A variant of the split vehicle routing problem with simultaneous deliveries and pickups for inland container shipping in dry-port based systems

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ABSTRACT

In this paper, we will study a typical problem in inland container shipping, concerning the barge transportation of maritime containers between a dry port and a set of seaport terminals. The barges depart from the dry port and visit a set of sea terminals, where containers need either to be dropped off or picked up. The goal is to achieve economies of scale with barges and avoid trucking as much as possible. The decision thus involves finding the best allocation of containers to barges in order to guarantee on-time delivery and meet capacity restrictions. The problem will be modeled as a variant of the split vehicle routing problem with simultaneous pickups and deliveries coupled with time features. The model includes parameters that can be tuned to improve barge utilization and travelling distance. A hybrid local search meta-heuristic algorithm, combined with a branch-and-cut solver, will be developed to solve the model. Numerical experiments have been conducted to test the performance of the algorithm and provide solution analysis for practical insights. Real-world data has been collected from a local barge operator based in the Port of Rotterdam region and will be used as input for the experiments. This will result in an in-depth analysis into current planning practices. The proposed framework complements existing models in the literature and contributes to the development of a comprehensive set of decision support tools, which help in the decision-making process for inland terminals.

1. Introduction

Inland shipping plays an important role in the transportation of maritime containers in the hinterlands. Public authorities, such as the European Commission (European Commission, 2019), promote the use of this mode of transportation to reduce the use of trucks. However, complex logistics systems and low margins make it difficult to boost inland shipping's competitiveness vis-à-vis trucking. The result is that trucking is still the preferred way to move containers in practice, due to higher flexibility and relatively low organizational costs (Zuidwijk and Veenstra, 2014).

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A typical problem in inland shipping is the transportation of export and import containers between inland and seaport terminals. Generally, barges depart from an inland terminal serving as a collection point for import and export containers. They then visit multiple sea terminals where export containers are unloaded and import containers are loaded. The barges end their route at the inland terminal, where the collected import containers are discharged (Fazi, 2019). The main decisions involved in this problem are the allocation of containers to barges, as well as the construction of barge routes, which are based mainly on the time features and location of the containers. Barge routes need to comply with capacity restrictions at all times, while adhering to the pick-up and drop-off time constraints of each container, since containers need to be transported to their destinations within their pre-determined time windows. When a container cannot be consolidated onto a barge for any reason, it has to be trucked, subsequently increasing the transportation cost (Bouchery et al., 2015). Hence, the goal is to minimize transportation costs by generating economies of scale with barges and by limiting truck transport.

In the literature, operational decisions for inland shipping have received increased attention over the past decade. However, there are still rather few contributions on this topic when compared to the tactical and strategic aspects of the problem. Fazi et al. (2015) developed a decision support system (DSS) for the transportation of import containers only and considering a predefined master route. The problem is solved meta-heuristically. Maraš et al. (2013) tackled the problem of determining the upstream and down-stream calling sequence, along with the number of laden and empty containers transported between any two ports. A few papers have addressed service network design problems for inland shipping: see for example Braekers et al. (2013) and An et al. (2015). Fazi (2019) developed a decision-making framework for the stowage of import and export containers on a barge, which involved the same transportation setting as proposed in this paper. The aim was to maximize the number of transported containers and, at the same time, ensure stability. However, the routing decision and the allocation of containers to the barge were provided as input to the problem. To our knowledge, the proposed operational problem has not been addressed in the literature. Our work extends the model of Fazi et al. (2015) by considering both export and import containers, and more realistic time constraints, all while not imposing a master route to barges. Moreover, the model to be proposed in the research complements the decision framework for the stowage problem presented in (Fazi, 2019) and serves as its input.

In this paper, we will formulate the problem mathematically, by adapting the split vehicle routing problem with simultaneous deliveries and pickups (SVRPSDP) as proposed by Mitra (2008). Next, we will develop a tailored hybrid meta-heuristic to solve the model. The algorithm consists of construction and deconstruction phases, as well as a local search with TABU lists and an MILP solver for solving the routing sub-problem. Finally, with an experimental framework based on real-world instances from a Dutch barge operator based in the Port of Rotterdam region, we will test the performance of our method and provide solution analysis for practical insights. In particular, we will highlight limitations found in the planning practices and the impact of tactical decisions on operational ones. Consequently, a discussion of the IT development required at the inland terminal end is provided.

This paper is structured as follows. In Section 2, we will situate our work in the framework of the available literature on inland container transport. In Section 3, we will formulate the problem and develop a mathematical model for it. In Section 4, we will describe the meta-heuristic. Section 5 contains a description of the real-world case we have at our disposal and the experiments. Section 6 will offer our comments, concerning opportunities for future research and practical implications, and thus conclude the paper.

2. Background

The literature on inland shipping has increased substantially over the past decade. Several papers analyze the evolution of inland shipping at an institutional and organizational level. Notteboom (2007) describes its development over the years, and how systems have adapted to it. Frémont and Franc (2010) conduct an analysis on the competitiveness of combined transport (barge-truck) versus road transport. Their study indicates how inland shipping requires adjustments to become not only cost-competitive but also more appealing to shippers, by facilitating custom clearance, increasing detention free times, etc. More recently, Kotowska et al. (2018) pointed out that inland shipping can be the most environmentally friendly and also the most cost-competitive mode of transport; however, several factors should be considered for this claim to be true, such as covered distance (Meers et al., 2014) and handling costs (Lu and Yan, 2015). Kotowska et al. (2018) claim that seaports need to rely on this modality so as to reduce the negative effects of container shipping in the hinterlands, such as pollutant emissions, noise, land occupancy, etc. Their study provides a set of steps that need to be taken by seaport authorities in order to increase the share of inland shipping in hinterland transport. Finally, van der Horst et al. (2019) investigate the coordination problems between terminal operators and barge operators in the Port of Rotterdam. Their study points out that current contractual relations may be an impediment to improved future performance of container barging.

From a strategic point of view, Caris et al. (2011) and Konings et al. (2013) investigate using a simulation approach vis-à-vis the benefits of different networks for the handling of barges at seaports. Their analysis indicates that, with central hub-and-spoke networks, barges can benefit from reduced waiting times as a result of limiting stops, though at the cost of increased handling operations. When it comes to hinterland infrastructure development, Roso et al. (2009) and Veenstra et al. (2012) indicate the increasing role that inland terminals provide in the success of intermodal transport. The first study analyzes the concept of the dry port, an inland terminal directly connected to the seaport, used as a regional collection center to centralize cargo and increase consolidation. The second one presents an extension of the notion of dry ports. With an "extended gate," shippers can leave or pick up their units at the inland terminal, just as they would if doing so directly at the seaport. In this way, the seaport is able to expand its control beyond the port premises and can use the inland terminal as a buffer. The goals of both concepts are to increase the utilization of both trains and barges, thus providing more control and flexibility for the shipper, and to create large inland hubs where large volumes are gathered, thus minimizing handling costs by avoiding a fragmented demand spread over several inland terminals. Recently, Tsao and Thanh

(2019) propose a dry-port network design problem, where three dimensions of sustainability are considered. The model helps decision makers to determine the optimal number, location, and capacity of dry ports and the volume of containers delivered to seaport.

