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Insights on the introduction of autonomous vessels to liner shipping networks

Gam Thi Hong Nguyen[1], Daria Ruzaeva[1], Julio Cesar Góez[1,2] and Mario Guajardo[1,2*]

*Correspondence: mario.guajardo@nhh.no

[1] Department of Business and Management Science, NHH Norwegian School of Economics, Helleveien 30, 5045 Bergen, Norway
Full list of author information is available at the end of the article

Abstract

This article investigates economic and operational effects of introducing autonomous vessels to liner shipping networks. By the formulation of optimization models, we analyze how fleet configurations with vessels of different capacity affect the cost and service level of liner shipping networks in both static and dynamic settings. We implement the model in a data instance that extends a data instance on the Baltic trade from conventional to autonomous vessels. Our results show that the introduction of autonomous vessels might lead to cost savings of 7.1% with respect to the fleet of conventional vessels. The main savings come from lower time charter costs and lower bunker costs. The results also suggest that a fleet configuration combining large with small vessels perform better, because of its better ability to accommodate to the asymmetry of the trade. The implementation of a flexible sailing schedule in the dynamic setting might lead to a great increase in the service level of the network, but at the expense of an increase in costs.

Keywords: Autonomous vessels, Liner shipping network design, Mathematical programming

Introduction

Autonomous vehicles have become a reality in the past decades and are progressively being adopted within all modes of transport. Autopilot systems have been used in aircraft and trains for many years and are now being developed for road transport by companies such as Tesla, Google, and General Motors. In maritime transportation, a number of initiatives towards autonomous shipping have gradually emerged. For example, in 2018, the world's first fully autonomous ferry was demonstrated by Rolls-Royce and Finferries in Finland (Rolls-Royce 2016, 2018). The ferry navigated autonomously on one sailing leg whilst the remote control took over the return leg. In another initiative, Yara International has been developing the first zero-emission autonomous container vessel Yara Birkeland (Kongsberg 2018). These and other initiatives provide evidence that the development of autonomous ships has become technically feasible (Xue et al. 2019). Moreover, this development is expected to reduce the occurrence of navigational accidents, due to increased safety and security (Wróbel et al. 2017; Zhou et al. 2021a). It is also expected that the development of autonomous ships will have implications in environmental and social aspects, and that it will motivate new business models for ship manufacturers (Munim 2019).

While there have been multiple research papers related to safety, navigation control, design, project and prototype, less attention has been paid to the interaction between economics and logistics aspects of autonomous ships (Gu et al. 2021). Some estimations emphasize the direct benefit of the reduction of crew cost, more cargo space, and lower fuel consumption, but also that new autonomous vessel will be more expensive to construct than the conventional ones (Danish Maritime Authority 2016). Additionally, it has been argued that port-related costs and monitoring cost from onshore control centers will be potentially higher for autonomous ships (Hogg and Ghosh 2016; Kretschmann et al. 2017). The trade-off between cost savings and additional expenses is at the core of the discussion for liner shipping companies and other key players on the market to take actions towards or against the autonomous shipping trend. In Rolls-Royce (2016), researchers argue that business opportunities perceived by the main actors in the shipping industry are crucial in bringing technological opportunities for autonomous shipping into practice.

The research question that triggers our work is what will be the impact of autonomous vessels in liner shipping network design. In addressing this question, our main goal is to derive insights on the potential economic and operational effects of the introduction of autonomous vessels to liner shipping networks. The liner shipping business plays a critical role in the global transportation service industry, which allows international trade of consumer goods between countries and continents. In fact, more than 80% of the world's merchandise trade by volume is carried by sea, equivalent to about 11 billion tons yearly (Sirimanne et al. 2019). The competitive market and the environmental pressures foster shipping companies to embrace the continuous technological development as an opportunity for implementing innovative solutions and becoming more efficient (Hasanspahić et al. 2021). In this regard, operating costs are affected significantly by the design of sailing routes. Similar to the public transport system, like bus, subway, train or ferry, the liner shipping business has an arrival and departure schedule with a sequence of port calls and a specific group of similar vessels determined and known in advance for each of its services. How to structure the route network to minimize the total cost is the purpose of the liner shipping network design problem (LSNDP). A vast body of literature has been devoted to this problem. However, most of the extant work has been limited to conventional vessels and to static routes. As noted in Christiansen et al. (2020), which recently reviews the literature on the LNSDP, the introduction of autonomous vessels in the container shipping industry may significantly change the way a network is designed and operated. The review asserts that, in comparison with networks and operation of conventional vessels, the adoption of autonomy will imply more smaller vessels sailing on-demand (depending on the cargo), which will turn the network design process into a dynamic routing problem. Therefore, in contrast to previous literature, we study the effect of autonomous vessels in liner shipping networks, considering both static and dynamic settings for the design of routes. Acknowledging the expected increase in the amount of smaller vessels aforementioned, our study also considers different fleet sizes, with particular focus on smaller vessels capacity in comparison to the rather large capacity of conventional ships in the more traditional LSNDP setups. The introduction of autonomous ships is also expected to render economic benefits to the shipping industry (Kretschmann et al. 2017). Thus, in our study, we also compare the performance of conventional and autonomous fleets along the economic dimension. As methodology, we adopt a mathematical programming framework, which allows us to formulate the problem as a mixed integer linear programming model. To feed the model, we perform numerical testing in the case of the regional Baltic trade, using a data instance of the LINER-LIB benchmark suite (Brouer et al. 2014) and extending it to the autonomous case.

The remainder of this article is organized as follows. In second section, we provide more background on liner shipping network design and refer to related literature. In third section, we formally describe the problem and formulate mathematical models to address it. In fourth section, we discuss the implementation of the models and compute numerical results. Fifth section briefly concludes and proposes avenues for future research.

Background

The LSNDP is an important problem for the maritime shipping industry, which has received large attention from the literature. Brouer et al. (2014) and Christiansen et al. (2020) provide comprehensive overviews on the main problem and its variants, which have been motivated by a number of studies in the area. For example, Fagerholt et al. (2009) address an application arising at the Höegh Autoliners company, where routes and voyages on a given planning horizon must be found so as to minimize costs and maximize profits. Meng and Wang (2011) study service frequency and other aspects in a liner shipping problem based on a long-haul liner service route of a global liner shipping company. Andersson et al. (2015) perform a case study considering a real deployment and routing problem on shipping trade. Karsten et al. (2015) and Trivella et al. (2021) study the implications of transit time and multi-commodity flows in liner shipping network design. Other works have introduced a public policy perspective into liner shipping network design, such as the studies conducted in China by Chen et al. (2021) and Zhou et al. (2021b).

In general, the LSNDP can be defined as follows: given a set of ports, a set of vessels, and a set of *demands* over a planning horizon, the problem aims at finding a set of *services* as to maximize the profit while ensuring that demand and capacity constraints are satisfied. In this context, a *demand* is defined by the number of containers, their origin, and their destination. A *service* involves a sequence of port calls at a determined frequency with a fixed arrival and departure schedule. It is typically assumed that a service is a round trip where the starting port and the ending port are the same. A service usually has a weekly frequency; however, smaller vessels calling smaller ports can have a biweekly frequency (Brouer et al. 2014). A set of services chosen to operate in a specific market is the backbone of the LSNDP's solution.

There are multiple types of service structure, depending on the number of times a ship visits a port in the service (Christiansen et al. 2020). When a port gets visited more than once in the same service, it is called a butterfly port. A simple or circular service allows each port to be called only once, which means no butterfly port is involved in the service. A service with all ports being butterfly nodes is defined as a pendulum service, while a service with only one butterfly node is a butterfly service. When the butterfly nodes in a service have more than two visits, the service is referred to as a complex service. Also, butterfly services allow the possibility of performing transshipments, that is, moving containers from one vessel to another in a port. In this paper, we limit ourselves to consider only simple and butterfly services without transshipments. For more complex services and transshipments we refer the reader to Reinhardt and Pisinger (2012), Plum et al. (2014) and Thun et al. (2017).

As for economic considerations, the main focus of the LSDNP has been on minimizing the total cost of the network (since the demand and revenues are usually assumed constant). Stopford (2009) outlines a detailed list of costs that are relevant in liner shipping services. These consider ship characteristics, service schedule, capacity utilization, ship costs, port and charges, deployment of containers, container handling, and administrative costs. As including all of these costs may render an overly complicated problem, the literature has attempted to consider a representative cost structure including some of these costs while keeping the problem solvable.

One of the questions that liner shipping planners need to answer is which fleet they should put in use for the market, including at least three elements: the number of ships, ship size, and sailing speed. These factors determine whether liner carriers can fulfil all demands within a given schedule and without excessive waste of capacity. Economies of scale are the main reason for building larger container vessels, as recognized in early literature (Lim 1998). Costs associated with ship characteristics like operating costs, capital costs and voyage costs give large ships an advantage in terms of the reduction in cost per TEU. However, the effect of economies of scale reduces progressively when the vessel size increases (Cullinane and Khanna 2000). Additionally, it is extremely costly to sail an empty or half-filled giant ship. Some may argue that huge ships can result in diseconomies of scale since they cannot call at small ports; therefore, a system of hub and spokes is required to consolidate enough demands for them at the hub port (Stopford 2009). In practice, it is almost impossible to have full capacity utilization on all sailing routes due to the imbalanced nature of global merchandise trade. A conventional round trip involves a head-haul leg and a back-haul leg. The head-haul leg (also called front-haul leg) refers to the trading route with higher fill rate and profitability. On the contrary, the back-haul leg is the back-home trip where it is considerably challenging to gather enough demand and freight rates are usually low. In practice, liner carriers often face the problem of lack of demand on their back-haul leg. For example, it has been estimated that the head-haul volumes transported on the westbound voyage Asia-Europe is twice that of the back-haul traffic on the eastbound voyage (Yap and Zahraei 2018). Fleet speed provides the flexibility to adapt to demand fluctuation; for instance, slow steaming when the freight rate and demand are low, or the bunker price is high; or speeding up to exploit the high demand in the peak season. The direct impact of ship characteristics on the voyage cost lies in the bunker consumption. While fuel cost per ton is rather out of control of liner carriers, fuel consumption, to some extent, can be influenced through the choice of sailing speed. This has motivated some variants of the LSNDP introducing sailing speed optimization (Alvarez 2009; Koza et al. 2020). In this paper, we rather focus on different fleet compositions, where the different speeds are associated to the different types of vessels in the fleet but remain constant over the sailing periods. In particular, our interest is to study fleets with and without autonomous vessels, and their respective operational and economical parameters. Although the LSNDP has been widely studied in the literature, the potential implications of autonomous shipping remains mostly unexplored. Some exceptions are the recent works by Msakni et al. (2020) and Akbar et al. (2021), which study the potential introduction of autonomous ships to a liner shipping network serving European and Norwegian ports. The fleet consists of conventional mother ships, which sail between Europe and the Norwegian coastline, and autonomous daughter ships, which serve small ports located along the Norwegian coastline. Their results suggest that the introduction of autonomous vessels leads to a considerable reduction of operating costs. The introduction of autonomous vessels is also under consideration in the context of urban transportation, as reported in recent case studies in cities from Germany (Aslaksen et al. 2021) and Norway (Gu and Wallace 2021).

