Transportation Research Part E 144 (2020) 102161

Contents lists available at ScienceDirect

Transportation Research Part E

journal homepage: www.elsevier.com/locate/tre

Dynamic barge planning with stochastic container arrivals

Volkan Gumuskaya [a,*], Willem van Jaarsveld [a], Remco Dijkman [a], Paul Grefen [a], Albert Veenstra [b]

[a] School of Industrial Engineering, Eindhoven University of Technology, The Netherlands
[b] Department of Technology and Operations Management, Rotterdam School of Management, The Netherlands

ARTICLE INFO

Keywords:
Hinterland transport
Uncertainty
Dynamism
Stochastic program
Multimodal transport
Barge planning

ABSTRACT

Barge transport suffers from a high degree of uncertainty resulting from unreliable container arrivals (e.g. due to deep sea vessel delays), and dynamism that leads to limited information availability during planning. This paper studies the impact of uncertainty and dynamism using real data of an inland terminal. Our method consists of iterating weekly operations for one year to evaluate the long term performance. Each iteration involves solving a stochastic program for planning barge calls, and then simulating actual events. We show that uncertainty has an impact of up to 53% and dynamism up to 20% on total costs.

1. Introduction

Multimodal transport has potential economic, societal and environmental advantages over road transport due to economies of scale facilitated by high capacity vehicles. A modal split with less road transport results in decreased carbon emissions, road congestion and unit transportation costs, a better connectivity and higher competitive power of the port (Parola et al., 2017). The critical role of modal split is recognized by governmental institutions and port authorities: In 2011, the European Commission set a target to shift 30% of all road freight transport over 300 km to rail or waterborne transport by 2030, and 50% by 2050. The Port of Rotterdam (PoR) aims to increase the share of barge transport in the Maasvlakte area to 45% by 2030. However, despite the favorable geographical conditions for barge transport and the efforts of the port authority, the modal split in PoR has been stable around 41%. A major cause of this is the inefficiency in the transport chain due to the coordination problems between the actors on operational level planning (van der Horst et al., 2019). The aforementioned coordination problems particularly arise due to high *uncertainty* and *dynamism* (Gumuskaya et al., 2020), which are particularly evident in hinterland transport. In practice, in a highly uncertain and dynamic environment, the transport operators prioritize satisfying customer requirements, while engaging in optimization of their operations to a very limited extent. This leads to an increase in the total costs and undermines the modal split.

In freight transport literature, the adverse effects of *uncertainty* such as demand variability or disturbances in services are commonly acknowledged (SteadieSeifi et al., 2014; Lium et al., 2009). Specifically for hinterland transport, the low reliability of deep sea vessel arrivals, delays in customs procedures and cargo preparation of export containers are major issues in operational level planning. For example, the estimated reliability of the 2M carrier alliance, defined as the proportion of actual arrivals within 24 h of the declared ETA, was reported to be as low as 26.5% in February 2018 on the Asia–North America East Coast (SeaIntel, 2018), and ranged between 60% and 80% during 2018 in Asia–Europe routes. In addition to the physical availability of the container, documentary and regulatory processes (e.g. problems with customs and carrier releases) prevent timely release of the containers

* Corresponding author.
E-mail addresses: v.gumuskaya@tue.nl (V. Gumuskaya), w.l.v.Jaarsveld@tue.nl (W. van Jaarsveld), r.m.dijkman@tue.nl (R. Dijkman), p.w.p.j.grefen@tue.nl (P. Grefen), veenstra@rsm.nl (A. Veenstra).

https://doi.org/10.1016/j.tre.2020.102161
Received 18 February 2020; Received in revised form 5 November 2020; Accepted 6 November 2020
Available online 13 November 2020

for inland transport. In previous research the aforementioned uncertain delays, which we broadly refer to as *uncertainty in container arrivals* for convenience, are recognized but are not analyzed quantitatively (Notteboom, 2006; van der Horst and de Langen, 2008; Gumuskaya et al., 2020).