From a tactical perspective, several contributions are available concerning ship routing and service network design. The problem typically involves constructing routes and schedules for either the short or medium term in order to optimize specific objectives, which may differ for liner or tramp shipping, for example. We recommend Agamez-Arias and Moyano-Fuentes (2017) and SteadieSeifi et al. (2014) for recent reviews on the subject. Although the majority of contributions are specific to liner shipping, a moderate amount of literature dedicated to inland shipping exists. Maraš et al. (2013) investigate the hinterland barge transport of containers arriving at or departing from a transshipment port. The problem involves determining a sequence of ports to be visited and the number of containers to be picked up and dropped off between any two ports, with the goal of maximizing profit. The problem is first modeled with a mixed integer linear programming formulation and then solved using CPLEX and an MIP heuristic. In a recent paper, Alfandari et al. (2019) extend the problem in Maraš et al. (2013) and propose an integrated approach by considering empty container balancing and repositioning, optimal turnaround time, and the optimal choice for the final port in the outbound direction. The problem is formulated with a new more efficient mathematical model approach than the one proposed in Maraš et al. (2013) and then solved exactly with an MILP solver. Ypsilantis and Zuidwijk (2019) propose the tactical design of barge scheduled transport services, including fleet selection and routing through the inland waterway network. The authors develop a tight MILP formulation for Fleet Size and Mix Vehicle Routing, especially adapted for the Port-Hinterland multi-modal barge network design. Fazi and Roodbergen (2018) study the effects of demurrage and detention tariffs on the scheduling of barge rides. By analyzing transport schedules, the authors quantify the effects of such tariffs and offer guidelines for their design.

From an operational point of view, besides the previously mentioned works Fazi et al. (2015) and Fazi (2019), we only found a few contributions. Zhen et al. (2018) have developed a mathematical formulation for modeling the problem of allocating tugs to non self-propelled barges for the movement towards inland ports. The model is solved via a branch-and-price approach. Tan et al. (2018) propose a joint ship schedule design and sailing speed optimization problem for a single inland shipping service, and consider the effects of non-identical streamflow speed and the uncertain dam transit time. A bi-objective programming model is developed to simultaneously minimize the total bunker consumption and the ship round-trip time. Similarly to Fazi (2019), Li et al. (2018) formulated a multi-port stowage problem for inland shipping aiming to maximize capacity utilization by ensuring that the least number of stacks is used. In their problem the weight of the containers is uncertain. Also in Li et al. (2018), the routing and the information of pickup and delivery loads are an input to the problem. Whereas in this paper, our focus is to provide a general framework that shapes that input. Finally, Rivera and Mes (2017) also propose a similar setting consisting of barges performing round trips and trucks as expensive alternative. They study the decision of selecting freights for transportation in long-haul trips and consider a multi-period horizon with uncertainty and develop a Markov Decision Process, solved by an Approximate Dynamic Programming algorithm. However, the study does not include routing decisions.

From a modeling perspective, the proposed problem is an adaptation of the split VRP with simultaneous pickup and delivery (SVRPSPD), since containers can be either picked up or delivered and the nodes can have both types of requests and can be visited multiple times. This version has not received much attention in the literature. The first study on SVRPSPD is that of Mitra (2005), who developed a Mixed Integer Linear programming formulation and a route construction heuristic. Later, Mitra (2008) proposed an alternative formulation and a parallel clustering technique. Wang et al. (2013) have proposed a variant with time windows. A hybrid heuristic algorithm has been developed and tested with modified classical instances. More recently, Qiu et al. (2018) have proposed the variant where customers' demands are discrete in terms of batches. They have developed a mathematical model and a tabu search algorithm.

In the proposed model, each container is accounted for separately, since each has a specific time window and a specific destination. Furthermore, the typical characteristics of inland shipping lead to a different objective function than does the classical problem. In fact, inland shipping entails very high fixed costs and low variable costs. Therefore, reducing the number of barges used, and, consequently, maximizing their utilization, has a greater impact on the total cost than reducing the distances traveled. Finally, delivery and pickup containers, export and import, respectively, feature time windows at sea terminals, while delivery containers also release dates from the dry port.

3. Problem formulation

In this section, we give full details of our problem on-hand. We first outline the problem setting. Next, the mathematical model is introduced.

3.1. Problem setting

We consider the problem of moving a set of containers between a dry port and a seaport composed of a set of terminals. A dry port is an inland terminal that serves as a collection point of import and export containers in the hinterland, and it is a common setting in this system (Fazi, 2019; Roso and Russel, 2018). Each sea terminal can deal with both classes of containers and can be visited multiple times. We take the point of view of the transportation planner of an integrated dry port system, who decides on the allocation of

containers to a heterogeneous fleet in a short term period, typically one week.

The information on containers is known in advance. Export containers are available at the dry port at specific times and must be delivered to their assigned destinations after a so-called opening date and before a closing date. Commonly, the closing date refers to the time the container is expected to be leaving the seaport to its final destination. Import containers are picked up at the seaport and are directed to the dry port. They can be picked up only after a specific time, which may be either the time they become physically available or the time imposed by the receiver, for example because of free storage time. Each features a due date for pickup, imposed by the receiver (Fazi and Roodbergen, 2018).

The transportation system consists of shuttle barges departing from the dry port and visiting a selection of seaport terminals to pickup and deliver containers. The fleet of barges is limited and capacitated, heterogeneous and immediately available. In the proposed setting, the cost for using a barge is typically independent from the travelled distance and reflects an economy of scale. The rationale is that for such shuttle services a large part of the covered distance in the transportation between a sea port and an inland terminal is fixed. Also for this reason, it is typical that barge owners offer their services to inland terminals for a predefined transport leg for an established price (Fazi et al., 2015). This assumption is common in scientific models tackling multimodal settings. See for example, Behdani et al. (2014) and Zuidwijk and Veenstra (2014); in these studies, costs are considered per TEU, assuming an average utilization. However, in the proposed model we also consider a routing cost to prefer, when possible, shortest routes.

With concern to trucks, they may be used as a buffer; either to handle containers that cannot be consolidated or to replace a low utilized barge. As our focus is on the planning of inland shipping, we do not aim to compose trips for trucks. Instead, we consider an average fixed cost for each trucked container to accommodate for this case. The reasons for the arrangement are: 1) normally there are limited number of seaport terminals in close geographical proximity, thus the lengths of the routes between a dry port and seaport terminals are similar; 2) the travelling distance between a dry port to sea ports are generally short, which makes the variable costs relating to mileage only accounts for a small portion of the overall costs compared to the fixed costs of dispatching a truck; 3) trucks, due to their flexibility, may also be used to deal with containers that are outside the scope of this research; for example, last mile delivery, empty container repositioning, transport between sea ports, and drayage operations in general. For such a system, the interested reader is referred to, among others, Moghaddam et al. (2020) or Vidović et al. (2017).

The objective of the planner is to minimize transportation costs, while ensuring that all containers are processed on time. As a side objective, the planner aims to reduce the number of stops for barges; this is to limit the chance of delays, due to congestion and the low priority that barges have for dock cranes against large container ships (Rivera and Mes, 2017; Konings et al., 2013).

