A Multi-Criteria Fleet Deployment Model for Cost, Time and Environmental Impact

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Abstract

Most conventional models in maritime logistics focus uniquely on cost-minimization, whereas the supply chain management literature and practice emphasize customer time-performance and delivery reliability. In addition, the environmental perspective, in particular carbon dioxide (CO_2) reductions, is highly relevant. This paper addresses this issue by formulating a bi-criterion fleet deployment model, which minimizes shipping costs and transit time under an environmental constraint. The model identifies the Pareto optimal frontier of cost, transit time and CO_2 emissions, in terms of generalized costs for the importer as well as the impact of potential delays. The approach is tested empirically on a network of maritime and railway routes connecting China and US East/West coast ports, which simulates the weekly containerized China-USA traffic. The US West Coast ports act as transshipment gateways/hubs via both the intermodal US rail system and the coast-to-coast domestic maritime routes traversing the Panama Canal. Customer preferences are represented through an opportunity cost of flow time. The numerical results show a convex operational cost curve as a function of time reductions, i.e., increasing marginal cost for time. However, given the correlation of slow steaming and line cost reductions, the results for emission restrictions show that the impact primarily affects shippers in the form of longer lead times, not liners that benefit from lower costs. Both results suggest that resolution of the conflict between liners and shippers will involve addressing difficult issues in market, regulatory and technological development.

Keywords: Fleet deployment; Liner shipping; MIP; Value of time; Maritime transport; Greenhouse gases.

1. Introduction

Modern supply chains are by definition related to the geographic dispersion of different locations and the corresponding distances between them (Stock *et al.*, 2000). The time needed to cover those distances (that is, the duration of the transport process throughout the chain, and its cost) is one of the main concerns of supply chain stakeholders. Since the world merchandise trade is dominated by China -it was the world's leading exporter (2,487 US$ billion) and the second leading importer (2,136 US$ billion) in 2018 (WTO, 2019) after the United States- this paper will focus on the China-US transoceanic supply chain, and approach the problem from three perspectives: the costs incurred by the transport operator (the 'myopic logistical economic perspective'), the total transit time (the 'customer private valuation perspective') and the means of transport's marginal pollution impact (the 'societal-environmental perspective'), by disentangling the interests of three classes of stakeholders with partially incommensurate interests. Whereas the operator often pursues low operational costs with the transport time as a secondary objective, the final customer looks for the fastest mode of transport at the lowest possible tariff. The valuation of time is private information for the client, just as the supply chain surplus from lower direct costs on the operator's side is only shared with the client if the competition demands it. The environmental impact is also uncertain and potentially addressed by pollution abatement fees or taxes, or through direct regulation of the type of fuel and/or transport technologies allowed. Even though these three perspectives are frequently paid lip service in analytical frameworks, the dominant modeling paradigm has been to optimize the myopic supply chain cost. All three perspectives concern supply chain stakeholders, whom we consider as different actors in a common process: the flow of goods along the logistical network. The decision can be considered part of the more general problem of transport mode selection in trans-national logistic networks; a decision that can be decomposed into a strategic management level and for shorter periods of time, a tactical level. The strategic decisions deal with the overall design and configuration of the network and its integration with suppliers and customers via the transport chains. The tactical level deals with product flows along the chain that link the raw material suppliers, production facilities, and distribution centers to the end customer. These decisions normally involve a unified approach that analyzes the characteristics of the whole network (plant locations, production technologies, plant capacities and others) in order to integrate them with suppliers and customers (Schmidt & Wilhelm, 2000).

1.1 Shipping industry

As a crucial element in supply chains, maritime transport dominates in terms of the volume of world merchandise trade; in 2018 a total of 11 billion tons of cargo were loaded, including 3.2 billion tons of oil and gas and 7.8 billion tons of dry cargo, including 1.88 billion tons of containerized traffic (24% of dry cargo), (UNCTAD, 2019). Although maritime transport is a heterogeneous activity, the shipping industry is mainly based on three different operational approaches: tramp, industrial and liner shipping (Lawrence, 1972). Tramp traffic (that operates to fulfill specific demands) and industrial shipping (mainly related to in-house traffic) both function with a high degree of flexibility, whereas liner shipping involves fixed schedules, defined port itineraries and public tariffs. Liner shipping is strongly associated with container traffic and is crucial to economic globalization, playing a fundamental role in international trade as a main component in transoceanic supply chains. In 2018 the global containerized trade sector grew by 2.6%, reaching 152 million TEU's (twenty equivalent units) and following the sustained growth tendency (5.8% on average) recorded over the last 20 years (UNCTAD, 2019). The global character of the liner shipping industry its heavy dependency on port and land infrastructures and increasing competition, have led to vertical and horizontal integration processes in order to gain size, strengthen their position in the market and increase their influence over regulatory bodies and public authorities. In parallel, in search for economies of scale, the size of the ships they operate has dramatically increased. Whereas in the 1970's container carriers of 2,500 TEU's were the reference, in 2020 ships up to 21,000 TEU's can be found covering the transpacific routes between China and the US west coast, or the Asia-Europe routes that links China and Europe via the Strait of Malacca and the Suez Canal. The strong interconnection between shipping lines and port infrastructures cannot be overemphasized. Regularity and schedule compliance are crucial factors in liner shipping operations, and both are strongly dependent on port performance. This fact, together with market pressure for more reliable services, has forced shipping companies to take control of the whole transport process through the integration of sea and land activities. Thus, industry actors have vertically integrated to include not only shipping but logistical and stevedoring activities (Tran & Haasis, 2015); expanding the scope of their activities within the supply chain. Horizontally, carriers have traditionally tended to form coalitions through, conferences and alliances to agree on common pricing strategies. While conferences aim to establish common route prices, alliances arise to address low capacity utilization that derives from the use of large container ships in a highly constrained environment (Haralambides, 2007). Due to the fixed schedule and defined routing, the efficiency of the operations of any fleet is directly linked to the number and type of ships that must be deployed on each route to minimize costs. This, together with the fact that shipping companies redeploy their fleets every 3-6 months to adapt the offer of slots to demand (Shuaian Wang & Meng, 2012), motivates the liner ship fleet deployment (LSFD) problem.

1.2 Time in maritime transport

Historically it has been believed that the demand for maritime transport is derived from the demand for goods. However, trade globalization and the preeminence of global supply chains have led to the view that the demand for maritime transport is not only a consequence of the need for goods, but an integrated process in which the service level, time performance and the competition for customers play an important role (Panayides, 2006). Time, throughout the supply chain, emerges as a key dimension in getting goods from producers into the hands of the final consumers as it can influence trade flows by being a 'barrier' and affect trade volume. Time can act as a trade barrier across three dimensions: lead time; just in time; and time variability. In uncertain demand environments a long lead time -strongly related to transport time in many cases- can have a negative influence on stock levels; leading to either run outs or oversupply, depending on the demand. Time variability on the other hand, is strongly correlated with the cost of buffer stocks, especially when it is associated with just-in-time systems (Nordås, Pinali, & Grosso, 2006), as it can compromise the competitiveness of a supplier even if it is able to deliver goods promptly.

1.3 Environmental aspects

An unwanted side effect of maritime traffic is the environmental impact of ship engine emissions, which is an issue of growing concern for industry, governments, and regulators. According to the International Maritime Organization (IMO) during the period 2007-2012, international shipping emitted annually on average 846 million tonnes of carbon dioxide (CO_2) and 866 million tonnes of carbon dioxide equivalent (CO_2e) for greenhouse gases (GHGs) combining CO_2, methane (CH_4) and nitrous oxide (N_2O). This accounts for approximately 2.6% and 2.4% of the annual global CO_2 and GHGs on a CO_2e basis, respectively. Forecasts indicate that by 2050, international shipping production of CO_2 emissions could grow by between 50% and 250%, depending on varying economic growth scenarios and technological development.

In 2011 the IMO issued a set of technical and operational measures that came into force in 2013, providing an energy efficiency framework for ship types that account for approximately 85% of CO_2 emissions from international shipping (Smith et al., 2014). These measures range from limiting speed and readjusting schedules to technical modifications to ship engines, affecting not only GHG but other gases, such as nitrogen oxides (NO_x), carbon monoxide (CO) and sulphurous oxides (SO_x). IMO regulations to reduce sulphur oxide (SO_x), emissions from ships first came into force in 2005, limiting sulphur content in their fuel oil. Since a ship's engine emission is directly related to its fuel consumption, which in turn is a function of its sailing speed, there is a direct relation between speed reduction (slow steaming), fuel consumption and emission reduction. This connection directly affects supply chain performance, given the importance of maritime transport within it.

