ensures that a leader cannot pick up an autonomous ship before the latter's earliest departure time. Thus, the backhaul problem is formulated as:

[M2]

$$\min \sum_{l \in L}[c_l \lambda_l + p_l \theta_l] + \sum_{f \in F}[c_f \lambda_f + p_f \theta_f] \tag{26}$$

subject to

Constraints (2)–(4), (6), (8)–(19), (22)–(25)

$$\tau_f + \lambda_f \geq \tau_l + \lambda_l - M(1-\phi_{l,f}), \forall l \in L, \forall f \in F \tag{27}$$

$$\tau_l + \lambda_l \geq T_f + \lambda_f - M(1-\phi_{l,f}), \forall l \in L, \forall f \in F. \tag{28}$$

3. Numerical case study

We conduct extensive numerical experiments on the freight distribution problem for a case study of the Bohai Bay of China. The backhaul problem is omitted for brevity since the two problems have similar formulations. All the numerical instances are solved by the CPLEX solver (version 12.8) on a personal computer equipped with an Intel Core eight-core processor clocked at 4.7 gigahertz and 32GB RAM clocked at 3200 megahertz.

The background and parameter values of the case study are introduced in Section 3.1. Section 3.2 examines the computational performance of **[M1]**. Sections 3.3–3.7 present the sensitivity analyses of the cost saving for: (i) the cost ratio between an autonomous ship and a conventional one; (ii) the penalty cost rate; (iii) the tightness of sailing time windows; (iv) the vessel train size limit u_l; and (v) the hub-and-spoke network topology.

3.1 Description of the case study and parameter values

We consider the waterway network between nine seaports around the Bohai Bay, as shown in Fig. 3. The Port of Tianjin is the largest port in Northern China. It is thus designated as the hub port. The rest are assumed to be feeder ports. The travel distances between any two of the nine ports are given in Table 2. The vessels' sailing speed is set to 15 knots (Colling and Hekkenberg, 2020). The travel times, $t_{i,j}$ $(i,j \in P)$, are calculated by dividing the sailing distance by the sailing speed.

Fig. 3. Positions of the nine seaports in the Bohai Bay (generated using Google Earth).

Table 2. Sailing distances (n mile) between the ports of the Bohai Bay.

Port ID	0 Tianjin	1 Dandong	2 Dalian	3 Lvshun	4 Yingkou	5 Qinhuangdao	6 Yantai	7 Qingdao	8 Lianyungang
0	0	335	220	164	266	134	203	443	511
1	335	0	135	201	338	283	195	332	400
2	220	135	0	86	223	168	90	278	346
3	164	201	86	0	162	107	101	309	377
4	266	338	223	162	0	173	227	446	514
5	134	283	168	107	173	0	172	391	459
6	203	195	90	101	227	172	0	247	315
7	443	332	278	309	446	391	247	0	102
8	511	400	346	377	514	459	315	102	0

Source: Marine Distance Tables for China Coast (NGDCNH, 2009).

For simplicity, we assume that all the conventional ships are identical and have the same sailing cost rate, $c_l = c_{\mathcal{L}} =$ \$500/h, $\forall l \in L$ (Colling and Hekkenberg, 2020). A similar assumption is made for all the autonomous ships. Since the practical cost data for autonomous ships are currently unavailable, we assume that an autonomous ship's sailing cost rate, $c_f = c_{\mathcal{F}}$, $\forall f \in F$, is expressed as a fixed proportion, $\alpha \in (0,1]$, of $c_{\mathcal{L}}$; i.e., $c_{\mathcal{F}} = \alpha c_{\mathcal{L}}$. The use of α is convenient for sensitivity analyses. More advanced autonomous ships would have lower

α values.[4] We further assume that the penalty cost rates, p_l and p_f, are equal and expressed as a ratio ρ times the sailing cost rate of a conventional ship; i.e., $p_l = p_f = \rho c_{\mathcal{L}}$ ($\forall l \in L, f \in F$). Unless otherwise specified, we set $\alpha = 0.7$ (Colling and Hekkenberg, 2020) and $\rho = 0.4$ (Zhang and Wang, 2020) in the following sections.

Each ship's destination feeder port, d_l ($l \in L$) or d_f ($f \in F$), is selected randomly from the eight feeder ports. Their earliest departure times are randomly generated from a uniform distribution over $[0, 24]$ h, i.e., $T_l, T_f \sim \mathrm{U}[0, 24], \forall l \in L, f \in F$. We further specify that a vessel's sailing time window is expressed by the minimum sailing time duration (i.e., t_{0,d_l} or t_{0,d_f}) times a slack coefficient denoted by δ_l for $l \in L$ and δ_f for $f \in F$. In other words, we set $T_l' = T_l + \delta_l t_{0,d_l}$ and $T_f' = T_f + \delta_f t_{0,d_f}$, where $\delta_l, \delta_f \geq 1$. A smaller slack coefficient means the time window is tighter. If $\delta_l = 1$, then the only way for vessel l to avoid a penalty is to depart the hub port immediately at T_l and take a direct sailing route to its destination. In this case, vessel trains (especially long ones) may be costly due to the high delay penalty. Coefficients δ_l and δ_f are also randomly generated from a uniform distribution: $\delta_l, \delta_f \sim \mathrm{U}[\bar{\delta} - \Delta, \bar{\delta} + \Delta]$, where $\bar{\delta}$ denotes the mean slack coefficient, and Δ indicates how varied the coefficients are. We set $\bar{\delta} = 1.3$ and $\Delta = 0.3$ unless otherwise specified.

We also assume all the vessel trains have the same size limit, i.e., $u_l = u$, $\forall l \in L$. For now, we specify $u = |F|$, meaning that no limitation on the vessel train size is imposed (note that $|F|$ is the total number of autonomous vessels). This renders the most optimistic case. Other values of u_l will be examined in Section 3.6.

3.2 Computational performance

We first examine the computational performance for instances where $|L| \in \{4, 6, 8, 10, 12\}$ and $|F| \in \{8, 16, 24, 32, 40, 48, 56, 64\}$. For each $(|L|, |F|)$, ten numerical instances are solved with randomly generated d_l, d_f, T_l, T_f, δ_l, and δ_f ($l \in L$, $f \in F$)

---

[4] When determining the value of α in reality, the purchase costs of autonomous and conventional ships can be amortized over their lifecycles and added to the sailing cost rates.

from distributions specified in Section 3.1. Denote $\bar{T}_{\text{CPU}}^{|L|,|F|}$ the average CPU time for solving the ten instances with $|L|$ leader vessels and $|F|$ followers.