In general, as pointed out in a recent survey by Gu et al. (2021), the literature on autonomous vessels has been much more inclined to address safety and design issues rather than its implications in logistics. Our article provides additional insights on the introduction of autonomous vessels in liner shipping, by the incorporation of the main features of the LNSDP in both static and dynamic settings. The latter responds to the higher flexibility that autonomous vessels are expected to introduce in shipping networks, due to smaller vessels that will facilitate more dynamic sailing schedules (Christiansen et al. 2020). The consideration of flexible service frequencies in liner shipping is, in fact, gaining more attention, as it may lead to significantly better solutions (Giovannini and Psaraftis 2019). We adopt a mathematical programming methodology to model the problem. The resulting model is then coded into a computational optimization software. To feed the model, we use data of the Baltics, taking as basis the benchmark suite LINER-LIB provided by Brouer et al. (2014). This benchmark suite has been used by a number of works on conventional vessels (e.g. Plum et al. 2014; Balakrishnan and Karsten 2017; Koza et al. 2020), but to our knowledge, our paper is the first one that discusses how to extend it to the case of autonomous vessels.

In light of the literature review above, the contribution of our article is two-fold. First, our work is one of the primary efforts studying the introduction of autonomous vessels in liner shipping network design, for which we formulate mathematical optimization models in static and dynamic versions. Second, our numerical computation allows us to derive insights on the introduction of autonomous vessels to liner shipping networks. These insights involve not only economic factors but also operational factors in terms of fleet composition and service levels.

Problem description and methodology

Given a set of ports P consisting of a subset of hub ports H and a subset of spoke ports S, the problem is to design a network consisting of cyclic services where all demands are satisfied, and the total operational costs are minimized over the planning horizon. A liner shipping network can be represented with a directed graph, where each port in P is a node, and (i, j) is an arc in the set of arcs A representing a direct sailing route from port i to port j. Demands between ports are denoted by the set D. The fleet is heterogeneous, consisting of different vessel classes C with a corresponding capacity e^c, and sets of vessels V^c for each class $c \in C$. As vessels of each class have a different design speed, the sailing time is defined for each class on each arc as t_{ij}^{c}. Vessels spend p units of time in a port, and the fuel cost varies for each class when sailing at sea or staying at port, denoted by h^c and g^c, respectively. The quantity of demand $m \in D$ is defined as b_i^m, which is greater than zero if port i is the origin for demand m, less than zero if port i is the destination of demand m, and zero otherwise. Each port i has fixed port call costs k_i, variable port call costs q_i and lifting costs l_i, associated with the port infrastructure, facilities and location. The daily charter rate of a vessel in class C is f^c. The number of spoke ports in the network is equal to n. All the demands are known in advance and are ready for transportation before the fleet starts sailing. All the demands must be satisfied, that is, all containers must be brought from their origin to their destination. Vessels must always depart from the hubs and finish their trip after going back to the hubs. This reflects the round-trip feature of services and it assures the match between the trip pre-condition and post-condition. Transshipments are not considered in our problem. The trip length for a vessel is no more than two weeks, which means a vessel may have either a weekly or a biweekly calling frequency at the hubs. Therefore, the corresponding service levels must secure a maximum transit time of 7 days and 14 days, respectively. To allow some flexibility and accounting for the importance of time deliveries, it is often assumed that this transit time might be a bit shorter than these upper bounds. In fact, as it is argued by Brouer et al. (2014), applying a strict requirement of 7 days and 14 days for the two port-call schedules can lead to the rejection of commercially valuable routes that violate the constraints with an insignificant margin. Therefore, we set a time window spanning from 6.3 to 7 days for the length of weekly services. Likewise, for a biweekly port call schedule, the length is allowed to be between 12.7 and 14 days. Time at port is set at a fixed amount of time, regardless of vessel types and ports. These practices are similar to what Brouer et al. (2014) consider in their model.

Methodology and data collection

We model the problem using a mathematical programming methodology, in which the decisions are represented by variables, the performance measure is expressed by an objective function, and the requirements are expressed by constraints in form of inequalities or equalities. In particular, since the decisions involve continuous and integer variables, and the objective function and constraints are linear functions of the variables, the resulting formulation is a mixed integer linear programming model. This is a well-established methodology in the literature dealing with the LNSDP, see for example the mixed integer linear programming model formulations in Meng and Wang (2011), Reinhardt and Pisinger (2012), Brouer et al. (2014), Plum et al. (2014) and Thun et al. (2017). Moreover, this methodology is also widely adopted in the broad scope of shipping optimization problems, as indicated in surveys by Tran and Haasis (2015), Brouer et al. (2017) and Song (2021).

Once the model is formulated, the data of the problem is then used in terms of sets and parameters as an input to the model. In what follows, we outline the mathematical formulation of the models for both the static and dynamic setups. It is noteworthy that the formulations in this section are presented in general terms, but the models are then run with different data, depending on whether the fleet corresponds to conventional or autonomous vessels. As detailed in fourth section, the data collection for our work is based on the LINER-LIB benchmark suite originally provided for conventional vessels in Brouer et al. (2014), and on extensions of this data set to the autonomous case following estimations from the relevant literature.

Static model with a fixed sailing schedule

Sets

H: Set of hub ports.
S: Set of spoke ports.
P: Set of all ports ($H \cup S$).
A: Set of arcs.
D: Set of demands (or commodities) from one port to another.
C: Set of different vessel classes.
V^c: Set of vessels in vessel class c.

Parameters

b_i^m: Quantity of demand m at port i. The parameter is positive if i is the origin for demand m, negative if i is the destination, and 0 otherwise.
o_i^m: Binary parameter equal to 1 if i is the origin of demand m and 0 otherwise.
d_i^m: Binary parameter equal to 1 if i is the destination of demand m, and 0 otherwise.
p: Time at port for a vessel in days.
n: Number of spoke ports.
g^c: Fuel cost for a vessel of class c while sailing at sea.
h^c: Fuel cost for a vessel of class c when staying at port.
k_i: Fixed port call costs at port i.
q_i: Variable port call costs at port i.
f^c: Daily time charter rate of a vessel of class c.
l_i: Lift costs at port i.
e^c: Capacity of a vessel of class c.
t_{ij}^c: Sailing time of a vessel of class c on arc (i, j).
t_{week}: A parameter with value 7, representing the number of days in a week.
r: Theoretical service length of a vessel with a weekly port call schedule in days.
β: Lower bound of the sailing time of a vessel with a weekly schedule.
M: A sufficiently large number.

Decision variables

x_{ij}^{mcv}: Quantity of demand m carried by a vessel v of class c on arc (i, j).
y_{ij}^{cv}: Binary variable equal to 1 if arc (i, j) is sailed by a vessel v of class c, and 0 otherwise.
s_{ij}^{cv}: Number of sails of vessel v of class c on arc (i, j).
u_i^{cv}: Integer variable used for sub-tour elimination.
w_1^{cv}: Binary variable equal to 1 if vessel v of class c has a weekly port call at the hub, and 0 otherwise.

w_2^{cv}: Binary variable equal to 1 if vessel v of class c has a biweekly port call at the hub, and 0 otherwise.

Objective function

The objective of the model is to minimize an operational cost function which consists of four cost items. First, it considers an item on bunker costs, related to the fuel that vessels use at sea and port. These are calculated considering the time spent by the vessels on those two activities and using the corresponding fuel cost parameters, as follows:

$$\text{Bunker costs} = \sum_{c\in C}\sum_{v\in V}\sum_{(i,j)\in A} g^c t_{ij}^c s_{ij}^{cv} + \sum_{c\in C}\sum_{v\in V}\sum_{(i,j)\in A} h^c p s_{ij}^{cv} \tag{1}$$

Secondly, the objective function considers port call costs, including a fixed cost term per sail and a variable cost term which depends on the capacity of the vessel. This is captured in the following expression:

$$\text{Port call costs} = \sum_{j\in P}\sum_{c\in C}(k_j + q_j e^c)\sum_{v\in V}\sum_{(i,j)\in A} s_{ij}^{cv} \tag{2}$$

Furthermore, the objective function considers a time charter cost term, which depends on the time charter rate. This rate represents the cost of leasing (charter in) a container vessel into the fleet or for a carrier to forward lease (charter out) an owned vessel to another carrier (Brouer et al. 2014). In practice, a carrier may have an owned fleet supplemented by chartering in and out to meet capacity requirements. Exploring different contract possibilities in this respect is out of the scope of our paper, thus we limit ourselves to account for this cost using the number of days each vessel is utilized and the daily charter rate as follows:

$$\text{Time charter costs} = \sum_{c\in C}\sum_{v\in V} f^c t_{week}(w_1^{cv} + 2w_2^{cv}) \tag{3}$$

The objective function also considers lifting costs from loading and unloading at origin and destination ports, respectively. The corresponding costs may vary across the different port locations and must be accounted throughout all the arcs traversed in the routes of the vessels, as follows:

$$\text{Lifting costs} = \sum_{m\in D}\sum_{c\in C}\sum_{v\in V}\sum_{(i,j)\in A} o_i^m l_i x_{ij}^{mcv} + \sum_{m\in D}\sum_{c\in C}\sum_{v\in V}\sum_{(i,j)\in A} d_j^m l_j x_{ij}^{mcv} \tag{4}$$