1.4 Objectives

The purpose of this paper is not to provide an integrated management decision for a single decision-maker, but to highlight intrinsic goal conflicts between the carrier, the final customer, and society. From the carrier side two types of transport are considered: sea and rail; the transshipment nodes between the two modes are incorporated. The total operational costs are minimized in several scenarios, and delays in some ports and GHG emission restrictions are included. From the customer perspective, the importer´s perception of the value of the coming goods strongly depends on transit time (Hummels & Schaur, 2013), (Nordås et al., 2006), especially when products with short lifecycles are traded. Since the cost of transport is normally inversely proportional to transit time, trade actors face a tradeoff between time and cost that results in the selection of a particular transport mode. This approach is reflected in the paper via a bicriterion mixed integer programming (MIP) model for the liner ship fleet deployment (LSFD) problem that includes a combined maritime and rail network. The rail network is considered as part of the maritime network with some particular attributes, and trains as a special type of ship with adapted characteristics. Consequently, rail ramps are assimilated to ports and all three port's handling operations - loading, unloading, and transshipment - apply equally to rail ramps and ports. We include the total weekly containerized maritime traffic China-USA in a stylized maritime and railway network, considering the latter as an extension of the former. The whole network is assumed to be served by a single integrated liner shipping company that transports all China-US traffic, turning the freight rail rates into an internal cost for the liner. We analyze the costs of the fleet, transport time, and the impact of potential CO_2 emission restrictions. The objective is to minimize the liner/railway fleets' costs and the total transportation time via a bi-criterion formulation to find the time-cost tradeoff frontier. If the importer perceives time to be an important factor, they will be willing to pay more to get the products delivered on time. On the other hand, if cost is a priority, less costly but slower options will be preferred. Environmental constraints impose additional burdens on all these actors in terms of cost and/or time so the tradeoff between cost and time due to restricted CO_2 emissions is also analyzed. Potential port delays at the US west-coast ports add additional constraints to the problem. The proposed fleet deployment problem draws on the LSFD problem with transshipment operations (Shuaian Wang & Meng, 2012) initially formulated as a mixed-integer nonlinear programming model with implicit container flow origin-based variables, that, adding a second vector of decision variables, is transformed into a mixed-integer linear programming model. Herrera et al., (2017) applied a related model to the Panama Canal expansion, adapting it to the Canal specificities to assess the impact of the increased Canal capacity in the costs of the liners operating the Trans-Canal routes. In the present paper the basic structure of this model is used incorporating a combined sea/railway network, the generalized cost including the transit time and the impact of CO_2 emissions restrictions. Initially we carry out a numerical simulation to minimize the operating costs of the fleet. In a second step we introduce the transit time and finally, we analyze the effect of CO_2 emissions restrictions.

The remainder of this paper is organized as follows: Relevant literature is reviewed in Section 2. The method employed, described in Section 3, is applied in Section 4; and the results obtained are analyzed in Section 5. Finally, Section 6 is dedicated to conclusions and possible further research.

2. Relevant literature

Three streams of literature are relevant to the object of the present paper. Literature regarding containership routing and scheduling problems at the strategic, tactical and operational planning levels has been reviewed by Meng *et al.*, (2014), including a detailed evaluation of studies at three levels: containership fleet size, mix and network design (strategic); frequency determination, fleet deployment, and speed optimization; and schedule design (tactical) and container booking and routing (operational). They underline the gap between theoretical studies and the liners' day to day operational challenges, and in doing so bring to light one of the main problems that academics encounter when conducting applied studies: liner shipping companies' sensitivity about their operating information, resulting in a lack of verifiable sources of data. As a network-based industry, network decisions play an important role for the liner's operation managers. Tran and Haasis, (2015) have undertaken a thorough literature review dealing with network optimization decisions in container liner shipping, through examining more than 120 papers and dividing the problem into three main categories: container routing, fleet management and network design. Network optimization is a crucial operational factor for the companies since fierce competition among the carriers leads to operations at the lowest possible cost, which implies very tight schedules. Schedule planning is one of the key elements in liners' decision-making process and highlights the network-based character of the industry. Three different categories of problems are involved: optimal routing and container flow; optimal design of the network; and efficient fleet operation. Some of the authors conclusions point to the increasing concentration, the growing tendency to deploy and operate mega-vessels, the emergency of great alliances connecting a great number of operators and the expansion of the industry towards hinterland operations. The existing mathematical models for the treatment of the container liner fleet deployment (CLFD) problem are reviewed by Wang and Meng, (2017), including container transshipment and routing, uncertain demand, empty container repositioning, ship sailing speed optimization and ship repositioning. In that review, fleet deployment with container transshipment and routing models are extensively analyzed, including path-based and origin-destination-link-based fleet deployment models. The origin-link-based fleet deployment model -used in this paper- is also examined, highlighting the advantage of this model regarding the number of flow variables, which is one order of magnitude smaller than in the O-D-link based model. Liner ship fleet deployment (LSFD) has been extensively studied in recent years. Wang and Meng, (2012) emphasize the importance of transshipment in the LSFD problem. They propose a MIP formulation for a model in which any amount of transshipment operations is permitted in any port. The number of transshipped containers is implicitly represented by origin-based container flow variables substantially reducing the number of required variables. An extended formulation of this model is used in the numerical simulations of this paper. Meng and Wang, (2012) treats the integrated problem linking the tactical level fleet deployment problem to the operational level container routing problem. Wang, (2013) adds further elements to this problem such as slot-purchasing, type of container ships and empty containers repositioning, developing a MILP model, and relaxing the number of transported containers as continuous variables. A fleet deployment problem involving cargo transshipment, multiple container routing options and uncertain demand is proposed by Wang and Meng, (2010), formulating the problem as a stochastic program maximizing the expected profit. Initially a sample average estimate is derived from a random sample to approximate the objective function, thereby solving the resulting deterministic program, by repeating the process with different samples until a candidate solution is obtained. The same type of problem is proposed by Meng *et al.*, (2012) but including in the deployed fleet not only the liner owned ships but charters ships from other liners.

The second stream concerns the time dimension. Time as a trade cost has been extensively studied by D. Hummels, (2001) analyzing the cost consequences of shipping times on trade, and the impact of time on trade patterns and international production organization. Regarding US trade he finds that each travelling day is worth 0.8 percent of the value of the good per day on average, equivalent to a 16% tariff for the average length (20 days) ocean shipment, estimating that each additional day in ocean transport decreases the probability that a country will export to the US from 1 percent (all goods) to 1.5 percent (manufactured goods). In a later work, (Hummels & Schaur, 2013) the authors undertake an analysis of the exporter's choice between fast and expensive air transport, and slow, inexpensive ocean transport. Using US imports data, the consumer valuation of time is estimated to an equivalent to an ad-valorem tariff of 0.6 to 2.1% per day in transit, with the parts and components trade comprising the most time sensitive flows.

Thirdly, the environmental aspect of shipping has given birth to a rich literature, especially dealing with CO_2 emissions. Cariou *et al.*, (2019), for example, identify the main factors influencing containerships' CO_2 emissions, concluding that the key reasons for the decrease in annual CO_2 emissions achieved in recent years can be found in fuel efficiency - due to technological evolution in the industry and slow steaming- and changes in network design aimed at shortening the sailed distance with resulting fuel savings. The hidden side effects of shipping emission reduction on supply chains have been studied by Luo, (2013), who reviewed existing studies and identified many of the secondary effects of shipping emission reduction, among them, the impact on world trade patterns and shipping industry market concentration. Luo analyzed the impact of an increase in ships' new building and scrapping activities as a consequence of fleets renewal to comply with emission rules and the influence of these rules on port development and operations. Other research contributions (Corbett, Wang, & Winebrake, 2009), (Lindstad, Asbjørnslett, & Jullumstrø, 2013), (Chang & Wang, 2014) emphasize the connection between speed and emission reduction, arguing that slow steaming is one of the most valuable tools to reduce GHG emissions in the shipping industry. The problem of CO_2 emissions in connection with supply chains have been studied among others by Nouira, Hammami, Frein, & Temponi, (2016), who assessed the impact of carbon-sensitive customers in the design of forward supply chains, including in this design -among other factors- transport mode selection.

3. Method

The LSFD problem involves a liner container shipping company that operates a network (set R)[1] of ship routes $r \in R$, serving on a weekly basis a set P of ports $p \in P$. Each ship route is defined by its port rotation:

$$p_{r1} \rightarrow p_{r2} \rightarrow \cdots \rightarrow p_{rN_r} \rightarrow p_{r1} \quad [1]$$

For any route R, the total number of ports of call is N_r the ith port of call is p_{ri} (i = 1, 2, …, N_r), and I_r = {1, 2, …, N_r} is the set of port indices. The set $I_{rp} \subset I_r$ is the set of port indices referred to a specific port $p \in P$. The routes are cyclical ($p_{r,\mathrm{N}_r+1} := p_{r1}$) and the voyage between the ports p_{ri} and $p_{r,i+1}$ is denoted as *leg i* of the ship route $r \in R$. This leg can be defined by a pair of consecutive ports $\left(p_{ri}, p_{r,i+1} \middle| i \in I_{\mathrm{r}}\right)$.