Fig. 4 plots $\bar{T}_{\text{CPU}}^{|L|,|F|}$ against $|F|$ for different values of $|L|$. The curves show that $\bar{T}_{\text{CPU}}^{|L|,|F|}$ increases rapidly with $|F|$ and $|L|$, except that $\bar{T}_{\text{CPU}}^{|10|,|56|} > \bar{T}_{\text{CPU}}^{|12|,|56|}$. The exception is probably due to the randomness in parameter values. When $|F| \leq 32$, an instance takes less than 40 seconds to solve on average. However, for a large instance with $|F| = 64$ and $|L| = 12$, the average CPU time is around 20 minutes. Thus, one may need to resort to heuristic methods for even larger-scale instances (which are not common in reality).

The computational efficiency is also significantly affected by the tightness of sailing time windows. This can be seen in Fig. 5, which plots the average CPU time (in milliseconds) of ten randomly generated instances against $\bar{\delta} \in \{1, 1.5, 2, 2.5, 3, 3.5, 4\}$. The case of $\bar{\delta} = 1$ indicates that no slack is available for any vessel. The value of Δ is set to 0 if $\bar{\delta} = 1$ and 0.5 otherwise. We set $|L| = 8$ and $|F| = 24$. All the instances have the same vessel OD pairs and earliest departure times.

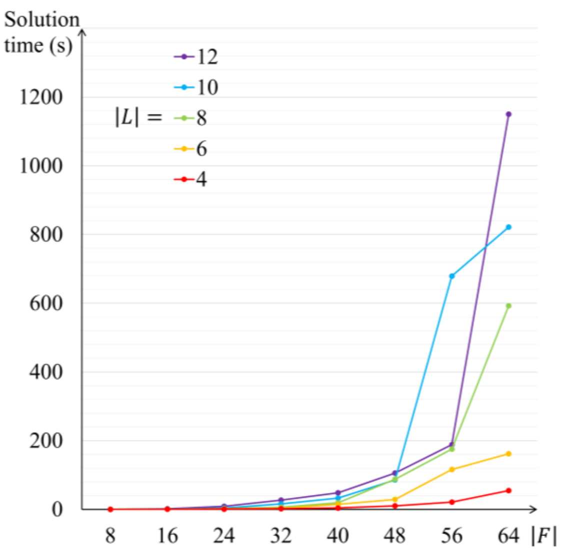


Fig. 4. Average solution time of [M1] against $|F|$ and $|L|$.

Fig. 5 shows that the CPU time plunges as $\bar{\delta}$ grows from 1 to 1.5. This indicates that instances with loose sailing time windows can be solved much faster. When $\bar{\delta}$ continues to grow, the curve decreases slowly and gradually becomes flat.

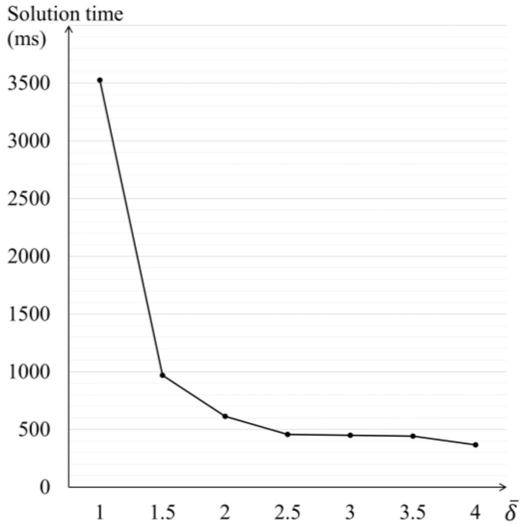


Fig. 5. Average solution time of [M1] against $\bar{\delta}$.

3.3 Sensitivity of the cost saving of vessel trains to the cost rate of autonomous vessels

We first examine the sensitivity of the strategy's cost saving to the ratio between the sailing cost rates of autonomous and conventional ships, i.e., α. The cost saving is calculated by comparing the overall cost of vessel trains against a benchmark scenario where all the vessels are conventional ones with the same cost and penalty rates. The parameter values are the same between the vessel-train and benchmark scenarios. In the latter scenario, each ship will travel individually and directly to its destination.

Specifically, we denote $r^{|L|,|F|}$ the percentage cost saving of the vessel train strategy with $|L|$ conventional leaders and $|F|$ autonomous followers over the benchmark scenario with $|L| + |F|$ conventional, manned vessels; i.e.,

$$r^{|L|,|F|} = (\mathrm{TC}_0^{|L|+|F|} - \mathrm{TC}^{|L|,|F|})/\mathrm{TC}_0^{|L|+|F|}, \tag{29}$$

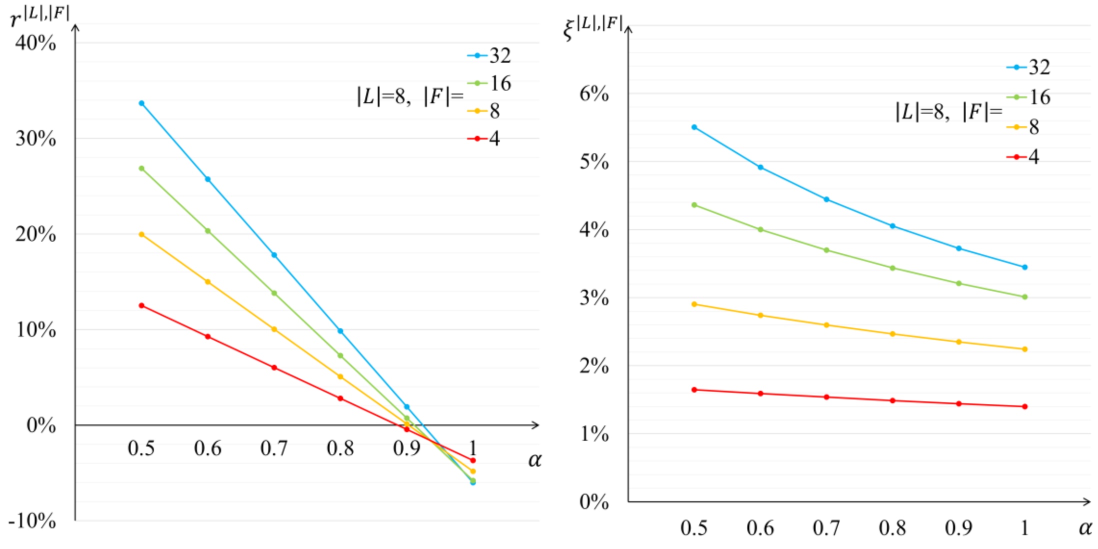
where $\mathrm{TC}^{|L|,|F|}$ and $\mathrm{TC}_0^{|L|+|F|}$ denote the minimum total costs of the vessel train strategy and the benchmark scenario, respectively. We further denote $\xi^{|L|,|F|}$ the share of penalty, $\mathrm{PC}^{|L|,|F|}$, in the overall cost for the vessel train case; i.e.,

