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The multi-port berth allocation problem with speed optimization and emission considerations

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Abstract

The container shipping industry faces many interrelated challenges and opportunities, as its role in the global trading system has become increasingly important over the last decades. On the one side, collaboration between port terminals and shipping liners can lead to costs savings and help achieve a sustainable supply chain, and on the other side, the optimization of operations and sailing times leads to reductions in bunker consumption and, thus, to fuel cost and air emissions reductions. To that effect, there is an increasing need to address the integration opportunities and environmental issues related to container shipping through optimization. This paper focuses on the well known Berth Allocation Problem (BAP), an optimization problem assigning berthing times and positions to vessels in container terminals. We introduce a novel mathematical formulation that extends the classical BAP to cover multiple ports in a shipping network under the assumption of strong cooperation between shipping lines and terminals. Speed is optimized on all sailing legs between ports, demonstrating the effect of speed optimization in reducing the total time of the operation, as well as total fuel consumption and emissions. Furthermore, the model implementation shows that an accurate speed discretization can result in far better economic and environmental results.

Keywords: Container terminal operations, Berth allocation problem, Speed optimization, Integer programming, Green maritime logistics

1. Introduction

Maritime transport has been growing in importance during the last decades, achieving a dominant role in the global transportation system. The 2015 edition of the Review of Maritime Transport (UNCTAD, 2015) estimates that the global seaborne trade increased by 3.4% in 2014, reaching over 9.84 billion tons, thus more than 80% of global merchandise trade by volume is carried by sea and handled by ports worldwide. In recent years, increasing fuel prices, growing congestion, depressed market conditions and environmental issues, such as air emissions, have brought a new perspective to maritime transportation. Therefore, in addition to being efficient from an economic perspective, the global maritime chain has to significantly improve its environmental friendliness (Psaraftis and Kontovas, 2013).

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The easiest way to estimate emissions from transportation (e.g. carbon dioxide, sulphur oxides etc) is to multiply the energy or fuel used by an appropriate emissions factor, which is the ratio of emissions produced per unit energy or unit fuel consumed (see Kontovas and Psaraftis (2016) for more on emissions calculations). For example, there is a linear relationship between fuel burned and CO_2 produced, with the proportionality constant being known as the carbon coefficient. These factors are empiricals, and for example, the IMO GHG study of 2014 used coefficients, which ranged from 3.114 kilograms CO_2 per kilogram fuel for Heavy Fuel Oil (HFO) to 3.206 kilograms CO_2 per kilogram fuel for Marine Diesel Oil (MDO).

The latest IMO study (IMO, 2014) provided updated estimates of CO_2 emissions from international shipping from 2007 to 2012. The 2012 figure, estimated by a bottom up method, was 796 million tonnes, down from 885 million (updated figure) in 2007, or 2.2% of global CO_2 emissions. CO_2 from all shipping was estimated at 940 million tonnes, down from 1,100 tonnes in 2007. According to a recent analysis (Psaraftis and Kontovas, 2009), containerships are the top CO_2 emitters in the world fleet, the high speed in comparison with other ship types being the major reason. This work focuses on two major interrelated challenges for the container shipping industry: (a) the increasing containerized trade opens up new opportunities for improving the cooperation between container terminal operators and liner shipping companies in order to reduce logistics costs and achieve efficient transportation systems, and (b) efficient and integrated operations, especially in terms of idle time minimization, correspond to savings in fuel consumption and bunker cost, but also in environmental benefits, in terms of reduced emissions.

More precisely the benefits from the integration that we present are as follows; (a) liner operators reduce their operating cost through fuel savings due to optimal speed selection and improved efficiency, (b) terminal operators streamline the use of the available berths increasing the efficiency of the terminals and (c) in most of the cases, there is also an environmental benefit due to reduced fuel consumption and, thus, ship air emissions. This work addresses the operations at container terminals along with speed optimization on all sailing legs between ports of a shipping network. We develop a novel formulation for the Berth Allocation Problem (BAP) under the perspective of tackling the above mentioned challenges and achieve a win-win-win solution for both the logistics parties at play (container ports and liner shipping companies) and the environment.

The classical BAP aims at allocating the berthing positions and times for the vessels arriving at the port. Our work extends the classical BAP by optimizing berthing decisions at multiple ports of a predetermined port-visiting route (string) along with optimizing the speed at each leg. Our problem deals with determining arrival times, berthing times and berthing positions for each vessel for each port in the string where the handling time for each vessel is known for each port-berth combination. In addition, the sailing speeds on each leg along the string are optimized. In short, we discretize the possible sailing speeds and select the optimal speed value for each leg. The total fuel consumption, which depends on the selected speed, is part of the objective function. By doing so, we achieve reductions in fuel costs and air emissions, as both of them are directly proportional to fuel consumption. In the classical BAP, the known arrival times either impose a hard constraint on berthing time (i.e. dynamic BAP, Imai et al. (2001)), or it is assumed that all vessels are available to be berthed at the time of planning (i.e. static BAP). In this paper, the multi-port BAP deals with determining the arrival time for each vessel at each port. The classical BAP distinguishes between discrete and continuous versions of the problem. In the discrete BAP, each vessel fits in a berth which has pre-determined borders (Buhrkal et al., 2011), while the continuous BAP relaxes this assumption and allows each vessel to berth at any discretized point (e.g. it can be completely continuous (Lee et al., 2010), discretized per each k^{th} meter (Iris et al., 2015)) along the quay. In this paper, the problem is modeled by using a discrete layout, where each vessel occupies one berth along the quay.

The sailing speed of each vessel is taken from a predefined set, which allows for variable arrival and berthing times at ports, thus avoiding an early arrival to a harbour if already busy, by slowing down on the sailing leg. The problem definition also allows for vessels to speed up in case the next terminal is available for berthing. Our scenario implies that the pool of ships is managed in a collaborative way, where the benefits and costs of the objective (total service time and fuel consumption minimization) are shared between shipping lines and port terminal operators. The realistic applicability of the above problem needs further investigation since shipping companies (that control the operation of vessels) and terminal / port operators (that control port operations such as berthing) are usually different entities with often conflicting interests. This is discussed in Sections 2.4 and 5.

The contribution of this paper is multi-fold. First of all, this study presents optimal solutions (for many instances) for the collaborative berth allocation and speed optimization problem for all ports and legs of a given shipping network. Secondly, we show that the collaborative problem presented in this paper can reduce emissions up to 42% in the entire network compared to the conventional design speed based planning in practice. Thirdly, we show that the increasing oil prices encourage slow steaming and in many cases even at the expense of prompt arrival to ports. Finally, the difference between emissions at sea and emissions during dwell times are also discussed in the context of berth availability for each port of the network.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature, provides an introduction to the BAP (see subsection 2.1), the integration of speed optimization into it (see subsection 2.3), and the co-operation of container shipping lines and terminal operators (Section 2.4). Section 3 describes the combined Multi-Port Berth Allocation and Speed Optimization Problem. In subsection 3.2, the integer linear programming formulation (ILP) is presented for the problem and enhancements for this formulation are communicated. Section 4 presents and discusses the results of some case studies and, finally, Section 5 presents the conclusions and a final discussion of the proposed model.

2. Background and Literature Review

Maritime container terminals represent a node of intermodal change between different means of transport. The handling of containers in a terminal is a complex process that includes operations in seaside, yardside and hinterland. Researchers have an increasing focus on the use of operations research (OR) methods in terminals operations (see the reviews Steenken et al. (2004), Stahlbock and Voß (2008), Kim and Lee (2015)). In this section, we first briefly review the traditional BAP studies, speed optimization studies, and then we extend the review to the combined problems of BAP and optimization of vessel arrival times. Finally we review the collaborative aspects with respect to terminal operators and liner companies. Davarzani et al. (2016) note that the eco-efficiency of ports and maritime logistics research is one of the most popular seminal areas.

2.1. BAP literature

Carlo et al. (2013), Bierwirth and Meisel (2015) and Iris et al. (2015) present literature reviews focusing on seaside operations of container terminals, including the BAP, where studies have been clustered with respect to problem definition, objective function properties and solution approaches. In this regard, due to the large variety of spatial, temporal and methodological problem settings, the research has produced a multitude of variants for the BAP.

In this study, we update the literature review on the traditional clustering using spatial and temporal properties of the BAP. Considering spatial attributes, the discrete BAP has been strongly put forward in Imai et al. (2001), Cordeau et al. (2005) and Buhrkal et al. (2011). Recently, Hu (2015), Hsu (2016), Lalla-Ruiz et al. (2016a) address variants of the discrete BAP. The pioneering study considering continuous BAP is Imai et al. (2005). Recently, it has been still in focus with the variants studied in Ursavas (2015), Iris et al. (2015), Mauri et al. (2016), etc. Moreover, in some related works, the quay is partitioned in a hybrid approach where some vessels might only fit in multiple berths (e.g. indented berths). We refer the reader to Kordi et al. (2016) for variants of such presentations. Considering the temporal attributes, most of the recent studies focus on the dynamic BAP, as introduced by Imai et al. (2001). While the studies addressed thus far solve the operational BAP, a new approach to temporal attributes is to consider cyclic vessel arrivals in a longer planning horizon where authors focus on assigning berths for vessels which arrive periodically (Jin et al., 2015, Imai et al., 2014, Peng et al., 2015).

There are various operational considerations for the BAP. All vessels must be berthed and processed within the planning horizon, and all vessels must be moored within the boundaries of the quay. The availability of some berthing positions might differ due to time windows (Cordeau et al., 2005), different priorities can be assigned to each vessel (Cheong et al., 2010), some of the vessels can have favorite berthing positions (Iris et al., 2015), or there could be different time-availabilities due to debts and tides (Lalla-Ruiz et al., 2016a). The goal of BAP is to provide fast and reliable services to vessels. Considering the objective function, models in the literature mostly aim at minimizing the sum of the waiting and handling times of vessels, or the total completion time. Other objectives are the minimization of the workload of terminal resources, the minimization of penalty costs associated either to the rejection of berthing or to the assignment of ships to non-desired berths, and the minimization of the deviation between the arrival order of vessels and the service order. Lalla-Ruiz et al. (2016b) formulate a mathematical model and propose heuristic methods to schedule the vessels in the waterway to arrive to a port system. They focus on the limited capacity of the waterway and discuss the effects of this problem on the BAP.

2.2. Speed optimization literature

Because of the non-linear relationship between speed and fuel consumption, a ship that sails slower will emit much less than the same ship going faster. In addition, emissions from ships are directly proportional to fuel burned. Therefore, the impact of a change in ship speed can be quite dramatic with respect to both ship operating costs and to emissions. As a common trend, slow steaming has been recently adopted by a large number of shipping liners, since it allows reducing fuel expenses, which, at high fuel prices, accounts for half to two thirds of voyage operating costs.

Lowering the speed alone cannot be the answer to emissions reduction, since negative economic consequences for shipping companies are likely to exclude them from the adoption.If one of the downsides of slow steaming is the longer sailing time, the minimization of time spent at ports by having a prompt berthing of vessels can offer the counterbalance to those negative effects. By reducing speed and arriving at port in a given time window instead of arriving early and then having to wait to be served, a ship may avoid a substantial amount of emissions, and, simultaneously, reduce operational cost (Kontovas and Psaraftis, 2011). Bottlenecks in container terminal operations, mainly regard the unavailability of berths and equipment, result in substantial idle times for ships at port. The most feasible way to reduce time in port is therefore through operational decisions regarding quayside operations (berth allocation, quay cranes scheduling, and vessel stowage). Still, dealing with speed is not new in the maritime transportation literature and this body of knowledge is rapidly growing. In Psaraftis and Kontovas (2013) some 42 relevant papers were reviewed and a taxonomy of these papers according to various criteria was developed. In Psaraftis and Kontovas (2015) and Psaraftis and Kontovas (2016) the taxonomy was amended and enlarged to include 51 papers, including some of the most recent ones.