In addition to the uncertainty in container arrivals, *dynamism* complicates barge planning. A barge operator has to decide which terminals to make calls at, and which containers to load/unload for a significant amount of time ahead of the actual handling. During this time gap, new information becomes available such as new incoming orders, delays and cancellations. Hence, the information is revealed throughout time leading to limited information at the moment of decision making (Pillac et al., 2013). Therefore, not only there is an uncertainty in container arrivals for the transport orders *already* received (with known origin–destination terminals and estimated arrival-due times), but also *new* transport orders arrive after the plan is already made (with no prior information). As a result of the uncertainty and dynamism, the efficiency of operational plans decreases, which undermine the competitiveness of barge transport.

To study the impact of uncertain delays and dynamism on barge planning, we design a solution procedure that determines weekly barge plans with an overall aim to minimize yearly costs taking into account uncertainty in container arrivals and dynamism in receiving orders. The overall procedure consists of planning barge calls for each *week* at discrete times iteratively, while the evaluation is based on the total cost of the whole *year* (See Fig. 1). At each iteration, the weekly problem is modeled as a two-stage stochastic mixed integer program (MIP) based on the *already* received orders (i.e. limited information) with an objective of minimizing the *expected* costs of one week. After the plan is set, the simulation starts: New transport orders arrive (of which the actual container arrival can be at the same week), actual container arrivals are simulated and *actual* costs are incurred (either barge or trucking costs), which are summed for the whole year and used for evaluation. The weekly problem is stochastic due to the delays in container arrivals represented by discrete scenarios; it is also dynamic as new orders may arrive for a given week *after* the planning is already made. Note that these new orders that were unknown at the time of planning may also lead to costs in the simulation stage. Moreover, the overall procedure is dynamic as it is permitted to postpone a container to the following weeks, which requires coupling of consecutive weeks, i.e. passing on the information of observed arrivals or delays to next week in order to calculate the conditional probabilities of arrival scenarios.

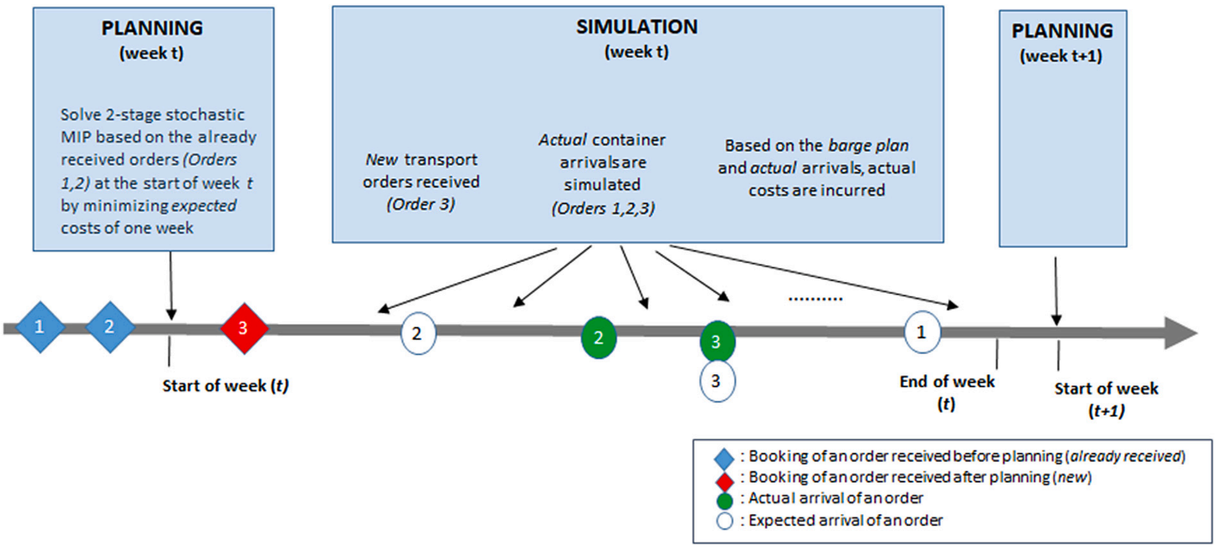

Fig. 1. The illustration of one iteration for week *t* as part of the overall procedure.