$$\xi^{|L|,|F|} = \mathrm{PC}^{|L|,|F|}/\mathrm{TC}^{|L|,|F|}. \tag{30}$$

We specify that $|L| = 8$ and $|F| \in \{4, 8, 16, 32\}$. For each $|F|$, ten instances with distinct vessel ODs and time windows are generated randomly. For each instance, we let α

vary from 0.5 to 1.0 at an interval of 0.1. Averages of $r^{|L|,|F|}$ and $\xi^{|L|,|F|}$ across the ten test instances are plotted against α in Fig. 6a and b, respectively.

As expected, the curves in Fig. 6a decrease with α. More importantly, Fig. 6a shows that the cost saving increases with the number of autonomous ships (except for the case where $\alpha = 1$), although a larger $|F|$ also means longer vessel trains and thus more detours and delays. For example, when there are 8 leader vessels and 32 autonomous ones, the optimal vessel train assignment plan and schedule can save up to 34% of the cost for $\alpha = 0.5$. Moderate cost savings (3–10%) can be attained even when $\alpha = 0.8$. This speaks to the great potential of autonomous vessel train operations.



(a) Percentage cost saving (b) Ratio of penalty to the total cost

Fig. 6. Percentage cost saving and share of penalty cost against α for vessel train operations.

The curves in Fig. 6a are approximately linear because over 90% of the total cost is the sailing cost, which is roughly a linear function of α; see in Fig. 6b that the share of penalty cost is less than 6%. The penalty cost takes a larger share when α is smaller and when there are more autonomous ships (so that the vessel trains are longer and more detours are incurred). This is also as expected.

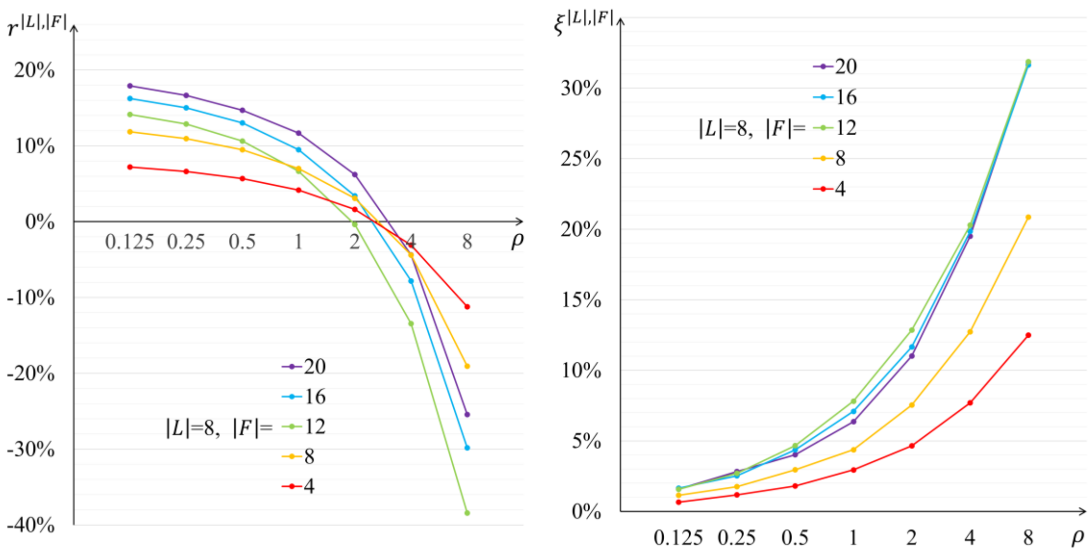
3.4 Sensitivity to the ratio of penalty cost rate

In this section, we fix the sailing cost rates and let the ratio between the penalty rate and the conventional vessels' sailing cost rate, ρ, vary. We set $|L| = 8$ and $|F| \in$

$\{4, 8, 12, 16, 20\}$. Ten randomly generated instances are examined for each $|F|$ and the average $r^{|L|,|F|}$ and $\xi^{|L|,|F|}$ are calculated. We let ρ increase from 0.125 to 8 at a rate of 2. In other words, the penalty rates, $p_{\mathcal{L}}$ and $p_{\mathcal{F}}$, take values in $\$\{62.5, 125, 250, 500, 1000, 2000, 4000\}$/h. A larger ρ indicates that vessels will try harder to complete their trips by the expected arrival times.

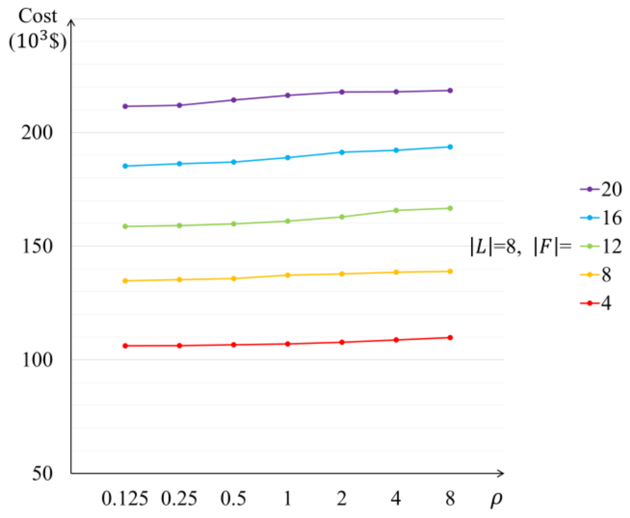
The results of $r^{|L|,|F|}$ and $\xi^{|L|,|F|}$ are plotted in Fig. 7a and b, respectively. Fig. 7a shows that the cost saving decreases as the penalty rate increases since no penalty is incurred in the benchmark scenario. The cost advantage of vessel train operations is observed for $\rho \leq 2$, meaning that vessel trains (with detours) are unsuitable for the shipment of highly time-sensitive goods. In addition, the sensitivity of cost saving to ρ is higher for larger values of $|F|$. This means that longer vessel trains transporting time-insensitive goods can achieve greater cost savings. This finding is confirmed by Fig. 7b, where the share of penalty cost is higher for $|F| \geq 12$.