3.2. Mathematical model

Consider a network consisting of a set of terminal nodes N. Within N, node 0 represents the dry port. The set of containers C is composed of a subset I of import containers and a subset E of export containers. Containers have standard size of either 20-foot or 40-foot, and this is indicated by W_c that takes value 1 for 20-foot containers and value 2 for 40-foot containers. Each export container $c \in E$ is available at the dry port at time R_c; it must be delivered to a specific sea terminal between an opening date O_c and a closing date D_c. Likewise, each import container $c \in I$ can be retrieved at the sea terminal between O_c and D_c. In this regard, we define parameter Z_{cj}, with $c \in C$ and $j \in N$, which is set to 1 if container c is destined/originated to/at sea terminal j, 0 otherwise. This information is known in advance. Finally, we define the time to load/unload a container as L.

Concerning the fleet, define set K consisting of $|K| - 1$ barges and one element that represents the number of trucks. Each barge has capacity Q_k. The transport time between two nodes is T_{ij}. Finally, we define a fixed cost H_k^B for using barge k, a cost H^T for each trucked container, and a cost γ for visiting a sea terminal. Note that H^T is an average cost and can be made dependent on the size of the container.

The description of the decision variables follows. f_{ck}, with $c \in C$ and $k \in K$, is a main binary decision variable, which equals 1 if container c is assigned to a barge or a truck k. Binary variable $x_{i,j}^k$, with $i, j \in N$ and $k \in 1...|K| - 1$, indicates, if 1, that barge k covers arc (ij), 0 otherwise. Next, we have positive real variables y_{ij}^k and z_{ij}^k, with $i, j \in N$ and $k \in 1...|K| - 1$, which indicate the volume of, respectively, import and export containers transported in leg (i, j) by barge k. In particular, y_{ij}^k defines the number of picked up containers up to terminal i and transported in arc (ij). Likewise, z_{ij}^k defines the number of export containers remaining after terminal i and transported in arc (ij). With variables p_j^k and d_j^k, with $j \in N$ and $k \in 1...|K| - 1$, we indicate import (pickup) and export (delivery) (sub-) demands handled by a barge k at node j. Note that a barge does not have to handle the whole demand of a sea terminal, since it can be visited by multiple barges. Finally, t_j^k is the time barge k reaches terminal j.

A list of all sets, variables and parameters is reported in Table 1.

We formulate the problem as follows:

$$min \sum_{c \in C} f_{c|K|} H^T + \sum_{k \in 1...|K|-1} \sum_{j \in N/\{0\}} x_{0,j}^k H_k^B + \sum_{k \in 1...|K|-1} \sum_{j \in N} \sum_{i \in N} T_{ij}^k x_{ij}^k + \sum_{k \in 1...|K|-1} \sum_{i \in N/\{0\}} \sum_{j \in N; j \neq i} \gamma x_{ij}^k \qquad (1)$$

subject to:

Table 1
Sets, parameters and variables.

Sets	
C	Set of containers
N	Set of docks, index 0 for the dry port
E	Set of export containers
I	Set of import containers
K	Set of barges and trucks, element $k = |K|$ represents trucks

Parameters	
Z_{cj}	1 if container c is destined to/originated at dock j, 0 otherwise
W_c	Size of container c
R_c	Release date of export container c
O_c	Opening date of container c
D_c	Closing date of container c
H^T	Cost for a trucked container
H^B_k	Cost for using barge k
Q_k	Capacity of barge k
T_{ij}	Barges' travel time between terminals i and j
L	Handling time per container
γ	Penalty for sea terminals' visits
M	A large value

Variables	
f_{ck}	Binary variable, equals 1 if container c is allocated to means k
$x^k_{i,j}$	Binary variable, equals 1 if barge k sails from terminal i to j
p^k_j	Import quantity loaded by barge k at sea terminal j
d^k_j	Export quantity unloaded by barge k at sea terminal j
$y^k_{i,j}$	Import quantity carried by barge k from terminal i to j
$z^k_{i,j}$	Export quantity carried by barge k from terminal i to j
t^k_j	Time barge k is at terminal j

$$\sum_{k \in K} f_{ck} = 1 \qquad \forall\, c \in C \tag{2}$$

$$\sum_{j \in N: j \neq i} x^k_{ij} - \sum_{j \in N: j \neq i} x^k_{ji} = 0 \qquad \forall\, i \in N, k \in 1 \ldots |K| - 1 \tag{3}$$

$$\sum_{j \in N/\{0\}} x^k_{0,j} \leqslant 1 \qquad \forall\, k \in 1 \ldots |K| - 1 \tag{4}$$

$$p^k_j = \sum_{c \in I} W_c Z_{cj} f_{ck} \qquad \forall\, k \in 1 \ldots |K| - 1, j \in N/\{0\} \tag{5}$$

$$d^k_j = \sum_{c \in E} W_c Z_{cj} f_{ck} \qquad \forall\, k \in 1 \ldots |K| - 1, j \in N/\{0\} \tag{6}$$

$$\sum_{i \in N; i \neq j} y^k_{ji} - \sum_{i \in N; i \neq j} y^k_{ij} = p^k_j \qquad \forall\, j \in N/\{0\}, k \in 1 \ldots |K| - 1 \tag{7}$$

$$\sum_{i \in N; i \neq j} z^k_{ij} - \sum_{i \in N; i \neq j} z^k_{ji} = d^k_j \qquad \forall\, j \in N/\{0\}, k \in 1 \ldots |K| - 1 \tag{8}$$

$$y_{ij}^k + z_{ij}^k \leqslant Q_k x_{ij}^k \qquad \forall\ i, j \in N, k \in 1\ldots \left|K\right| - 1 \tag{9}$$

$$t_0^k \geqslant R_c f_{ck} \qquad \forall\ c \in E, k \in 1\ldots|K| - 1 \tag{10}$$

$$t_j^k \geqslant t_i^k + \sum_{c \in C} LZ_{ci} f_{ck} + T_{ij}^k - \left(1 - x_{ij}^k\right)M \qquad \forall\ i, j \in N, k \in 1\ldots \left|K\right| - 1 \tag{11}$$

$$t_j^k \leqslant t_i^k + \sum_{c \in C} LZ_{ci} f_{ck} + T_{ij}^k + \left(1 - x_{ij}^k\right)M \qquad \forall\ i, j \in N, k \in 1\ldots \left|K\right| - 1 \tag{12}$$

$$t_j^k \geqslant O_c Z_{cj} - (1 - f_{ck})M \qquad \forall\ c \in C, j \in N/\{0\}, k \in 1\ldots|K| - 1 \tag{13}$$

$$t_j^k Z_{cj} \leqslant D_c + (1 - f_{ck})M \qquad \forall\ c \in C, j \in N/\{0\}, k \in 1\ldots|K| - 1 \tag{14}$$

$$f_{ck} \in \{0, 1\} \qquad \forall\ c \in C, k \in K \tag{15}$$

$$x_{ij}^k \in \{0, 1\} \qquad \forall\ i, j \in N, k \in 1\ldots|K| - 1 \tag{16}$$

$$y_{ij}^k, z_{ij}^k \in \mathbb{R}^+ \qquad \forall\ i, j \in N, k \in 1\ldots \left|K\right| - 1 \tag{17}$$

$$t_j^k, p_j^k, d_j^k \in \mathbb{R}^+ \qquad \forall\ j \in N, k \in 1\ldots \left|K\right| - 1 \tag{18}$$