The containers are reflected as twenty equivalent units (TEU's). At any port $p \in P$, the costs (USD/TEU) related to the containers' loading and discharge are $\hat{c}_p$ and $\tilde{c}_p$, where $\bar{c}_p$ is the transshipment cost. Note that transhipment is a source of income for container terminals. For liners, if transhipment is not providing an operational cost advantage but only an additional handling cost, this cost cannot be passed on to the end customer as it is not value-added. This is also the reason why shipping companies tend to avoid it. To encourage transshipment operations among the liners, ports make $\bar{c}_p < \hat{c}_p + \tilde{c}_p$. The number of containers d_{od} (TEUs/week) transported between each pair of origin $o \in P$ and destination $d \in P$ ports is considered as the input for the fleet deployment problem. The liner shipping company deploys a fleet (set ϑ) of ships of type $v \in \vartheta$, each with a fixed operating cost c_v^{opr}(USD/week). This cost does not depend on the number of voyages and includes the cost of the spare parts,

[1] All notation is listed in Table A. 1

lubricants, fuel for the auxiliary power plant, maintenance, repair, crew and administration. For a ship $v \epsilon \vartheta$ the berth occupancy charges at port $p \epsilon P$ are c_{pv}^{ber} (USD/h). The maximum capacity of a ship $v \epsilon \vartheta$ is Cap_v (TEU's) being N_v^{own} the number of ships of type $v \epsilon \vartheta$ owned by the liner. It is assumed that all ships deployed on a specific ship route belong to the same ship type. For operational reasons it is difficult for ships with different sailing speeds to maintain a reliable service frequency. Additionally, it is difficult to maintains operational efficiency in ports if ships of different capacities are deployed. Constraints like the ports and/or canals' physical or geographical characteristics prevent some types of ships from being deployed on some routes. Consequently, a sub-set $\vartheta_r \subset \vartheta$ is defined for the candidate ships that can be deployed on the route $r \epsilon R$. To maintain the schedule, the number of ships to be deployed on a route is dependent on the round-trip time (sailing time plus port operations time); that is, the model assures that the number of ships sailing in any week, equals the number of weeks of the round-trip. The total sailing time -including the pilot time $t_{r,i}^{fix}$ necessary for port entrance of a ship type $v \epsilon \vartheta_r$ deployed on a route $r \epsilon R$ sailing at a speed s_{rv}^{spd} on a leg i of length p_{ri}^{dis} is denoted by τ_{rv}^{fix}:

$$\tau_{rv}^{fix} = \sum_{i \epsilon I_r} (t_{r,i}^{fix} + p_{ri}^{dis}/s_{rv}^{spd}) \qquad \forall r \epsilon R; \ \forall v \epsilon \vartheta_r \qquad [2]$$

Port operations time on the other hand, is related to the efficiency and number of quay cranes operating a ship at the corresponding port. For a ship $v \epsilon \vartheta$, the average time needed for loading/unloading one TEU at a port $p \epsilon P$ is defined by t_{pv} (h/TEU).

The operating costs of a ship route $r \epsilon R$ deployed with m_r of type $v \epsilon \vartheta_r$ can be divided in three parts: costs associated with the ship ($m_r c_v^{opr}$), costs associated to the route (voyage costs c_{rv}^{fix}) depending only on the type of ship v, and the cost of berthing at each port that depends on the time berthed and the corresponding berthing charges. The voyage costs c_{rv}^{fix} include the fuel cost and the port entrance charges. For a route $r \epsilon R$ deployed with ships of type $v \epsilon \vartheta_r$, each of them consuming fuel priced at p_v^{fuel} (\$/ton) at a rate of $\tilde{c}_v^f$ (ton/h) and paying a call fee of $c_{p_{ri}v}^{entr}$ at the entrance of the ports the voyage cost is:

$$c_{rv}^{fix} = \sum_{i \epsilon I_r} [c_{p_{ri}v}^{entr} + (p_{ri}^{dis}/s_{rv}^{spd}) \tilde{c}_v^f p_v^{fuel}] \quad \forall r \epsilon R; \ \forall v \epsilon \vartheta_r \qquad [3]$$

In addition to these costs, total costs also include container handling costs at the different ports.

The LSFD problem is to determine the types and number of ships that a liner shipping company must deploy on the served routes, as well as the number of transshipped containers at the different ports of the network to satisfy the weekly container demand and minimize the total weekly cost. Noting that the round-trip time of a route depends on the sailing time -that defines the weekly number of ships in operation- and the number of containers handled at the ports on the route, the problem, formulated as a LSFD model, will involve two types of decision variables: variables related to fleet deployment and those related to the container flow with container transshipment operations. The former type includes the number of ships m_r deployed on route $r \in R$ necessary to maintain a regular service and a binary variable x_{rv} that takes the value of 1 if the ship route $r \in R$ is deployed with ships of the type ($v \in \vartheta_r$), being 0 otherwise. To linearize the corresponding model using the big-M modelling method an additional variable m_{rv} is introduced, denoting the number of ships of type $v \in \vartheta$ deployed on the route $r \in R$. The latter type includes the number of containers (TEUs/week) originating from port $o \in P$ and loaded at the *i*th port of call on the $r \in R$ ship route, denoted by $\hat{z}^o_{ri}$, the number of containers (TEUs/week) originating from port $o \in P$ and discharged at the *i*th port of call on the $r \in R$ ship route, denoted by $\tilde{z}^o_{ri}$ and the number of containers (TEUs/week) originating from port $o \in P$ and stowed on board the ships sailing on the *i*th leg of the $r \in R$ route, denoted by f^o_{ri}. To linearize the model the variable z_{riv} corresponding to the total number of containers handled in a ship $v \in \vartheta$ at the *i*th port of the route $r \in R$ is equally introduced.

To model the LSFD problem a set of two vectors of decision variables is assembled:

$$\mathbf{x} = (m_r, x_{rv}, \hat{z}^o_{ri}, \tilde{z}^o_{ri}, f^o_{ri} | r \in R, v \in \vartheta, i \in I_r, o \in P, d \in P, o \neq d) \quad [4]$$

$$\hat{\mathbf{x}} = (m_{rv}, z_{riv} | r \in R, v \in \vartheta_r, i \in I_r) \quad [5]$$

The proposed mixed-integer linear programming model includes the costs related to the ships in operation, the voyage costs, the cost of berthing, and the transshipment and handling costs. Two additional parameters are added to include the time perception of the importers. We have not considered the cost of fixed capital, supposing that the different liners operate in unison without any competition between them, acting *de facto* as a single liner that manages a combined maritime-railway fleet, which oversees all China-US maritime containerized traffic. To highlight the importance of the costs of traversing the Panama Canal, these are considered separately, and are not included in the voyage costs c^{fix}_{rv}. To that effect, two new sub-sets are defined: the set of routes including the Canal ($R_c \subset R$) and the set of port indices ($I_{rc} \subset I$) of the last port of call before the Canal transit in the route $r \in R_c$. In compliance with the Canal rules, a tariff c^{canalc}_{ri} per TEU on board ships traversing ($f^o_{ri} \mid r \in R_c, i \in I_{rc}$); and c^{canalv}_{riv} per TEU in vessel capacity (Table A. 2) are applied. For the set of rail routes, a new sub-set $R_{rl} \subset R$ is defined. The land route distances are expressed in nautical miles (nm) and the sailing and running speeds in nm/h (knots). Due to the different nature of the ship and rail networks, all the rail costs except the fuel costs have been integrated into a single cost related to the rail voyage. Therefore, fixed operating costs, berthing and entrance costs and the handling and transshipment costs are equal to zero in the rail network. The remaining cost is a rail specific fixed voyage cost ($c^{fixrl}_{rv} \mid r \in R_{rl}, v \in \vartheta_r$) related to the net average rail freight cost (c^{rf}) of the US railway system:

$$c_{rv}^{fixrl} = \sum_{i\epsilon I_r} p_{ri}^{dis}\, c^{rf} \qquad \forall r \,\epsilon\, R_{rl};\;\; \forall v \,\epsilon\, \vartheta_r \tag{6}$$

In sum, the minimum total weekly cost $TC'(\boldsymbol{x},\widehat{\boldsymbol{x}})$ of a joint group of liner shipping companies and rail operators, acting as a single entity and deploying m_{rv} ships and trains of type $v \,\epsilon\, \vartheta_r$, on the routes $r \,\epsilon\, R$, to attend a weekly demand d_{od}, is obtained as:

$$\begin{aligned}
\min_{\boldsymbol{x},\widehat{\boldsymbol{x}}} TC'(\boldsymbol{x},\widehat{\boldsymbol{x}}) = & \sum_{r\epsilon R}\sum_{v\epsilon\vartheta_r}\left(m_{rv}c_v^{opr} + c_{rv}^{fix}x_{rv}\right) \\
& + \sum_{r\,\epsilon\, R_{rl}}\sum_{v\epsilon\vartheta_r} c_{rv}^{fixrl}x_{rv} \\
& + \sum_{r\epsilon R_c}\sum_{i\epsilon I_{r_c}}\sum_{o} c_{ri}^{canalc}\; f_{ri}^{o} + \sum_{r\epsilon R_c}\sum_{v\epsilon\vartheta_r}\sum_{i\epsilon I_{r_c}} c_{riv}^{canalv}x_{rv} \\
& + \sum_{r\epsilon R}\sum_{i\epsilon I_r}\sum_{v\epsilon\vartheta_r} c_{p_{ri}v}^{ber}t_{p_{ri}v}z_{riv} \\
& + \frac{1}{2}\sum_{p\epsilon P}\bar{c}_p\left[\sum_{r\epsilon R_p}\sum_{i\epsilon I_{rp}}\sum_{o\epsilon P}(\hat{z}_{ri}^{o} + \tilde{z}_{ri}^{o}) - \sum_{d\epsilon P} d_{pd} - \sum_{o\epsilon P} d_{op}\right] \\
& + \sum_{o\epsilon P}\sum_{d\epsilon P}(\hat{c}_o + \tilde{c}_d)\, d_{od}
\end{aligned} \tag{7}$$

s.t.