Fig. 7c plots the sailing cost against ρ. The figure shows that the sailing cost only increases slightly as ρ grows. This occurs because there is little room to adjust the optimal vessel assignment and routing when ρ is high.



(a) Percentage cost saving

(b) Ratio of penalty to the total cost



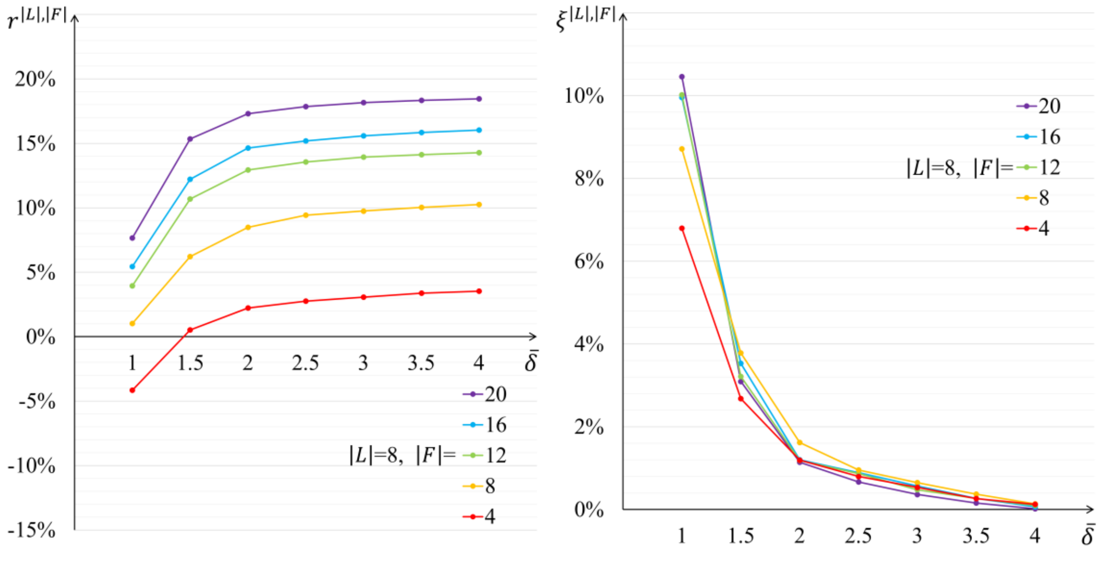
(c) Sailing cost

Fig. 7. Percentage cost saving, share of penalty cost, and sailing cost against ρ.

3.5 Sensitivity to the tightness of sailing time windows

In addition to the cost parameters, one may also be interested in knowing how the cost saving of vessel trains is affected by the tightness of sailing time windows (which also reflects the time sensitivity of the cargo to some degree). Thus, we plot $r^{|L|,|F|}$ and $\xi^{|L|,|F|}$ against $\bar{\delta} \in \{1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0\}$ in Fig. 8a and b, respectively. We still set $|L| = 8$ and $|F| \in \{4, 8, 12, 16, 20\}$. The Δ is set to 0 when $\bar{\delta} = 1.0$ and 0.5 otherwise. Each point in Fig. 8a and b still represents the average value of ten randomly generated instances.

Fig. 8a shows that the cost saving grows with $\bar{\delta}$, which is as expected. The growth rate declines significantly when $\bar{\delta} \geq 2$, revealing that the benefit of vessel trains is approaching its maximum. This is confirmed by Fig. 8b, which manifests that the penalty cost drops drastically below 2% of the total when $\bar{\delta} \geq 2$. Comparison across different values of $|F|$ in Fig. 8a unveils that the cost saving is slightly more sensitive to $\bar{\delta}$ for a larger $|F|$. This is because longer vessel trains tend to have higher penalty costs. We also find that the sailing cost is insensitive to $\bar{\delta}$. But the results are omitted in the interest of brevity.



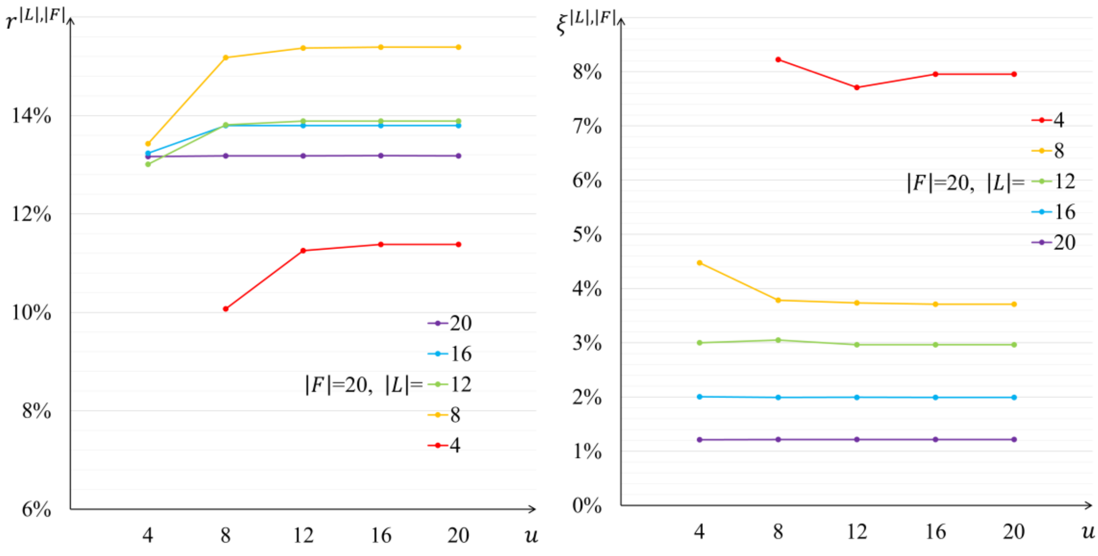
(a) Percentage cost saving (b) Ratio of penalty to the total cost

Fig. 8. Percentage cost saving and share of penalty cost against $\bar{\delta}$.