The objective function (1) minimizes the sum of the transportation costs and the number of visited terminals. Constraints (2) impose that every container is allocated to either a barge or a truck. Constraints (3) concern flow conservation. Constraints (4) impose that each barge is used at most once. With Equalities (5) and (6) the import (pickup) and export (delivery) sub-demands handled by barge k at sea terminal j are computed. Equalities (7) and (8) are flow equations for import (pickup) and export (delivery) quantities at terminal j handled by barge k, respectively; they ensure that both sub-demands are satisfied. Capacity constraints and activation of transport legs are imposed by (9). From Constraints (10)–(14) time-related conditions are modeled. With (10), we impose that a barge departs only when all allocated export containers are available. Inequalities (11) and (12) compute the arrival of a barge at a certain node and include the total time for loading/unloading each container at the previous node. With (13) and (14), we impose that the containers are handled at the related sea terminal within their time window. In this formulation, the pickup and delivery flow constraints are enough to guarantee sub-tour elimination. Finally, Constraints (15)–(18) define the nature of the variables.

In terms of formulations, the presented model includes elements of the VRPSPD presented in (Montanes and Galvao, 2006). The main difference is in the definition of variables p_j^k and d_j^k. In our model, they are variables that depend on the number of containers related to sea terminal j that are allocated to a barge k by means of constraints (2). This implies that a sea terminal can be visited multiple times by different barges. In (Montanes and Galvao, 2006), p_j and d_j are the whole pickup and delivery quantities of a customer j, which is visited by only one vehicle. Finally, our model also considers time windows that are defined on container level.

4. Solution method

In this paper, we propose a hybrid meta-heuristic approach consisting of construction and deconstruction phases, a local search component with TABU lists and an MILP solver that constructs feasible minimum-cost routes for barges. Meta-heuristic approaches are a prevalent choice to solve this type of routing problems, especially when aiming to solve large scale instances. See for example Qiu et al. (2018) for a TABU search approach, Wang et al. (2010) for a competitive decision algorithm, and Mitra (2008) for a parallel clustering technique. Very few exact approaches have been developed in the literature and mainly for the VRPSPD, see for example Dell'Amico et al. (2006) and Subramanian et al. (2011). Although exact methods are useful to generate new lower bounds for well-known data or provide optimal solutions, their limitation is mainly the long running time to solve large instances, which is an important aspect for real-world applications (Kalayci and Kaya, 2016).

The solution method comprises two components, a greedy algorithm for finding an initial solution, and the meta-heuristic to improve upon that solution. The following subsections are dedicated to their description.

4.1. A greedy algorithm for the initial solution

A greedy algorithm is developed to construct the initial solution. The algorithm initially sorts containers based on their reference sea terminal and order the list according to a First-Come-First-Serve sequence of terminals on the river way. Specifically, based on the

river structure and tributaries we consider a most convenient route that, departing from the dry port, visits all sea terminals. Henceforth, this sequence is defined as "master route". Next we sort available barges by the largest capacity.

The allocation procedure starts by selecting the first available container and barge from the lists. Once a container is inserted, the route is created, respecting the given sequence from the sorting process. Iteratively, transport loads for each transport leg are computed. If the insertion is feasible, the container is removed from the list and the next container is selected. If the allocation is not feasible, the container is removed from the barge, and the next container selected. Once the last container is checked, the next barge is selected, if available, and the procedure restarts the allocation phase by screening the list of remaining containers from the beginning.

Transportation times are computed iteratively as soon as a container is inserted and a new terminal is visited. If export containers are allocated, we first set the departure time from the dry port equal to the latest available export container at the dry port. If no export container is allocated, the departure time is initially set to 0. Based on traveling times, the arrival time at each node is computed. If the time windows of the allocated containers are all respected, the insertion is accepted. Otherwise, the procedure computes the largest gap from the time windows. If there are positive gaps, meaning the barge is too late, the container is rejected. If there are negative gaps, the departure time is postponed by the largest gap; if there are still exceeded time windows, the container is rejected and the next one available is selected.

The procedure stops when either all containers are allocated or all barges have been filled. Finally, the containers that have not been allocated are trucked. Below, we provide the pseudocode of the greedy algorithm.

Algorithm 1. Greedy algorithm for initial solution

```
 1: Sort set C by: reference terminal
 2: Sort set N by: capacity
 3: Initialize allocation list: L
 4: Step 0: c = 0 k = 0
 5: Step 1: insert c in k
 6: Step 2: build route and compute timings
 7: if insertion feasible then
 8:    insert c in L
 9: end if
10: Step 3: new selection c
11: while c < |C| & c ∉ L & k < |K| − 1 do
12:    c ← c + 1
13:    if c = |C| then
14:       k ← k + 1, c = 0
15:    end if
16: end while
17: if k = |K| − 1 then
18:    Go to step 4
19: else
20:    Go to step 1
21: end if
22: Step 4: stop. Truck all containers c ∈ L. Compute solution s_start.
```

4.2. A hybrid local search algorithm with TABU lists

The meta-heuristic starts from the initial solution and searches the solution state space randomly via two operators and a shaking function. The local search focuses on the allocation of containers to the barges and uses TABU lists to prevent unnecessary or inconvenient moves to certain solutions. As soon as a potentially cheaper allocation is found, the solver tries to find a feasible route, if the master route is not. Due to a very dense network, typical for inland shipping, the computational time is expected to be reasonable.

4.2.1. Operators and functions

The main operator selects a container and moves it to a randomly selected means of transport. This operator is also endowed with a function that updates the capacity of the barge. Specifically, it "downgrades" the barge of origin if the load is lower or equal than the capacity of an empty available barge, and it "upgrades" the barge of destination if the load is greater than current capacity and lower than the capacity of an empty available barge. The second operator swaps two randomly selected containers allocated to different barges.

Containers are chosen randomly by the operators. The way they are treated strongly depends on their impact to the bundle in terms of timing. On one hand, a container with a very large time window has little impact on a bundle allocated to a barge compared to a container with a tight time window. The same can be argued for containers that are immediately available at the dry port. These non-critical containers cannot be moved to trucks, but only to other barges. On the other hand, "critical" containers that have either the earliest due date or the latest opening date or the latest release date can be moved to both barges and trucks. Once a critical container is moved out to another means of transport a TABU list prevents the container to be moved again to the original barge for a certain number of iterations. Also, once a critical container is moved from a barge, the algorithm activates a randomized greedy

procedure that selects for a certain number of iterations only containers allocated to trucks and tries to move them to that barge.

A shaking function is also activated once the meta-heuristic is not able to refine the best solution found for a number of iterations. The function empties the least utilized barge, which is later inserted in a TABU list. Once a barge is in the TABU list, it cannot be selected by the shaking function. Finally, this TABU list is emptied as soon as all barges have been selected. Below a pseudo-code of the meta-heuristic.