We now briefly analyse the impact of including fuel optimization in the objective of a BAP formulation. Fagerholt et al. (2010) focus on reducing fuel emissions, by determining the optimal speed on shipping routes while satisfying port time window constraints. The arrival time within the time window of each port is discretized and the problem is solved as a shortest path problem on a directed acyclic graph. Computational tests show that the potential for reducing fuel consumption, and hence environmental emissions, is substantial. The speed optimization problem presented in Reinhardt et al. (2016) determine the sailing speed of the vessel in a leg and affects both the bunker consumption and the duration of the sailing in the leg. Reinhardt et al. (2016) solve the liner shipping network optimization, accounting for fuel consumption minimization on the sailing legs through an approximated piecewise linear function for the speed-fuel consumption relationship. The focus is on the shipping liner, hence only berthing times and not berthing positions are optimized. Results from a real-life data set show that it is possible to reduce fuel consumption significantly simply by rescheduling the port visit times. Finally, Wang (2015) focuses on a tactical liner ship route schedule design problem with speed optimization where authors incorporate time windows of ports as hard constraint.

2.3. Collaborative problems in seaside operations: BAP and optimization of vessel arrival times literature

Collaborative problems between liner shipping companies and terminals are mostly formulated by integrating the BAP with the determination of ship arrival times. Whenever the decisions about vessel arrival time is incorporated into the BAP and its variants, the collaboration is realized. In the literature, there are different ways of determining vessel arrival times with respect to the berth allocation or scheduling related problems. Golias et al. (2009) consider the amount of emissions produced hourly by each vessel in idle mode for berthing (just during mooring) and they plan the vessel arrivals accordingly. The authors try to reduce fuel consumption and vessel emissions by minimizing the total waiting time of vessels, based on the assumption that the shorter the waiting time is, the less the fuel consumption and vessel emissions. The model developed by Alvarez et al. (2010) allows variable vessels arrival times for the BAP. Fuel consumption minimization is included in the objective and three berthing policies are compared: First-Come-First-Served policy, estimated arrival time method and global optimization of speed, berth, and equipment allocation. Golias et al. (2010) focus on the berth scheduling problem by considering the bunker cost for all vessels in transit to their next port of call. Lang and Veenstra (2010) present simulation models for ship arrivals with the aim of suggesting ships to speed up or to slow down in order to arrive on time for an available berth. The objective includes fuel costs, delay costs and costs related to possible re-routings of containers which are not loaded/unloaded. Du et al. (2011) focus on the leg from vessels' current positions to the terminal for which the BAP is solved. They incorporate the tardiness and the fuel costs for all vessels. Du et al. (2015) address virtual-arrival policy which is based on reducing a vessels speed to meet the arrival time which is also a decision variable of the problem. For a single port, the problem optimizes traditional BAP variables along with the arrival time to port and the speed in the last leg. Chang and Jhang (2016) study decreasing the speed to 12 knots and transferring fuel 20 nautical miles (nm) away from the destination port. Results for a Taiwanese port show that CO_2 emissions reductions of about 41% have been achieved. Recently Andersson and Ivehammar (2017) applied a similar approach for a Baltic port where they showed that significant cost benefits can be achieved by adjusting speed instead of anchoring. Chang and Jhang (2016) and Andersson and Ivehammar (2017) are not optimization based studies. These two papers evaluate the performance of suggested scenarios.

Meisel and Bierwirth (2009) and Iris et al. (2015) focus on the integration of the berth allocation and the determination of the number of quay crane (QC) to assign. They allow vessels to speed up and arrive earlier than an Expected Arrival Time (EAT), while they impose a cost of earliness (compared to EAT) in the objective function and this is a reflection of the speed-up cost for the liner shipping company. Hu et al. (2014) focus on the fuel consumption and vessel emissions in the BAP, also determining the number of QCs to serve each vessel. The vessels can slow down, while maintaining the scheduling integrity of shipping service. Du et al. (2011), Hu et al. (2014) and Du et al. (2015) consider one port, and the fuel consumption-speed relation is linearized adopting the Second-Order Cone Programming (SOCP) transformation which is an equivalent transformation. The resulting transformation model is a mixed-integer convex quadratically-constrained model (See Wang et al. (2013) for an improved outer approximation that can handle general fuel consumption more efficiently).

Another collaboration between terminals and shipping companies can be achieved by integrating the BAP with ship routing and scheduling problem. Pang et al. (2011) solve the tramp shipping routing problem by considering berthing time clash avoidance with different vessels in a given terminal. In a later study, authors consider a deep integrated version of this problem with the transhipment possibility (Pang and Liu, 2014). Recently Dulebenets et al. (2016) focus on the policy agreement between liner shipping companies and terminal operators where each terminal offers a set of port handling rates. The proposed model minimizes the liners total route service cost by selecting the optimal handling rate at each port and the optimal vessel speed between each port of call on the port rotation.

The tactical problems such as the berth template design problem (Imai et al., 2014), the service allocation problem, and the integration of these problems (Lee and Jin, 2013) are also collaborative problems since they consider priorities of the shipping liner and adjust the available terminal resources with respect to these requirements. Recently Wang et al. (2015b) improve the level of collaboration for the existing tactical berth allocation problem by proposing two new collaborative mechanisms which are based on the utilities associated with the operations start days of each liner string and inventory cost of transshipment containers.

The multi-port BAP, speed optimization and emission considerations along the string in the berth allocation problem are novel aspects that our study brings into the state-of-the-art. Most previous studies (Du et al. (2015), Chang and Jhang (2016), Andersson and Ivehammar (2017), etc.) focus on a single port for such a problem.

2.4. Stakeholder's co-operation and co-opetition

Container terminals and shipping lines are the backbone of container shipping. In most of the cases, these two entities are not the same and they both have conflicting objectives. In addition, there is fierce competition both between the various shipping companies, and also between terminal operators, especially the neighboring ones.

The competition among shipping lines that service similar trading lines has always been extremely tough. However, in order to respond to this intense competition, liner companies cooperate in various ways, e.g. through slot purchase or exchange agreements, vessel sharing, joint ventures, and cargo sharing. Today, every major liner shipping company is part of an alliance, such as the 2M Alliance (Maersk and MSC) and the CKYHE Alliance (Cosco, K-Line, Yang Ming, Hanjin, Evergreen).

The practical applicability of our formulation assumes a strong cooperation between shipping lines and the operators of the terminals that are being served. Direct comparison with the scenario under which these players do not cooperate is not possible given the way that our problem is formulated but it is straightforward that in that case the ships will have to wait to be berthed as in most cases the vessel will arrive earlier. Thus, in order to achieve a good synchronization of berth availability, terminal operators have to be persuaded to commit themselves to such a collaborative scheme. This kind of cooperation is very challenging, especially given the conflicting economic interest of the parties. However, this kind of collaboration is receiving increased attention by the key industry players. Liner shipping companies are integrating their operations with terminal operators and inland transport companies. The top container lines have made agreements with various ports, and have also acquired some of them, in what is referred to as vertical integration. This integration occurs when a company acquires another company operating in the inbound or outbound logistics chain for the acquiring firms products or services (Lee and Song, 2015). This is the case where the shipping line and the terminal operator are the same entity, or under the same group of companies, e.g. the COSCO group operates a shipping line and various terminals such as in Hong Kong, Taiwan and Singapore. In addition, large shipping companies have various agreements with major terminals that include priority or even prompt berth in terminals.

The co-operation between ports and terminals has not been as strong as the one between shipping lines. There is some cooperation between terminals within the same port or within the same region, but this is also limited. This may change in the future especially given the fact that port terminal operators are expanding globally. For example, PSA operates terminals in Europe (e.g Antwerp and Genoa) and Asia (e.g Singapore and Dalian), APMT has a big global network of ports in Europe (Aarhus, Rotterdam, Bremerhavem, Giaoio Tauro), USA (Tacoma, Los Angeles, New Orleans, Houston, Miami) and Asia (Yokohama, Dalian, Shanghai, Kaohsiung etc).

Several studies on competition and cooperation between container shipping lines and ports can be found in the literature. Some general surveys on the issue are, among others, the editorial of Panayides and Cullinane (2002), the review paper of Lee and Song (2015) and Lee and Song (2017). Lee and Song (2015) examine the environmental challenges that maritime logistics operators have recently faced and investigate strategic ways for maritime logistics operators to effectively manage competition and co-operation with their rivals. In addition, the same authors (see Lee and Song (2017)) have co-authored an excellent survey on research in the field of ocean container transport discussing a wide range of issues, among others on competition and cooperation between carriers, ports and terminals. Panayides and Cullinane (2002) address the issue of competitive advantage in several areas of related literature covering topics such as vertical integration and logistics strategy, strategic alliances, mergers and acquisitions, networks, economies of scale, regulation, pricing and shipper relationships.

A number of papers have provided overviews on specific issues, e.g., competition and cooperation between ocean carriers (Heaver et al. (2000); Notteboom (2004); Cariou (2008); Caschili et al. (2014)); vertical cooperation between ocean carriers and related service providers (Heaver et al. (2000); Panayides and Cullinane (2002); Notteboom (2004); Cariou (2008); Frémont (2009)); competition and cooperation between ports/terminals (Heaver et al. (2001); Song (2003); Notteboom (2004)), and Notteboom and de Langen (2015) and Lee and Lam (2015) for ports in Europe and Asia, respectively. Heaver et al. (2000) present an overview of cooperation agreements including alliances and mergers among shipping lines, conferences, vertical integration of liner companies with terminal operators or inland transport companies with a main focus on the competitive position of the ports in the structure.

3. Problem definition and mathematical model

This paper deals with problems of container terminals and liner shipping companies in an integrated approach. The subproblem related to container terminals aims at solving the discrete BAP of ports in the string of each vessel. More specifically, the BAP determines the berthing position, berthing start and end time for each vessel at each port. The subproblem related to each liner shipping company deals with selecting the optimal speed on each sailing leg along each string and determining port arrival times. Note that in this study we consider the transportation between terminals that are in different geographical locations. Our formulation can also cover the case where berths are within the same port but at different terminals. In this case, the berths should be predefined in the model.

In our multi-port BAP, a number of different ports are visited by a set of vessels. Each vessel sails along a predetermined string (route between ports) and visits all ports in the string. Each port operator allocates vessels to the available berths, serves the vessels by unloading and loading containers and let them depart for the next port of the string. In this sense, the sailing speed between each pair of ports is decided, and thus, arrival time for each port is calculated by considering the distance between ports. What is more, berthing times for all vessels at ports are variable and dependent on the selected speed and the availability of berths at each port. Additionally, we assume that the handling time for each vessel at each port is dependent on selected berth since terminals mostly make the yard assignment and QCs planning beforehand. This results in berth-dependent handling times. It is also assumed that a discrete BAP is adopted where each vessel can occupy exactly one berth.