3.6 Sensitivity to the vessel train size limit

This section investigates the sensitivity of cost savings to the size limit $u_l = u$ $(\forall l \in L)$. The $r^{|L|,|F|}$ and $\xi^{|L|,|F|}$, averaged across ten randomly generated instances, are plotted against $u \in \{4, 8, 12, 16, 20\}$ in Fig. 9a–b, respectively. For simplicity, we set $|F| = 20$ and $|L| \in \{4, 8, 12, 16, 20\}$. But the case of $u = 4$, $|L| = 4$, and $|F| = 20$ is infeasible and thus removed.

Fig. 9a shows for each value of $|L|$ that, as expected, the cost saving first grows with the size limit and then converges when u is sufficiently large (e.g., when $u \geq 4$ for $|L| = 20$, and $u \geq 8$ for $|L| = 12$ and 16). This means that vessel train operations can attain the maximum benefit with a limited threshold of vessel train size. Comparison across the different values of $|L|$ in Fig. 9a reveals that when the number of autonomous ships is fixed, $r^{|L|,|F|}$ first increases and then decreases as $|L|$ grows (e.g., for $u \geq 8$, $r^{8,20} > r^{12,20} > r^{16,20} > r^{20,20} > r^{4,20}$). It first increases because more leader vessels can reduce the vessel train sizes and thus the detours and delays. However, when $|L|$ is sufficiently large (≥ 8), further increasing $|L|$ will undermine the percentage cost saving since leader vessels are more expensive than autonomous ones. This finding implies that the benefit of vessel trains may peak at a certain ratio between the numbers of leader and follower vessels.



(a) Percentage cost saving (b) Ratio of penalty to the total cost

Fig. 9. Percentage cost saving and share of penalty cost against u.

Fig. 9b reveals that the share of penalty cost is insensitive to u, except for a moderately larger share when $|L|$ and u are both small. In addition, the penalty share diminishes as $|L|$ increases, manifesting that more leader vessels can reduce the vessel delays due to the smaller train sizes. Lastly, the sailing cost is again insensitive to u, and the results are omitted for brevity.

3.7 Sensitivity to the network topology

Our last batch of sensitivity analyses pertains to the effect of network topology on cost saving. The network topology will affect the routing of vessel trains and the detour distances. An extreme case is where all the ports are located along a one-dimensional waterway, and the hub port resides at the waterway's end. This type of waterway network, despite its very simple topology, is common in the real world, e.g., a river where the hub port is a seaport located at its estuary (Zhen et al., 2018). The case is extreme because any vessel train dispatched from the hub port will take no detour during its journey. Thus, this topology represents an optimistic case for vessel train operations where the cost saving is maximized. This section compares the cost savings on this extreme waterway network against those on the Bohai Bay network.

Specifically, we consider a one-dimensional hypothetic network illustrated in Fig. 10. The network contains a hub port located at the left end of the river and eight feeder ports. For comparison, the distances between the feeder ports and the hub are set to the same values as in the Bohai Bay case. The other parameters, including the OD pairs and the associated time windows, are set to the same values between the two networks.

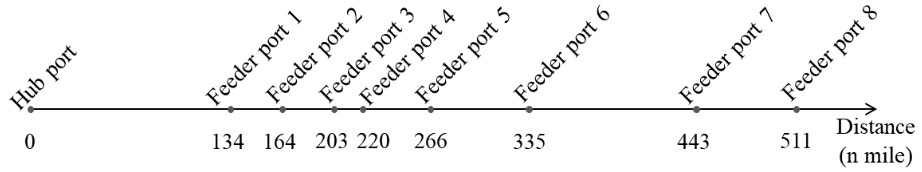
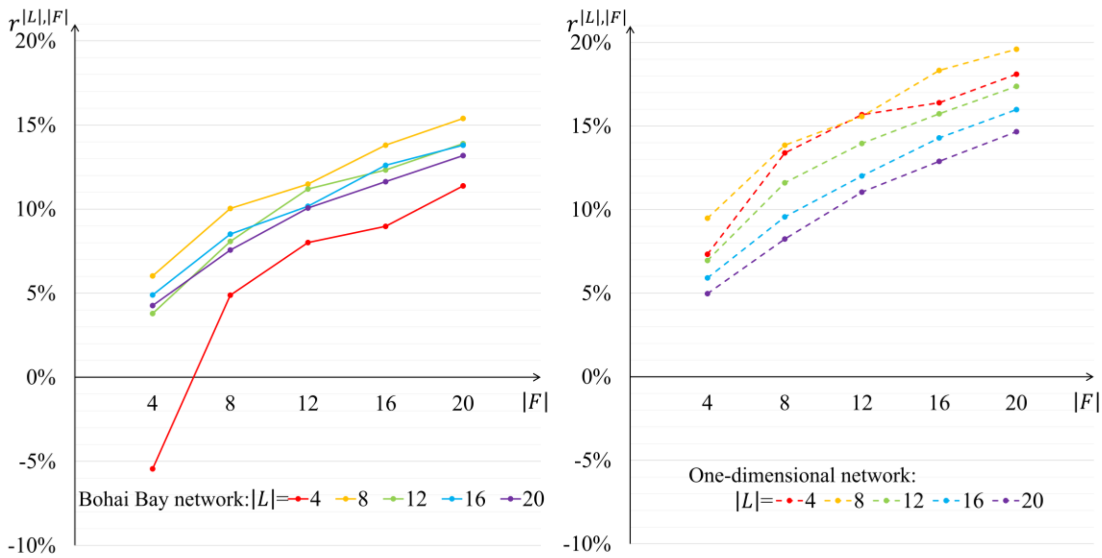


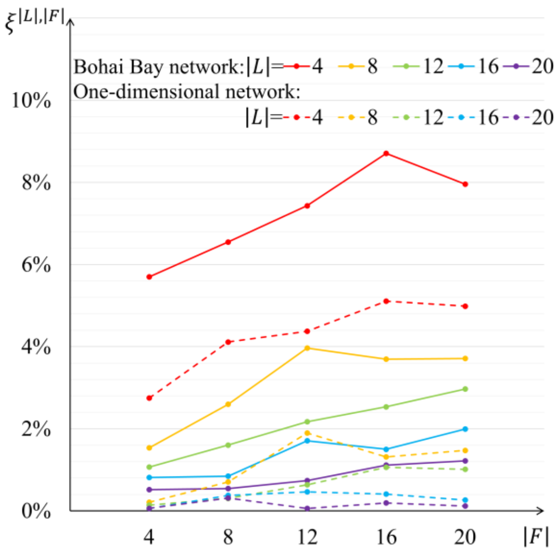
Fig. 10. Distances from the hub to the feeder ports in the one-dimensional hypothetic network.