Algorithm 2. Meta-heuristic: for conciseness only operator 1 is described

```
 1: Initialize: Tabu lists T1, T2, T3, z = 0, h = 0, sol = s_start, op = 0, m = 0
 2: Set values: Z, max_it, M. Set sizes Tabu lists
 3: Step 1: select c: c ∉ T1
 4: if c is not critical in j: f_cj = 1 then
 5:    select barge randomly k: f_ck = 0 & ck ∉ T2
 6: else
 7:    select randomly a barge or truck k: f_ck = 0
 8: end if
 9: Step 2: build route and compute timings
10: update selected barges capacity if possible
11: if insertion feasible then
12:    compute new solution, new_sol
13:    if c was critical in j then
14:       insert pair cj in T2
15:       op = 1
16:    end if
17: else
18:    c in T1, h ← h + 1
19: end if
20: Step 3: sol ← new_sol
21: if sol(h) = sol(h − 1) then
22:    z ← z + 1
23: end if
24: if z = Z then
25:    empty barge j ∉ T3 with the least utilization
26:    insert j in T3
27:    if T3 contains all barges then
28:       empty T3
29:    end if
30: end if
31: Step 4: m = 0
32: if op = 1 then
33:    while m < M do
34:       try to insert trucked container j: f_c|K|−1 = 1
35:       m ← m + 1
36:    end while
37: end if
38: op = 0
39: Step 5: h ← h + 1
40: if h = max_it then
41:    Stop
42: else
43:    Update T1, T2. Go to Step 1
44: end if
```

4.2.2. Routing construction

Once a new solution is found, the local search constructs a route based on the river direction, that is, an established master route. If the algorithm cannot find a feasible solution, either for exceeding time windows or capacity restrictions, the MILP solver is summoned for that specific barge $\bar{k}$ and the allocated subset of containers $\overline{C}$. The sub-model that is solved is the following:

$$min \sum_{k \in 1 \ldots |K|-1} \sum_{j \in N} \sum_{i \in N} T_{ij}^k x_{ij}^k \tag{19}$$

subject to:

$$\sum_{j \in N: j \neq i} x_{ij}^{\bar{k}} - \sum_{j \in N: j \neq i} x_{ji}^{\bar{k}} = 0 \quad \forall \ i \in N \tag{20}$$

$$\sum_{j \in N/\{0\}} x_{0,j}^{\bar{k}} \leqslant 1 \tag{21}$$

Fig. 1. Sea terminals in the Port of Rotterdam. Larger circles identify multiple close terminals. Some container terminals may also serve as container depots.

$$\sum_{i\in N; i\neq j} y_{ji}^{\bar{k}} - \sum_{i\in N; i\neq j} y_{ij}^{\bar{k}} = p_j^{\bar{k}} \qquad \forall j \in N/\{0\} \tag{22}$$

$$\sum_{i\in N; i\neq j} z_{ij}^{\bar{k}} - \sum_{i\in N; i\neq j} z_{ji}^{\bar{k}} = d_j^{\bar{k}} \qquad \forall j \in N/\{0\} \tag{23}$$

$$y_{ij}^{\bar{k}} + z_{ij}^{\bar{k}} \leqslant Q_{\bar{k}} x_{ij}^{\bar{k}} \qquad \forall i, j \in N \tag{24}$$

$$t_0^{\bar{k}} \geqslant R \tag{25}$$

$$t_j^{\bar{k}} \geqslant t_i^{\bar{k}} + T_{ij}^{\bar{k}} - (1 - x_{ij}^{\bar{k}})M \qquad \forall i, j \in N \tag{26}$$

$$t_j^{\bar{k}} \leqslant t_i^{\bar{k}} + T_{ij}^{\bar{k}} + (1 - x_{ij}^{\bar{k}})M \qquad \forall i, j \in N \tag{27}$$

$$t_j^{\bar{k}} \geqslant O_j \qquad \forall j \in N/\{0\} \tag{28}$$

$$t_j^{\bar{k}} \leqslant D_j \qquad \forall j \in N/\{0\} \tag{29}$$

$$x_{ij}^{\bar{k}} \in \{0, 1\} \qquad \forall i, j \in N \tag{30}$$

$$y_{ij}^{\bar{k}}, z_{ij}^{\bar{k}} \in \mathbb{R}^+ \qquad \forall i, j \in N \tag{31}$$

$$t_j^{\bar{k}} \in \mathbb{R}^+ \qquad \forall j \in N \tag{32}$$

Note that $p_j^{\bar{k}}$ and $d_j^{\bar{k}}$ are now input for the model. Also we define O_j and D_j, as the time window at terminal j. O_j is computed as the maximum opening time at dock j within the selected containers $\overline{C}$: $Z_{ij} = 1$. Likewise, D_j is computed as the least due date at dock j. Finally, R is the maximum release date of export containers within set $\overline{C}$.

5. Numerical experiments

The aim of this numerical section is twofold. First, to assess the performance of the meta-heuristic against a MILP solver, specifically CPLEX 12.9.2. Secondly, to provide solutions analysis and generate practical insights, using real world instances. We first introduce the case study and relevant characteristics for the creation of the instances. Next, we discuss the technical setting and the parametrization of the meta-heuristic. Finally, we show the results of the two experiments.

5.1. Case study and instances generation

Due to the practical relevance of the proposed problem, the instances are based on the case of a Dutch barge operator active in the Port of Rotterdam region, who provided data (2016–2018) on handled container. The dry port is located in the North Brabant, a province in the south of the Netherlands, about 120 km away from the Port of Rotterdam, with an average travel time for barges of 11 h.

The Port of Rotterdam seaport consists of several terminals. The data set considers 36 terminals within the port. Fig. 1 shows two main agglomerations of terminals where the majority of the containers is handled, and in particular: the closest area to the North Sea (Maasvlakte terminals), and the City terminal located further to the east. For the distances, we refer to (Fazi et al., 2015).

The barge operator (BO) manages a fleet of barges consisting of 5 privately owned small-medium size vessels. Capacities in TEU are: 104, 99, 81, 52, 28. The BO has contracts with the barge owners to hold regular services between the sea port and the dry port.

Table 2
Data for instance generation.

Data	Experiment 1	Experiment 2
$|C|$	*Unif* [100, 600]	Based on data set
$|N|$	*Unif* [10, 20]	Based on data set
R_c	*Unif* [0, 24]	Based on data set
D_c	*Unif* [24, 196]	Based on data set
O_c	*Unif* $[D_c - 120, D_c - 24]$	Based on data set
T_{lj}^k	Fazi et al. (2015)	
Q_k (TEU)	104, 99, 81, 52, 28	
H_k^B(€)	3700, 3600, 3400, 2800, 1800	
H^T 40-foot(€)	200	
H^T 20-foot(€)	140	

The BO estimated that the rental cost for each round trip is respectively: €3700, €3600, €3400, €2800, €1800. These costs reflect an economy of scale. The BO also owns a fleet of truck. Fixed average cost for trucking a 40-foot container is set to €200, and for a 20-foot container to €140. Note that these costs are based on the guidelines of the barge operator and are purely indicative of the real cost. However, they are in line with the costs used in previous research (Behdani et al., 2014).