Our contributions are two-fold: First, our experiments yield important insights regarding the impact of uncertain delays and dynamism on the performance of barge planning. We show that uncertain delays in container arrivals increase total costs up to 53% compared to the deterministic case. We also show how dynamism leads to limited information at decision time, and increases costs up to 20%. During the computational experiment, we test different planning horizons from 1 day to 14 days planning ahead, and illustrate that more than half of the time the best performance is achieved with a horizon of 3 days. Second, from a methodological point of view, we contribute a novel approach: Our stochastic program is applied repeatedly in combination with simulation in a multi period fashion with realistic order sizes. The stochastic program plays the role of planning agent, while the simulation plays the role of real world execution. In this manner, uncertainty and dynamism are both incorporated, and their impact on the long term performance is analyzed in a realistic context. While stochastic programming is widely applied as a methodology in other domains, in hinterland transport domain there are just few examples, none of which combines it with simulation nor involves uncertain container arrivals or dynamism.

Against this background, the remainder of this paper is organized as follows: In Section 2, we review the literature on barge planning with an emphasis on stochastic and dynamic aspects. In Section 3, the problem setting is described in detail. In Section 4, the overall solution procedure, which consists of planning weekly barge calls with a two-stage stochastic mixed integer model and simulation of actual events are explained. In Section 5, the setup of computational experiment and the results are discussed. Finally, in Section 6 we conclude the paper and discuss further research ideas.

2. Literature review

SteadieSeifi et al. (2014) provide a structured overview of planning problems in multimodal transportation in three levels: strategic, tactical and operational. Barge planning, as we discuss in this paper, addresses both tactical and operational aspects as both weekly service schedules (i.e. the day of visits and which container terminal to call) and assignment of individual containers to the services are determined. The previous research on barge planning mainly employ a deterministic view: Fazi et al. (2015) study barge planning as a deterministic problem in two levels, and develop a metropolis algorithm, which is quite similar to simulated annealing algorithm. Firstly, a master route is determined for visiting the sea terminals, and then the routing within each sea terminal (i.e. rotation plan) is specified. Braekers et al. (2013) study the round-trip services of a barge that aims to maximize its revenues by fulfilling transport orders taking into account the empty container repositioning. They model the problem separately from the barge operator's and shipping line's perspective and conclude that shipping lines can reduce costs by integrating barge planning with empty container repositioning. Bredström et al. (2015) formulate the routing of barges and the amount of inventory to be carried by each barge (i.e. bulk transport) in discrete time units as a mixed integer model, while the capacity of the barges depend on the routes due to varying water depths. Choong et al. (2002) study the impact of planning horizon on empty container management of barge transport.

In both operational and tactical levels, uncertainty and dynamism are two important factors that define the formulation and the solution approach. In particular, barge planning involves a high uncertainty (i.e. demand, container availabilities, call handlings) and dynamism (arrival of orders throughout time, rescheduling of rotation plans) that has a crucial impact on how decision making is done (Gumuskaya et al., 2020). Uncertainty and dynamism work together in that gradual availability of uncertain events obliges decisions to be made with limited information, which inevitably decrease the quality of the solution. Next, we discuss how dynamism and uncertainty are studied in literature.