We set $|L|, |F| \in \{4, 8, 12, 16, 20\}$ and calculate the $r^{|L|,|F|}$ and $\xi^{|L|,|F|}$, averaged across ten randomly generated instances, for either network and each pair of $(|L|, |F|)$. The results are plotted against $|F|$ in Fig. 11a–c. The solid and dashed curves in these figures represent the Bohai Bay case and the one-dimensional network case, respectively.

Fig. 11a–b show that for both networks, the cost saving increases with $|F|$, which is as expected. Deploying eight leader vessels brings the highest cost savings in both networks. However, the performance of the case with four leader vessels differs largely between the two networks. For the Bohai Bay network, $|L| = 4$ renders the lowest cost savings due to the high costs of detours and delay penalty. On the other hand, for the one-dimensional network, $|L| = 4$ produces the second-highest cost savings among all values of L tested. The minimum cost savings occur in the latter network with $|L| = 20$ because conventional ships are more costly.



(a) Percentage cost saving for the Bohai Bay case (b) Percentage cost saving for the one-dimensional network



(c) Ratio of penalty to the total cost

Fig. 11. Percentage cost saving and share of penalty cost for the two networks.

Comparing Fig. 11a and b reveals that vessel trains operating in the one-dimensional network produce greater cost savings than in the Bohai Bay case. This is due to the elimination of detours and the significant delay reductions. As $|L|$ increases from 4 to 20, the gap between the two networks diminishes from 6–12% to 1–2%. This is because in a regular hub-and-spoke network (e.g., the Bohai Bay case), fewer leaders render longer vessel trains and thus more detours and delays. Contrarily, vessel trains will take more direct routes with lower delays when more leaders are available.

Fig. 11c confirms that the delay penalty is much smaller in the one-dimensional network.

4. Conclusions

This paper formulated the optimal scheduling of autonomous vessel trains for freight distribution and backhaul problems in hub-and-spoke networks. An autonomous vessel train is formed by a conventional (manned) leader vessel and several autonomous follower vessels. The leader vessel will escort all the autonomous followers throughout their journeys. This strategy allows for safely operating autonomous vessels with limited autonomy level, thus expediting the replacement of conventional vessels with this more economical and environmentally friendly type of vessels.

Novel models were developed to minimize vessel trains' sailing cost and lateness penalty by optimally assigning the autonomous vessels to leaders and determining the optimal departure time and the port calling sequence of each vessel train. The models were solved by CPLEX.

Computational tests show that, albeit the CPU runtimes soar as the problem size grows, a typical problem of a practical scale (e.g., with 9 ports, 10 leader vessels, and 50 autonomous vessels) can be solved in several minutes. Thus, practitioners can readily use our models to generate optimal autonomous vessel train assignments and schedules for daily feeder service operations in inland waterway, sea-river, and short-sea networks.

Extensive numerical experiments were conducted to examine the cost savings of vessel train operations in or near the Bohai Bay of China compared to a benchmark scenario with conventional ships only. Sensitivity analyses were performed to unveil the cause-and-effect relations between the cost savings and key operating factors, including the autonomous vessels' cost rate, fleet composition of leader and follower vessels, penalty cost rate, tightness of sailing time windows, vessel train size limit, and shipping network topology.

Findings from the numerical results can inform practitioners on implementing the autonomous vessel train strategy. First, the results manifest the great economical potential of autonomous vessels even though they must be piloted by manned ships. For example, when a conventional leader pilots 1–4 autonomous vessels on average, the strategy can save up to 18% of the cost if operating an autonomous vessel is 30% cheaper than a conventional one and 34% if that is 50% cheaper (see Fig. 6a). Even greater savings can be achieved when vessel trains are operated in a one-dimensional waterway network, e.g., the Yangtze River of China; see Section 3.7. This is because the detours incurred by vessel train operations would be minimal. In addition, the strategy is more suitable for time-insensitive cargo, which has either a loose sailing time window or a lower penalty rate (Fig. 7a and 8a), thanks to the lower detour and delay costs incurred.

On the other hand, increasing the maximum size of vessel trains would only improve the cost saving moderately (Fig. 9a). In fact, too few leader vessels would render longer vessel trains, more detours, and greater delays, which increase the cost. Our numerical results suggest that a sufficient number of leader vessels (eight in the Bohai Bay case study) should be used to attain the best performance of vessel trains (see Fig. 9a and 11a).

In summary, our study is the first to jointly optimize the assignment of autonomous ships to vessel trains, the sequences of ports of call, and the schedules of vessel trains. The results show sizable economic benefits of this novel operating strategy and how key operating factors affect the performance of vessel trains. We believe our study will shed light on more advanced research on autonomous ship scheduling problems accounting for further technological and operational details. These research works will motivate real-world implementations of autonomous ships during the transitional period toward full autonomy.

As the first study to optimize vessel train operations under limited autonomy, our work adopts idealizations to simplify the models. For example, we assumed a fixed sailing speed for all the vessels and a fixed sailing cost rate independent of the speed. In reality, a vessel's bunker cost is a function of its sailing speed (Wang and Meng, 2012), and a vessel train should be able to adjust its speed to meet the target delivery times. For fixed-demand liner shipping networks, shipping companies might be interested in optimizing the fleet of conventional manned ships and autonomous vessels, especially the ratio between the two types of vessels. A more sophisticated scheduling model may also consider the transshipment of autonomous ships between different vessel trains and the deadheading problem of vessel trains. These issues will be addressed in future research.

Acknowledgments

This study is supported by a General Research Fund (Project No. 15224818) provided by the Research Grants Council of Hong Kong and a grant provided by the Hong Kong Polytechnic University (Project ID: P0001008).

References

Ahvenjärvi, S., 2016. The human element and autonomous ships. *TransNav: International Journal on Marine Navigation and Safety of Sea Transportation*, 10(3), 517–521.