$$\sum_{v\epsilon\vartheta_r} x_{rv} = 1 \qquad \forall r \,\epsilon\, R \tag{8}$$

$$m_{rv} \leq\; M_1 x_{rv} \qquad \forall r \,\epsilon\, R;\; \forall v \,\epsilon\, \vartheta_r \tag{9}$$

$$168 m_{rv} + M_2(1 - x_{rv}) \geq \tau_{rv}^{fix} + \sum_{i\epsilon I_r} t_{p_{ri}v}z_{riv} \qquad \forall r \,\epsilon\, R;\; \forall v \,\epsilon\, \vartheta_r \tag{10}$$

$$\sum_{o\epsilon P} f_{ri}^{o} - \sum_{v\epsilon\vartheta_r} Cap_v x_{rv} \leq 0 \quad \forall r \,\epsilon\, R;\;\; \forall i \,\epsilon\, I_r \tag{11}$$

$$f_{r,i-1}^{o} + \hat{z}_{ri}^{o} = f_{ri}^{o} + \tilde{z}_{ri}^{o} \qquad \forall r \,\epsilon\, R;\;\; \forall i \,\epsilon\, I_r;\; \forall o \,\epsilon\, P \tag{12}$$

$$\sum_{r \epsilon R_d} \sum_{i \epsilon I_{rd}} (\tilde{z}_{ri}^o - \hat{z}_{ri}^o) = d_{od} \quad \forall o \epsilon P; \; \forall d \epsilon P; \; d \neq o \qquad [13]$$

$$z_{riv} \leq M_3 x_{rv} \quad \forall r \epsilon R; \; \forall i \epsilon I_r; \; \forall v \epsilon \; \vartheta_r \qquad [14]$$

$$z_{riv} + M_4(1 - x_{rv}) \; \geq \sum_{o \epsilon P} (\hat{z}_{ri}^o + \tilde{z}_{ri}^o) \;\; \forall r \epsilon R; \; \forall i \epsilon I_r; \; \forall v \epsilon \vartheta_r \qquad [15]$$

$$f_{ri}^o = 0 \quad \forall r \epsilon R \quad \forall i \epsilon I_r; \;\; \text{o} = p_{ri+1} \qquad [16]$$

$$\tilde{z}_{ri}^o = 0 \quad \forall r \epsilon R \quad \forall i \epsilon I_r; \;\; \text{o} = p_{ri} \qquad [17]$$

$$x_{rv} \in \{0,1\} \qquad \forall r \epsilon R; \quad \forall v \epsilon \vartheta_r \qquad [18]$$

$$m_{rv} \in \mathbb{Z}^+ \cup \{0\} \;\; \forall r \epsilon R; \; \forall v \epsilon \vartheta_r \qquad [19]$$

$$\hat{z}_{ri}^o \geq 0 \quad \forall r \epsilon R; \quad \forall i \epsilon I_r; \; \forall o \epsilon P \qquad [20]$$

$$\tilde{z}_{ri}^o \geq 0 \quad \forall r \epsilon R; \quad \forall i \epsilon I_r; \; \forall o \epsilon P \qquad [21]$$

$$f_{ri}^o \geq 0 \quad \forall r \epsilon R; \quad \forall i \epsilon I_r; \; \forall o \epsilon P \qquad [22]$$

$$z_{riv} \geq 0 \quad \forall r \epsilon R; \quad \forall i \epsilon I_r; \; \forall v \epsilon \vartheta_r \qquad [23]$$

Constraints [8] ensure that only one type of ship can operate on each route. Constraints [9] and [10] are the (weekly) service frequency constraints. Given that a round trip normally does not take more than 15 weeks: M_1=15 and $M_2 = 15$weeks x 168 h/week = 2520. The number of containers transported on each leg of each route is constrained by [11]. Constraints [12] and [13] enforce flow conservation at each port of every route. Constraints [14] and [15] define z_{riv} since constraint [15] must be binding in the optimal solution if $x_{rv} = 1$. For the extreme case that a full shipload of containers is discharged, and another one loaded, at a given port: $M_3 = M_4 = 2 \max \{Cap_v, \forall v \epsilon \vartheta\}$. Constraint [16] enforces that a container originated from a given port *o* does not return to that same port. Constraint [17] prevents a container from being unloaded at a port *o* if it originated from that same port. Constraints [18] to [23] define the non-negativity and/or integer attributes of the decision variables.

To introduce time in the model, two additional parameters are considered:

$$T^{tst} = \sum_{r \epsilon R} \sum_{i \epsilon I_r} \sum_{v \epsilon \vartheta_r} \sum_{o \epsilon P} \tau_{rv}^{fix} f_{r,i-1}^o \qquad [24]$$

$$T^{trans} = \sum_{p\epsilon P} t_p^{trans} \frac{1}{2}\left[\sum_{r\epsilon R_p}\sum_{i\epsilon I_{rp}}\sum_{o\epsilon P}(\hat{z}_{ri}^{o} + \tilde{z}_{ri}^{o}) - \sum_{d\epsilon P} d_{pd} - \sum_{o\epsilon P} d_{op}\right] \quad [25]$$

The parameter T^{tst} (in hours-TEU) defines the product of the total number of containers on board along every route r times the total sailing time of that route. Each element of the time-flow expression [24] therefore refers to the time that the containers are on board the ships sailing the leg p_{ri-1}- p_{ri} of the route r (including the time to enter the ports). The parameter T^{trans} (in hours-TEU) defines the total sum of the product of the estimated average time of transshipment operations at the corresponding ports times the sum of the number of transshipped containers at each port. Each element of the time-transshipment expression [25] therefore refers to the time that the total number of transshipped containers are waiting at each port for transshipment. The estimated average time of transshipment operations denoted as t_p^{trans} is set at 3.5 days.

To account for the relative importance of cost and time we use terms [24] and [25] as objective functions. Thus, we obtain a bicriterion function $L_n(\boldsymbol{x}, \widehat{\boldsymbol{x}})$ representing the total cost and the total transportation time. To find the Pareto-efficient set for the bicriterion problem, a convexification of the bicriterion function in [26] is used for a range of alternatives, ranging from a pure cost minimization (the liner's perspective), $\alpha_n = 0$, to pure time minimization (the end customer perspective), $\alpha_n = 1$:

$$L_n(\boldsymbol{x}, \widehat{\boldsymbol{x}}) = (1-\alpha_n)TC'(\boldsymbol{x}, \widehat{\boldsymbol{x}}) + \alpha_n(T^{tst} + T^{trans}) \quad [26]$$

$$0 \le \alpha_n \le 1;\ n = 0 \dots 10\ \ (\alpha_n = 0.1 * n)$$

Note that the convexity property of the actual efficient frontier can only be guaranteed for continuous real variables, in the case of the current mixed-integer programming model the frontier is non-convex. Thus, the convex weighting method obtains efficient points, but not the entire frontier, that may be "hidden" in non-convex, dominated segments. The lower the time involved in shipping the referenced number of TEUs, the higher the operating costs are. On the other hand, the only way to reduce total operating costs consists in accepting that the containers remain longer on route.

The comparison of the different discrete points of the efficient frontier allows an estimation of the trade-off ratio between shipment time and operating cost for the shipper. These comparisons describe the technically viable trade-offs between time and cost for the supplier of the transport service which depend on each of the specific solutions that compounds the efficient frontier. The opportunity value for the user is here an empirical parameter obtained by Hummels and Schaur (2013), assumed constant over the range of solutions obtainable. The contribution of this work is then in the identification of time- cost technically feasible combinations, which is preferred by the transport services' final consumer. A third criteria is introduced in the model to assess the environmental impact of the fleet deployment decisions, through evaluating the impact of a reduction of CO_2 both in the operation of the fleet and in the customer's perception of the delivery time. This criterion (defined as the CO_2 emission from transport operations) is formulated via an additional constraint that imposes a reduction in the fleet's CO_2 emissions. An additional parameter is used to calculate the fleet's total CO_2 emissions:

$$\varepsilon = \sum_{r \epsilon R} \sum_{v \epsilon \vartheta_r} \sum_{i \epsilon I_r} E_v^{factor} (p_{ri}^{dis} / s_{rv}^{spd}) \, \hat{c}_v^f x_{rv} \qquad [27]$$

The reduction is not achieved by implementing technical changes or improvements, as it is assumed to be a fixed state-of-the-art technology, but via speed limitations (slow steaming). Reductions in other GHG emissions, such as SO_2, might be achieved by reducing fuel sulphur content or implementing technical measures, such as exhaust gases filters. However, this analysis is limited to CO_2, which is by far the main contributor to a ship's GHG emissions.

3.1 The model as a representation of a liner fleet's operations

The model represents the main aspects of a liner's fleet operation since it reflects the costs of the entire fleet in one week. Certain characteristics, however, must be qualified. The stationary structure of the model does not allow for variations in weekly demand, as it is forecast for the entire period of operations. The only variations in the number of loaded and unloaded TEU's at the different ports arise from the variability in the volume of transhipped containers at the different ports and among the different transport modes, which could lead to congestion in the event of significant upward variations. Congestion problems in ports have a double consequence: on the sea side of the equation there is a queuing effect due to the accumulation of ships waiting to berth, and on the land side, a slowdown in operations due to the buildup of container inventory. These effects can be made endogenous using *clearing functions*. A clearing function defines the expected output in a planning period of a production resource as a function of a set of state variables that describe the volume of work available to the resource in that planning period (Missbauer & Uzsoy, 2020). Experience with supply chain network design (Sourirajan, Ozsen, & Uzsoy, 2007) indicates that taking into account congestion can lead to different solutions from those that overlook it. However, our static model represents a marginal volume for overall port operations in the East Coast ports, without real influence on the effective level of congestion. Thus, we have chosen to model the consequences of the aggregate congestion as exogenous parameters rather than as endogenous effects, using as primary parameter for congestion effects the pilot time ($t_{r,i}^{fix}$) necessary for port entrance. In the model, the variations of this pilot time parameter are used to model unforeseen events, such as strikes or natural disasters, which are not linked to demand variations. Using the pilot time parameter as a general parameter to capture congestion at port entry, we observe the relevant impact on the overall flowtime that the model evaluates.