Adding up all the cost items above, the objective function of the model is expressed as follows:

$$\begin{aligned} \min & \sum_{c\in C}\sum_{v\in V}\sum_{(i,j)\in A} g^c t_{ij}^c s_{ij}^{cv} + \sum_{c\in C}\sum_{v\in V}\sum_{(i,j)\in A} h^c p s_{ij}^{cv} + \sum_{j\in P}\sum_{c\in C}(k_j + q_j e^c)\sum_{v\in V}\sum_{(i,j)\in A} s_{ij}^{cv} \\ & + \sum_{c\in C}\sum_{v\in V} f^c t_{week}(w_1^{cv} + 2w_2^{cv}) + \sum_{m\in D}\sum_{c\in C}\sum_{v\in V}\sum_{(i,j)\in A} o_i^m l_i x_{ij}^{mcv} + \sum_{m\in D}\sum_{c\in C}\sum_{v\in V}\sum_{(i,j)\in A} d_j^m l_j x_{ij}^{mcv} \end{aligned} \tag{5}$$

Constraints

Demand constraints

$$\sum_{c\in C}\sum_{v\in V}\sum_{(i,j)\in A} x_{ij}^{mcv} - \sum_{c\in C}\sum_{v\in V}\sum_{(j,i)\in A} x_{ji}^{mcv} = b_i^m, i \in P, m \in D \tag{6}$$

$$\sum_{(j,i)\in A} x_{ji}^{mcv} - \sum_{(i,j)\in A} x_{ij}^{mcv} + b_i^m d_i^m \leq 0, m \in D, i \in S, c \in C, v \in V \tag{7}$$

$$\sum_{m\in D} x_{ij}^{mcv} \leq e^c s_{ij}^{cv}, c \in C, v \in V, (i,j) \in A \tag{8}$$

Constraints (6) ensure that all demands are satisfied. Constraints (7) ensure that demand m will not be unloaded at port i, unless port i is its destination. The capacity constraints (8) state that the number of containers shipped on an arc must be lower than the capacity of a vessel that sails this arc. Note that the parameter value for the capacity of a vessel v on arc (i, j) might differ from the physical capacity of the vessel, since vessel v may sail through arc (i, j) for several times during the planning horizon. For example, if the physical capacity of vessel v is 450 FFE and it sails through arc (i, j) twice, the real capacity of vessel v on arc (i, j) is 900 FFE.

Route constraints

$$\sum_{(i,j)\in A} s_{ij}^{cv} - \sum_{(j,i)\in A} s_{ji}^{cv} = 0, i \in P, c \in C, v \in V \tag{9}$$

$$\sum_{j\in S} y_{ij}^{cv} - w_1^{cv} - w_2^{cv} \geq 0, c \in C, v \in V, i \in H \tag{10}$$

$$u_i^{cv} - u_j^{cv} + (n+1)y_{ij}^{cv} \leq n, c \in C, v \in V, i \in S, j \in S, i \neq j \tag{11}$$

Constraints (9) are cyclic constraints to ensure that if a vessel enters a port, it also leaves that port. Constraints (10) enforce all vessels to start from the hub ports. Constraints (11) are sub-tour elimination constraints.

Network constraints

$$s_{ij}^{cv} - y_{ij}^{cv} \geq 0, c \in C, v \in V, (i,j) \in A \tag{12}$$

$$My_{ij}^{cv} - s_{ij}^{cv} \geq 0, c \in C, v \in V, (i,j) \in A \tag{13}$$

$$\sum_{(i,j)\in A} y_{ij}^{cv} - w_1^{cv} - w_2^{cv} \geq 0, c \in C, v \in V \tag{14}$$

$$Mw_1^{cv} + Mw_2^{cv} - \sum_{(i,j)\in A} y_{ij}^{cv} \geq 0, c \in C, v \in V \tag{15}$$

Logic constraints (12) and (13) express the relationship between the number of sails s_{ij}^{cv} and the binary variable y_{ij}^{cv}, allowing a vessel to sail an arc multiple times. The two constraints require that either both variable y_{ij}^{cv} and s_{ij}^{cv} are positive, or both are equal to 0. Constraints (14) and (15) state that if a vessel does not sail any arc, it should not be counted as in use, while if a vessel sails an arc, it should be considered as in use either on a weekly or biweekly basis.

Schedule constraints

$$w_1^{cv} + w_2^{cv} \leq 1, c \in C, v \in V \tag{16}$$

$$\sum_{(i,j) \in A} (t_{ij}^c + p) s_{ij}^{cv} - M w_2^{cv} \leq r w_1^{cv}, c \in C, v \in V \tag{17}$$

$$\sum_{(i,j) \in A} (t_{ij}^c + p) s_{ij}^{cv} + M w_2^{cv} \geq \beta r w_1^{cv}, c \in C, v \in V \tag{18}$$

$$\sum_{(i,j) \in A} (t_{ij}^c + p) s_{ij}^{cv} - M w_1^{cv} \leq 2 r w_2^{cv}, c \in C, v \in V \tag{19}$$

$$\sum_{(i,j) \in A} (t_{ij}^c + p) s_{ij}^{cv} + M w_1^{cv} \geq 2 \beta r w_2^{cv}, c \in C, v \in V \tag{20}$$

Constraints (16) ensure that if a vessel sails, it can have either weekly port call or biweekly port call schedule at the hubs. Constraints (17)–(20) express the relationship between sailing time and weekly/biweekly port calls, setting lower and upper bounds that depend on the value of the parameters r and β. Recall that as we introduced previously in this section, the idea here is to allow for transit times that are a bit shorter than the exact 7 and 14 days for weekly and biweekly services, respectively.

Domain constraints

$$x_{ij}^{mcv} \geq 0, m \in D, c \in C, v \in V, (i,j) \in A \tag{21}$$

$$s_{ij}^{cv}, u_i^{cv} \in Z^+, c \in C, v \in V, (i,j) \in A \tag{22}$$

$$y_{ij}^{cv}, w_1^{cv}, w_2^{cv} \in 0, 1, c \in C, v \in V, (i,j) \in A \tag{23}$$

Constraints (21)–(23) define the domain of the decision variables.

Dynamic model with a flexible sailing schedule

In the dynamic setting, the demands arrive on different days throughout the planning horizon, and the sailing of the vessels is triggered every time a threshold (expressed as a percentage of the capacity) is reached. Note that we consider only an homogeneous fleet of vessels in this case, so in the formulation below we drop the index c that we had used to refer to the different classes of vessels in the static setting.

Objective function

$$\min? \sum_{v \in V} \sum_{(i,j) \in A} gt_{ij} y_{ij}^{v} + \sum_{v \in V} \sum_{(i,j) \in A} hpy_{ij}^{v} + \sum_{j \in P} (k_j + q_j e) \sum_{v \in V} \sum_{(i,j) \in A} y_{ij}^{v} + \sum_{v \in V} \sum_{(i,j) \in A} (t_{ij} + p) f y_{ij}^{v} + \sum_{m \in D} \sum_{v \in V} \sum_{(i,j) \in A} o_i^m l_i x_{ij}^{mv} + \sum_{m \in D} \sum_{v \in V} \sum_{(i,j) \in A} d_j^m l_j x_{ij}^{mv} \quad (24)$$

The components in the objective function (24) consider the same four cost items considered in the objective function of the static model, but in a slightly different manner. First, since the dynamic model is set to be solved consecutively every day on the planning horizon, every vessel is restricted to visit each port at most once in every run of the model. Therefore, the cost items on bunker and port calls are expressed in terms of the variables y_{ij}^{v} instead of the variables s_{ij}^{cv}. Likewise, since in this dynamic version there are no predefined weekly or biweekly port calls, the binary variables w_1^{cv} and w_2^{cv} are not considered, thus the time charter cost terms must be re-calculated accordingly using the variables y_{ij}^{v}. That is, when a vessel sails on arc (i, j), the time charter rate must be charged on the sum of the time t_{ij} that takes to sail from port i to port j plus the time p at port, as expressed in the fourth term of the objective function above. The two last terms, which capture the lifting costs, remain unchanged with respect to the static setup, as these are calculated every time a port is visited, independently of whether the schedule is based on a flexible or fixed weekly or biweekly calls.

Constraints

$$\sum_{v \in V} \sum_{(i,j) \in A} x_{ij}^{mv} - \sum_{v \in V} \sum_{(j,i) \in A} x_{ji}^{mv} = b_i^m, i \in P, m \in D \quad (25)$$

$$\sum_{(j,i) \in A} x_{ji}^{mv} - \sum_{(i,j) \in A} x_{ij}^{mv} + b_i^m d_i^m \le 0, m \in D, i \in S, v \in V \quad (26)$$

$$\sum_{m \in D} x_{ij}^{mv} \le y_{ij}^{v} e, v \in V, (i,j) \in A \quad (27)$$

$$\sum_{(i,j) \in A} y_{ij}^{v} - \sum_{(j,i) \in A} y_{ji}^{v} = 0, i \in P, v \in V \quad (28)$$

$$\sum_{j \in S} y_{ij}^{v} - w^{v} \ge 0, v \in V, i \in H \quad (29)$$

$$u_i^v - u_j^v + (n+1) y_{ij}^{v} \le n, v \in V, i \in S, j \in S, i \ne j \quad (30)$$

$$\sum_{j \in S} y_{ij}^{v} \le 1, v \in V, i \in H \quad (31)$$

Demand constraints are comparable to those in the static model. It is required that all demands must be transported to their destination (constraints (25)), no transshipment is allowed (constraints (26)), and the amount shipped on a vessel cannot be greater than the vessel's capacity (constraints (27)). The expressions (28), (29) and (30) model route constraints on cycles, on starting sailing from the hubs, and on the prevention of subtours among spoke ports, respectively. Constraints (31) require that all the demands from the hubs are transported on the sailing day. That is, vessels cannot visit the hub ports more than once in one service to pick up new demands; instead, the fleet size must, at least, be able to pick up all the demands at the hub at once.