Our problem aims at minimizing the costs of both the terminal and the liner shipping company. Besides, we consider the objective of minimizing total fuel consumption, and as a result the minimization of total air emissions. More information is provided in the following sections.

3.1. Fuel consumption model

Most of the papers that consider speed optimization assume that daily fuel consumption is a cubic function of ship speed, as follows:

$$F(s) = \left(\frac{s}{s_d}\right)^3 \cdot f_d \tag{1}$$

The cubic approximation is reasonable for some ship types, such as tankers, bulk carriers, or ships of small size, but may not be realistic at slow or near-zero speeds and for some other ship types such as high-speed large container vessels. In addition, the ships payload (i.e the amount of cargo carried) influences fuel consumption too. A realistic closed-form approximation of fuel consumption that takes both speed and payload into account is presented in Psaraftis and Kontovas (2013). However, without loss of generality in this work we assume a cubic relationship. An extension to incorporate the above inputs is straightforward assuming that the number of containers onboard the vessel are known.

In Eq.(1), $F(s)$ is the fuel consumption function measured in ton/hour, while s_d is the design speed of the vessel, s is the travelling speed measured in knots (nautical miles per hour), and f_d is the fuel consumption in ton/hour at the design speed. In order to obtain the fuel consumption unit ($\gamma_{i\delta}$), measured in ton/km, $F(s)$ is divided by s in Eq. (2).

$$\gamma_{i\delta} = \frac{F(s)}{s} = \frac{\left(\frac{s}{s_d}\right)^3 \cdot f_d}{s} \tag{2}$$

We model the multi-port berth allocation problem as a Integer Linear Programming (ILP) model. Therefore, a linearization approach is adopted in order to include the fuel consumption in the objective function. There are ways to linearize the fuel consumption function. Hu et al. (2014) tackle the non-linear fuel consumption in the BAP model through a SOCP transformation. The non-linearity can be simplified by using linear regression (Lang and Veenstra, 2010), or a discretization of times and speeds can be applied (Alvarez et al., 2010). In our case, the linearization is achieved through a discretization of the sailing speeds δ. We create the set S of different speeds (δ) where vessels can choose one of them to sail between each pair of ports on the string. For simplicity, no restrictions are imposed on the selected speeds for ships, thus assuming a homogeneous pool of vessels in terms of engines and sizes. The travelling time per unit distance Δ^{δ} is associated to each speed and a distance matrix for the sailing legs between the pairs of ports is given. The fuel consumption unit $\gamma_{i\delta}$ is assumed to be a function of the speed δ on the sailing leg and the specific ship i. All values for the fuel consumption unit are computed based on Eq. (2) for each vessel where the known design speed s_d, the range of sailing speed and the fuel consumption at the design speed f_d (ton/km) are used. The fuel consumption cost is computed as the product of the fuel consumption unit cost $\gamma_{i\delta}$ and the distance sailed d (km).

3.2. Mathematical Model

We formulate our mathematical model similarly to the Multiple Depot Vehicle Routing Problem with Time Windows (MDVRPTW) model for a single port presented in Cordeau et al. (2005). The MDVRPTW is defined on a graph $G^{k,p} = (V^{k,p}, A^{k,p})$ where the set of vertices $V^{k,p} = N \cup \{o(k,p), d(k,p)\}$ contains each berth k at each port p with an origin node $o(k,p)$ and a destination node $d(k,p)$ (o-d represent the starting and ending berth respectively). The set of ships N is the group of customers that must be allocated to berth k at each port p. The set of arcs

$A^{k,p} \subseteq V^{k,p} \times V^{k,p}$ is a subset of all the possible combinations of vertices.

Each ship i at each port p has a berthing start time-window $Start_i^p$ which must be met. The berthing end time-window is soft. If the berthing end time exceeds the expected finishing time EFT_i^p for ship i at port p, the delay cost is imposed. For the origin and destination vertices, the time window $[s^{kp}, e^{kp}]$ depends on the berth (vehicle) k at port p as berths can be available at different times. The handling time h_i^{kp} is the time needed to process each ship, and it is given for all the berths and ports in its string. Each ship i can start berthing after it arrives to the respective port.

Figure 1 illustrates the network diagram of a single ship travelling through four ports (p) where each port has four berths (b). The ship 1 visits the ports in the sequence of 1-2-3-4. In port 1, it berths to berth 1 at time unit T_1^{11}. After operations end at port 1, it sails from port 1 to port 2 at a speed of v_1^{15}. Then it berths at berth 2 at port 2, etc. The same figure also points out the waiting, handling times at port p and sailing times between port p and $p\prime$. The waiting time for a ship is the time difference between the berthing start time (T_i^{kp}) and ship arrival time (a_i^p). ΔEFT_i^p corresponds to delay. Meanwhile, $a_i^{p\prime}$ is the time when the ship arrives the next port $p\prime$.

Figure 1: Problem definition for the Multi-port Berth Allocation Problem: an example case

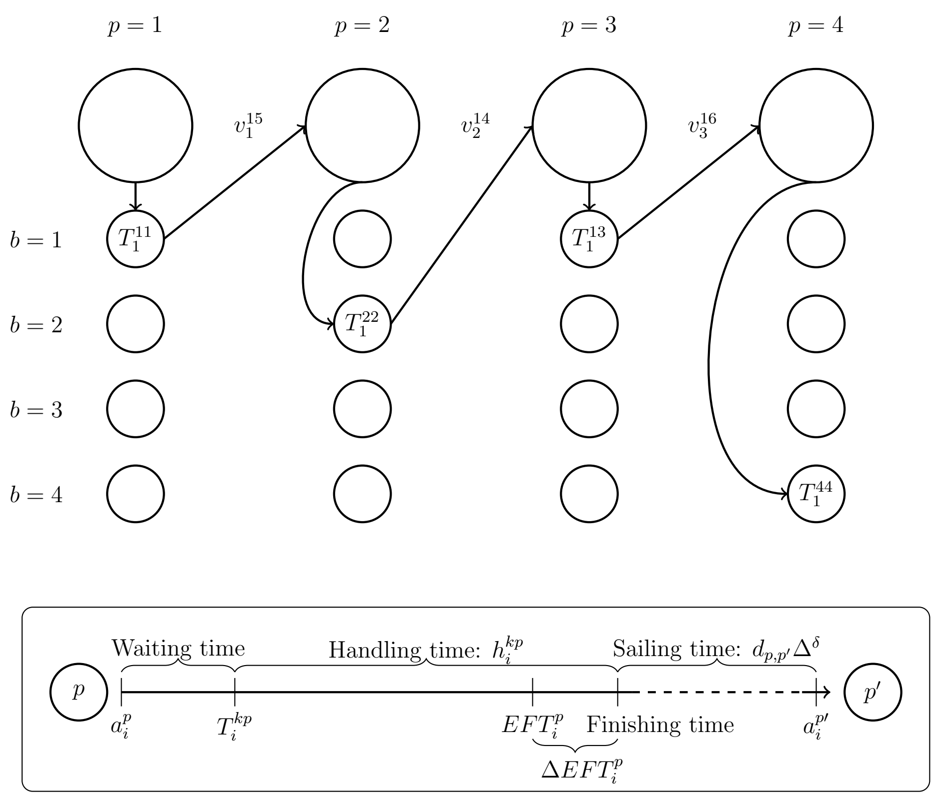
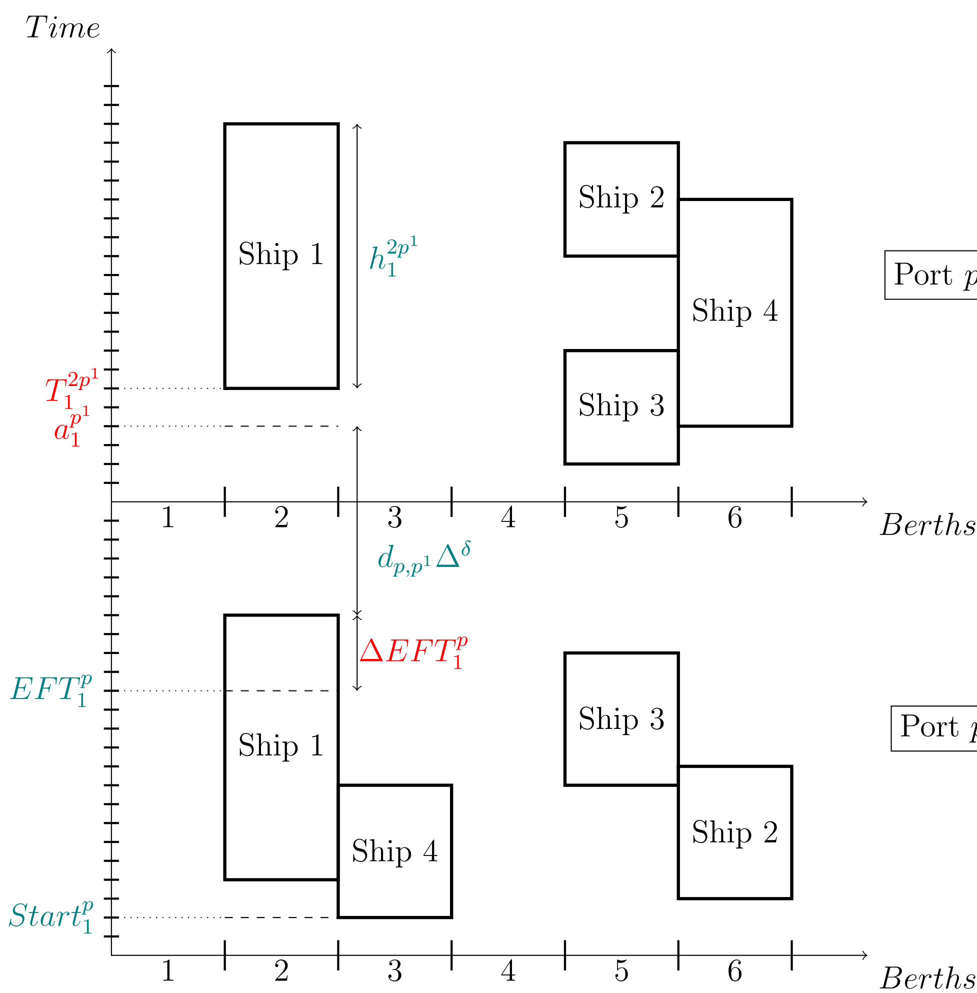


Figure 2 illustrates another example solution in a time-berth diagram. In Figure 2, there are two ports (p, p^1) to be visited by 4 ships, and p^1 is the successor port of p for all ships. Each ship is represented by a rectangle (x-axis projection is its occupied berth, y-axis projection is its handling time) and it fits into one selected berth. In Figure 2, berth-axis is discretized for each separate berths, while time-axis is discretized as a unit of hours. The green-colored notation represents parameters, while red-colored rotation represents decisions of the problem. Ship 1 starts berthing at port p later than its berthing start time window ($Start_1^p$), while it ends later than EFT_1^p. This means operations are late for ΔEFT_1^p hours. Then it sails for port p^1. The sailing time ($d_{p,p^1}\Delta^\delta$), which depends on the ship speed on the sailing leg and distance between p and p^1, is the difference between the departing time of the vessel at port p and the arrival time of the vessel at the port p^1. It is calculated as the product between the sailing distance and the travelling time for a unit of distance at the selected speed δ. Note that time-axis is not perfectly scaled in Figure 2, traditionally sailing time between ports ($d_{p,p^1}\Delta^\delta$) is significantly larger than the handling time of the vessel ($h_1^{2p^1}$). A set of discrete speeds S is defined in order to compute the fuel consumption for a unit distance for every ship travelling at a certain speed from one port to the next. In Figure 2, ship 1 arrives at port p^1 at $a_1^{p^1}$ and it waits until berthing starts at $T_1^{1p^1}$. One can calculate the idle time for Ship 1 as the difference between $T_1^{1p^1}$ and $a_1^{p^1}$.