In the first experiment, we test the performance of the meta-heuristic with 20 randomly generated instances, considering solely transportation costs. The parameters related to the containers follow the trends in the available data set. In particular, for each instance, we set the number of containers to be random between 100 and 600, and the number of terminals between 10 and 20. The terminal locations are assigned randomly.

In the data set, the number of export containers may vary significantly week by week, whereas import containers have a more steady presence. To consider this, for each instance we randomly generated a number within [0.05, 0.7]. Then, this number is the probability for each container to be export in that instance. The same approach is used to assign the size, either 20 or 40 foot, to the containers. The probability to be a 40-foot container is in the range [0.75, 0.9]. For each instance, time features in hours are randomly chosen from selected weeks from the data set and normalized, considering time 0 to be the start of planning period. Advance information on the availability of export containers at the inland terminal typically does not exceed 24 h. Due dates are in the range [24, 196]. The opening dates, when not available in the data set, were randomly generated between 2 and 5 days before the due date. Finally, handling time per container is set to 10 min.

With concern to the second experiment, we draw 5 instances from the data set. The data matches handled containers in selected weeks where complete data is available, including the final implemented decisions of the planners. In this regard, alphanumerical codes are assigned to barged containers, indicating import and export voyages, the used barge, and the sequential voyage number. In this way, we are able to generate insights on the planning procedures. We summarize the data used for both experiments in Table 2.

Table 3
Results on a set of randomly generated instances. UB and LB stand respectively for upper bound and lower bound for the minimization problem. Column "Gap(UB)" reports the gap between the meta-heuristic solution and the best integer solution found by CPLEX. Column "Gap(LB)" reports the gap with the lower bound.

		MH					CPLEX					
Inst.	Cont.	Sol.	Time (sec.)	# stops	AVG. Util	St. Dev.	UB	LB	MIP gap	Time	Gap(UB)	Gap(LB)
1	150	12840	8,10	28	0,51	0	12840	12220	0,05	495	0,00	0,05
2	194	9640	54,02	27	0,76	81	10380	9235	0,11	1412	0,08	0,04
3	219	21900	2,12	27	0,63	90	22100	21900	0,01	3123	0,01	0,00
4	291	18750	3,00	39	0,86	98	19570	16550	0,15	719	0,04	0,13
5	322	21750	16,50	41	0,84	32	21750	17950	0,17	3212	0,00	0,21
6	327	27230	0,15	45	0,69	49	30170	26350	0,13	546	0,11	0,03
7	344	28290	0,08	35	0,69	0	28290	27850	0,02	2655	0,00	0,02
8	354	16130	59,57	45	0,81	129	16130	13496	0,16	2751	0,00	0,20
9	361	19490	2,36	50	0,88	0	19630	17250	0,12	649	0,01	0,13
10	370	19110	3,56	53	0,82	296	20750	14555	0,30	1975	0,09	0,31
11	370	21930	26,33	35	0,8	18	23870	19650	0,18	2673	0,09	0,12
12	376	23050	24,30	45	0,81	65	23510	22850	0,03	900	0,02	0,01
13	377	17350	33,17	42	0,88	537	21210	14450	0,32	3037	0,22	0,20
14	387	18030	7,50	51	0,84	82	19850	17221	0,13	1614	0,10	0,05
15	390	21830	10,58	43	0,81	43	21990	21750	0,01	1123	0,01	0,00
16	396	17450	12,60	49	0,96	332	20890	15650	0,25	712	0,20	0,12
17	417	26780	0,41	57	0,81	66	27600	25100	0,09	666	0,03	0,07
18	467	23360	11,41	60	0,85	274	24500	20940	0,15	2953	0,05	0,12
19	480	23880	1,68	71	0,91	32	24560	23400	0,05	1459	0,03	0,02
20	498	29880	24,00	63	0,82	41	31820	29800	0,06	558	0,06	0,00

Table 4

Results on a set of real-world instances. Column "MH(γ)" reports the results of the algorithm considering the extra cost for additional stops.

Instance	Cont.	Planner				MH				MH(γ)			
		Cost	# stops	AVG. Util		Cost	# stops	AVG. Util	Gap	Cost	# stops	AVG. Util	Gap
1	145	16080	9	0,47		9620	25	0,81	−0,40	14260	17	0,52	−0,11
2	184	13160	13	0,67		8860	23	0,77	−0,33	11540	16	0,99	−0,12
3	226	16900	12	0,63		11640	28	0,89	−0,31	13260	23	0,84	−0,22
4	230	18020	14	0,52		11240	31	0,8	−0,38	16480	23	0,59	−0,09
5	351	18580	16	0,77		14500	47	0,94	−0,22	16300	33	0,66	−0,12

5.2. Meta-heuristic setting, parametrization and technical remarks

The greedy algorithm and the meta-heuristic are coded in C++ and run on an Intel(R) Core(TM)2 DUO machine with 2.93 GHz and 8.00 GB RAM memory. The sub-models within the meta-heuristic are integrated in CPLEX using the Concert Technology in C++. For the full MILP model, we also use CPLEX running on a high performing machine, with a 24 Intel Xeon 2.5 GHz cores and 128 GB of internal memory, using in default conditions twenty-four threads. The time limit for this computation was set to 1 h per instance.

The parameters of the meta-heuristic were drawn after a preliminary experimentation. The stopping criteria is set to 20 million of iterations. The probability for selecting operator 1 was set to 80%. The shaking function is activated after 100.000 iterations from the last improvement to the best solution found. The probability to select a container allocated to a truck was set to 60%. The probability that a "critical" container is moved to a truck was set to 60%.

5.3. Results on randomly generated instances

In Table 3, results are displayed. We indicate the total number of TEU. For the meta-heuristic, labeled as "MH," we report the best solution found among all parameterizations, along with related timing to reach the solution. For CPLEX, we report the best integer solution (upper bound for the minimization problem), the best lower bound, and the timing when the best integer solution is found during the set time frame. In case, $UB \neq LB$, CPLEX ran out of time without finding the optimal solution. However, we report the timing when the best feasible solution was found. Finally, in the last two columns, we display the gaps between the UB and LB from CPLEX with the meta-heuristic solution.

These results show a good performance of the algorithm against CPLEX, both in terms of solution quality and speed. For none of the instances, CPLEX is able to find the optimal solution. The gaps between the best feasible solutions (UB) and the best solutions from the algorithm are on average 6%, with a maximum gap of 22%. In three cases, the values match. The maximum MIP gap is 32% with an average of 12%. On the other hand, the maximum gap between the meta-heuristic solutions and the LBs is 31% with an average of 9%. In terms of speed, the algorithm is able to generate its best solutions within a minute. On the contrary, CPLEX takes on average 27 min to reach the best solution with a maximum of 53 min. Finally, in terms of consistency, the algorithm shows small standard deviations.

5.4. Results on real-world instances

The results shown here involve a set of real-world instances drawn from the available data set. The instances refer to containers handled in specific weeks of the data set and consist of containers sent via barge and via truck. The aim of this experiment is to highlight any improvement to the solution of the barge planners and analyze patterns in the decision-making process.