4. Application

A schematic network of the US railway system (Figure 1) including the ramps of Chicago (CHI) and Atlanta (ATL) is added to a network of maritime routes connecting the port of Shanghai (SHA) in China with the ports Seattle (SEA), Oakland (OAK) and Los Angeles (LAX) in the US West-coast, Balboa (BLB) and Colon (MIT) at both ends of the Panama Canal and Houston (HOU), Miami (MIA), Norfolk (ORF) and New York (NYC), in the US East-coast:

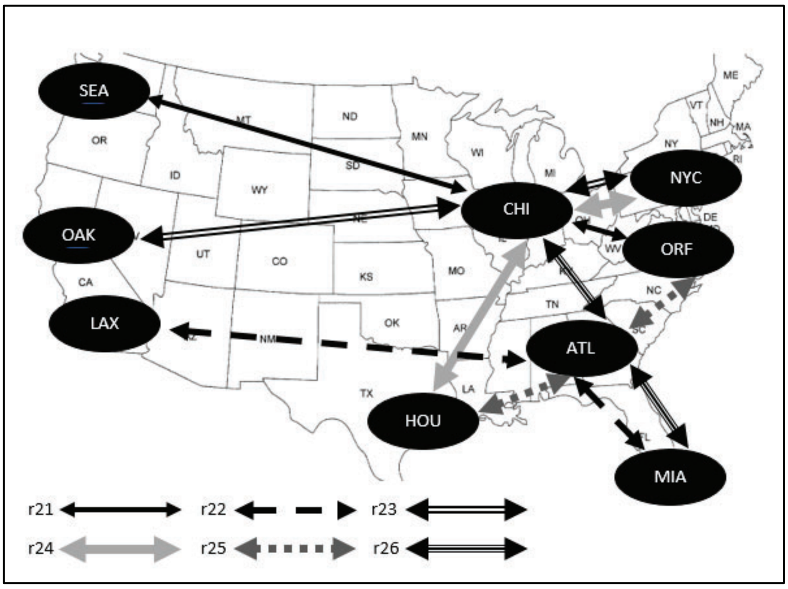

Figure 1. US rail routes with ports and ramps (CHI and ATL).

All these nodes are connected by a set of sea and rail routes, each of them forming a closed loop ending at the departure (►) point. Two of the sea routes are Transpacific, connecting China and the US West-coast. The third is an intercoastal route connecting US coasts via the Panama Canal:

r11	SHA-SEA-LAX-OAK	► **SHA**
r12	SHA-BLB-NYC-ORF-HOU-MIT	► **SHA**
r13	OAK-BLB-MIA-HOU-MIT-LAX	► **OAK**

Appendix A includes a graphic illustration of these routes (Figure A. 1 and Figure A. 2). The maritime network is combined with a rail one connecting the ports (acting at the same time as rail ramps) with the rail ramps of Chicago (CHI) and Atlanta (ATL) through the following six routes:

r21	SEA-CHI-ORF-CHI	► **SEA**
r22	LAX-ATL-MIA-ATL	► **LAX**

r23 OAK-CHI-NYC-CHI ► **OAK**

r24 HOU-CHI-NYC-CHI ► **HOU**

r25 HOU-ATL-ORF-ATL ► **HOU**

r26 MIA-ATL-CHI-ATL ► **MIA**

The length of each leg and its corresponding port of call is displayed in the Table 1 for each route. Given that every route is a closed loop, the last column is the distance between the final and initial ports/ramps of call:

Route	Port position/Leg distance (nm)											
	1	nm	2	nm	3	nm	4	nm	5	nm	6	nm
r11	SHA	5094	SEA	1139	LAX	369	OAK	5398	-	-		-
r12	SHA	8571	BLB	2011	NYC	287	ORF	1705	HOU	1528	MIT	8610
r13	OAK	3246	BLB	1239	MIA	970	HOU	1528	MIT	2951	LAX	369
r21	SEA	1908	CHI	858	ORF	858	CHI	1908	-	-	-	-
r22	LAX	2288	ATL	674	MIA	674	ATL	2288	-	-	-	-
r23	OAK	2096	CHI	794	NYC	794	CHI	2096	-	-	-	-
r24	HOU	1116	CHI	794	NYC	794	CHI	1116	-	-	-	-
r25	HOU	847	ATL	737	ORF	737	ATL	847	-	-	-	-
r26	MIA	674	ATL	625	CHI	625	ATL	674	-	-	-	-

Table 1. Routes: voyage distances and ports/rail ramps of call

For operational reasons, the liner shipping companies tend to operate uniform fleets on every route with the set of ships deployed on each route comprising the same type of ship. To allow the use of different ships on the routes, multiple lines are included on each route. Twelve identical lines (ln) are considered for the route r11 (ln1101-ln1112), eighteen for r12 (ln1201-ln1218) and seven for r13 (ln1301-ln1307). The rail routes include 20 lines each: (ln2101-ln2120) for r21, (ln2201-ln2220) for r22 and so on.

Using data from the U.S. Census Bureau (https://usatrade.census.gov/) to represent actual trade, the simulations are carried out with a total export/import traffic China-US (Jan-Dec 2017) of 194,108 TEU's/week transported at different sailing speeds, with an average weight of 9 ton/TEU each. The import/export traffic of the different states is assembled in eight groups according to the pattern displayed in Figure 2 and proportionally assigned to the different ports/ramps, one per group, except the California group traffic that is assigned to OAK and LAX:

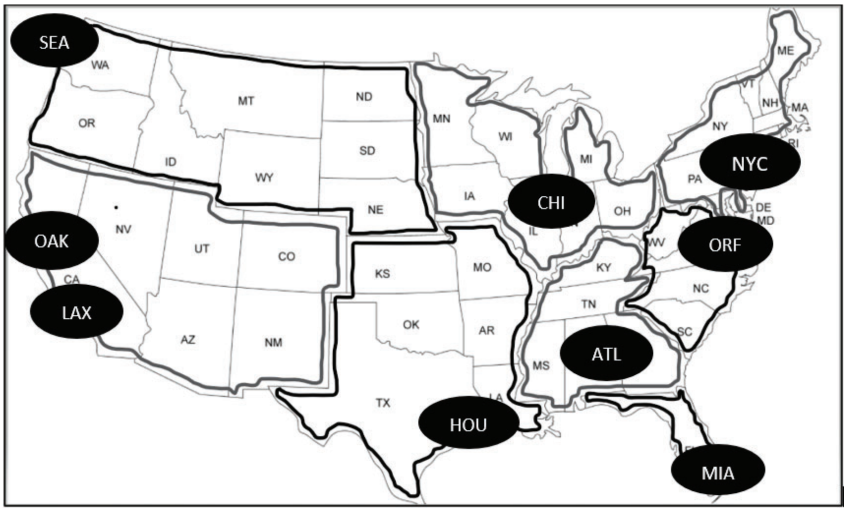

Figure 2. Assignment of US states to ports and ramps.

The ports at both ends of the Panama Canal (BLB and MIT) are included only as transshipment ports with no demand. The assignment of the demand of the different groups of states to the ports and ramps of the network is summarized in Table 2:

Ports	SEA	OAK	LAX	HOU	MIA	ORF	NYC	CHI	ATL
Export to SHA	5200	20546	20546	17082	4347	9731	21304	16639	14789
Import from SHA	5635	9157	9157	8303	2076	7535	8333	6474	7254

Table 2. Demand (TEU's/week). Total demand: 194,108 TEU's/week

15 types of ships are considered, each with a different capacity and sailing speed, plus a train type, coded as an additional type of vessel (Table 3). The ships consume Intermediate Fuel Oil (IFO) priced at 400$/ton whereas the train locomotives consume diesel fuel priced at 650$/ton with respective CO_2 emissions factors (E_v^{factor}) of 3.114 and 3.206 Kg of CO_2 per ton of consumed fuel/diesel oil.

Type	Code	$\boldsymbol{Cap_v}$	$\boldsymbol{s^{spd}_{rv}}$	$\hat{c}^{f}_{v}$	$\boldsymbol{c^{opr}_{v}}$	$\boldsymbol{c^{entr}_{priv}}$	$\boldsymbol{c^{ber}_{priv}}$	$\boldsymbol{t^{fix}_{r,i}}$	$\boldsymbol{t_{priv}}$
		TEU's	Knots	Tn/h	USD/week	USD	USD/h	h	h/TEU
Ship	v11	5,000	18	2.31	70,000	7,000	1,500	4	0.010
	v12		21	3.84					
	v13		24	6.04					
	v21	8,000	18	3.45	80,000	9,000	2,100		0.008
	v22		21	5.74					
	v23		24	8.92					
	v31	10,000	18	4.91	90,000	10,500	3,100		0.008
	v32		21	8.16					
	v33		24	12.68					
	v41	12,000	18	5.45	105,000	12,000	3,900		0.007
	v42		21	9.11					
	v43		24	14.39					
	v43	18,000	18	7.59	130,000	16,000	4,900		0.006
	v43		21	12.62					
	v43		24	19.61					
Train	v06	5,600	40	15.87	*	*	*		0.020

Table 3. Fleet characteristics

Not all routes can be travelled by the largest ships. Considering the restrictions in the Panama Canal, the maximum capacity of the ships deployed on the route r12 is limited to 12,000 TEUs. The route r13 performs as a coast-to-coast sea alternative to the rail, transshipping containers from the other two transoceanic maritime routes. Due to the limited draft of some of its ports, the ships deployed on this route are restricted to a capacity of 10,000 TEUs.