Akbar, A., Aasen, A. K. A., Msakni, M. K., Fagerholt, K., Lindstad, E., Meisel, F., 2021. An economic analysis of introducing autonomous ships in a short-sea liner shipping network. *International Transactions in Operational Research*, 28(4), 1740–1764.

Bhoopalam, A. K., Agatz, N., Zuidwijk, R., 2018. Planning of truck platoons: A literature review and directions for future research. *Transportation Research Part B: Methodological*, 107, 212–228.

Brooks, S. K., Greenberg, N., 2022. Mental health and psychological wellbeing of maritime personnel: A systematic review. *BMC Psychology*, 10(1), 139.

Burmeister, H.-C., Rødseth, Ø. J., 2016. Maritime unmanned navigation through intelligence in networks. Available: http://www.unmanned-ship.org/munin/ [Accessed January 10, 2022].

Chen, J., Ye, J., Zhuang, C., Qin, Q., Shu, Y., 2022. Liner shipping alliance management: Overview and future research directions. *Ocean & Coastal Management*, 219, 106039.

Chen, L., Haseltalab, A., Garofano, V., Negenborn, R. R., 2019. Eco-VTF: Fuel-efficient vessel train formations for all-electric autonomous ships. *The 18th European Control Conference (ECC)*, 2543-2550.

Chen, L., Hopman, H., Negenborn, R. R., 2018. Distributed model predictive control for vessel train formations of cooperative multi-vessel systems. *Transportation Research Part C: Emerging Technologies*, 92, 101–118.

Chen, L., Huang, Y., Zheng, H., Hopman, H., Negenborn, R., 2020. Cooperative multi-vessel systems in urban waterway networks. *IEEE Transactions on Intelligent Transportation Systems*, 21(8), 3294–3307.

Christiansen, M., Fagerholt, K., Ronen, D., 2004. Ship routing and scheduling: Status and perspectives. *Transportation Science*, 38(1), 1–18.

Colling, A., Hekkenberg, R., 2020. Waterborne platooning in the short sea shipping sector. *Transportation Research Part C: Emerging Technologies*, 120, 102778.

Escario, J. B., Jimenez, J. F., Giron-Sierra, J. M., 2012. Optimisation of autonomous ship manoeuvres applying Ant Colony Optimisation metaheuristic. *Expert Systems with Applications*, 39(11), 10120–10139.

Ghaderi, H., 2019. Autonomous technologies in short sea shipping: Trends, feasibility and implications. *Transport Reviews*, 39(1), 152–173.

Goel, A., 2010. Truck driver scheduling in the European Union. *Transportation Science*, 44(4), 429–441.

Goel, A., 2014. Hours of service regulations in the United States and the 2013 rule change. *Transport Policy*, 33, 48–55.

Goel, A., Archetti, C., Savelsbergh, M., 2012. Truck driver scheduling in Australia. *Computers & Operations Research*, 39(5), 1122–1132.

Gu, Y., Goez, J. C., Guajardo, M., Wallace, S. W., 2020. Autonomous vessels: State of the art and potential opportunities in logistics. *International Transactions in Operational Research*, 28(4), 1706–1739.

Hu, Q., Gu, W., Wang, S., 2022a. Optimal subsidy scheme design for promoting intermodal freight transport. *Transportation Research Part E: Logistics and Transportation Review*, 157, 102561.

Hu, Q., Gu, W., Wang, S., 2022b. Optimal scheduling of autonomous truck platoons with limited platoon size. Working paper.

Hu, Q., Gu, W., Wang, S., 2022c. Driver scheduling for autonomous truck platoons. Working paper.

Hu, Y., Zhang, A., Tian, W., Zhang, J., Hou, Z., 2020. Multi-ship collision avoidance decision-making based on collision risk index. *Journal of Marine Science and Engineering*, 8, 640.

Huang, L., Tan, Y., Guan, X., 2022. Hub-and-spoke network design for container shipping considering disruption and congestion in the post COVID-19 era. *Ocean & Coastal Management*, 225, 106230.

Höyhtyä, M., Huusko, J., Kiviranta, M., Solberg, K., Rokka, J., 2017. Connectivity for autonomous ships: Architecture, use cases, and research challenges. *2017 International*

Conference on Information and Communication Technology Convergence (ICTC), 345-350.

Im, I., Shin, D., Jeong, J., 2018. Components for smart autonomous ship architecture based on intelligent information technology. *Procedia Computer Science*, 134, 91–98.

Kalouptsidi, M., 2021. The role of shipping in world trade. Available: https://econofact.org/the-role-of-shipping-in-world-trade [Accessed January 27, 2022].

Karlis, T., 2018. Maritime law issues related to the operation of unmanned autonomous cargo ships. *WMU Journal of Maritime Affairs*, 17(1), 119–128.

Khare, N., Singh, P., 2012. Modeling and optimization of a hybrid power system for an unmanned surface vehicle. *Journal of Power Sources*, 198, 368–377.

Klein, N., Guilfoyle, D., Karim, M. S., McLaughlin, R., 2020. Maritime autonomous vehicles: New frontiers in the law of the sea. *The International & Comparative Law Quarterly*, 69(3), 719–734.

Kremer, J., 2021. News and media Yara Birkeland. Available: https://www.yara.com/news-and-media/press-kits/yara-birkeland-press-kit/ [Accessed January 10, 2022].

Kretschmann, L., Burmeister, H.-C., Jahn, C., 2017. Analyzing the economic benefit of unmanned autonomous ships: An exploratory cost-comparison between an autonomous and a conventional bulk carrier. *Research in Transportation Business & Management*, 25, 76–86.

Lesch, V., Breitbach, M., Segata, M., Becker, C., Kounev, S., Krupitzer, C., 2021. An overview on approaches for coordination of platoons. *IEEE Transactions on Intelligent Transportation Systems*, 23(8), 10049–10065.

Liang, X., Zhang, Y., Yang, G., 2021. Platoon control design for unmanned surface vehicles subject to input delay. *Scientific Reports*, 11(1), 1481.

Liu, Y., Zhao, X., Huang, R., 2022. Research on comprehensive recovery of liner schedule and container flow with hard time windows constraints. *Ocean & Coastal Management*, 224, 106171.

Liu, Z., Zhang, Y., Yu, X., Yuan, C., 2016. Unmanned surface vehicles: An overview of developments and challenges. *Annual Reviews in Control*, 41, 71–93.