In multimodal transport, *dynamism* is often reflected by the container orders arriving through time. In vehicle routing problem literature for example, the most common aspect of dynamism is the online arrival of orders during the operation causing limited information (Pillac et al., 2013). Fazi and Roodbergen (2018) study the impact of demurrage and detention costs on barge planning. They show that when transport orders are revealed throughout time, this leads to limited information while planning, which in turn has an impact of up to 31% on total costs compared to the complete information case. They also illustrate how this impact changes with respect to the length of the planning horizon. van Riessen et al. (2016) propose a decision tree based algorithm that allows assigning incoming orders to the available services instantaneously in real time. The method includes setting up decision trees based on the optimal solutions of various instances. Similarly, Mes and Iacob (2016) propose an online support tool for planners that is used to support human planner in assigning orders to the available services. First, for each origin–destination pair, a set of rules are run and unrealistic paths are eliminated. Second, for the incoming orders, the human planner is provided a pareto optimal solution set to assign incoming orders to the services based on a multi objective approach considering cost, delays and emissions. Another aspect of dynamism involves the *disturbances* happening during the execution, such as service breakdowns, delays or congestion. van Riessen et al. (2015) study the impact of disturbances in services such as early, delayed or canceled departures. Qu et al. (2019) propose a replanning algorithm due to the disturbances in a hinterland transport network. Bock (2010) proposes a real time improvement procedure for freight forwarder transportation networks, where vehicle routing is integrated with multimodal transport chains. The procedure is executed in a rolling horizon fashion and involves a *process* layer (i.e. actual realizations) and an *adaptation* layer (i.e. planning and optimization). In process layer, the plans from adaptation layer is frozen for a certain duration while actual realizations and disturbances occur such as new order arrivals, disruptions or delays subject to uncertainty. In light of the actual realizations and disturbances during the frozen period, an algorithm checks if better solutions exist for the future planning horizon, and if so plans are updated. As a result of using more information in this dynamic improvement procedure, significant cost savings are reported. Li et al. (2015) formulate the planning of a horizontally integrated intermodal freight transport operator with a receding horizon control approach in two levels. In the first level, the flow between the nodes (terminals) are determined for the given demand; while in the second level, the individual assignment of containers are made under the dynamic conditions such as disturbances (e.g. new or canceled bookings) or traffic congestion. Feng et al. (2017) and Douma et al. (2009) focus on the dynamics within the port, and employ a multi agent approach to model the interaction of barges (i.e. making rotation plans and making call requests) and the terminal operators (i.e. accepting or rejecting call requests from the barges) located in the port. Gharehgozli and Zaerpour (2018) refers to this interaction and show that the limited information or delays in barge arrivals have a negative impact on stack utilization in container terminals, and that the uncertainty leads to more reshuffling.

Uncertainty is a daily challenge in freight transport that causes deterministic solutions to perform poorly in real life (Bai et al., 2014) necessitating stochastic solutions. It is the fundamental reason of the curse of dimensionality through the exponential growth of the number of scenarios in stochastic models (Rivera and Mes, 2017). The problems often become intractable to be solved to optimality for realistic instances; scenario sampling, working with small sized instances (Lium et al., 2009) and using metaheuristics are popular ways to deal with this problem. Xu et al. (2015) formulate container allocation in a synchromodal transport network as a two-stage stochastic integer programming model with random demand without empty container repositioning. They propose a genetic algorithm based on simulated annealing and show its advantages over genetic algorithm or simulated annealing algorithm used alone. They use a one time decision making moment without dynamism. Rivera and Mes (2017) formulate planning of long haul round trips between an inland terminal and a number of terminals in the port as an MDP (Markov Decision Process) problem, which involve both dynamic (orders arrive daily) and stochastic aspects (the number, origin or destination of orders are uncertain), and is solved by Approximate Dynamic Programming (ADP). This study also incorporate the multi-horizon approach of barge planning. Zweers et al. (2020) study operational transport planning in the hinterland of the Port of Rotterdam, where the number of containers that can be loaded/unloaded in a container terminal is uncertain. They assume a single inland terminal and multiple terminals in the port. The problem is modeled as a two-stage stochastic program with recourse and solved with methods such as Sample Average Approximation (SAA) and heuristics. Nabais et al. (2015) focus on allocation of containers to the transport capacity in discrete decision points so as to achieve a modal split using a model predictive approach. The objective is to anticipate future peaks based on the current and past orders and transport capacity, and thus the uncertainty is implicitly taken into account. Dullaert and Zamparini (2013) focus on the reliability of the service lead times on a barge network, and they offer a simulation based framework to assist practitioners in decision making in order to improve the speed or reliability of services.