For rail destinations we consider a daily rail service of two "standard" trains/day with a capacity of 400 TEUs each. As mentioned, trains are considered to be a special type of ship. To match them to the weekly maritime service, the daily rail service is turned into a weekly-equivalent rail service with a single train of 5600 TEUs, equivalent to 14 "standard" trains. To calculate the route cost c^{fixrl}_{rv}, the average 2017 US freight rail rate (https://www.aar.org/data/average-u-s-freight-rail-rates-since-deregulation) is transformed into a cost per TEU and nautical mile, and applied to an equivalent train (Eq. train). After deducting the rail fuel cost (included in c^{fix}_{rv} as the fuel cost of the special ship matched to the trains) we obtain a net average rail freight cost (c^{rf}) as in Table 4 to be integrated along the rail routes to produce the route cost:

Average US freight rail rate (USD/ton-mile)	**0.0415**
Average US freight rail rate (USD/TEU-nm)	0.4299
Average US freight rail rate (USD/Eq. train-nm)	2,407.44
Eq. train fuel cost (USD/nm)	257.85
c^{rf} **(USD/nm)**	2.149,59

Table 4. Rail parameters

To capture the monetary value of the customer perception of time we draw on data from Hummels (2001) and Hummels and Schaur (2013). Departing from the modal choice of firms between air and maritime transport, Hummels and Schaur (2013), use timely delivery as an element to identify quality differentiation in trade. They end up by estimating a parameter that allows translating delays in days into a price equivalent form, considering that any point in the world can be reached by plane in one day. This parameter shows the marginal cost of delivery time increases beyond the second day. The ratio between cost and the value of the goods shipped allows the calculation of this cost in a tariff equivalent form. [2]

Using import trade data from the United States Census Bureau for 2017 (https://usatrade.census.gov/) we calculate a weighted average of the tariff equivalents of all the goods imported from China to the different US (continental) states involved in the simulation. Firstly, we calculate the composition in tons of each TEU, assuming each standardized container weighs nine tons, and follow the same pattern as the composition in tons of all imports at national level. Secondly, the value of each component/type of good of the standardized container results from applying the average value in USD per ton, obtained from global national data, to each of the components of the standardized TEU. The total value of each TEU corresponds to the sum of the value of all its components (44,449.4 USD). All in all, the final composition of each TEU mimics the average yearly composition of US imports from China. Thirdly, we apply the corresponding tariff equivalent parameter made available by Hummels and Schaur to the values by component/type of good. The sum of all these values represents the value of each day of delay by TEU (287.8 USD), which means that each additional day in transit is equivalent to imposing a 0.65% ad-valorem tariff for the importer to the average value of each TEU. Table 5 displays the distribution of the importers' time opportunity costs for different US states, averaging 0.65%, and ranging from 0.37% (Louisiana) to 1.16% (North Dakota). The importers of the states with lower values than the average will be less sensitive to delivery time delays; and the opposite for values higher than the average. Since the time opportunity costs depends on the type of goods imported, no clear geographical distribution pattern

[2] We are thankful to both authors, Hummels and Shaur, for sharing with us some estimates of this tariff equivalent parameter for different categories of goods (HS2 and HS4). These estimations do not incorporate product fixed effects because there are product categories with few observations. We were advised about the potential lack of robustness of these more detailed estimations, therefore the responsibility of using them is only ours. We used the results of the model in which the dependent variable is the relative air to ocean value discounted by the number of shipments proxy. This specification includes country fixed effects.

regarding the sensitivity of US importers (grouped by states) to delivery time changes can be observed:

State	TOC	State	TOC	State	TOC
Louisiana	0.37	Pennsylvania	0.65	Oklahoma	0.68
Montana	0.42	Illinois	0.65	Texas	0.69
West Virginia	0.52	Ohio	0.65	Indiana	0.69
Maine	0.53	Alabama	0.65	Oregon	0.69
Rhode Island	0.53	Arizona	0.65	North Carolina	0.70
New York	0.55	Delaware	0.66	South Dakota	0.70
Missouri	0.55	Iowa	0.66	Virginia	0.70
Washington	0.55	Mississippi	0.66	Nebraska	0.71
New Hampshire	0.55	California	0.66	Nevada	0.72
Massachusetts	0.57	Kentucky	0.67	Colorado	0.72
Minnesota	0.59	Maryland	0.67	Connecticut	0.72
New Jersey	0.59	Wisconsin	0.68	Georgia	0.73
Idaho	0.61	South Carolina	0.68	Michigan	0.74
Vermont	0.64	Florida	0.68	New Mexico	0.83
Kansas	0.64	Tennessee	0.68	Wyoming	0.88
Arkansas	0.64	Utah	0.68	North Dakota	1.16

Table 5. US states time opportunity cost (TOC) as average tariff equivalent (in %)

The slope of the generalized costs line is derived from this average tariff equivalent and implies that the importer is ready to pay 287.8 USD for the reduction of one day in transit. Now we can use this average tariff equivalent to identify which of the feasible combinations between transportation time and cost is optimal for the importer. This optimal combination would correspond to the one with the minimum generalized cost for users.

5. Results

Two simulations are carried out. In the first one -the baseline simulation- the time necessary for port entrance ($t_{r,i}^{fix}$) is set at 4 h for all ports except the Canal entrance ports (BLB and MIT) that are set at 24 h to compensate for Canal traversing time since the real Canal traversing speed is always much lower than the cruise speed. Due to the short distance to be sailed along the Canal, fuel consumption is not adjusted. In the second simulation, potential troublesome situations that produce delays, such as port strikes or natural disasters are modeled, focusing on the US Pacific Coast ports (SEA, OAK and LAX). The time ($t_{r,i}^{fix}$) required to enter these ports is set at 480 hours, while simulating a disruptive situation like a port strike or a natural disaster is represented by a delay of 20 days. The complexity of the model is 163,478 decision variables, including 5,358 binary variables; 40,502 constraints and in all 854,798 non-zero elements. The model was solved on an iMac 3.6 Ghz 8-core machine with 8 GB RAM running CPLEX solver using GAMS 1.5.2. The computing times vary in function of the convex weights in the bicriterion model from 5,361 seconds to 56,882 seconds. The dual gap tolerance was set to 0.001, but four of the runs were halted after 300,000 nodes with relative gaps ranging between 0.033 and 0.047.

To better reflect the trade-off between costs and transportation time, the total costs and the time involved are divided by the total number of referenced TEU's, which produces the average cost and time per TEU. The resulting efficient tradeoff curve is illustrated in Figure 3 for the benchmark (no-delay) and the 20 days delay scenario. The lower curve corresponds to the normal no-delay situation: four hours to enter each port (including pilotage) except for the two Panama Canal entry ports. In the upper curve the entry-port time at US west coast ports is set at 20 days, with other ports remaining as in the benchmark curve.

The trade-off depends on many model parameters such as average speed, berth occupancy charges, port-entry times etc. At the benchmark curve, reducing the cost/TEU from 2,562.98 USD to 1,033.61 USD can be accomplished at the cost of increasing the average time/TEU from 13.26 days to 15.27 days. Note that this model reassigns the whole intermodal traffic shifting between trains and ships, and among different shipping routes, in each of the iterations considered. The set of efficient points show an asymptotic behavior at the extremes. Increasing port-entry times shifts the benchmark curve away from the origin, showing that similar costs to the benchmark can only be achieved at the expense of an increase in the total number of hours. Similarly, keeping the benchmark time implies an increase in total operating costs. The iso-cost curves for each delay scenario are based on the empirical assessment for the US importers' value of time perception. This allows us to determine the optimal solution as the tangential point between the iso-cost curve and the efficient bi-criteria frontiers already derived in Figure 3 for the two situations. Note that the iso-cost curve is derived for the importer's valuation, whereas the trade-off curve that results from the bicriterion formulation expresses the overall impact cost of liner operations; both import and export:

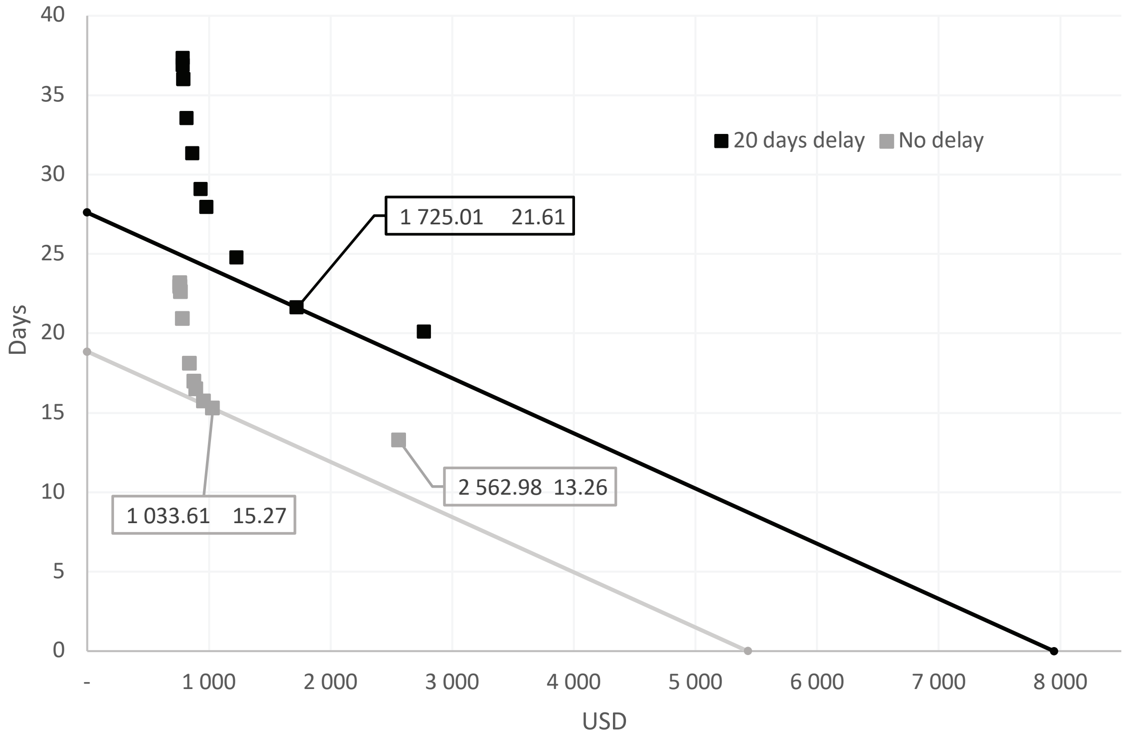

Figure 3. Unitary cost-time trade-off for imports

For the 20-day delay situation, importers would be ready to accept increased total delays to avoid higher costs. Table 6 decomposes this delay in terms of operating costs and time opportunity cost compared to the initial no-delay scenario. The opportunity cost of the average number of days that the containers are on their way is calculated by multiplying the number of days by the average value associated with the reduction of one day in transit (287.8 USD), which corresponds to an average tariff equivalent of 0.65%. In fact, importers are ready to accept up to six days of extra delay and an increase is 691.40 USD per container when the delay is 20 days.

It can be seen that carriers assume only 28.63% of the total impact of the delay in the generalized costs while the importers bear the rest, making them the most affected agents in this disruptive situation. States with time opportunity costs higher than the average (see Table 5), will support higher total generalized costs.

Delay (days)	Operating costs impact ($)	Time (days)	Time Opportunity cost	Generalized cost ($)
No-delay	1,033.61	15.27	4,394,71	5,428.32
20	1,725.01	21.26	6,118.63	7,843.64
Difference	691.40	5.99	1,723.92	2,415.32

Table 6. Cost increases (USD/TEU) associated with the different delays

In cases like strikes or other operational or administrative problems at ports, the total increase in operating costs should be compared to the cost of identifying the origin of the delays. Although there is no direct internalization of the time opportunity costs by the shipping companies, the readjustments in the use of the different transport modes and routes can be considered a response to the pressure to reduce costs and time by the clients.

A sensitivity analysis carried out reducing the amount (287.8 USD) that the customer is ready to pay for the reduction of one day in transit, reveals that the final outcome obtained remains stable unless the reduction in this amount goes beyond a 50% reduction.

Should the problem require a public administration response, such as in cases of infrastructure damage due to terrorist attacks or natural disasters, decisions from the public sector may consider those weekly total generalized costs.

A third simulation is carried out by limiting the fleet's CO_2 emissions. In the baseline simulation there are no delays and no limits imposed on CO_2 emissions. In that scenario the parameter ε in [27] is named ε^{bsl}. Now the emissions are limited to 80% of ε^{bsl}, adding an additional constraint to the model:

$$\varepsilon^{emr} \leq 0.8\ \varepsilon^{bsl} \qquad [28]$$

where ε^{emr} corresponds to the total emissions of the fleet in this second simulation. The Figure 4 shows the results:

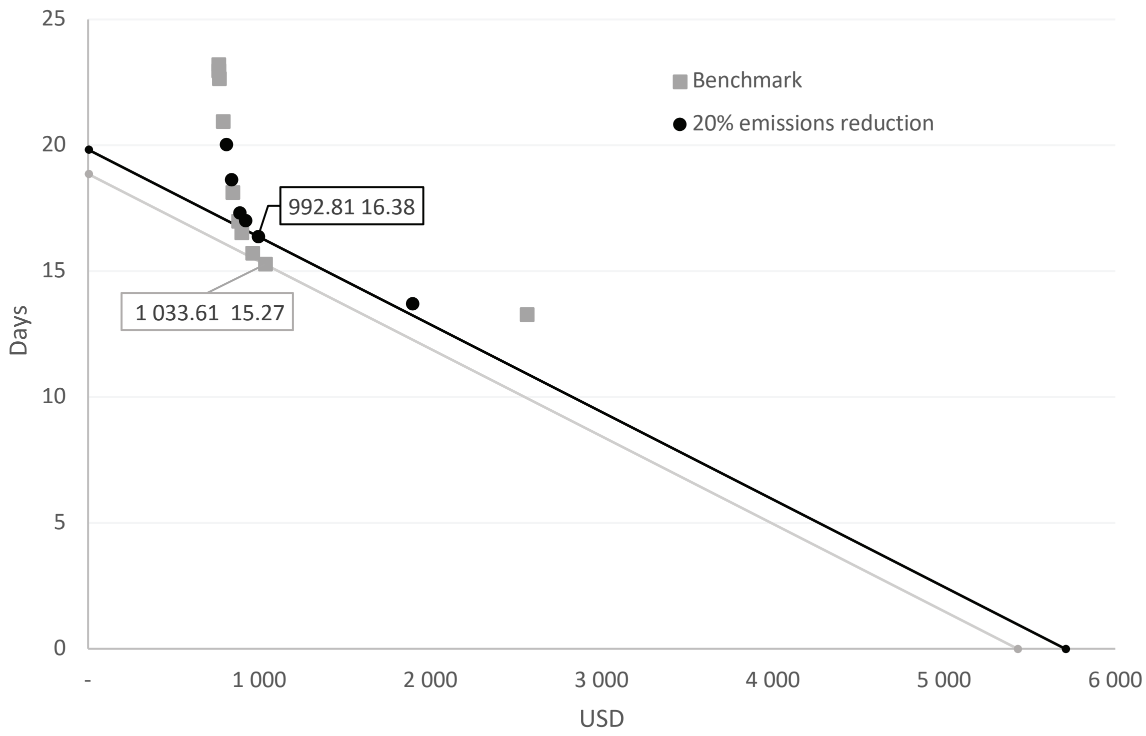

Figure 4. Emissions reduction. Unitary cost-time trade-off for imports

As displayed, a reduction of the fleet's CO_2 emissions implies a decrease in the operating costs and an increase in the transit time, implying that the customers face a time opportunity cost that is not compensated for by the reduction in operating costs; therefore, generating an increase in total costs.

When the emphasis is given to cost minimization (i.e. the weight of operating costs is much higher than that attached to the total time involved), the slowest vessels are chosen, leaving no room therefore for further reductions in speed in order to reduce CO_2 emissions. However, already from an equal weighting of the cost-time criteria, the model is capable of incorporating a 20% reduction in total emissions, and the new trade-off curve starts to diverge from the baseline. As can be observed in Table 7, in this emissions reduction scenario the liners are saving 3.95% of their operating costs whereas the time opportunity cost borne by the importers increased by 7.27%, with a corresponding 5.13% increase in total costs:

CO_2 reduction (%)	Operative costs impact ($)	Time (days)	Time Opportunity cost	Generalized cost ($)
0	1,033.61	15.27	4,394.71	5,428.32
20	992.81	16.38	4,714.16	5,636,97
Difference	-40.8	1.11	319.45	278.65

Table 7. Costs (USD/TEU) associated with emissions reduction

As Table 8 indicates, the relative weight of the fuel costs is the main cause of the positive impact caused by emissions reduction on the liner's operative costs. Slow steaming implies a larger fleet in operation but the decrease in fuel consumption offsets the increase in the residual cost:

	20% emissions reduction	Benchmark	Difference
Fuel costs (USD)	40,384,171.67	49,830,642.15	- 9,446,470.48
Remaining costs (USD)	151,935,315.34	150,800,527.73	1,134,787.61
Total (USD)	192,319,487.01	200,631,169.88	- 8,311,682.87

Table 8. Relative weight of fuel costs

The total CO_2 emitted by the fleet changes from 366.82 tons in the baseline scenario to 293.08 tons in the emissions reduction scenario. The evaluation of the marginal impact associated with the reduction of one ton of CO_2 is presented in Table 9:

	TOTAL		
	Operative Costs	Time Opportunity Costs	Generalized Costs
Total cost difference (USD)	- 7,919.606.40	62,007.800.60	54,088,194.20
CO_2 reduced (tons)	73.74	73.74	73.74
USD/Ton CO_2	- 107,399.06	840,897.76	733,498.70
Weekly demand (TEU's)	194,108	194,108	194,108
Marginal cost (USD/ ton CO_2/TEU)	- 0.55	4.33	3.78

Table 9. Impact of the unitary reduction of CO_2 emissions

As can be seen, the total abatement operative cost per ton of CO_2 is -107,399.06 USD, implying that on average the liner sees a positive cost impact per TEU equivalent to 0.55 USD. Since imposing limits on CO_2 emissions without any other technical modification to the ships means sailing speed reductions and consequently, savings in fuel consumption, the cost of these measures is borne exclusively by the importers who see how their time opportunity costs increase by 4.33 USD/TEU, due to the increased delivery time.

The sensitivity of the results with respect to the CO_2 reduction is illustrated in Figure 5 below where the cost components for the operating cost (liner) and time opportunity cost (consumer) are illustrated. A reduction below 35% leads to an infeasible outcome since no vessel category can obtain further savings through speed or size. As seen in the Figure, environmental restrictions are hitting the customer hard whereas the shipping company benefits, both in relative and absolute terms. A maximal reduction of 35% in CO_2 leads to a 7.1% decrease in operating cost and 18% increase in the cost of time for the importer.