Figure 2: Representation of some parameters (in green) and decision variables (in red) in the multi-port berth allocation and speed optimization problem



The aim of the problem is to find the optimal sequence of ships mooring at each berth for every port by determining arrival times, berthing start time, handling time, berthing position for each vessel at each port along the string, and the sailing speed for each vessel in each leg between ports.

The objective function covers minimizing the cost of idleness, delay, handling and the fuel consumption. The delay cost is associated to every hour of lateness from the expected finishing time, while idleness cost is linked to the waiting time before berthing. There is a trade-off between the fuel consumption and time-dependent cost components (earliness, delay costs). Every time a vessel speeds up, fuel consumption increases in order to meet a hard time-window or reduce the delay/earliness costs. Another trade-off is between the handling time of the ship and time-depending cost components. Assuming that a shorter handling time is selected by the current terminal, the ship could be forced to wait to berth (earliness cost) in the consecutive port since it arrives earlier than the starting time-window. The sum of overall costs will represent the overall cost for both the terminal operator and the liner company.

Sets, parameters and decision variables for the Berth Allocation and Speed Optimization Problem are detailed as follows:

Sets and Parameters

N	Set of ships
P	Set of ports
P_i	Set of ports to be visited by vessel $i \in N$ sorted in visiting order
B_p	Set of berths at port $p \in P$
$V^{k,p}$	Set of vertices, $V^{k,p} = N \cup \{o(k,p), d(k,p)\}$, with $o(k,p)$ = origin node for arcs and $d(k,p)$ = destination node for arcs, both defined for every berth and port
$A^{k,p}$	Set of arcs (i,j) with i,$j \in V^{k,p}$, $i \neq j$
S	Set of speeds
$Start_i^p$	Minimum starting time of activities for ship $i \in N$ at port $p \in P_i$
EFT_i^p	Expected finishing time of activities for ship $i \in N$ at port $p \in P_i$
s^{kp}	Starting time of activities for berth $k \in B_p$ at port $p \in P$
e^{kp}	Ending time of activities for berth $k \in B_p$ at port $p \in P$
h_i^{kp}	Handling time of ship $i \in N$ at berth $k \in B_p$ at port $p \in P_i$
$d_{p,p\prime}$	Distance between each pair of subsequent ports p and $p\prime$ with p, $p\prime \in P$
P_{iL}	The last port that will be visited by ship $i \in N$ in the string
$\gamma_{i\delta}$	Fuel consumption for a unit distance when ship $i \in N$ travels at speed $\delta \in S$
Δ^δ	Travelling time when sailing at speed $\delta \in S$ for a unit distance
$M1_{ij}^{kp}$	Big-M, $M1_{ij}^{kp} = e^{kp} - \min\limits_{c \in (i,j)} \{Start_c^p\}$
$M2_i^{kp}$	Big-M, $M2_i^{kp} = e^{kp} - h_i^{kp}$
F_c	Fuel consumption cost
H_c	Handling activities cost
I_c	Idleness cost
D_c	Delay cost

Decision Variables

$x_{ij}^{kp} \in \mathbb{B}$	1 if ship j immediately succeeds ship i at berth $k \in B_p$ at port $p \in P$ where $(i, j) \in V^{k,p}$; 0 otherwise
$v_p^{i\delta} \in \mathbb{B}$	1 if ship $i \in N$ sails from port p to $p\prime$ ($p, p\prime \in P$) at the speed $\delta \in S$; 0 otherwise
$a_i^p \in \mathbb{Z}^+$	Arrival time of ship $i \in N$ to port $p \in P_i$
$T_i^{kp} \in \mathbb{Z}^+$	Time at which ship $i \in N$ berths at berth $k \in B$ at port $p \in P_i$ (berthing start time)
$T_{o(k,p)}^{kp} \in \mathbb{Z}^+$	Time at which berth $k \in B_p$ at port $p \in P$ starts berthing ships, (i.e. time at which the first ship berths)
$T_{d(k,p)}^{kp} \in \mathbb{Z}^+$	Time at which berth $k \in B_p$ at port $p \in P$ finishes berthing ships, (i.e. time at which the last ship departs)
$T_i^p \in \mathbb{Z}^+$	Time at which port $p \in P_i$ opens activities for ship $i \in N$
$\Delta EFT_i^p \in \mathbb{Z}^+$	Difference between effective finishing time and EFT_i^p for ship $i \in N$ at port $p \in P_i$

$$Min \qquad \sum_{i\in N}\sum_{p\in P_i}\sum_{k\in B_p} I_c(T_i^{kp}-a_i^p)+\sum_{i\in N}\sum_{p\in P_i}\sum_{k\in B_p} H_c\left(h_i^{kp}\sum_{j\in N\cup\{d(k,p)\}} x_{ij}^{kp}\right)$$

$$+\sum_{i\in N}\sum_{p\in P_i} D_c\Delta EFT_i^p+\sum_{i\in N}\sum_{p\in P_i}\sum_{\delta\in S} F_c(\gamma_{i\delta}d_{p,p\prime}\upsilon_p^{i\delta})$$

subject to

$$\sum_{k\in B_p}\sum_{j\in N\cup\{d(k,p)\}} x_{ij}^{kp}=1 \qquad \forall i\in N,\forall p\in P_i \tag{3}$$

$$\sum_{j\in N\cup\{d(k,p)\}} x_{o(k,p)j}^{kp}=1 \qquad \forall p\in P,\forall k\in B_p \tag{4}$$

$$\sum_{j\in N\cup\{o(k,p)\}} x_{jd(k,p)}^{kp}=1 \qquad \forall p\in P,\forall k\in B_p \tag{5}$$

$$\sum_{j\in N\cup\{d(k,p)\}} x_{ij}^{kp}-\sum_{j\in N\cup\{o(k,p)\}} x_{ji}^{kp}=0 \qquad \forall i\in N,\forall p\in P_i,\forall k\in B_p \tag{6}$$

$$T_i^{kp}+h_i^{kp}-T_j^{kp}\le(1-x_{ij}^{kp})M1_{ij}^{kp} \qquad \forall(i,j)\in A^{k,p},\forall p\in\{P_i\cap P_j\},\forall k\in B_p \tag{7}$$

$$\sum_{k\in B_p} T_i^{kp}+\sum_{k\in B_p} h_i^{kp}\left(\sum_{j\in N\cup\{d(k,p)\}} x_{ij}^{kp}\right)+\sum_{\delta\in S}\Delta^\delta d_{p,p\prime}\upsilon_p^{i\delta}\le a_i^{p\prime} \qquad \forall i\in N,\forall p,p\prime\in P_i\setminus\{P_{iL}\}:\ \{p\prec p\prime\} \tag{8}$$

$$T_i^p\ge Start_i^p \qquad \forall i\in N,\forall p\in P_i \tag{9}$$

$$\Delta EFT_i^p\ge T_i^p+\sum_{k\in B_p} h_i^{kp}\left(\sum_{j\in N\cup\{d(k,p)\}} x_{ij}^{kp}\right)-EFT_i^p \qquad \forall i\in N,\forall p\in P_i \tag{10}$$

$$a_i^p\le T_i^p \qquad \forall i\in N,\forall p\in P_i \tag{11}$$

$$\sum_{k\in B_p} T_i^{kp}\ge T_i^p \qquad \forall i\in N,\forall p\in P_i \tag{12}$$

$$T_i^{kp}\le\left(\sum_{j\in N\cup\{d(k,p)\}} x_{ij}^{kp}+\sum_{j\in N\cup\{o(k,p)\}} x_{ji}^{kp}\right)M2_i^{kp} \qquad \forall i\in N,\forall p\in P_i,\forall k\in B_p \tag{13}$$

$$T_{o(k,p)}^{kp}\ge s^{kp} \qquad \forall p\in P,\forall k\in B_p \tag{14}$$

$$T_{d(k,p)}^{kp}\le e^{kp} \qquad \forall p\in P,\forall k\in B_p \tag{15}$$

$$\sum_{\delta \in S} v_p^{i\delta} = 1 \qquad \forall i \in N, \forall p \in P_i \setminus \{P_{iL}\} \tag{16}$$

$$x_{ij}^{kp} \in \{0,1\} \qquad \forall (i,j) \in A^{kp}, \forall p \in P, \forall k \in \ B_p \tag{17}$$

$$v_p^{i\delta} \in \{0,1\} \qquad \forall i \in N, \forall p \in P_i, \forall \delta \in S \tag{18}$$

$$a_i^p \in \mathbb{Z}^+, \Delta EFT_i^p \in \mathbb{Z}^+, T_i^p \in \mathbb{Z}^+ \qquad \forall i \in N, \forall p \in P_i \tag{19}$$

$$T_{o(k,p)}^{kp} \in \mathbb{Z}^+, T_{d(k,p)}^{kp} \in \mathbb{Z}^+ \qquad \forall p \in P, \forall k \in B_p \tag{20}$$

$$T_i^{kp} \in \mathbb{Z}^+ \qquad \forall i \in N, \forall p \in P_i, \forall k \in B_p \tag{21}$$

The objective function is a cost minimization, both for the terminal operators and the liner shipping company. It consists of four cost elements, namely, the cost of idle time, the cost operational cost, the cost of delays and the total bunker cost. The terminal related component covers the minimization of handling costs and delay costs. Delay costs is associated to every hour of delay beyond the expected finishing time for each ship at each port (ΔEFT_i^p). The costs related to the liner company cover the ship idleness costs before berthing (i.e. lost opportunity cost) and the cost of fuel consumption in each leg. The idle time for ships before berthing is defined as the positive difference between the berthing and the arrival time ($T_i^{kp} - a_i^p$). The total fuel consumption is also minimized for all the ships.

Constraint (3) ensures that each ship moors at one berth at each port in its string. Constraints (4) and (5) are attributed to one origin and one destination vertex of each berth and each port. They ensure that only one ship will be berthed as the origin and destination vertex. The flow conservation for all arcs (representing a ship, port and berth combination) is assured by constraint (6). Constraint (7) generates the berthing schedule for each port, ensuring that if the vertex i assigned before j , the berthing time of j should be later than berthing end time of i (which is calculated by adding the handling time of i to berthing start time). We should also clarify the *big-M* values in (7). $M1_{ij}^{kp}$ is the largest possible time window assuming that ship berths at the earliest possible ($Start_i^p$) until the time when berth closes for berthing (e^{kp}). For each ship and for each related port, the arrival time at a port is controlled by constraint (8) where it makes sure that the operation ending time for a vessel at a given port $\left(\sum_{k \in B_p} T_i^{kp} + \sum_{k \in B_p} h_i^{kp} \left(\sum_{j \in N \cup \{d(k,p)\}} x_{ij}^{kp} \right) \right)$ added by the sailing time to the next port ($\sum_{\delta \in S} \Delta^\delta d_{p,p\prime} v_p^{i\delta}$) should set the arrival time at the port $p\prime$ which is the next port in the string after port p. Constraint (8) is formulated for all ports of ship i except the last port in the string. Time window restrictions for the ports and ships are imposed by constraint (9) where a Lower Bound (LB) is set for the variable T_i^p by considering starting time of activities at each port for each ship. Constraint (10) sets the delay time ΔEFT_i^p, it takes the berthing time and the processing time into account. Constraint (11) sets that the berthing time for each ship i at port p (T_i^p) is later than the arrival time of that ship at the port (a_i^p), while the relation between the decision variables T_i^p and T_i^{kp} is set by constraint (12) where the opening time T_i^p is less-than or equal to the berthing time T_i^{kp} for all berths. Constraint (13) sets the berthing time to zero for those ships whose berth and port combinations are not active in the solution. The *big-M* in constraint (13) is the upper bound on T_i^{kp} and is calculated by subtracting h_i^{kp} from the closing time of the given berth. The time window for berth opening and closing times are imposed by constraint (14) and (15). Constraint (16) ensures that exactly one speed ($v_p^{i\delta}$) is selected between each port pairs (leg). The domains for all the decision variables are in (17)-(21). The above model will be referred as the base formulation.