To our knowledge, this paper is the first study to analyze the impact of uncertainty in container arrivals on barge planning quantitatively. Rivera and Mes (2017) and Zweers et al. (2020) are most related to this paper in that their main problem is also determining a rotation plan between a single inland terminal and multiple terminals located in the port. There are significant contextual and methodological differences though: The uncertainty in Zweers et al. (2020) is the number of containers that can be loaded/unloaded in a terminal for a given order set, while in Rivera and Mes (2017) the orders are completely stochastic (i.e. origin, destination, and time requirements are unknown). In this paper, we assume the orders have expected arrivals, but their actual arrival date is uncertain. In our paper and Rivera and Mes (2017), a multi horizon approach is adopted and the orders are received dynamically through time, while Zweers et al. (2020) plan a single period without dynamism. Methodologically, Zweers et al. (2020) and our paper use a stochastic programming formulation, while Rivera and Mes (2017) use an MDP formulation. Rivera and Mes (2017) and our paper explicitly consider time requirements of the container in terms of an arrival and due date, while Zweers et al. (2020) exclude the time dimension (See Table 1).

Table 1
Comparison with the most relevant papers.

Paper	Uncertain factor	Order receiving	Planning horizon	Modeling approach
Rivera and Mes (2017)	Number, Origin–Destination, Container arrival date, Due date	Dynamic	Multi period with time dimension	MDP
Zweers et al. (2020)	The number of containers that can be loaded and unloaded at a deep-sea terminal	Static	Single period, no time dimension	Stochastic program
This paper	Container arrival dates	Dynamic	Multi period with time dimension	Stochastic program & Simulation

3. Problem setting

In this section, we provide the details of the problem we address and our assumptions. More specifically, we explain the typical activities of the barge during a week, the requirements to fulfill transport orders and the details of decision making activity of the barge operator.

The problem we describe is inspired from the operations of an inland terminal operating a single barge. Since this is a typical case in The Netherlands, we also consider a single barge in the mathematical model noting that it is possible to extend the model with a larger fleet. We assume a network N, consisting of terminals $k \in N$ as nodes, and a barge making trips between the single inland terminal ($k = 0$) and terminals located in the port ($k \in \{1, 2, \ldots, |N| - 1\}$)(See Fig. 2). One round trip takes two days, and a port visit is followed by an inland terminal visit immediately in the consecutive day or vice versa. According to the inland terminal we based this study on, a one-way sailing time is around 10–11 h on average. For example, one round trip is as follows: At the first day, the barge is at the port and spends 24 h for making the calls. The next day it sails to the inland terminal, loads/unloads the containers and sail back to the port, which in total makes another 24 h and the pattern repeats itself. The time spent at the port is higher than the time spent at the inland terminal due to the sailing and waiting time between the multiple calls. At the inland terminal only one call is made, the quay is dedicated to the barge so there is no waiting time. In other words, the barge alternates between the port and the inland terminal each day, so a container picked up at the port (or inland terminal) at day t will arrive at the inland terminal (or port) at day $t + 1$. During a port visit, the maximum number of calls is limited due to factors such as sailing time within the port, disturbances in call handlings or disruptions (Douma et al., 2009). Also in practice the barge operators put buffer times between barge calls and limit the number of calls in a given port visit against such uncertainties. During a port visit, the waiting times, travel times and mooring times, which depend on the number of calls, dominate the actual load/unload times characterized by the number of individual containers. Therefore, the main limiting factor is the number of calls, while the number of containers to be loaded/unloaded at each call is typically ignored.

The barge operator decides which terminals (k) to make calls at which days (t) within the planning horizon of week w (T_w), i.e. the rotation plan, characterized by the decision variable X_k^t. In the course of events, terminals oblige the barge operator to finalize the rotation plan a number of days ahead. This has an important implication as it is possible that new transport orders arrive between the rotation plan is decided and the day the call is actually made, which leads to limited information at the time of decision making moment. Indeed, this is the direct impact of dynamism: after the rotation plan is made, new orders arrive that were unknown at the time of decision making moment, but these orders have to be handled possibly causing additional costs. We assume this decision making moment to be discrete at the start of each week, which is quite a common assumption in literature (van Riessen