In this dynamic setting, the total demand quantity is still deterministic, but the arrival time of the different demands is random. Each demand has the same probability of arriving on any day of the horizon. The total demand pending on a given day is compared against a threshold. A vessel sails when this threshold is reached. The smaller the threshold is, compared to the total demand of the whole planning period, the more frequently the vessels sail, which leads to a shorter waiting time of demands at their departure port but a potential high costs due to the lack of consolidation possibilities.

Results and discussion

Brouer et al. (2014) introduce the LINER-LIB benchmark suite, based on historical data from Maersk Line and publicly available sources. To date, this data suite has only been used on conventional vessels. Therefore, before reporting numerical results, we discuss below how to extend these data to the case of autonomous vessels.

Data

We take as basis the data set for the Baltics of the LINER-LIB benchmark suit, which includes 12 ports located in seven countries, as illustrated in Fig. 1.

The fleet consists of four feeders with capacity 450 FFE and two feeders with capacity 800 FFE. Their design speed is 12 and 14 knots, and they consume 18.8 and 23.7 tons of bunker per day at design speed, and 2.4 and 2.5 tons per day when idle, respectively. The sailing time between the ports for each vessel class is calculated as distance divided by

Fig. 1 Ports location in the Baltic instance of the LINER-LIB benchmark suite (Brouer et al. (2014))

sailing speed. In the schedule constraints, we consider parameter values r equal to 7 and β equal to 0.9.

We consider the same demand per port as the original data instance of the Baltics in Brouer et al. (2014). The LINER-LIB suite also provides cost parameters, such as fixed and variable port call costs and lifting costs. Bunker costs are calculated by multiplying the daily vessel consumption by the flat bunker price of USD 600 per ton used by Brouer et al. (2014). Therefore, the bunker costs per day for feeders of 450 FFE are USD 11,280 at sea and USD 1440 when idle. The bunker costs for feeders of 800 FFE are USD 14,220 and USD 1500 at sea and at port, respectively. The time charter rate per day is USD 5000 for the 450 FFE feeders and USD 8000 for the 800 FFE feeders.

In order to obtain parameters for autonomous vessels, we need to make some adjustments in the original data instance, for which we follow closely other references. Economic effects of the introduction of autonomous vessels are considered by various researchers. While different authors agree on lower crew costs, they all analyze it in a trade-off with a cost increase due to other factors such as higher construction cost of new buildings (Danish Maritime Authority 2016) and higher costs at the shore control center and at ports (Hogg and Ghosh 2016; Kretschmann et al. 2017).

A cost saving potential lays in crew wages and crew related costs which include salaries and all living expenses of the crew such as hotel system, medical expenses and safety equipment. Based on Kretschmann et al. (2017), the share of crew wages in total operational costs is 45%, and the share of store costs that will be eliminated in autonomous vessels is 3%. Therefore, the operational costs are reduced by 48%, which implies that the operational costs are USD 2600 per day for the 450 FFE feeders and and USD 4160 per day for the 800 FFE feeders.

The decrease of voyage costs of autonomous vessels is driven by reduced air resistance, lighter ship weight and lower electricity consumption associated with the hotel system. These factors, in their turn, contribute to the reduction of auxiliary engine fuel consumption. Different estimates of the fuel consumption reduction rate are presented in the literature. Following Kretschmann et al. (2017), we set a reduction of 6% in fuel consumption. This means that the fuel consumption when sailing at sea for feeders of 450 FFE and 800 FFE is 17.7 tons per day 22.3 tons per day, respectively.

As the LINER-LIB benchmark suite does not contain information for feeders with capacity lower than 450 FFE, we need to make some assumptions for the data on the vessels of 200 FFE. The design speed of these feeders is assumed to be 11 knots which is slightly lower than the design speed of bigger feeders and is in line with existing vessels of similar size. Fuel consumption at sea is found using multiple linear regression with explanatory variables capacity, and design speed based on the whole fleet provided by Brouer et al. (2014). The value obtained after running this regression is fuel consumption for a conventional vessel of 200 FFE. This value is then reduced by 6% to reflect the savings associated to the higher efficiency of autonomous ships (Kretschmann et al. 2017). The results of this calculation is an estimated fuel consumption at sea for traditional vessels and autonomous vessels of 8.03 and 7.55 tons per day, respectively. We proceed in analogous way to estimate the daily time charter (TC) rate. We first estimate the TC rate for a traditional vessel of 200 FFE running a linear regression over the capacity based on the whole fleet. Then, we reduce such

Table 1 Operating costs at the different ports (in USD)

Port	Lifting cost per FFE	Port call cost per FFE	Fixed port call cost conventional vessels	Fixed port call cost, autonomous vessels
DEBRV	199	14	11,795	14,154
DKAAR	429	7	11,861	14,233
FIKTK	137	52	1182	1418
FIRAU	196	127	18,552	22,262
NOAES	684	130	24,098	28,918
NOBGO	365	119	17,435	20,922
NOKRS	141	180	24,076	28,891
NOSVG	315	13	1227	1472
PLGDY	84	138	23,817	28,580
RUKGD	233	27	1062	1274
RULED	270	37	722	866
SEGOT	247	13	26,838	32,206

Table 2 Parameters for conventional and autonomous vessels according to their size

Parameters	Conventional vessels		Autonomous vessels		
Capacity, FFE	450	800	200	450	800
Design speed, knots	12	14	11	12	14
Fuel consumption at sea, tons/day	18.8	23.7	7.6	17.7	22.3
Fuel consumption when idle, tons/day	2.4	2.5	2.3	2.4	2.5
Daily TC rate, USD	5000	8000	2190	2600	4160

value by 48% to estimate the TC rate for autonomous vessels, following the shares that the cost of wages and stores represent over the total operating costs, as estimated in Kretschmann et al. (2017). The resulting daily TC rates for traditional and autonomous vessels is of 4210.87 and 2189.65, respectively. Note, however, that in practice the time charter rates are volatile, heavily dependent on factors such as demand and supply availability, seasonality, and expectations about the future progress of the market. As we stick to the deterministic case, we refer the reader to Alvarez et al. (2011) for how an approach accounting for uncertainty can be deployed in this respect.

Whereas there is no crew on board while sailing at open sea, approaching and berthing require hiring a boarding crew at ports. Such a service might be offered by ports where local workers facilitate approaching and berthing of autonomous ships. This leads to an increase of 20% in port call costs (Kretschmann et al. 2017). A summary of operating costs per port and parameters for conventional and autonomous vessels are given in Tables 1 and 2, respectively.

Regarding time at port, Brouer et al. (2014) use a 24-h port time for all vessels, including both feeders and trans-ocean container ships. In the example of the eight building-blocks of liner costs, Stopford (2009) estimate that the port time for a vessel of 1,200 TEU is 0.7 days. Even though there is no linear relationship between the vessel size and time spent at port, it is reasonable to assume that smaller vessels use less time per port call than much larger vessels. Since the fleet employed in the Baltic instance involves only feeders with the maximum capacity of 800 FFE, the port time is estimated to be approximately 0.5 days, for both conventional and autonomous vessels.

Numerical results

The models are implemented in the modelling tool AMPL, using the solver Gurobi Optimizer version 9.0.2, with a time limit of 2 h. For the static model, we consider five different fleet configurations: a fleet of conventional vessels with a capacity of 450 FFE and 800 FFE; a fleet of autonomous vessels with those same capacities; a fleet of autonomous vessels combining capacities of 200 FFE and 450 FFE; a fleet of autonomous vessels combining capacities of 200 FFE and 800 FFE; and a fleet of autonomous vessels with an homogeneous capacity of 200 FFE. The results obtained are shown in Table 3.

It can be seen that the introduction of autonomous vessels leads to a decrease of total costs and, as a result, to an increase of profit due to a reduction of time charter costs and bunker costs compensated by higher port call costs. When switching from the conventional fleet to the autonomous fleet, and keeping the same vessel capacities, the total costs decrease by 3.2%. The lifting costs remain the same for all fleet configurations. The main contribution to the total operating costs reduction is made by the time charter costs due to the lower wages and storage expenses; they decrease by around 40%. The bunker costs for autonomous ships are about 6% lower, which also contributes to the cost savings.

Fleet configuration has an impact on the total costs and the route structure, as vessels of different sizes may be used on routes with different length and demand volume. The lowest costs are achieved by the fleet of autonomous vessels of capacity 200 and 800 FFE, which conduces to an overall cost reduction of 7.1% with respect to the fleet of conventional vessels. In contrast, the highest costs are incurred by the fleet of autonomous vessels of 200 FFE. The fleet of 200 and 800 FFE in all cases attains the lowest bunker costs and the lowest port call costs. Comparing to the fleet of conventional vessels, the fleet of autonomous vessels of capacity 200 and 800 FFE, achieves a cost reduction of 16.4% in bunker costs, 9.2% in port call costs, and 44.9% in time charter costs. The fleet with vessels of 200 FFE leads to the highest operating costs which are greater than the

Table 3 Results of the static LSNDP (in thousand USD)

Fleet configuration	Profit	Revenue	Total cost	Bunker	Port call	Time charter	Lifting
Conventional 450 and 800	267	4055	3787	422	758	294	2313
Feeders of 450 FFE				*113*	*376*	*70*	
Feeders of 800 FFE				*309*	*382*	*224*	
Autonomous 450 and 800	391	4055	3664	398	800	153	2313
Feeders of 450 FFE				*107*	*396*	*36*	
Feeders of 800 FFE				*291*	*404*	*116*	
Autonomous 200 and 450	368	4055	3687	506	694	173	2313
Feeders of 200 FFE				*76*	*258*	*46*	
Feeders of 450 FFE				*430*	*436*	*127*	
Autonomous 200 and 800	538	4055	3517	353	688	162	2313
Feeders of 200 FFE				*76*	*258*	*46*	
Feeders of 800 FFE				*276*	*430*	*116*	
Autonomous 200	33	4055	4021	528	874	307	2313

operating costs of the best performing fleet by 14%. The highest growth is related to the time charter costs and the bunker costs, which are affected by a large increase in the number of vessels needed to transport all the demands in the network. The routes constructed by the LSNDP are outlined in Table 4 and drawn in Fig. 2.