In Table 4, we report the results of the experimentation, consisting of the solution of the planners and of the meta-heuristic. In particular, we provide the solutions with and without penalty γ for extra stops. When γ was considered, the reported cost concerns only the transportation cost.

These experiments show very large gaps between the implemented plans of the planners and the solutions from the meta-heuristic, with the largest being 40%. Overall, the utilization of the barges in the meta-heuristic solutions is much higher than the real solution. On the other hand, it is striking to see how the planners try to reduce the number of stops in barge trips. The reason for this is twofold. First, the planners try to ease the construction of the solutions by sorting containers belonging to the same terminal. Second, their aim is to reduce the possibility of congestion and delays due to additional handling operations.

When the meta-heuristic considers a cost γ for each stop at the sea terminals, results become closer in terms of stops to the ones of the planners. Note that γ does not reflect a real cost, rather it is used to recreate certain type of solutions. The higher the penalty, the fewer the number of stops in a trip. This is roughly the rationale behind the planner's way of allocating containers. We tried several values for γ from 100 to 3000. Higher values did not produce meaningful results. The reduction of stops raises the cost either for more trucks needed or for more barges used, but with lower utilization. As is evident from the second instance, the meta-heuristic is forced to empty barges and use more trucks in order to reduce the number of stops. This obviously entails greater operational costs, even though utilization of barges is already high.

A deeper look into the planners' implemented solutions provided some interesting insights. It turns out that not all solutions were feasible for the given model in terms of time windows. In some cases, barges took too many hours to complete the round trip. In fact, barges waited outside the seaport before all time windows were open. This entails very low efficiency in terms of barge utilization, but offers more possibilities for bundling containers belonging to the same dock. Furthermore, in a few cases, time windows do not seem to be respected at all. This could be explained by the fact that a large part of the planning time is spent in bargaining with shippers and sea terminals on determining a suitable pickup or delivery time that may fit with certain solutions.

In addition, it is notable that a few trips were carrying a number of containers so small that they could not generate any economy of scale. In those cases, sending containers via truck would have been more cost-effective. This is why the results could not match up, even with very large values of γ. There could be several reasons for this. First, in some cases, barge operators rent barges for a specific period of time and so a sunk cost is involved, plus the fixed cost per trip taken into account in our model. Barge operators may simply prefer this option so as to justify the initial investment, even though it is not cost efficient. Second, for barge operators, it is crucial to show that the majority of cargo is processed via barge. Third, the complexity of the problem may simply lead to poor solutions.

6. Discussion and final remarks

In this paper, we have tackled an important planning problem, involving the transportation of maritime containers between a dry port and seaport terminals by barge. Export containers should be transported from the dry port to the seaport to preassigned sea terminals within a time windows. Whereas, import containers available at the seaport terminals must be picked up within a time window and transported to the dry port. Trucks are available as a buffer to transport those containers that could not be consolidated, generating a large cost. The main objective is to efficiently use the available fleet of barges in order to generate economies of scale, while meeting time restrictions. The problem was modelled as an adaptation of the split VRP with simultaneous pickups and deliveries, proposed for the first time in Mitra (2005). The peculiarity of our model is that each demand quantity (i.e., container) is treated singularly and each has also an assigned time windows. We tackled this by endowing the original model with bin packing constraints that help to compute the pickup and delivery quantities at each node as well as keeping track of the time windows. The model was solved with a hybrid local search algorithm endowed with TABU lists and a MILP solver to tackle subrouting problems.

Numerical experiments, based on the case of a Dutch barge operator, showed a very good performance of our approach against CPLEX for large instances. Also, they were aimed to provide managerial insights on current planning practices. In particular, we could highlight several decisions that led to low utilized barges, missed consolidation opportunities, and violated time windows. This is the result of manual planning procedures that lean on basic "greedy" approaches based on rule of thumb. For example, consolidating only containers originated or destined to the same sea terminal, or rushing the utilization of available barges without a global consideration of all available containers.

This paper fills a gap in the literature on inland shipping by complementing the stowage model presented in Fazi (2019). The literature review showed a lack of studies on this subject concerning operational decisions. Hence, this work opens up several opportunities for future research. First of all, the current model can be extended to include transfer of containers between different sea terminals or other inland terminals. In these cases, containers may be both picked up and discharged on route. Next, from a multimodal perspective, it may be worth investigating how containers can be prioritized based on agreed tariffs and how these can be handled using different modalities (i.e., rail and truck) in a synchromodal way (Giusti et al., 2019; Tavasszy et al., 2017; Perboli et al., 2017). Also the proposed model can help to assess which containers should be handled in case of overbooking practices. Based on time windows, penalties, priorities and available capacity, the planner may decide to buffer certain containers to other modalities, or activate extra barge services. Finally, definitions of parameters is a crucial aspect in the model and having advance information of upcoming containers may be beneficial, especially in terms of release date of new export containers. In particular, it might be beneficial to estimate import container return times after they have been discharged at the inland terminal and delivered to the shipper. Knowing the return time may not only help in scheduling future barge trips but also in reusing the empty container and in generating extra profit. Several elements may help in the analysis, such as final delivery location, type of cargo, type of container, the shipper, etc.

From a practical perspective, this paper highlights the need of IT platforms endowed with optimization algorithms to support the decision making of planners. Although support tools currently exist, to our knowledge they are not endowed with optimization engines. These systems can be classified mainly as data management software used by the planners to download spreadsheets, upload planning decisions, get updates, and communicate with the other stakeholders (using the same system). In some cases, planners have to refer to data from different software, and evaluate which one is more reliable. The consequences are rushed rule of thumb based decisions, less time for actual planning, and lack of a global overview. Hence, the proposed model can be useful to improve the situation and support daily planning.

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References

Agamez-Arias, A.d.M., Moyano-Fuentes, J., 2017. Intermodal transport in freight distribution: a literature review. Transport Rev. 37, 782–807.

Alfandari, L., Davidović, T., Furini, F., Ljubić, I., Maraš, V., Martin, S., 2019. Tighter mip models for barge container ship routing. Omega 82, 38–54.

An, F., Hu, H., Xie, C., 2015. Service network design in inland waterway liner transportation with empty container repositioning. Eur. Transport Res. Rev. 7, 9.

Behdani, B., Fan, Y., Wiegmans, B., Zuidwijk, R., 2014. Multimodal schedule design for synchromodal freight transport systems. Behdani, B., Fan, Y., Wiegmans, B., & Zuidwijk, R., 424–444.

Bouchery, Y., Fazi, S., Fransoo, J., 2015. Hinterland transportation in container supply chains. In: Handbook of Ocean Container Transport Logistics. Springer, pp. 497–520.

Braekers, K., Caris, A., Janssens, G.K., 2013. Optimal shipping routes and vessel size for intermodal barge transport with empty container repositioning. Comput. Ind. 64, 155–164.

Caris, A., Macharis, C., Janssens, G., 2011. Network analysis of container barge transport in the port of Antwerp by means of simulation. J. Transp. Geogr. 19, 125–133.