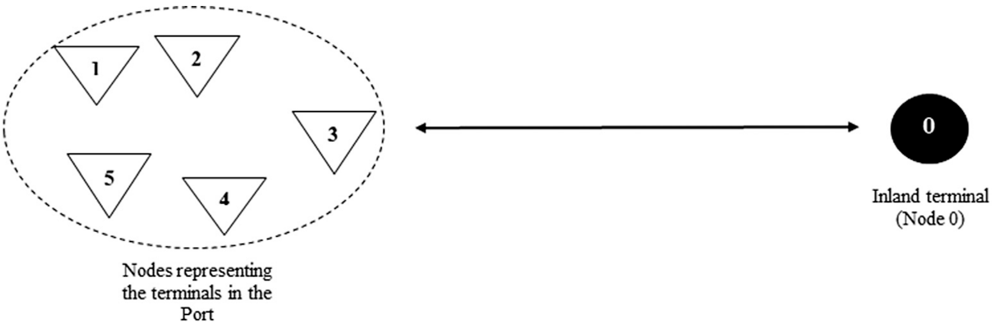

Fig. 2. An example representation of the network with 1 inland terminal and 5 terminals in the port.

et al., 2016; Lium et al., 2009; Fazi et al., 2015). Each call incurs a cost of C^B, which represents the fuel cost of the additional travel from one terminal to another. Note that typically the loading/unloading of the containers is charged to the customer, and thus not included in this model as a cost item for the barge operator.

At the start of each week w, the barge operator has a list of import and export transport orders already received (I_w). Each order i has an *expected* arrival date a_i at its origin node $o_i \in N$, and needs to be delivered to its destination node $d_i \in N$ with a due date b_i. The orders arrive throughout time, and there is no time restriction for the shipper to place an order. For example, the order can be placed at the same day as the expected arrival of the container or two weeks before. As discussed in Section 1, due to the delays in deep sea vessel arrivals or preparation of cargo, the arrival dates of containers (a_i) are uncertain. Neither previous research nor the data we have provides a reliable estimation of the probability distribution function of this uncertainty. We assume that the delays of container arrival are independent and identical random variables with known discrete probability mass functions. Due dates, on the other hand, are deterministic due to static cargo closing times, service quality concerns or demurrage and detention conditions (Although demurrage and detention times can be violated, the penalties are so high that operators rarely do so). In the cases where the due dates are not met, the container has to be trucked immediately, and each container trucked incurs a cost of C^T. This may be a result of operator's plan and/or because the arrival of container is delayed. If a container i has a due date beyond planning horizon ($b_i > max\{T_w\}$), there is no need for trucking immediately as it may be postponed to the next week in the hope that it will be picked up by barge then.

Regarding the operations of the inland terminal we get inspired from, the capacity of the barge was not the main limiting factor in planning. The utilization rates were around 70% or less on average, making the barge capacity shortages infrequent. This is in line with the business model of barge transport: unit costs are much lower than trucking making it economically viable to hire a larger barge than typically necessary, thus ensuring that the capacity is only rarely a limiting factor. Note that this is also appropriate given that the costs of too much capacity (a barge that is a bit larger than needed) are much lower than the costs of too little capacity: Any container that does not fit the barge must be trucked at high costs. Reference numbers for these costs are 25 – 50 euros per TEU for additional barge capacity, versus 250 euros per TEU for trucking; we obtained these numbers from contacts at an inland terminal. Therefore, from the perspective of planning the barge visits, it is reasonable to ignore the barge capacity constraint. Also, from methodological perspective capacitated models cause tractability issues. In the computational experiment, a high number of instances need to be solved for the sensitivity analysis of the parameters. Each instance involves 52 iterations of the weekly problem for a high number of container orders, requiring the weekly plan to be solved quite fast. Due to these factors, we model the weekly problem ignoring the barge capacity, which means that the barge is big enough to hold all demand. This permits us to model the problem without time-space network representation that is typically an issue for tractability in combinatorial optimization even in the deterministic case and with a relatively low number of container orders. Hence, we can make a thorough analysis of the uncertainty in container arrivals, which is the focus of this paper. To test the validity of the results, we made an additional run where capacity is imposed on the barge, and show that the main observations still hold (See Section 5.2.6).

Next we discuss the overall solution approach and the mathematical model of the weekly problem.