The figures show both simple and butterfly route structures for all fleet configurations. The routes for the fleets with conventional and autonomous vessels of 450 and 800 FFE are almost identical. The Baltic instance has an asymmetric nature, with high demand from Bremerhaven (DEBRV) to Saint Petersburg (RULED) and low demand on the back-haul leg. Moreover, the demands between ports in Norway (NOBGO, NOSVG, NOKRS) and the hub (DEBRV) are low and the distances are short. This fact explains why the fleet of 200 and 800 FFE has performed the best among the autonomous fleets, as the smallest feeders are used to sail the Norwegian ports with low demands and the biggest feeders are used to sail the destinations with higher demands such as Saint Petersburg (RULED), Aarhus (DKAAR) or Gothenburg (SEGOT). The autonomous fleet with ships of 200 FFE, on the other hand, incurs high costs as it has to employ many small vessels to satisfy the demand in the farthest port, Saint Petersburg (RULED).

The results on capacity utilization displayed in Table 5 give an idea of how well the fleets' capacity fits in the network. The fleet of autonomous vessels of 200 FFE has the

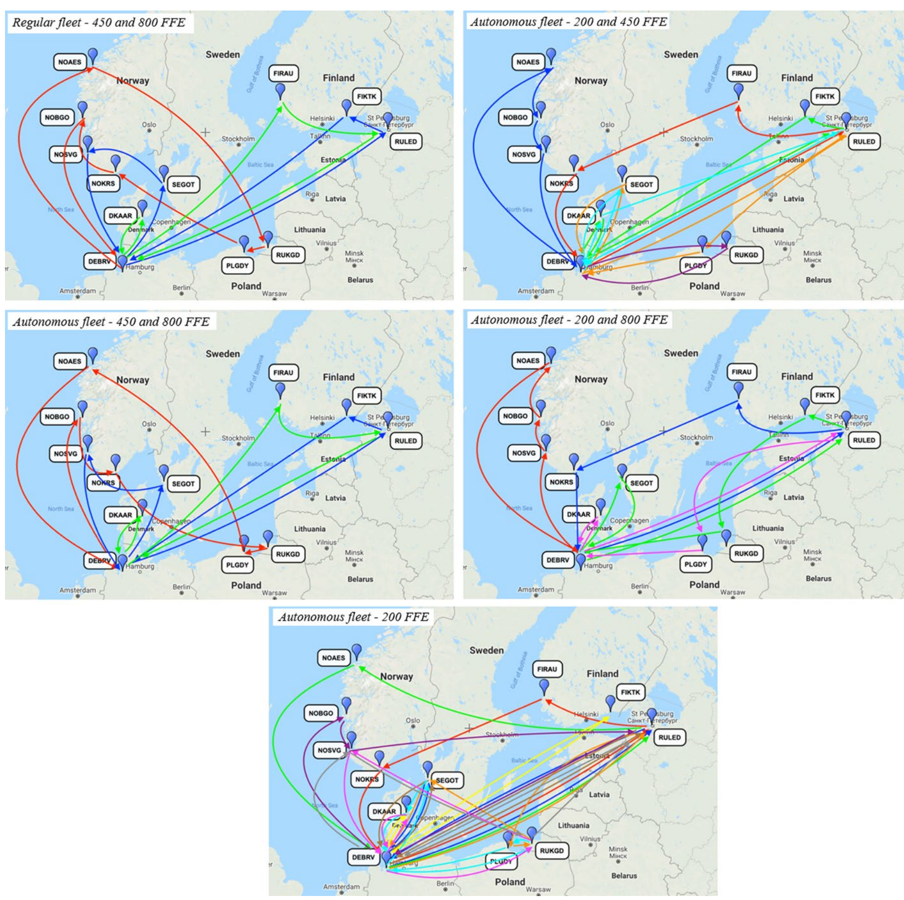

Fig. 2 Routes obtained for the different fleets

Table 4 Vessels, service types and routes in the solution obtained for the different fleets

Fleet	Vessel no.	Capacity	Service	Route
Conventional 450–800	1	450	Simple	DEBRV - NOAES - RUKGD - PLGDY - NOKRS - NOBGO - DEBRV
	2	800	Butterfly	DEBRV - RULED - FIKTK - DEBRV - SEGOT - NOSVG - DEBRV
	3	800	Butterfly	DEBRV - DKAAR - DEBRV - FIRAU - RULED - DEBRV
Autonomous 450–800	1	450	Simple	DEBRV - NOBGO - NOKRS - RUKGD - PLGDY - NOAES - DEBRV
	2	800	Butterfly	DEBRV - RULED - FIKTK - DEBRV - SEGOT - NOSVG - DEBRV
	3	800	Butterfly	DEBRV - DKAAR - DEBRV - FIRAU - RULED - DEBRV
Autonomous 200–450	1	200	Simple	DEBRV - RULED - FIRAU - NOKRS - DEBRV
	2	200	Butterfly	DEBRV -NOAES - NOBGO - NOSVG - DEBRV
	3	450	Butterfly	DEBRV -DKAAR - DEBRV - RULED - FIKTK - DEBRV
	4	450	Butterfly	DEBRV - RULED - PLGDY - DEBRV - SEGOT - DEBRV
	5	450	Simple	DEBRV - RUKGD - DEBRV
	6	450	Butterfly	DEBRV -DKAAR - RULED - DEBRV - SEGOT - DEBRV
Autonomous 200–800	1	200	Simple	DEBRV - NOSVG - NOBGO - NOAES - DEBRV
	2	200	Simple	DEBRV - RULED - FIRAU - NOKRS - DEBRV
	3	800	Butterfly	DEBRV - RULED - FIKTK - RUKGD - DEBRV - SEGOT - DEBRV
	4	800	Butterfly	DEBRV - DKAAR - DEBRV - RULED - PLGDY - DEBRV
Autonomous 200	1	200	Simple	DEBRV - RULED - FIRAU - NOKRS - DEBRV
	2	200	Butterfly	DEBRV - RULED - DEBRV - SEGOT - DEBRV
	3	200	Simple	DEBRV - RULED - NOAES - DEBRV
	4	200	Simple	DEBRV - RULED - PLGDY - RUKGD - SEGOT - DEBRV
	5	200	Butterfly	DEBRV - DKAAR - DEBRV - FIKTK - DEBRV
	6	200	Butterfly	DEBRV - RULED - DEBRV - SEGOT - DEBRV
	7	200	Butterfly	DEBRV - RUKGD - PLGDY - DEBRV - SEGOT - DKAAR - DEBRV
	8	200	Butterfly	DEBRV - DKAAR - DEBRV - RUKGD - NOSVG - DEBRV
	9	200	Simple	DEBRV - NOBGO - NOSVG - RULED - DEBRV
	10	200	Simple	DEBRV - NOSVG - RUKGD - RULED - DEBRV

Table 5 Results of LSNDP for capacity utilization under the fixed schedule

Fleet configuration	Average capacity utilization rate (%)
Autonomous 450 and 800	71
Feeders of 450 FFE	76
Feeders of 800 FFE	68
Autonomous 200 and 450	67
Feeders of 200 FFE	76
Feeders of 450 FFE	63
Autonomous 200 and 800	64
Feeders of 200 FFE	67
Feeders of 800 FFE	62
Autonomous 200	73

Table 6 Results of LSNDP under fixed schedule and dynamic schedule (in thousand USD)

Schedule types	Profit	Revenue	Total cost	Bunker	Port call	Time charter	Lifting	Avg. util. rate (%)
Fixed schedule	33	4055	4021	528	874	307	2313	73
Dynamic schedule	−514	4055	4569	650	1249	356	2314	54
Changes	−1646%	0%	14%	23%	43%	16%	0%	−27

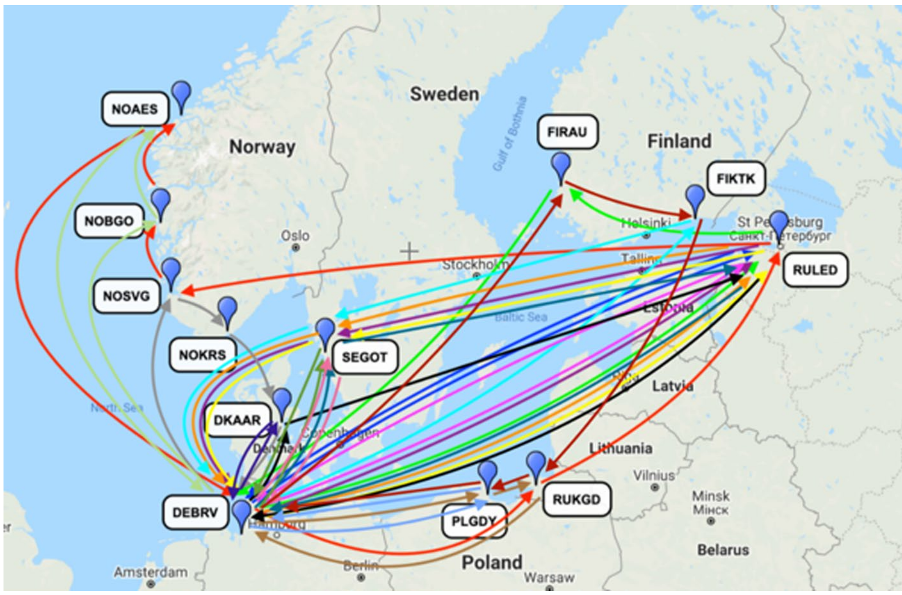

Fig. 3 Routes obtained for the LSNDP with dynamic schedule

highest utilization rate among the different fleets, which can be explained by the ease of filling up smaller vessels. Note, however, that the fleet of only 200 FFE vessels has the highest operating cost compared to the other fleets, because it needs a considerable number of vessels to satisfy the demand. While the other fleets use from three to six container ships to serve the network, the 200 FFE fleet uses ten ships. The fleet of vessels of 200 and 800 FFE capacity, which has the lowest operating cost, has the lowest utilization rate.

Dynamic scheduling

The fleet of 200 FFE vessels is used in the dynamic model, and its result is compared with the result of the static model using the same fleet configuration. The use of vessels of 200 FFE capacity is in line with future perspectives on autonomy in shipping, which have pointed to the use of smaller vessels in more dynamic settings (Christiansen et al. 2020). Figure 3 shows the routes obtained for this case. Note we have used a demand threshold value equal to 75% of the capacity of a basic fleet (which consists of ten vessels of 200 FFE), to determine when a vessel sails. Table 6 outlines a comparison between the results of sailing a fleet of only 200 FFE vessels under a fixed schedule and flexible schedule.