Dell'Amico, M., Righini, G., Salani, M., 2006. A branch-and-price approach to the vehicle routing problem with simultaneous distribution and collection. Transport. Sci. 40, 235–247.

European Commission, 2019. Mid-term progress report on the implementation of the NAIADES II action programme for the promotion of inland waterway transport. https://ec.europa.eu/transport/sites/transport/files/legislation/swd20180428-naiades2.pdf (accessed January 3rd, 2020).

Fazi, S., 2019. A decision-support framework for the stowage of maritime containers in inland shipping. Transport. Res. Part E: Logist. Transport. Rev. 131, 1–23.

Fazi, S., Fransoo, J.C., van Woensel, T., 2015. A decision support system tool for the transportation by barge of import containers: A case study. Decis. Support Syst. 79, 33–45.

Fazi, S., Roodbergen, K.J., 2018. Effects of demurrage and detention regimes on dry-port-based inland container transport. Transport. Res. Part C: Emerg. Technol. 89, 1–18.

Frémont, A., Franc, P., 2010. Hinterland transportation in Europe: Combined transport versus road transport. J. Transp. Geogr. 18, 548–556.

Giusti, R., Manerba, D., Bruno, G., Tadei, R., 2019. Synchromodal logistics: An overview of critical success factors, enabling technologies, and open research issues. Transport. Res. Part E: Logist. Transport. Rev. 129, 92–110.

van der Horst, M., Kort, M., Kuipers, B., Geerlings, H., 2019. Coordination problems in container barging in the port of rotterdam: an institutional analysis. Transport. Plann. Technol. 42, 187–199.

Kalayci, C.B., Kaya, C., 2016. An ant colony system empowered variable neighborhood search algorithm for the vehicle routing problem with simultaneous pickup and delivery. Expert Syst. Appl. 66, 163–175.

Konings, R., Kreutzberger, E., Maraš, V., 2013. Major considerations in developing a hub-and-spoke network to improve the cost performance of container barge transport in the hinterland: The case of the port of Rotterdam. J. Transp. Geogr. 29, 63–73.

Kotowska, I., Mańkowska, M., Pluciński, M., 2018. Inland shipping to serve the hinterland: the challenge for seaport authorities. Sustainability 10, 3468.

Li, J., Zhang, Y., Ma, J., Ji, S., 2018. Multi-port stowage planning for inland container liner shipping considering weight uncertainties. IEEE Access 6, 66468–66480.

Lu, C., Yan, X., 2015. The break-even distance of road and inland waterway freight transportation systems. Maritime Econ. Logist. 17, 246–263.

Maraš, V., Lazić, J., Davidović, T., Mladenović, N., 2013. Routing of barge container ships by mixed-integer programming heuristics. Appl. Soft Comput. 13, 3515–3528.

Meers, D., Vermeiren, T., Macharis, C., 2014. Intermodal break-even distances: A fetish of 300 kilometres? Sustainable Logist. 6, 217–243.

Mitra, S., 2005. An algorithm for the generalized vehicle routing problem with backhauling. Asia-Pacific J. Oper. Res. 22, 153–169.

Mitra, S., 2008. A parallel clustering technique for the vehicle routing problem with split deliveries and pickups. J. Oper. Res. Soc. 59, 1532–1546.

Moghaddam, M., Pearce, R.H., Mokhtar, H., Prato, C.G., 2020. A generalised model for container drayage operations with heterogeneous fleet, multi-container sizes and two modes of operation. Transport. Res. Part E: Logist. Transport. Rev. 139, 101973.

Montanes, F., Galvao, R., 2006. A tabu search algorithm for the vehicle routing problem with simultaneous pick-up and delivery service. Comput. Oper. Res. 33, 595–619.

Notteboom, T., 2007. Inland waterway transport of containerised cargo: From infancy to a fully fledged transport mode. J. Maritime Res. 4, 63–80.

Perboli, G., Musso, S., Rosano, M., Tadei, R., Godel, M., 2017. Synchro-modality and slow steaming: New business perspectives in freight transportation. Sustainability 9, 1843.

Qiu, M., Fu, Z., Eglese, R., Tang, Q., 2018. A tabu search algorithm for the vehicle routing problem with discrete split deliveries and pickups. Comput. Oper. Res. 100, 102–116.

Rivera, A.E.P., Mes, M.R., 2017. Anticipatory freight selection in intermodal long-haul round-trips. Transport. Res. Part E: Logist. Transport. Rev. 105, 176–194.

Roso, V., Russel, D., 2018. Adoption of the dry port concept: a diffusion of innovation assessment. NOFOMA: Relevant Logistics and Supply Chain Management Research.

Roso, V., Woxenius, J., Lumsden, K., 2009. The dry port concept: Connecting container seaports with the hinterland. J. Transp. Geogr. 17, 338–345.

SteadieSeifi, M., Dellaert, N.P., Nuijten, W., Van Woensel, T., Raoufi, R., 2014. Multimodal freight transportation planning: A literature review. Eur. J. Oper. Res. 233, 1–15.

Subramanian, A., Uchoa, E., Pessoa, A.A., Ochi, L.S., 2011. Branch-and-cut with lazy separation for the vehicle routing problem with simultaneous pickup and delivery. Oper. Res. Lett. 39, 338–341.

Tan, Z., Wang, Y., Meng, Q., Liu, Z., 2018. Joint ship schedule design and sailing speed optimization for a single inland shipping service with uncertain dam transit time. Transport. Sci. 52, 1570–1588.

Tavasszy, L., Behdani, B., Konings, R., 2017. Intermodality and synchromodality. In: Ports and Networks. Routledge, pp. 251–266.

Tsao, Y.C., Thanh, V.V., 2019. A multi-objective mixed robust possibilistic flexible programming approach for sustainable seaport-dry port network design under an uncertain environment. Transport. Res. Part E: Logist. Transport. Rev. 124, 13–39.

Veenstra, A., Zuidwijk, R., van Asperen, E., 2012. The extended gate concept for container terminals: Expanding the notion of dry ports. Maritime Econ. Logist. 14, 14–32.

Vidović, M., Popović, D., Ratković, B., Radivojević, G., 2017. Generalized mixed integer and vns heuristic approach to solving the multisize containers drayage problem. Int. Trans. Oper. Res. 24, 583–614.

Wang, K., Ye, C., Ning, A., 2010. Competitive decision algorithm for the split vehicle routing problem with simultaneous pickup and delivery and time windows. In: 2010 International Conference on Future Information Technology and Management Engineering. IEEE, pp. 371–375.

Wang, Y., Ma, X., Lao, Y., Wang, Y., Mao, H., 2013. Vehicle routing problem: simultaneous deliveries and pickups with split loads and time windows. Transport. Res. Rec. 2378, 120–128.

Ypsilantis, P., Zuidwijk, R., 2019. Collaborative fleet deployment and routing for sustainable transport. Sustainability 11, 5666.

Zhen, L., Wang, K., Wang, S., Qu, X., 2018. Tug scheduling for hinterland barge transport: A branch-and-price approach. Eur. J. Oper. Res. 265, 119–132.

Zuidwijk, R.A., Veenstra, A.W., 2014. The value of information in container transport. Transport. Sci. 49, 675–685.