Luo, F., Larson, J. (2022). A repeated route-then-schedule approach to coordinated vehicle platooning: Algorithms, valid inequalities and computation. *Operations Research*, 70(4), 2477-2495.

Meersman, H., Moschouli, E., NanwayBoukani, L., Sys, C., van Hassel, E., Vanelslander, T., van de Voorde, E., 2020. Evaluating the performance of the vessel train concept. *European Transport Research Review*, 12(1), 1–11.

Meng, Q., Wang, S., Andersson, H., Thun, K., 2014. Containership routing and scheduling in liner shipping: Overview and future research directions. *Transportation Science*, 48(2), 265–280.

Mitsui O.S.K. Lines, 2022. World's first successful sea trial of autonomous sailing on a commercial container ship voyage. Available: https://www.mol.co.jp/en/pr/2022/22007.html [Accessed September 1, 2022].

Munim, Z. H., 2019. Autonomous ships: A review, innovative applications and future maritime business models. *Supply Chain Forum: An International Journal*, 20(4), 266–279.

Naeem, W., Xu, T., Sutton, R., Tiano, A., 2008. The design of a navigation, guidance, and control system for an unmanned surface vehicle for environmental monitoring. *Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment*, 222(2), 67–79.

NGDCNH, 2009. Marine distance tables for China coast. The Navigation Guarantee Department of The Chinese Navy Headquarters, China Navigation Publication Press.

Psaraftis, H. N., 2019. Ship routing and scheduling: The cart before the horse conjecture. *Maritime Economics & Logistics*, 21(1), 111–124.

Rødseth, Ø. J., 2017. From concept to reality: Unmanned merchant ship research in Norway. *2017 IEEE Underwater Technology (UT).*

Rogerson, S., Santén, V., Svanberg, M., Williamsson, J., Woxenius, J., 2020. Modal shift to inland waterways: dealing with barriers in two Swedish cases. *International Journal of Logistics Research and Applications*, 23(2), 195–210.

Rolls-Royce, 2018. Rolls-Royce and Finferries demonstrate world's first fully autonomous ferry. Available: https://www.rolls-royce.com/media/press-releases/2018/03-12-2018-rr-and-finferries-demonstrate-worlds-first-fully-autonomous-ferry.aspx [Accessed September 1, 2022].

Romano, A., Yang, Z., 2021. Decarbonisation of shipping: A state of the art survey for 2000–2020. *Ocean & Coastal Management*, 214, 105936.

Ronen, D., 1983. Cargo ships routing and scheduling: Survey of models and problems. *European Journal of Operational Research*, 12(2), 119–126.

Schuler, M., 2021. Autonomous tug to embark on landmark remotely-operated voyage around Denmark. Available: https://gcaptain.com/autonomous-tug-to-embark-on-landmark-remotely-operated-voyage-around-denmark/ [Accessed September 1, 2022].

The Maritime Executive, 2022. Keppel O&M demonstrates Singapore’s first autonomous tug. Available: https://maritime-executive.com/article/keppel-o-m-demonstrates-singapore-s-first-autonomous-tug [Accessed September 1, 2022].

Tvete, H. A., 2022. The ReVolt – A new inspirational ship concept. Available: https://www.dnv.com/technology-innovation/revolt/ [Accessed January 10, 2022].

UNCTAD, 2020. Review of maritime transport 2020. United Nations Conference on Trade and Development. Available: https://unctad.org/system/files/official-document/rmt2020_en.pdf [Accessed November 1, 2021].

UNCTAD, 2021. Global trade update November 2021. United Nations Conference on Trade and Development. Available: https://unctad.org/system/files/official-document/ditcinf2021d4_en.pdf [Accessed January 27, 2022].

van Brummelen, J., O’Brien, M., Gruyer, D., Najjaran, H., 2018. Autonomous vehicle perception: The technology of today and tomorrow. *Transportation Research Part C: Emerging Technologies*, 89, 384–406.

van Pampus, M. J., Haseltalab, A., Garofano, V., Reppa, V., Deinema, Y. H., Negenborn, R. R., 2021. Distributed leader-follower formation control for autonomous vessels based on model predictive control. *2021 European Control Conference (ECC)*, 2380-2387.

Wahlström, M., Hakulinen, J., Karvonen, H., Lindborg, I., 2015. Human factors challenges in unmanned ship operations – insights from other domains. *Procedia Manufacturing*, 3, 1038–1045.

Wang, S., Meng, Q., 2012. Sailing speed optimization for container ships in a liner shipping network. *Transportation Research Part E: Logistics and Transportation Review*, 48(3), 701–714.

Wiercx, M., van Kalmthout, M., Wiegmans, B., 2019. Inland waterway terminal yard configuration contributing to sustainability: Modeling yard operations. *Research in Transportation Economics*, 73, 4–16.

Wu, W., Peng, Z., Liu, L., Wang, D., 2022. A general safety-certified cooperative control architecture for interconnected intelligent surface vehicles with applications to vessel train. *IEEE Transactions on Intelligent Vehicles*, in press.

Xing, W., Zhu, L., 2022. Assessing the impacts of Sanchi incident on Chinese law concerning ship-source oil pollution. *Ocean & Coastal Management*, 225, 106227.

Yang, D., Jiang, L., Notteboom, T., 2019. Innovative solutions for shipping market turmoil: The search for profitability, sustainability and resilience. *Transport Policy*, 82, 75–76.

Yu, Y., Chen, L., Shu, Y., Zhu, W., 2021. Evaluation model and management strategy for reducing pollution caused by ship collision in coastal waters. *Ocean & Coastal Management*, 203, 105446.

Zhang, L., Chen, F., Ma, X., Pan, X., 2020. Fuel economy in truck platooning: A literature overview and directions for future research. *Journal of Advanced Transportation*, 2020, 2604012.

Zhang, S., Chen, J., Wan, Z., Yu, M., Shu, Y., Tan, Z., Liu, J., 2021. Challenges and countermeasures for international ship waste management: IMO, China, United States, and EU. *Ocean & Coastal Management*, 213, 105836.

Zhang, W., Wang, S., 2020. Autonomous vessel scheduling. *Journal of the Operations Research Society of China*, 8(3), 391–414.

Zhen, L., Wang, K., Wang, S., Qu, X., 2018. Tug scheduling for hinterland barge transport: A branch-and-price approach. *European Journal of Operational Research*, 265(1), 119–132.