The results indicate that the fixed schedule outperforms the flexible schedule in both cost and capacity utilization. In fact, the bunker cost and the port call cost rise substantially under the dynamic schedule, as more port visits are made and more vessels sail on the same legs. For example, seven ships are needed to transport the demand from Bremerhaven (DEBRV) to Saint Petersburg (RULED). After then, two of these seven ships can sail back to Bremerhaven with the demand from Saint Petersburg to Bremerhaven. In total, the network needs seven vessels to serve the leg between these two ports and seven port visits at Saint Petersburg. In the dynamic schedule, the demand from Bremerhaven to Saint Petersburg arrives on day 3, while the demand for the opposite direction arrives on day 5. When the network is designed on day 3, the optimization problem acknowledges that there is no demand back from Saint Petersburg to Bremerhaven. Seven vessels are assigned on the leg on day 3 to fulfil the demand requirement. On day 5, two more ships are assigned to sail to Saint Petersburg, which then transport demand from Saint Petersburg to Bremerhaven. To sum up, nine vessels are needed in the dynamic sailing schedule to serve the leg that requires only seven vessels under the fixed schedule. The difference in the number of vessels used on the leg explains why the bunker cost and port call cost in the former sailing schedule are considerably higher than those in the dynamic case. This happens not only on the Bremerhaven–Saint Petersburg leg, but also on other legs where the demands from both sides are triggered in different days.

The time charter cost increases 16% in the flexible schedule with respect to the fixed schedule. Similar to the bunker cost and port call cost, the rise in the time charter cost is due to the significant increase in the number of vessels in the fleet. In the flexible schedule, the time charter cost is calculated based on the time the vessels are in use, including time sailing at sea and time waiting at port. When a vessel in the dynamic sailing schedule finishes the course of routes to which it is assigned, time charter cost is no longer accumulated on the vessel. On the contrary, when a vessel has a weekly port call frequency at the hub in the fixed schedule, the time charter cost is counted on the whole week. Similarly, the time for the charter costs is two weeks for the vessels with the biweekly frequency. The number of vessels in use for the dynamic schedule is nearly double than for the fixed schedule. The average capacity utilization rate of the dynamic sailing schedule is comparatively low, that is, 54%, while the rates in the fixed schedule are above 68%. This low fill-up rate reflects the potential disadvantage of the dynamic sailing schedule due to the lack of consolidation possibility, i.e. small demands are transported separately. Moreover, the network asymmetry can be worse when looking at each sailing day as a network on its own. For example, on sailing day 3, the ratio of the demand from the hub to the spoke ports to the demand from the spoke ports back to the hub is 2.18. This ratio in the whole Baltic instance is 1.49. The imbalance of the demand on the head-haul and the back-haul leg results in vessels sailings in ballast to relocate for the next shipment.

Although the results above suggest that flexible schedule hurts liner shipping companies from the cost and capacity utilization perspective (given that the overall demand is fixed), the potential advantage of this type of schedule lies in the shorter lead time, which help increasing the service level. Here, the lead time includes both the time that demands wait at their original port and the time they travel at sea. The waiting time at port is counted from the day a demand arrives at its origin to the day it is loaded on a vessel for transportation. The time at sea, or transit time, is the time when a demand stays on a vessel to travel to its origin. Figure 4 shows the distribution of these time measures.

It can be seen that, in general, the lead time and the time that the demands wait at their original port under the dynamic schedule are shorter, while the time at sea under both schedules is more or less the same. The distribution of the lead time in the dynamic schedule skews to the left with a long tail to the right, which indicates that most of the demands are transported to their destination port within a short time. More than half of the demands reach their target port within 5.78 days. Only a few shipments use more than 13 days to travel to their destination. In the fixed schedule, the distribution tends to have a bell shape, rather than skewing towards one side. No demands use less than 5.63 days for transportation, and quite a few demands spend more than 16.13 days to reach their destination port, counting from the day they arrive at the loading port.

In both schedules, the distribution of the waiting time at the original port skews to the left. However, the skewness in the dynamic schedule is far more extreme than in the fixed schedule. The reason for this is that in the former schedule the sailing event is triggered three times during the week, immediately when the threshold is reached. None of the demands from the hub to spokes has to wait more than two days to be loaded on board for the journey to their destination port. The demands that wait longer are those from the spokes back to the hub since they have to wait for the arrival of the ships to pick them up. Under the fixed schedule, more than half of the demands waits at their original port for over 4.9 days. A few shipments have to spend more than 14.1 days at the departure port before there is an available spot for them on a vessel sailing towards their destination port.

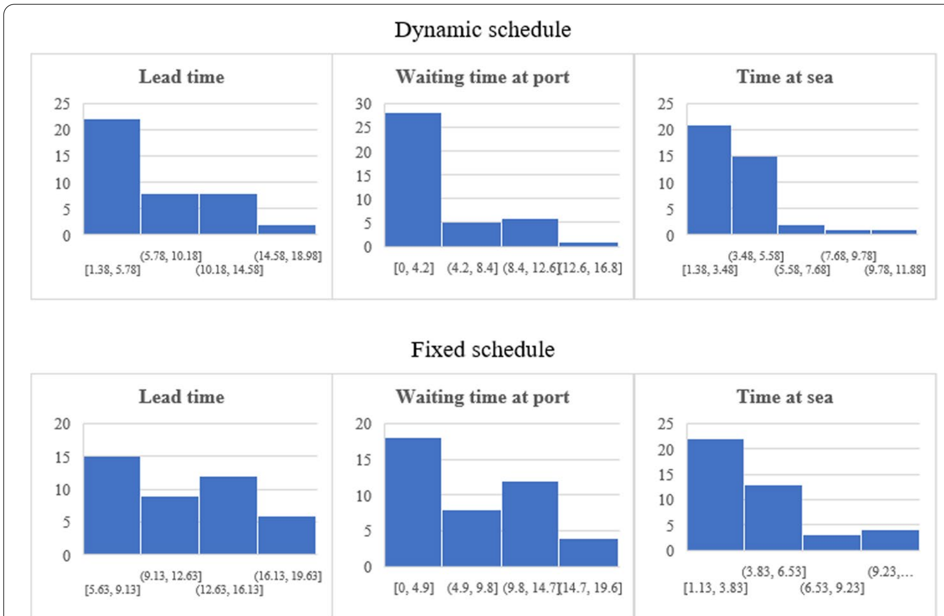

Fig. 4 Distribution of lead time, waiting time, and time at sea for the dynamic and fixed schedules (in days)

The mechanism of the optimization of LSNDP tries to minimize the time that a demand spends at sea, since this is time when the major part of the total cost is incurred and where the liner shipping companies have more flexibility to reduce costs. In both schedules, the majority of demands is brought to their destination in a short time after being loaded on board. In the dynamic schedule, it takes less than 5.58 days for most of the demands to arrive at their unloading point. Under the fixed schedule, a bit longer time is needed. However, very few shipments use more than 6.98 days to travel to their destination.

Sensitivity analysis

To explore how the solutions are affected by changes in demand, we run the models in two alternative demand scenarios. In a high demand scenario, the original demand volumes are increased by 15%, while in a low demand scenario, the original demand volumes are decreased by 10%. These appear reasonable based on the projected development of the maritime cargo flows in the Baltic Sea towards 2030. As a reference, the forecasts of the Institute of Shipping Economics and Logistics have pointed out possible volume increases in the Baltics ranging from 9 to 22% in a growing market, but also a possible volume reduction of 10% in adjusted calculations. Here, the interaction of opposite phenomena, such as population growth and technological innovations versus stricter environmental regulations and pandemic consequences may incline the trend to either a growing or contracting scenario (ISL 2014; Matczak 2018; Condon et al. 2020).

Tables 7 and 8 show the results for the different fleets in the low and high demand scenario, respectively. Similar to the trend observed in the original demand scenario, the introduction of autonomous vessels reduces costs in comparison to the conventional fleet. In particular, when keeping the same capacities (that is, 450 and 800 FFE) the autonomous fleet reduces the total costs of the conventional fleet by 3.5% in the low demand scenario, which is close to the 3.2% obtained in the original demand scenario. The reduction is a bit more moderate in the high demand scenario, since the decrease in time charter costs is somewhat less pronounced in comparison to the increase in port call costs, but still enough as to render total cost savings of 1.5%.

Table 7 Results of the static LSNDP for the low demand scenario (in thousand USD)

Fleet configuration	Profit	Revenue	Total cost	Bunker	Port call	Time charter	Lifting
Conventional 450 and 800	125	3649	3524	425	723	294	2082
Feeders of 450 FFE				127	438	70	
Feeders of 800 FFE				298	284	224	
Autonomous 450 and 800	249	3649	3400	400	765	153	2082
Feeders of 450 FFE				120	462	36	
Feeders of 800 FFE				281	303	116	
Autonomous 200 and 450	279	3649	3370	479	651	158	2082
Feeders of 200 FFE				53	233	31	
Feeders of 450 FFE				426	418	127	
Autonomous 200 and 800	427	3649	3222	330	663	147	2082
Feeders of 200 FFE				53	233	31	
Feeders of 800 FFE				276	430	116	
Autonomous 200	11	3649	3638	480	800	276	2082

Table 8 Results of the static LSNDP for the high demand scenario (in thousand USD)

Fleet configuration	Profit	Revenue	Total cost	Bunker	Port call	Time charter	Lifting
Conventional 450 and 800	432	4663	4231	519	730	322	2660
Feeders of 450 FFE				363	587	210	
Feeders of 800 FFE				156	143	112	
Autonomous 450 and 800	496	4663	4167	519	799	189	2660
Feeders of 450 FFE				226	538	73	
Feeders of 800 FFE				292	260	116	
Autonomous 200 and 450	497	4663	4166	569	729	207	2660
Feeders of 200 FFE				104	266	61	
Feeders of 450 FFE				465	463	146	
Autonomous 200 and 800	649	4663	4013	441	703	208	2660
Feeders of 200 FFE				159	412	92	
Feeders of 800 FFE				282	292	116	
Autonomous 200	141	4663	4522	593	931	337	2660

Table 9 Results of LSNDP for capacity utilization under the fixed schedule

Fleet configuration scenario	Average capacity utilization rate	
	Low (%)	High (%)
Autonomous 450 and 800	64	65
Feeders of 450 FFE	61	65
Feeders of 800 FFE	65	64
Autonomous 200 and 450	61	72
Feeders of 200 FFE	76	86
Feeders of 450 FFE	57	64
Autonomous 200 and 800	66	72
Feeders of 200 FFE	76	71
Feeders of 800 FFE	62	73
Autonomous 200	68	71

The autonomous fleet of combined capacities of 200 and 800 FFE is again the one with best performance, achieving 8.6% and 5.2% with respect to the conventional fleet in the low and high demand scenarios, respectively. Similar to the original demand scenario, this performance is driven mainly by lower bunker costs and lower port call costs. These results emphasize the benefits of a fleet combining small and large capacity vessels, which can complement well with each other to cope with legs demanding low and high volumes, respectively. In contrast, the fleet containing only 200 FFE vessels is the one that incurs in highest costs, as many more vessels are needed to satisfy the demands, which is especially costly to serve the farthest ports.