3.3. Enhancements on the formulation

In this study, we formulate a class of valid inequalities, variable fixing methods and new bounds on variables to improve the performance of the base formulation. These enhancement methods intend the improve both LP relaxation and final results. This model will be referred as the enhanced formulation throughout the rest of the paper.

More specifically, we now formulate a class of valid inequalities that aim at improving the LB on T_i^{kp}. For each vessel pair that shares the same port in their strings, we can formulate an inequality that ensures that if ship j is successor of ship i in the same berth k of given port p, the berthing start time of j should be larger than berthing start time window of i added by the handling time of ship i (h_i^{kp}). Constraint (22) sets this link.

$$(Start_i^p + h_i^{kp})x_{ij}^{kp} \leq T_j^{kp} \qquad \forall (i,j) \in A^{k,p}, \forall p \in \{P_i \cap P_j\}, \forall k \in B_p \tag{22}$$

Another set of valid inequalities ensures that two vessels cannot follow one another at the same time. More formally, for each vessel pair that shares the same port, the vessels should hold a predecessor relationship for a given berth that they share in their strings. Constraint (23) ensures that $x_{ij}^{kp} + x_{ji}^{kp}$ is at most one for such cases.

$$x_{ij}^{kp} + x_{ji}^{kp} \leq 1 \qquad \forall (i,j) \in A^{k,p}, \forall p \in \{P_i \cap P_j\}, \forall k \in B_p \tag{23}$$

Next two constraints serve as variable fixing methods. For each vessel pair that shares the same port, for a given berth k if berthing starting time of ship i added by processing times of ships i and j goes beyond the closing time window of that berth k, ship i cannot be the predecessor of ship j. Constraint (24) ensures this fix.

$$x_{ij}^{kp} = 0 \qquad \forall (i,j) \in A^{k,p}, \forall p \in \{P_i \cap P_j\}, \forall k \in B_p : \{Start_i^p + h_i^{kp} + h_j^{kp} \geq e^{kp}\} \tag{24}$$

Constraint (25) ensures that a given vessel cannot be scheduled for ports which are not in its string. The validity of this variable fixing is evident since the objective function minimizes the overall cost, thus it will not allow these variables to take the value of one.

$$\sum_{k \in B_p} \sum_{j \in N \cup \{d(k,p)\}} x_{ij}^{kp} = 0 \qquad \forall i \in N, \forall p \in \{P \setminus P_i\} \tag{25}$$

The next enhancement is an inequality that sets a LB on arrival time variables (a_i^p). Assuming that $p\prime$ is the successor of port p in the string of ship i, the arrival time of ship to port $p\prime$ is at least the sum of earliest start time at port p added by minimum handling time for ship i at port p and the minimum time it takes to sail from port p to port $p\prime$ with the use of highest speed ($\delta_i^{p,p\prime}$) in this leg.

$$a_i^{p\prime} \geq Start_i^p + \min_{k \in B_p}\{h_i^{kp}\} + \delta_i^{p,p\prime} \qquad \forall i \in N, \forall p, p\prime \in P_i \setminus \{P_{iL}\} : \{p \prec p\prime\} \tag{26}$$

Constraint (26) guarantees that arrival time is calculated by assuming that ship starts the berthing at the earliest possible time in predecessor port ($Start_i^p$), the minimum handling time is achieved ($\min_{k \in B_p}\{h_i^{kp}\}$) and it sailed as fast as possible to reach the given port.

4. Computational Results

All models are solved with the CPLEX version 12.5 by using a computer with Intel Core i5 processor (2.30 GHz) and 8 GB RAM memory. All running times are measured in seconds in each table, while a CPLEX time limit of 3 hours has been imposed for all tests. Due to memory restrictions only 4 threads are active per experiment.

4.1. Data and experimental settings

The data set includes 30 instances of various number of vessels, ports and berths. Instances are generated by using the benchmark instances presented in Cordeau et al. (2005). The number of vessels ranges from 4 to 20, while the ports taken into consideration are 3 or 4. The number of berths in each port varies from 3 to 15 where it is assumed that each port has the same number of berths. Values have been randomly generated for the time windows and handling times, inspired by the instances provided by Cordeau et al. (2005). The model has been tested on two main sets of time windows which are loose or tight. The loose time windows are on average three times larger than the tight time windows.

All time parameters are in hours, while distances are in kilometers. The travelling time for a unit distance for each speed (km/hour) is calculated as the inverse of the speed $1/\delta$ (hour/km). The per unit distance fuel consumption is calculated based on the cubic relationship introduced in equation (2). For reasons of simplicity, and although the model presented can be used to solve generic instances, we assume one vessel type is used and that the strings travelled by each vessel are identical. The ship modelled is a 1700 TEU feeder vessel with a fuel consumption of 42 ton/day at the normal operational speed of 19 knots. Assuming this design speed and fuel consumption, the values for $\gamma_{i\delta}$ at the different speeds δ have been calculated. With reference to the speed δ, we adopt a discretization in 11 levels, covering the range 14-19 knots. The fuel consumption coefficient F_c is calculated by assuming an average cost of 250 \$/ton of bunker oil, while it is assumed that the cost of one hour of work at the port corresponds to \$200 for the handling activities coefficient H_c and the idleness coefficient I_c. Furthermore, a cost of 300\$/hour has been assigned as delay cost. The objective is expressed in thousands of US dollars. Finally, the fuel price has been identified as the most important parameter that affects the results, therefore a sensitivity analysis has been performed with prices for bunker oil being 400 \$/ton, 600 \$/ton and 800 \$/ton.

4.2. Results

Table 1 presents the results for the base and the enhanced formulations. In Table 1, the first column indicates the properties of the instance. It presents the number of vessels ($|N|$), the number of ports in the string ($|P|$), the number of berths at each port ($|B_p|$) and the attribute of the time-windows (tight or loose). The columns denoted by "Z" show the best Upper Bounds (UB) obtained, while

Table 1: Computational results - Base vs Enhanced formulation

$\lvert N\rvert - \lvert P\rvert - \lvert B_p\rvert - TW$	Base formulation				Enhanced formulation			
	Z	LB	Gap	T_{OPT} (s)	Z	LB	Gap	T_{OPT} (s)
4-3-3-L	175600	175600	0%	0.5	175600	175600	0%	0.6
5-3-3-L	233800	233800	0%	1.2	233800	233800	0%	1.4
6-3-3-L	257800	257800	0%	1.7	257800	257800	0%	3.7
6-3-4-L	374600	374600	0%	7.3	374600	374600	0%	7.9
10-4-4-L	601600	601600	0%	58.4	601600	601600	0%	68.1
10-4-3-L	418600	418600	0%	47.4	418600	418600	0%	27.4
4-4-4-L	237000	237000	0%	0.5	237000	237000	0%	0.5
5-4-4-L	295500	295500	0%	0.5	295500	295500	0%	0.6
6-4-4-L	353000	353000	0%	1.3	353000	353000	0%	1.1
12-5-3-L	490300	490300	0%	5099.9	490300	490300	0%	4856.2
10-6-3-L	403900	403900	0%	13.9	403900	403900	0%	8.7
15-10-3-L	598000	598000	0%	2.0	598000	598000	0%	3.0
15-10-4-L	846500	846500	0%	3.5	846500	846500	0%	5.4
20-10-3-L	800000	800000	0%	7.0	800000	800000	0%	8.6
20-12-3-L	790000	790000	0%	4.3	790000	790000	0%	7.6
4-3-3-T	203500	203500	0%	0.7	203500	203500	0%	0.7
5-3-3-T	261300	261300	0%	1.3	261300	261300	0%	1.5
6-3-3-T	336700	336700	0%	2.9	336700	336700	0%	3.2
6-3-4-T	718400	718400	0%	4.1	718400	718400	0%	4.9
10-4-4-T	1200100	1200100	0%	1799.3	1200100	1200100	0%	1202.1
10-4-3-T	732800	732800	0%	853.7	732800	732800	0%	355.7
4-4-4-T	272500	272500	0%	1.6	272500	272500	0%	1.7
5-4-4-T	354800	354800	0%	4.7	354800	354800	0%	4.5
6-4-4-T	395600	395600	0%	9.0	395600	395600	0%	15.9
12-5-3-T	490300	487600	0.54%	*	490300	488400	0.38%	*
12-5-4-T	481900	481900	0%	387.0	481900	481900	0%	185.0
10-5-4-T	719100	719100	0%	644.1	719100	719100	0%	287.3
15-10-4-T	976500	961100	1.57%	*	974100	961000	1.34%	*
20-10-3-T	809000	801000	0.99%	*	809000	801500	0.93%	*
20-12-3-T	-	790000	-	*	797000	790000	0.88%	*

Note: TW: Time Windows where L and T respectively represent loose and tight TWs, Z: upper bound, LB: lower bound, Gap: (Z-LB)/Z,
* : the time limit of 3 hours has been reached,
- : no integer solution is found at the end of 3 hours.

"LB" reports the best lower bound found. Each "Gap" is calculated between respectively UB and LB. The "T_{OPT}" columns are time spent solving the mathematical model.

The results in Table 1 show that 26 of 30 instances are solved to optimality with both formulations. For all sets of instances, the solution time increases with the size of the problem. In particular, it is influenced by the number of ships and ports in the visiting sequence. Regarding the number of berths, we should note that under a fixed number of ships, increasing the number of berths leads to reduced solution time: this is mainly a result of the higher number of feasible solutions. The solution times are also influenced by time windows for ships and berths, and the handling times. For most of the instances, the solution time increases with tighter time windows.

As concerns the selection of the optimal speed, in the first set of instances with loose time windows, in most of the cases the lowest speed is selected on all the legs. Tighter time windows allow for the choice of almost all possible speed values in the given set, resulting in generally higher average speeds.

With reference to the results based on our enhanced model, the use of enhancements improves both computational time and optimality gap on average. There are four instances which cannot be solved to optimality after three hours. These instances have a gap of 1.03% for the base formulation, while the enhanced formulation obtains a gap of 0.88% for these instances. Base formulation cannot find a feasible UB at the end of the three hours of time limit for 20 vessels routed through 12 ports with 3 berths, while the enhanced formulation solves this instance with a gap of 0.88%. In relation to the 26 instances which are solved to optimality, the base formulation has an average solution time of 344.5 seconds, while the enhanced formulation has an average of 271.6 seconds. These results show that the computational time has been improved by 21.1%, while the average gap has been improved by 14.5% with the use of suggested enhancements. In the remainder of the paper, we will use the enhanced formulation to carry out the sensitivity analysis.