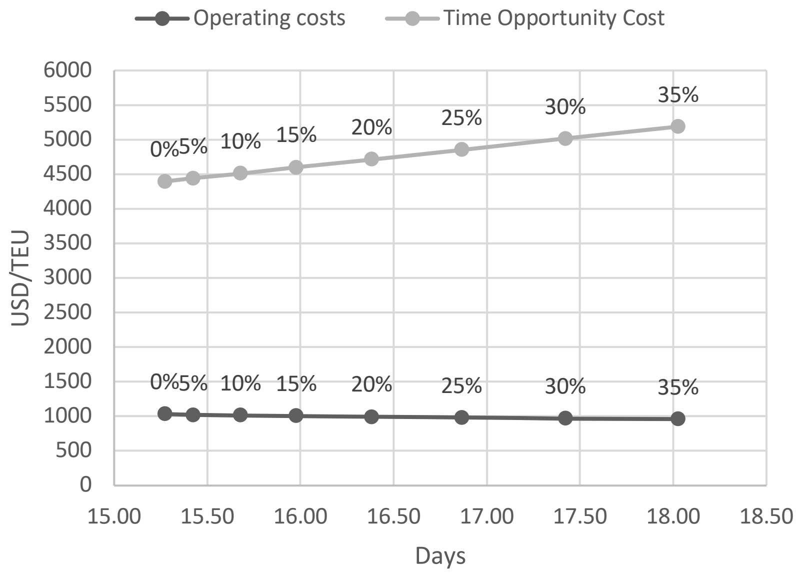

Figure 5 Cost components (operating cost, time cost) vs CO2 reductions.

From the liner's point of view, these limitations have the same effect as the slow steaming policies that have been applied in recent years to save fuel. The customer's perception, however, can be different. In both cases longer transit times can have a negative effect on their perception of the carrier's service quality but in the case of slow steaming it is the liner who is responsible for the delays, whereas the emission restrictions are imposed by public authorities.

6. Conclusions

The value that the customer assig*n*s to delivery time plays an important role in transport mode selection, therefore, the incorporation of operating time in the objective function is a valuable improvement. Shorter product lifecycles, increased retail competition and impatience in customer preferences are all signs of this tendency. Most of the general supply chain management strategies in the recent past have emphasized coherence between the operational features of the physical chain and the competitive features of the business, evoking strategies such as responsiveness, agility and JIT.

Our model fills a gap between the maritime transport literature, which continues to focus on cost minimization, and contemporary supply chain concerns. The numerical results highlight the non-linear tradeoff in time-cost performance, indicating the consequences that a liner-dominated policy might have on importers' inventory, ordering and customer service performance.

The second important contribution that the model makes is to quantify the goal conflicts with respect to environmental sustainability policies. The results here clearly show the correlation between the emission reduction policy and the liners' interests, contrasting with the importers' increasing costs in terms of time. In our setting of no technological changes, this finding predicts maritime industry support for general international reductions in CO_2 emissions whereas the opposite might be true for manufacturers of high-technology and perishable goods. On the other hand, the competitive pressure from end customers may create an incentive for carriers to invest in new technologies to reduce emissions without influencing the transport time; that is, the general cost of the routes.

The perspective in the current model is that of a central planner, ignoring the decentralized decision making of the individual liners, port operators and shippers facing market interaction through prices and other communication. The intention with this simplification is to focus attention on the crucial trade-off between cost and time at the highest level, the qualitative conclusions of which remain valid even in the decentralized scenario. Further research might investigate whether the solutions obtained in our centralized model are also stable equilibria in a market equilibrium model.

Other areas of further study might focus on port congestion. The sustained increase in port traffic is forcing a continuous process of investment in equipment to keep handling times at acceptable levels. Traffic distribution studies between different ports on the main maritime routes associated with the analysis of queuing phenomena produced by demand peaks and consequent congestion, would contribute to a better allocation of port resources.

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APPENDIX A

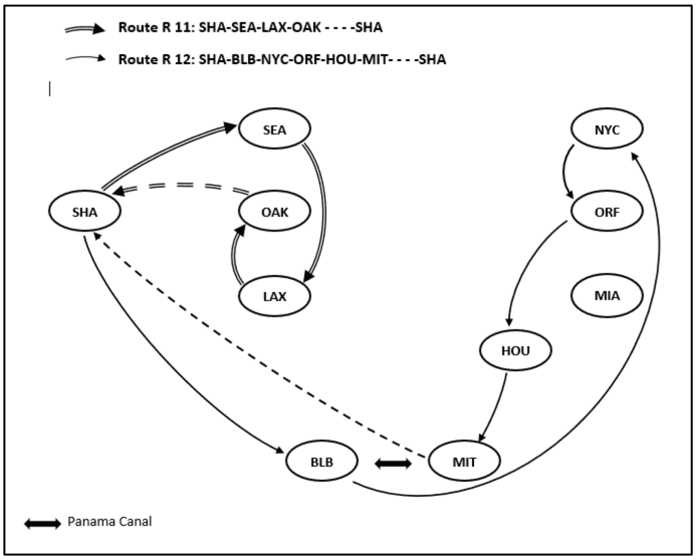

Figure A. 1. Intercontinental maritime routes

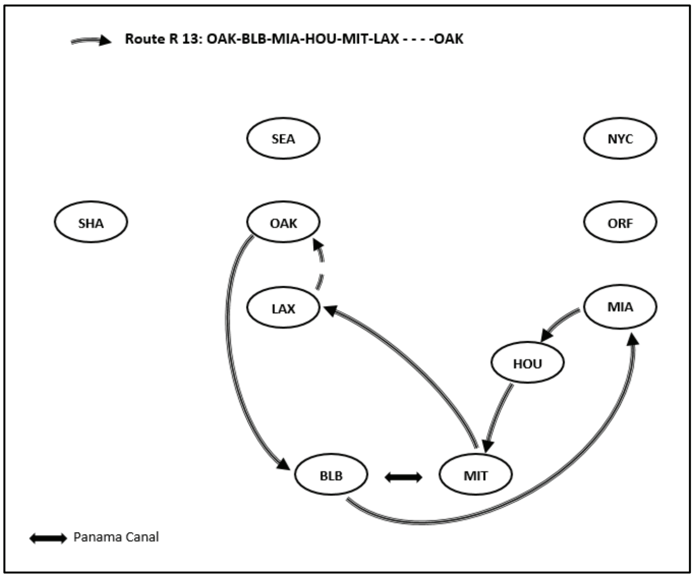

Figure A. 2. Coast to coast maritime route.

Cap_v	Maximum capacity of each ship type
c_{pv}^{ber}	Berth occupancy charges at each port per ship type
c_{ri}^{canalc}	Tariff applied to the number of TEUs on board the ships traversing the Canal
c_{riv}^{canalv}	Tariff applied to the ships transiting the Canal according to their capacity
$c_{p_{ri}v}^{entr}$	Call fee for entrance at each port per type of ship
$\tilde{c}_v^f$	Fuel consumption per type of ship
c_{rv}^{fix}	Voyage costs per ship and route
c_{rv}^{fixrl}	Rail specific fixed voyage cost per train and route
c_v^{opr}	Fixed operating cost per ship type
$\hat{c}_p$	Loading cost at each port
$\tilde{c}_p$	Discharging cost at each port
$\bar{c}_p$	Transhipment cost at each port
c^{rf}	Average rail freight cost of the US railway system
d	Destination ports
d_{od}	Number of containers transported between origin and destination ports
ε^{emr}	Limited emissions parameter
E_v^{factor}	Emissions factor
ε	Emissions parameter
ε^{bsl}	Baseline emissions parameter
f_{ri}^o	Containers stowed on board the ships per origin, route and port position
I_r	Set of port indices on each route

I_{rc}	Sub-set of port indices of the last port of call (per route) before the Canal transit
I_{rp}	Set of port indices referred to a specific port on each route
m_r	Number of ships per route
m_{rv}	Number of ships per type and route
M_1	Maximum round-trip time in weeks
M_2	Maximum round-trip time in hours
M_3	Two times the maximum capacity of a ship
M_4	Two times the maximum capacity of a ship
N_r	Total number of ports of call on each route
o	Origin ports
p	Ports
p_{ri}^{dis}	Length of each leg
p_v^{fuel}	Price of fuel per type of ship
P	Set of ports
p_{ri}	The *i*th port of call on each route
r	Ship routes
R	Set of ship routes
R_c	Sub-set of set of routes including the Panama Canal
R_{rl}	Sub-set of rail routes
s_{rv}^{spd}	Sailing speed
τ_{rv}^{fix}	Sailing time
$t_{r,i}^{fix}$	Pilot time necessary for port entrance

t_p^{trans}	Estimated average time of transshipment operations
t_{pv}	Average time per ship needed for loading/unloading one TEU at each port
T^{tst}	Number of containers onboard multiplied by the route sailing time
T^{trans}	Average time of transshipment multiplied by volume of transshipped containers
v	Type of ship
ϑ	Set of ships
ϑ_r	Sub-set of candidate ships that can be deployed on a route
x_{rv}	Binary variable
$\hat{z}_{ri}^o$	Loaded containers per origin, route, and port position
$\tilde{z}_{ri}^o$	Unloaded containers per origin, route, and port position
z_{riv}	Total number of containers handled per ship type, route, and port position

Table A. 1. Notation

Ship capacity TEUS's	5,000	8,000	10,000	12,000	18,000
Vessel tariffs (USD/ship)	30,000	40,000	50,000	60,000	90,000
Cargo tariffs (USD/TEU)	40	40	35	35	35

Table A. 2 Applied Panama Canal tariffs.