Table 9 shows the results on capacity utilization obtained for both the low and high demand scenarios. Recall that in the original demand scenario, the homogeneous fleet of autonomous vessels with 200 FFE capacity was the one with highest capacity utilization. This is still the case for the low demand scenario. However, in the high demand scenario, the combined fleet of 200 and 450 FFE and also the combined fleet of 200 and 800 FFE achieve a slightly higher capacity utilization than the other configurations. This is a reasonable trend, as higher demand can facilitate larger vessels to utilize more of their capacity.

Table 10 summarizes the results to the static and dynamic scheduling problems, in both the low and high demand scenarios. In line with the results discussed for the original scenario, the dynamic schedule performs poorly in cost and capacity utilization metrics. This poor performance is more pronounced in the low demand scenario, where the port call costs for the dynamic case are much higher than in the static case. This is driven by the higher amount of vessels and trips needed by the dynamic solution. Moreover, more vessels and more trips come along with less cargo per trip, which explains the low utilization rate in the dynamic solutions particularly in the low demand scenario, where this metric reaches only 52%. Higher demand helps raising the average capacity utilization to 56% in the high demand scenario, but still the fixed schedule solution is significantly superior with a 71%.

On the other hand, the lead times of the dynamic schedule are much shorter than the lead times of the static schedule in both the low and high demand scenarios. As can be seen on the left plots of Fig. 5, in the dynamic solution to the low scenario, most of the demands are shipped in less than 5.38 days, while in the static solution the majority of the shipments are in the interval from 7.51 to 15.11 days. The positive effect of a dynamic schedule in this service level metric is even more noticeable in the high demand scenario, as illustrated on the right plots of Fig. 5. In the fixed schedule for this scenario, the majority of the shipments take from 7.51 to 15.11 days, and the longest lead time is 22.71. In contrast, in the dynamic solution most shipments take less than 5.08 days, and the longest lead time is of 12.48 days, which is considerably shorter than what the static solution obtained. A higher rate of demand in the dynamic setting helps to reach faster the threshold for sailing, which implies less waiting time at port and, in consequence, the shorter lead times observed in these results.

Discussion

Our numerical results suggest that switching from conventional to autonomous vessels may be beneficial for liner shipping companies, due to the higher fuel efficiency of autonomous vessels and their lower operating costs. In particular, the highest percentage

Table 10 Results of LSNDP under fixed schedule and dynamic schedule in the low and high demand scenarios (in thousand USD)

Schedule types	Profit	Revenue	Total cost	Bunker	Port call	Time charter	Lifting	Avg. util. rate (%)
Low scenario								
Fixed schedule	11	3649	3638	480	800	276	2082	68
Dynamic schedule	−573	3649	4222	606	1202	332	2082	52
Changes	−5387%	0%	16%	26%	50%	20%	0%	−23
High scenario								
Fixed schedule	141	4663	4522	593	931	337	2660	71
Dynamic schedule	−497	4663	5160	746	1347	406	2661	56
Changes	−452%	0%	14%	26%	45%	20%	0%	−21

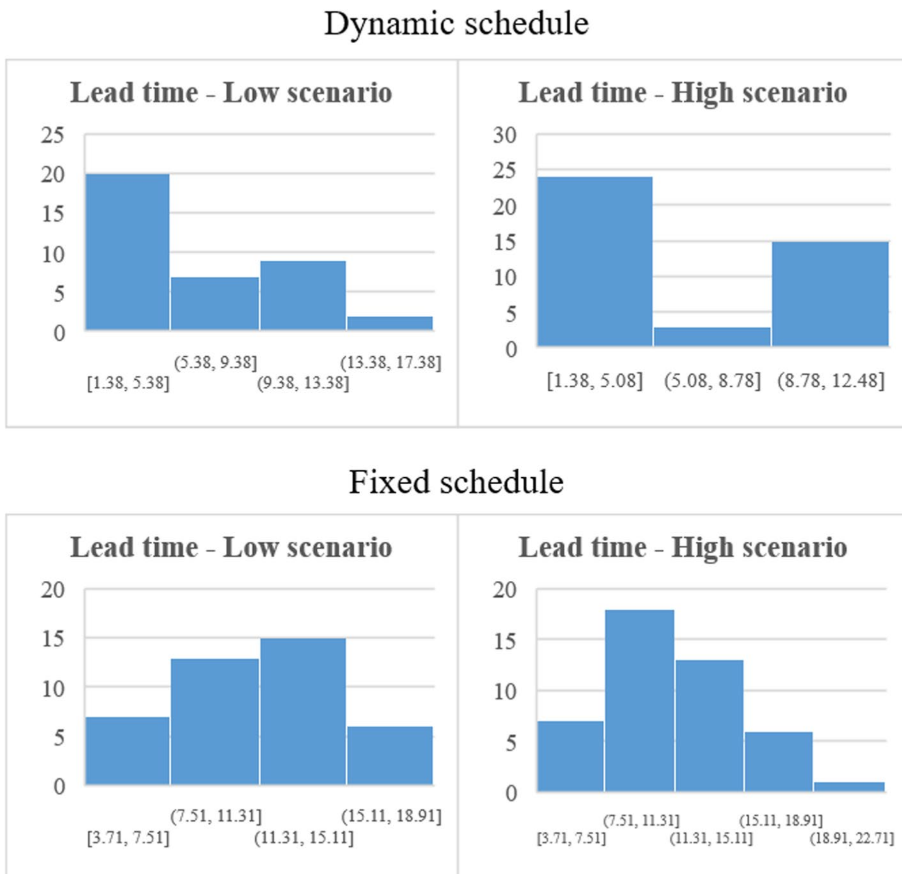

Fig. 5 Distribution of lead time for the dynamic and fixed schedules (in days) in both the low and high demand scenarios

cost reduction comes from lower time charter expenses, then bunker, and then port call costs.

The cost-element analysis indicates that the fleet of vessels of 200 FFE and 800 FFE has the best performance among the fleet configurations with the highest profit. The combination of large ships (to serve the long legs with high demand volume) and small feeders (to serve the short routes with low demand) brings great flexibility to adapt to the asymmetric demand of the network. When the demand fluctuates, the fleet's capacity can be adjusted easily by adding up more small feeders or cease the usage of them. Thus, whenever the demand increases, one more vessel of a capacity of 200 FFE is chartered in to take care of the additional demand.

None of the fleet configurations has outperformed the others significantly in terms of capacity utilization. One of the fundamental issues of overseas transportation is the unbalanced demand between the head-haul and the back-haul leg. In the Baltic sea network, the demand from the hub (Bremerhaven) to the other spoke ports is 2937 FFE, while the demand flowing back is 1967 FFE. Therefore, when the vessels sail back from the spokes, it is impossible to fill up the existing capacity. Most ships in the class of 450 FFE and 800 FFE have sailing routes of two weeks, which allow them to gather the demand from the multiple spoke ports to increase the fill-up rate on the way back to

Bremerhaven (DEBRV). In general, the fleet configuration plays an important role in both economic performance and capacity utilization. While large ships contribute to economies of scales, small vessels provide the flexibility to adjust to the market demand.

The results from the dynamic case denote a conflict between the economic loss and the operational benefit. On the one hand, the dynamic schedule outperforms the fixed schedule in terms of transporting time due to a significantly short waiting time that the demands spend at their departure port. On average, the lead time when sailing under a flexible schedule, which counts from the day the demands arrive at their departure port to the day they reach their destination, is only half of that when vessels have a fixed port call schedule. This benefit may help the liner shipping companies which implement the flexible sailing schedule to increase their service level. On the other hand, when it comes to minimize operating cost and increase the fill-up rate, the dynamic schedule leads to a loss in profit and low capacity utilization of the fleet. An enormous number of vessels are required in order to meet the demand constraint, which causes a substantial rise in all vessel-related costs, including bunker cost, variable port call cost and time charter cost. The problem of overcapacity is severe due to the lack of consolidation possibility for small demands. Moreover, many vessels sail between ports in ballast to relocate their position for the next shipment, as the network asymmetry on one sailing day can be much worse than the imbalance of the whole Baltic sea instance. It should be acknowledged that the results from the flexible sailing schedule are affected by the choice of the threshold level. Also, it is worth notice that in the comparison of the fixed and dynamic scheduling, the overall demand is the same. In practice, we may expect that a better service level may trigger higher demand, since customers may be attracted to use services securing shorter lead times.