Figure 3 illustrates the optimal solution for instance 6-3-3-T which deals with 6 vessels sailing on a string of 3 ports, where each port contains 3 berths. Vessels are assigned to a single speed for each leg out of the set of 11 discrete speeds, ranging from 14 to 19 knots. Figure 3 represents the berth-time diagram for each port where times are expressed in hours. The lower base of each rectangle represents the berthing time, while the dotted lines are the arrival times to that port.

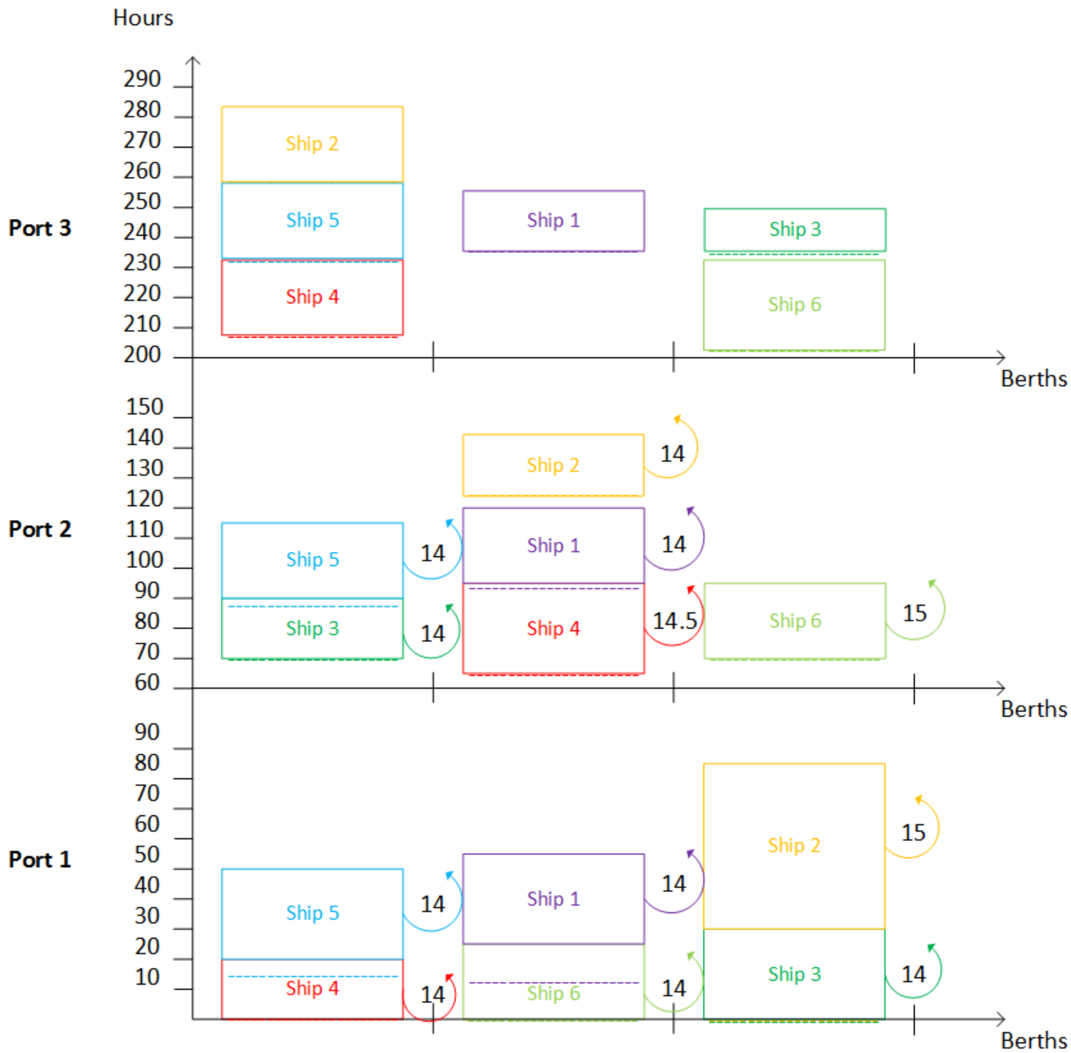
The maximum completion time of the string corresponds to 282 hours when ship 2 finishes its operations at port 3. One can notice that the solution allows some ships to overtake others on some sailing legs. For example, ship 3 departs from port 2 at hour 90, while ship leaves port 2 four hours later at hour 94. The optimal solution suggests that ship 6 moors at berth 3 of port 3 approximately 40 hours before the ship 3 moors at the same berth. Regarding the speeds, most vessels sail at the lowest speed (14 knots) in all sailing legs, while in only 3 legs vessels sail at higher speeds. The average speed across all vessels and strings is 14.2 knots, suggesting that slow steaming is preferred even in the case of tight time windows.

4.3. Sensitivity analysis

The fuel price has been identified as the single most important parameter that affects the results. Therefore we perform a sensitivity analysis with prices for bunkers corresponding to 250 $/ton, 400 $/ton, 600 $/ton and 800 $/ton. We report the results for instances 5-3-3-T (5 ships visiting 3 ports, each of which has 3 available berths) and 10-4-4-T (10 ships visiting 4 ports, each of which has 4 available berths). We use tight time windows because loose time windows would most likely cause ships to select the lowest speed in order to reduce fuel costs. Results compare the discretized speeds case (speeds ranging from 14 to 19 knots), which is the scenario where the involved parties are co-operating, and the single speed case, where all vessels sail with a uniform normal operating speed of 19 knots.

For each instance and bunker cost, Table 2 presents: the average speed per vessel along each string (in vector format), the total average speed of all ships, the value of the objective function, the total waiting time for all vessels, the total handling time of ships in the 3 or 4 ports visited and the total fuel consumption for sailing on all legs. Note that this consumption does not include consumption for waiting to be berthed and while at port; these figures are reported in the next Section where we

Figure 3: Representation of the solution for instance 6-3-3-T



Note: Values within arrows represent the chosen speeds (knots) for each ship on the subsequent sailing leg

discuss the environmental impact.

These results show that, by assuming a higher fuel price, slowing down the vessels is prioritized over the prompt arrival to ports. This is somewhat expected based on the high effect of fuel prices in total fuel costs, which is the major cost component. For example, in instance 5-3-3-T, the average speed drops from 14.85 kn to 14 kn when the fuel price increases from 250 $/ton to 400 $/ton. Similarly, in instance 10-4-4-T, the average speed drops from 15.65 kn to 14 kn for the same price increase.

With respect to the idle times for ships waiting to be berthed, in the discretized speeds case, the total times are generally increasing as a result of the sailing times being decreased. In the case of the single uniform speed (19 knots), we would expect higher waiting times resulting from earlier arrivals to ports. We can observe this tendency in instance 10-4-4-T, showing generally higher idle times in the single speed case, while for instance 5-3-3-T we can notice a lower total waiting time in comparison with the discretized speed case. In this specific instance, time windows constraints may have had an effect on the berth allocation (with a better distribution of vessels along the space-time

Table 2: Results of the fuel price sensitivity analysis

Instance	Speed levels	Fuel cost ($/ton)	Average speed (in kn) (for each vessel)	Average speed (kn)	Objective Value Total Cost ($)	Waiting Time (hours)	Handling time (hours)	Fuel Cons. at sea (ton)
5-3-3-T	11	250	(14.5, 15, 14, 16, 14.75)	14.85	261375	37	400	576
	11	400	(14, 14.5, 14, 14.5, 14)	14.20	344600	38	400	548
	11	600	(14, 14, 14, 14, 14)	14	453000	38	400	540
	11	800	(14, 14, 14, 14, 14)	14	561000	38	400	540
5-3-3-T	1	250	(19, 19, 19, 19, 19)	19	347300	28	400	995
	1	400	(19, 19, 19, 19, 19)	19	496400	28	400	995
	1	600	(19, 19, 19, 19, 19)	19	695200	28	400	995
	1	800	(19, 19, 19, 19, 19)	19	894000	28	400	995
10-4-4-T	11	250	(16.3, 16.6, 15.6, 14.8, 15.5, 15.5, 15.2, 16.5, 15, 15.3)	15.65	1200100	77	990	2130
	11	400	(14.5, 15, 14, 15, 14.3, 14.3, 14.3, 15.7, 14, 14.3)	14.55	1475980	83	985	1732
	11	600	(14.3, 14.3, 14.2, 14, 14, 14.2, 14, 14.7, 14, 14)	14.2	1813280	117	985	1648
	11	800	(14, 14, 14, 14, 14, 14, 14, 14, 14, 14)	14	2139500	121	990	1620
10-4-4-T	1	250	(19, 19, 19, 19, 19, 19, 19, 19, 19, 19)	19	1263500	113	990	2984
	1	400	(19, 19, 19, 19, 19, 19, 19, 19, 19, 19)	19	1715800	125	1000	2984
	1	600	(19, 19, 19, 19, 19, 19, 19, 19, 19, 19)	19	2298000	133	990	2984
	1	800	(19, 19, 19, 19, 19, 19, 19, 19, 19, 19)	19	2899500	133	990	2984

diagram) and thus on the total waiting time.

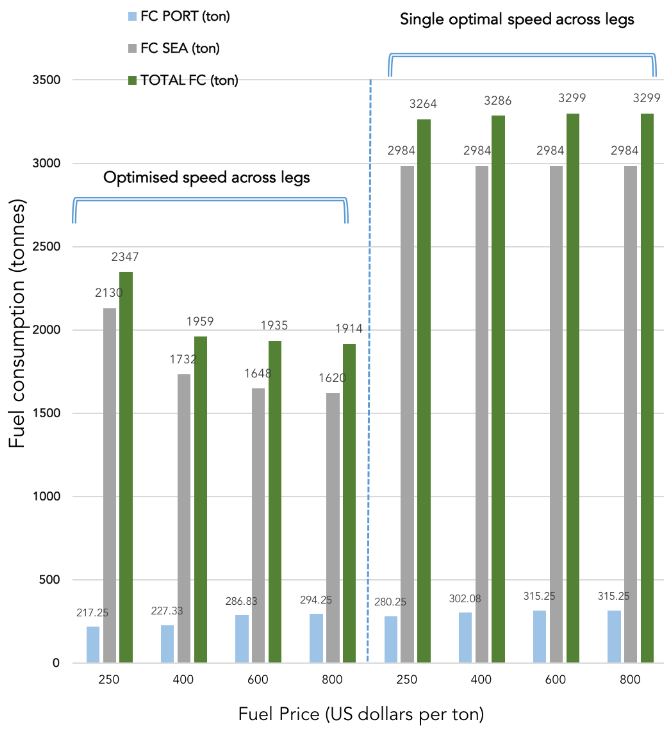
4.4. Discussion on the environmental performance

In Section 4.3 we highlighted that most vessels sail at the lowest speed (14 knots) in all sailing legs, while in only 3 legs vessels do sail at higher speeds. The average speed across all vessels and strings is 14.2 knots, suggesting that slow steaming is preferred even in the case of tight time windows. We will now present the environmental impact of our formulation that includes speed optimization compared to the case where vessels sail at the normal operational speed. As mentioned previously, in our instances we assumed that all vessels are identical. The ship modelled is a 1700 TEU feeder vessel with a fuel consumption of 42 ton/day at the normal operational speed of 19 knots. It is furthermore assumed that the fuel consumption at port is 2 ton/day. Therefore, the total fuel consumption can be calculated as the sum of consumptions (i) at sea, (ii) waiting to be berthed and (iii) at port. Given the waiting time and time at port as output of the optimization model, the final calculation is straightforward.

Table 3: Total fuel consumption results from 2 instance variants

Instance	Speed levels	TW	Fuel cost ($/ton)	Average fleet speed (kn)	Objective Total Cost ($)	FC PORT (ton)	FC SEA (ton)	TOTAL FC (ton)
5-3-3-T	11	Tight	250	14.85	261375	98.08	576	674
	11	Tight	400	14.20	344600	99.83	548	648
	11	Tight	600	14	453000	99.83	540	640
	11	Tight	800	14	561000	99.83	540	640
5-3-3-T	1	Tight	250	19	347300	82.33	995	1077
	1	Tight	400	19	496400	82.33	995	1077
	1	Tight	600	19	695200	82.33	995	1077
	1	Tight	800	19	894000	82.33	995	1077
10-4-4-T	11	Tight	250	15.65	1200100	217.25	2130	2347
	11	Tight	400	14.55	1475980	227.33	1732	1959
	11	Tight	600	14.2	1813280	286.83	1648	1935
	11	Tight	800	14	2139500	294.25	1620	1914
10-4-4-T	1	Tight	250	19	1263500	315.25	2984	3264
	1	Tight	400	19	1715800	313.33	2984	3286
	1	Tight	600	19	2298000	315.25	2984	3299
	1	Tight	800	19	2899500	315.25	2984	3299

Figure 4: Comparison between the single uniform speed case and the optimal speed one - Instance 10-4-4-T



The total fuel consumption is presented in Table 3 for instances 5-3-3-T and 10-4-4-T, both with tight time windows. The two instances include variants with 4 different fuel prices (250, 400, 600 and 800 USD per ton). As in the previous section, we compare the results of the optimization model in the discretized speed case (the sailing speed of all legs can be chosen from a set of 11 discrete speeds ranging betweeen 14 and 19 knots), with the results of the optimization in the single speed case (all vessels sail at the operational speed of 19 knots). Note that these are the extreme cases since the optimization results have average speeds close to the lower allowed speed of 14 knots and the normal operational speed equals to 19 knots.

Table 4 presents a comparison of the results of our model speed optimization under the various discretized speeds and a uniform speed of 19 knots. The last two columns are the absolute and relative fuel savings.

We further illustrate the results of the 10-4-4-T instance in Figure 4. In line with what is discussed in the previous section, higher fuel prices result in lower average speeds and, thus, fuel consumption at sea decreases. The differences in fuel consumption between the case where speed is optimized across legs and the one where the vessels sail at a uniform speed of 19 knots are quite dramatic. Note that fuel consumption in port does not change that drastically. As speed decreases, time in port generally increases and so does fuel consumption. Thus, further reductions could be achieved by optimizing land-side operations.

Finally, as we can see in Figure 5, which illustrates the results presented in Table 4, fuel savings can reach up to 42% when utilizing an optimized speed model instead of sailing at uniform speed. Given that fuel cost and air emissions from ships are proportional to fuel burned, the percentage reductions presented are very similar for fuel consumption, bunker costs and ship air emissions. This actually highlights the importance of the model presented in this paper.

Figure 5: Speed optimized in every leg versus sailing at a fixed speed

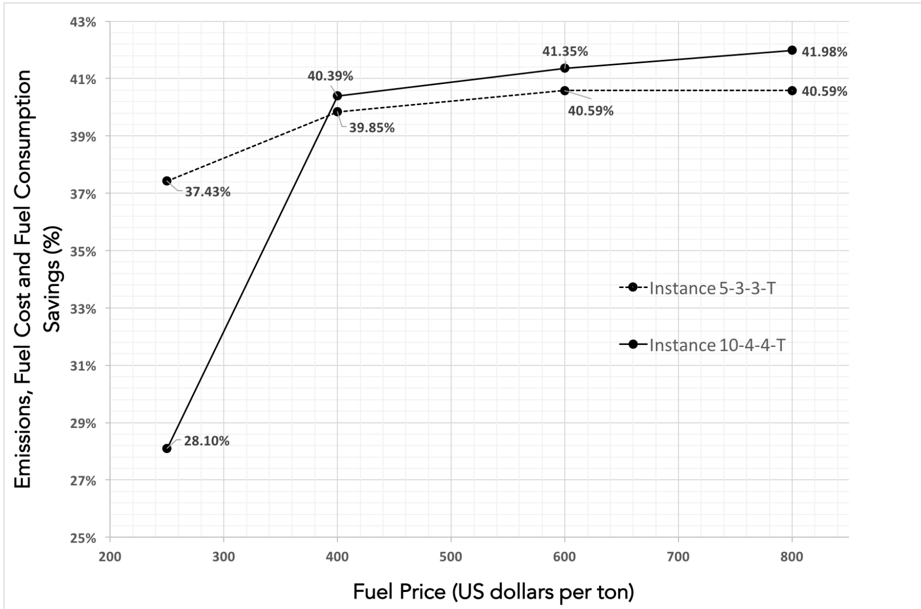


Table 4: Comparison between optimal results and sailing at fixed speed

Instance	Ships	Berths	Ports	Fuel price ($/ton)	Average fleet speed (kn)	Total Fuel Cons. (ton)	%
5-3-3-T	5	3	3	250	14.85	-403	-37.43%
	5	3	3	400	14.20	-429	-39.85%
	5	3	3	600	14	-437	-40.59%
	5	3	3	800	14	-437	-40.59%
10-4-4-T	10	4	4	250	15.65	-917	-28.01%
	10	4	4	400	14.55	-1327	-40.39%
	10	4	4	600	14.2	-1364	-41.35%
	10	4	4	800	14	-1385	-41.98%

5. Further Discussion and Conclusions

In this paper we present a novel formulation by integrating the Berth Allocation Problem (BAP) with vessel speed optimization for multiple ports in a string, under environmental considerations, in particular ship air emissions. Trade-offs in the objective function, especially the trade-off between fuel consumption and total dwell times, has also been investigated.

More specifically, drawing from a well-studied MDVRPTW model for the BAP, which describes the allocation of vessels to berths of a single port while minimizing the total service time (Cordeau et al., 2005), we develop a novel formulation for the BAP which incorporates the minimization of the fuel consumption on the sailing legs between multiple ports. This problem thus expands the traditional BAP by considering the speed of the vessels and consequently arrival times and departure times as decision variables of the problem. In order to incorporate the cubic relationship between speed and fuel consumption in the integer linear programming model, a discretization of the speed has been adopted. One of the results is that better solutions can be obtained by using more accurate, and a higher degree of discretization of the speed variable. Furthermore, savings around 40% can be achieved on fuel and air ship emissions when comparing our model with a situation in which each vessel sails at the design speed.

The developed multiple-port formulation contributes to the enhancement of the collaboration, providing an operational model for the multiple ports BAP under speed optimization and emission considerations. A discussion on the economic and environmental costs and benefits highlights that a realistic implementation of the above model heavily depends on the cooperation, collaboration and information sharing between the involved parties. In this view, the adjustment of the weight coefficients of the objective function accordingly to the operators' priorities could allow balancing between the different needs.

On the computational aspect, almost all instances are solved to optimality. What is more, many enhancements, which contribute to improve the solution times and optimality gaps, are suggested. Incorporating real data from operators and including multiple vessel types and different ports space restrictions are possible research directions. Moreover, in order to ensure operational efficiency at the container port, a possible extension could be to combine our formulation with the berth template design problem (Jin et al., 2015), or with the ship loading problem (Iris and Pacino, 2015). Other extensions such as continuous partitioning of the berth and better equivalent transformations for speed and fuel consumption relationship (such as SOCP) are subject to future studies.

The practical applicability of our formulation assumes a strong cooperation between terminal operators (the ones in our networks) and shipping lines. In our framework shipping lines are probably benefitting more than terminal operators due to fuel savings. Hence their willingness to participate in such a scheme is likely higher than that of terminal operators. On this issue, Wang et al. (2015a) proposes two collaborative mechanisms between container shipping lines and port operators to facilitate port operators to make proper berth allocation decisions. However, in order to achieve a good synchronization of berth availability, terminal operators have to be persuaded to commit themselves to such a collaborative scheme. This problem deserves further investigation on the exact economic benefit. Our perspective is that terminals will benefit from streamlining their operations and, also, by possibly allowing for more vessels to be berthed.

In practice, there are some solid examples of cooperation between terminals and shipping lines. This is the case where the shipping line and the terminal operator are the same entity, or under the same group of companies. This kind of integration allows shipping lines to have a berthing priority in their terminals, stable services and better control over the shipments; e.g. COSCO is involved in terminals in Hong Kong; APL Terminals, who operate terminals in Hong Kong, Kaohsiung, Rotterdam, Long Beach and others, are part of the Maersk Group and so on. Due to the benefits for all the involved players it seems that this kind of cooperation will be increased in the future.

Collaboration between ports is probably more difficult to achieve but not impossible. This actually requires a joint planning of berthing activities, which may be a bit challenging. In any case, we have described collaborations between terminals in Asia, and having in mind that ports are expanding globally and shipping lines integrate vertically with terminal operations, our proposed configuration seems realistic. Song (2003) proposes a new strategic option known as co-opetition, the combination of competition and co-operation, for the port industry, and explains a case of co-opetition between the container ports in Hong Kong and South China. Co-opetition, a term coined by Noorda (1993) is based on a mixture of competition and co-operation, thus having the strategic implication that those engaged in the same or similar markets should consider a win-win strategy, rather than a win-lose one. Through this new option, the actors build up a stronger position in their markets, so that they can increase their market power (Song, 2003) and also enhance their environmental performance.