Conclusions

This paper has investigated the effects of introducing autonomous vessels in the LSNDP, from both economic and operational perspective. Two models were implemented by extending a data instance of the Baltic trade from conventional to autonomous vessels. We tested different fleet combinations of three capacity level, including 800 FFE, 450 FFE and 200 FFE. A static model provided a basis for comparison of the economic performance between the conventional fleet and autonomous fleet, and among various fleet configurations. Our results have shown that, with a fixed sailing schedule, a fleet of autonomous vessels incurs a lower operating cost than a fleet of conventional crewed ships due to the cost savings mainly on time charter and bunker. Among the fleet configurations, the autonomous fleet of 800 and 200 FFE vessels outperformed all the other fleets and, in particular, it achieved a cost reduction of 7.1% with respect to the fleet of conventional vessels of 400 and 800 FFE capacity. The homogeneous fleet of autonomous vessels of 200 FFE capacity had the lowest profit due to the substantial number of vessels needed to meet the demand for transportation. The considerable difference in the profit between the best and the worst performing fleets suggests that the fleet structure should be chosen carefully. A wrong choice of fleet configuration can push up the operating cost of the network significantly. In addition, the results for the dynamic setting suggest that while the flexible schedule offers an advantage in terms of service level with considerably shorter lead time than the fixed schedule, this benefit comes along with higher costs.

This article has been one of the first attempts to study the potential effects of autonomous vessels in liner shipping network design. Important topics for future research are the incorporation of transshipments and the repositioning of empty containers. Also, since some parameters such as the demand and time charter costs are inherently uncertain in practice, the development of a stochastic approach is also an interesting avenue for further investigation.

Abbreviations
AMPL: A Mathematical Programming Language software; DEBRV: Bremerhaven, Germany; DKAAR: Aarhus, Denmark; FFE: Forty-foot equivalent unit; FIKTK: Kotka, Finland; FIRAU: Rauma, Finland; LSNDP: Liner shipping network design problem; NOAES: Aalesund, Norway; NOBGO: Bergen, Norway; NOKRS: Kristiansand, Norway; NOSVG: Stavanger, Norway; PLGDY: Gdynia, Poland; RUKGD: Kaliningrad, Russia; RULED: Saint Petersburg, Russia; SEGOT: Gothenburg, Sweden; TC: Time charter; TEU: Twenty-foot equivalent unit; USD: United States dollar.

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Author contributions
GTHN: Methodology, Software, Investigation, Data curation, Writing. DR: Methodology, Software, Investigation, Data curation, Writing. JCG: Conceptualization, Methodology, Writing. MG: Conceptualization, Methodology, Software, Writing. All authors read and approved the final manuscript.

Availability of data and materials
The main part of the data comes from the LINER-LIB benchmark suite publicly available (see reference Brouer et al. 2014 in the manuscript), while the parameter settings for the autonomous case are given throughout our manuscript. In addition, we remain willing to make all of these openly available in any other format that journal would suggest.

Declarations

Competing interests
The authors declare that they have no competing interests.

Author details
[1]Department of Business and Management Science, NHH Norwegian School of Economics, Helleveien 30, 5045 Bergen, Norway. [2]SNF - Centre for Applied Research at NHH, Bergen, Norway.

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References
Akbar A, Aasen AK, Msakni MK, Fagerholt K, Lindstad E, Meisel F (2021) An economic analysis of introducing autonomous ships in a short-sea liner shipping network. Int Trans Oper Res 28(4):1740–1764
Alvarez JF (2009) Joint routing and deployment of a fleet of container vessels. Maritime Econ Log 11(2):186–208
Alvarez JF, Tsilingiris P, Engebrethsen ES, Kakalis NM (2011) Robust fleet sizing and deployment for industrial and independent bulk ocean shipping companies. INFOR Inf Syst Oper Res 49(2):93–107
Andersson H, Fagerholt K, Hobbesland K (2015) Integrated maritime fleet deployment and speed optimization: case study from roro shipping. Comput Oper Res 55:233–240
Aslaksen IE, Svanberg E, Fagerholt K, Johnsen LC, Meisel F (2021) A combined dial-a-ride and fixed schedule ferry service for coastal cities. Transp Res A Policy Pract 153:306–325
Balakrishnan A, Karsten CV (2017) Container shipping service selection and cargo routing with transshipment limits. Eur J Oper Res 263(2):652–663
Brouer BD, Alvarez JF, Plum CE, Pisinger D, Sigurd MM (2014) A base integer programming model and benchmark suite for liner-shipping network design. Transp Sci 48(2):281–312
Brouer BD, Karsten CV, Pisinger D (2017) Optimization in liner shipping. 4OR 15(1):1–35
Chen K, Su S, Gong Y, Xin X, Zeng Q (2021) Coastal transportation system green policy design model based on shipping network design. Int J Log Res Appl 1–22
Christiansen M, Hellsten E, Pisinger D, Sacramento D, Vilhelmsen C (2020) Liner shipping network design. Eur J Oper Res 286(1):1–20
Condon J, Gailus S, Neuhaus F, Peña-Alcaraz M (2020) Global freight flows after covid-19: whatś next? McKinsey Insights
Cullinane K, Khanna M (2000) Economies of scale in large containerships: optimal size and geographical implications. J Transp Geogr 8(3):181–195

Danish Maritime Authority (2016) Pre-analysis on autonomous ships. https://www.dma.dk/Documents/Publikationer/Autonome%20skibe_DTU_rapport_UK.pdf. Accessed 05 Aug 2021
Fagerholt K, Johnsen TA, Lindstad H (2009) Fleet deployment in liner shipping: a case study. Maritime Policy Manag 36(5):397–409
Giovannini M, Psaraftis HN (2019) The profit maximizing liner shipping problem with flexible frequencies: logistical and environmental considerations. Flex Serv Manuf J 31(3):567–597
Gu Y, Wallace SW (2021) Operational benefits of autonomous vessels in logistics—a case of autonomous water-taxis in Bergen. Transp Res E Log Transp Rev 154:102456
Gu Y, Goez JC, Guajardo M, Wallace SW (2021) Autonomous vessels: state of the art and potential opportunities in logistics. Int Trans Oper Res 28(4):1706–1739
Hasanspahić N, Vujičić S, Čampara L, Piekarska K (2021) Sustainability and environmental challenges of modern shipping industry. J Appl Eng Sci 19(2):369–374
Hogg T, Ghosh S (2016) Autonomous merchant vessels: examination of factors that impact the effective implementation of unmanned ships. Aust J Maritime Ocean Affairs 8(3):206–222
ISL (2014) Short sea shipping in the Baltic sea region. https://www.hellenicshippingnews.com/wp-content/uploads/2014/09/tbx_hhm_isl_study_short_sea_shipping_in_the_bsr.pdf. Accessed 17 Mar 2022
Karsten CV, Pisinger D, Ropke S, Brouer BD (2015) The time constrained multi-commodity network flow problem and its application to liner shipping network design. Transp Res E Log Transp Rev 76:122–138
Kongsberg (2018) Autonomous ship project, key facts about YARA Birkeland. https://www.kongsberg.com/maritime/ship-types/autonomous-ships. Accessed 05 Aug 2021
Koza DF, Desaulniers G, Ropke S (2020) Integrated liner shipping network design and scheduling. Transp Sci 54(2):512–533
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. Res Transp Bus Manag 25:76–86
Lim S-M (1998) Economies of scale in container shipping. Maritime Policy Manag 25(4):361–373
Matczak M (2018) Exploring the future of shipping in the Baltic Sea. https://vasab.org/wp-content/uploads/2018/08/20180730_FutureShippingQuoVadis.pdf. Accessed 17 Mar 2022
Meng Q, Wang S (2011) Optimal operating strategy for a long-haul liner service route. Eur J Oper Res 215(1):105–114
Msakni MK, Akbar A, Aasen AK, Fagerholt K, Meisel F, Lindstad E (2020) Can autonomous ships help short-sea shipping become more cost-efficient? In: Operations research proceedings 2019. Springer, pp 389–395
Munim ZH (2019) Autonomous ships: a review, innovative applications and future maritime business models. Supply Chain For Int J 20:266–279
Plum CE, Pisinger D, Sigurd MM (2014) A service flow model for the liner shipping network design problem. Eur J Oper Res 235(2):378–386
Reinhardt LB, Pisinger D (2012) A branch and cut algorithm for the container shipping network design problem. Flex Serv Manuf J 24(3):349–374
Rolls-Royce (2016) Remote and autonomous ship—the next steps. https://www.rolls-royce.com/~/media/Files/R/Rolls-Royce/documents/customers/marine/ship-intel/aawa-whitepaper-210616.pdf. Accessed 17 Mar 2022
Rolls-Royce (2018) Rolls-Royce and Finferries demonstrate world's first fully autonomous ferry. https://www.rolls-royce.com/media/press-releases/2018/03-12-2018-rr-and-finferries-demonstrate-worlds-first-fully-autonomous-ferry.aspx. Accessed 17 Mar 2022
Sirimanne SN, Hoffman J, Juan W, Asariotis R, Assaf M, Ayala G, Benamara H, Chantrel D, Hoffmann J, Premti A et al (2019) Review of maritime transport 2019. In: United Nations conference on trade and development, Geneva, Switzerland
Song D (2021) A literature review, container shipping supply chain: planning problems and research opportunities. Logistics 5(2):41
Stopford M (2009) Maritime economics, 3rd edn. Routledge, London
Thun K, Andersson H, Christiansen M (2017) Analyzing complex service structures in liner shipping network design. Flex Serv Manuf J 29(3):535–552
Tran NK, Haasis H-D (2015) Literature survey of network optimization in container liner shipping. Flex Serv Manuf J 27(2):139–179
Trivella A, Corman F, Koza DF, Pisinger D (2021) The multi-commodity network flow problem with soft transit time constraints: application to liner shipping. Transp Res E Log Transp Rev 150:102342
Wróbel K, Montewka J, Kujala P (2017) Towards the assessment of potential impact of unmanned vessels on maritime transportation safety. Reliab Eng Syst Saf 165:155–169
Xue J, Van Gelder P, Reniers G, Papadimitriou E, Wu C (2019) Multi-attribute decision-making method for prioritizing maritime traffic safety influencing factors of autonomous ships' maneuvering decisions using grey and fuzzy theories. Saf Sci 120:323–340
Yap WY, Zahraei SM (2018) Liner shipping alliances and their impact on shipping connectivity in southeast Asia. Maritime Bus Rev
Zhou X-Y, Liu Z-J, Wang F-W, Wu Z-L (2021a) A system-theoretic approach to safety and security co-analysis of autonomous ships. Ocean Eng 222:108569
Zhou J, Zhao Y, Niu X (2021b) Two-phase optimization models for liner shipping network based on hub ports cooperation: from the perspective of supply-side reform in China. J Adv Transp

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