References

J. F. Alvarez, T. Longva, and E. S. Engebrethsen. A methodology to assess vessel berthing and speed optimization policies. *Maritime Economics & Logistics*, 12:327–346, 2010. 5, 9

P. Andersson and P. Ivehammar. Green approaches at sea the benefits of adjusting speed instead of anchoring. *Transportation Research Part D: Transport and Environment*, 51:240 – 249, mar 2017. 6

C. Bierwirth and F. Meisel. A follow-up survey of berth allocation and quay crane scheduling problems in container terminals. *European Journal of Operational Research*, 244(3):675–689, 2015. 3

K. Buhrkal, S. Zuglian, S. Ropke, J. Larsen, and R. Lusby. Models for the discrete berth allocation problem: a computational comparison. *Transportation Research Part E: Logistics and Transportation Review*, 47(4):461–473, 2011. 2, 4

P. Cariou. Liner shipping strategies: an overview. *International Journal of Ocean Systems Management*, 1(1):2–13, 2008. 8

H. J. Carlo, I. F. Vis, and K. J. Roodbergen. Seaside operations in container terminals: literature overview, trends, and research directions. *Flexible Services and Manufacturing Journal*, pages 1–39, 2013. 3

S. Caschili, F. Medda, F. Parola, and C. Ferrari. An analysis of shipping agreements: the cooperative container network. *Networks and Spatial Economics*, 14(3-4):357–377, 2014. 8

C. C. Chang and C. W. Jhang. Reducing speed and fuel transfer of the green flag incentive program in kaohsiung port taiwan. *Transportation Research Part D: Transport and Environment*, 46:1 – 10, jul 2016. 6

C. Y. Cheong, K. C. Tan, D. K. Liu, and C. J. Lin. Multi-objective and prioritized berth allocation in container ports. *Annals of Operations Research*, 180(1):63–103, 2010. 4

J.-F. Cordeau, G. Laporte, P. Legato, and L. Moccia. Models and tabu search heuristics for the berth-allocation problem. *Transportation science*, 39(4):526–538, 2005. 4, 9, 17, 23

H. Davarzani, B. Fahimnia, M. Bell, and J. Sarkis. Greening ports and maritime logistics: A review. *Transportation Research Part D: Transport and Environment*, 48:473 – 487, oct 2016. 3

Y. Du, Q. Chen, X. Quan, L. Long, and R. Y. Fung. Berth allocation considering fuel consumption and vessel emissions. *Transportation Research Part E: Logistics and Transportation Review*, 47(6): 1021 – 1037, 2011. ISSN 1366-5545. 5, 6

Y. Du, Q. Chen, J. S. L. Lam, Y. Xu, and J. X. Cao. Modeling the impacts of tides and the virtual arrival policy in berth allocation. *Transportation Science*, 49(4):939–956, nov 2015. 6

M. A. Dulebenets, M. M. Golias, and S. Mishra. The fleet deployment problem with variable vessel sailing speeds and port handling times. *KSCE Journal of Civil Engineering*, pages 1–11, 2016. 6

K. Fagerholt, G. Laporte, and I. Norstad. Reducing fuel emissions by optimizing speed on shipping routes. *Journal of the Operational Research Society*, 61(3):523–529, 2010. 5

A. Frémont. Shipping lines and logistics. *Transport Reviews*, 29(4):537–554, 2009. 8

M. Golias, M. Boile, S. Theofanis, and C. Efstathiou. The berth-scheduling problem maximizing berth productivity and minimizing fuel consumption and emissions production. *Transportation Research Record: Journal of the Transportation Research Board*, 2166:20–27, 2010. 5

M. M. Golias, G. K. Saharidis, M. Boile, S. Theofanis, and M. G. Ierapetritou. The berth allocation problem: Optimizing vessel arrival time. *Maritime Economics & Logistics*, 11(4):358–377, 2009. 5

T. Heaver, H. Meersman, F. Moglia, and E. Van de Voorde. Do mergers and alliances influence european shipping and port competition? *Maritime Policy & Management*, 27(4):363–373, 2000. 8

T. Heaver, H. Meersman, and E. Van de Voorde. Co-operation and competition in international container transport: strategies for ports. *Maritime Policy & Management*, 28(3):293–305, 2001. 8

H.-P. Hsu. A {HPSO} for solving dynamic and discrete berth allocation problem and dynamic quay crane assignment problem simultaneously. *Swarm and Evolutionary Computation*, 27:156 – 168, 2016. 4

Q.-M. Hu, Z.-H. Hu, and Y. Du. Berth and quay-crane allocation problem considering fuel consumption and emissions from vessels. *Computers & Industrial Engineering*, 70:1–10, 2014. 6, 9

Z.-H. Hu. Multi-objective genetic algorithm for berth allocation problem considering daytime preference. *Computers & Industrial Engineering*, 89:2 – 14, 2015. 4

A. Imai, E. Nishimura, and S. Papadimitriou. The dynamic berth allocation problem for a container port. *Transportation Research Part B: Methodological*, 35(4):401–417, 2001. 2, 4

A. Imai, X. Sun, E. Nishimura, and S. Papadimitriou. Berth allocation in a container port: using a continuous location space approach. *Transportation Research Part B: Methodological*, 39(3): 199–221, 2005. 4

A. Imai, Y. Yamakawa, and K. Huang. The strategic berth template problem. *Transportation Research Part E: Logistics and Transportation Review*, 72:77–100, 2014. 4, 6

IMO. Third imo ghg study 2014. Technical report, International Maritime Organization (IMO), April 2014. URL `http://www.imo.org/en/OurWork/Environment/PollutionPrevention/AirPollution/Pages/Greenhouse-Gas-Studies-2014.aspx`. 2

Ç. Iris and D. Pacino. *A Survey on the Ship Loading Problem*, pages 238–251. Springer International Publishing, 2015. ISBN 978-3-319-24264-4. 24

Ç. Iris, D. Pacino, S. Ropke, and A. Larsen. Integrated berth allocation and quay crane assignment problem: Set partitioning models and computational results. *Transportation Research Part E: Logistics and Transportation Review*, 81:75–97, 2015. 3, 4, 6

J. G. Jin, D.-H. Lee, and H. Hu. Tactical berth and yard template design at container transshipment terminals: A column generation based approach. *Transportation Research Part E: Logistics and Transportation Review*, 73:168–184, 2015. 4, 24

H. K. Kim and H. Lee. *Container Terminal Operation: Current Trends and Future Challenges*, pages 43–73. Springer International Publishing, 2015. 3

C. Kontovas and H. N. Psaraftis. Reduction of emissions along the maritime intermodal container chain: operational models and policies. *Maritime Policy & Management*, 38(4):451–469, 2011. 5

C. A. Kontovas and H. N. Psaraftis. Transportation emissions: Some basics. In *Green Transportation Logistics*, pages 41–79. Springer, 2016. 2

S. Kordi, T. Davidovi, N. Kova, and B. Dragovi. Combinatorial approach to exactly solving discrete and hybrid berth allocation problem. *Applied Mathematical Modelling*, 2016. 4

E. Lalla-Ruiz, C. Expsito-Izquierdo, B. Melin-Batista, and J. M. Moreno-Vega. A set-partitioning-based model for the berth allocation problem under time-dependent limitations. *European Journal of Operational Research*, 250(3):1001 – 1012, 2016a. 4

E. Lalla-Ruiz, X. Shi, and S. Voss. The waterway ship scheduling problem. *Transportation Research Part D: Transport and Environment*, pages –, oct 2016b. 4

N. Lang and A. Veenstra. A quantitative analysis of container vessel arrival planning strategies. *OR spectrum*, 32(3):477–499, 2010. 5, 9

C.-Y. Lee and D.-P. Song. Ocean container transport in global supply chains: Overview and research opportunities. *Transportation Research Part B: Methodological*, 95:442 – 474, jan 2017. 7

D.-H. Lee and J. G. Jin. Feeder vessel management at container transshipment terminals. *Transportation Research Part E: Logistics and Transportation Review*, 49(1):201 – 216, 2013. 6

D. H. Lee, J. H. Chen, and J. X. Cao. The continuous Berth Allocation Problem: A Greedy Randomized Adaptive Search Solution. *Transportation Research Part E: Logistics and Transportation Review*, 46(6):1017–1029, 2010. 2

E.-S. Lee and D.-W. Song. Competition and co-operation in maritime logistics operations. In *Handbook of Ocean Container Transport Logistics*, pages 477–496. Springer, 2015. 7

P. T.-W. Lee and J. S. L. Lam. Container port competition and competitiveness analysis: Asian major ports. In *Handbook of Ocean Container Transport Logistics*, pages 97–136. Springer, 2015. 8

G. R. Mauri, G. M. Ribeiro, L. A. N. Lorena, and G. Laporte. An adaptive large neighborhood search for the discrete and continuous berth allocation problem. *Computers & Operations Research*, 70: 140 – 154, 2016. 4

F. Meisel and C. Bierwirth. Heuristics for the integration of crane productivity in the berth allocation problem. *Transportation Research Part E: Logistics and Transportation Review*, 45(1):196–209, 2009. 6

R. Noorda. Co-opetition. *Electronic Business Buyer*, 8(12):8–12, 1993. 24

T. E. Notteboom. Container shipping and ports: an overview. *Review of network economics*, 3(2), 2004. 8

T. E. Notteboom and P. W. de Langen. Container port competition in europe. In *Handbook of Ocean Container Transport Logistics*, pages 75–95. Springer, 2015. 8

P. M. Panayides and K. Cullinane. Competitive advantage in liner shipping: a review and research agenda. *International Journal of Maritime Economics*, 4(3):189–209, 2002. 7, 8

K.-W. Pang and J. Liu. An integrated model for ship routing with transshipment and berth allocation. *IIE Transactions*, 46(12):1357–1370, 2014. 6

K.-W. Pang, Z. Xu, and C.-L. Li. Ship routing problem with berthing time clash avoidance constraints. *International Journal of Production Economics*, 131(2):752 – 762, 2011. 6

J. Peng, Z. Zhou, and R. Li. A collaborative berth allocation problem with multiple ports based on genetic algorithm. *Journal of Coastal Research*, 73(sp1):290–297, 2015. 4

H. N. Psaraftis and C. A. Kontovas. Co2 emission statistics for the world commercial fleet. *WMU Journal of Maritime Affairs*, 8(1):1–25, 2009. 2

H. N. Psaraftis and C. A. Kontovas. Speed models for energy-efficient maritime transportation: A taxonomy and survey. *Transportation Research Part C: Emerging Technologies*, 26:331–351, 2013. 1, 5, 9

H. N. Psaraftis and C. A. Kontovas. Slow steaming in maritime transportation: Fundamentals, trade-offs, and decision models. In *Handbook of Ocean Container Transport Logistics*, pages 315–358. Springer, 2015. 5

H. N. Psaraftis and C. A. Kontovas. Green maritime transportation: Speed and route optimization. In *Green Transportation Logistics*, pages 299–349. Springer, 2016. 5

L. B. Reinhardt, C. E. Plum, D. Pisinger, M. M. Sigurd, and G. T. Vial. The liner shipping berth scheduling problem with transit times. *Transportation Research Part E: Logistics and Transportation Review*, 86:116–128, 2016. 5

D.-W. Song. Port co-opetition in concept and practice. *Maritime Policy and Management*, 30(1): 29–44, 2003. 8, 24, 25

R. Stahlbock and S. Voß. Operations research at container terminals: a literature update. *Or Spectrum*, 30(1):1–52, 2008. 3

D. Steenken, S. Voß, and R. Stahlbock. Container terminal operation and operations research-a classification and literature review. *OR spectrum*, 26(1):3–49, 2004. 3

UNCTAD. Review of maritime transport. Technical report, United Nations Conference on Trade and Development, 2015. URL `http://unctad.org/en/PublicationsLibrary/rmt2015_en.pdf`. 1

E. Ursavas. Priority control of berth allocation problem in container terminals. *Annals of Operations Research*, pages 1–20, 2015. 4

S. Wang. Optimal sequence of container ships in a string. *European Journal of Operational Research*, 246(3):850–857, 2015. 5

S. Wang, Q. Meng, and Z. Liu. A note on berth allocation considering fuel consumption and vessel emission. *Transportation Research Part E: Logistics and Transportation Review*, 49(1):48 – 54, 2013. 6

S. Wang, A. Alharbi, and P. Davy. *Ship Route Schedule Based Interactions Between Container Shipping Lines and Port Operators*, pages 279–313. Springer International Publishing, Cham, 2015a. 24

S. Wang, Z. Liu, and X. Qu. Collaborative mechanisms for berth allocation. *Advanced Engineering Informatics*, 29(3):332 – 338, 2015b. ISSN 1474-0346. 6