4. Solution approach

As discussed in Section 3, the barge operator is obligated to make rotation plans and communicate with the terminals at discrete times. While making rotation plans, the operator needs to determine a planning horizon. In one extreme, setting a long horizon (e.g. one year) and solving the problem at once would reflect the long term performance of the system. But this is not realistic due to the arrival of orders through time. Orders are received typically within 10 days to the expected arrival of the container; which means, with a one year horizon, the operator would have very little information at the time of decision making. In the other extreme, the horizon could be set to the minimum time requested by the terminals. This will lead to a more informed decision since a higher portion of orders will be known, but poses other problems: a shorter planning horizon causes myopic decisions in long run, barge plan is a prerequisite for pre/end haulage planning, and terminals prefer receiving call requests in a timely manner.

As a result we design a solution approach, which consists of determining rotation plans for a fixed planning horizon, and iterating for a long period of time to see the steady state behavior (See Fig. 3). For convenience, by default we assume the planning horizon

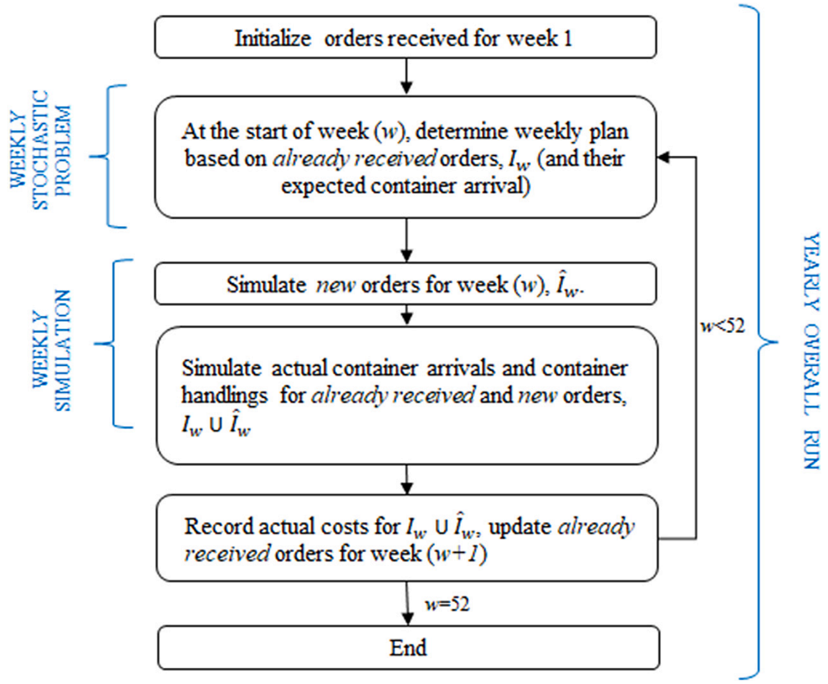

Fig. 3. The representation of the steps of the overall solution procedure.

to be one week, and we iterate over a one-year horizon. Note that in the computational experiment, we test the results with different planning horizons.

Overall, the solution approach consists of a total run of 52 iterations (weeks). At each iteration, there are two main phases: first, determining the weekly plan based on the orders that are known (already received) and their expected arrival times; and second, simulating the week based on the plan and simulated (actual) order arrivals. More precisely, at the start of each week w, the weekly barge planning problem is solved taking into account the container orders, I_w. These container orders are: those that are expected to arrive during week w, the ones that already arrived at week $w-1$ but were postponed, and the ones that were expected to arrive at week $w-1$ but have not arrived yet due to delays. Based on I_w, a two-stage stochastic MIP is solved to determine the weekly rotation plan, i.e. which terminals to call at which days, in order to minimize total expected costs for the week (See Section 4.1 for details). After the MIP is solved and the weekly rotation plan is set, a simulation is run to observe actual realizations. In the simulation, new transport orders are received (which could be expected to arrive at week w or later), actual arrivals of all orders for week w are generated, and the containers that are barged, the ones that are trucked and the ones that are postponed are determined. The actual costs are incurred and recorded and a new iteration starts for week $w+1$ (See Section 4.2 for details).

Next, the details of the weekly planning phase are provided. Afterwards, we will explain the details of simulation phase.

4.1. Mathematical model for the weekly problem

The weekly planning problem itself is a combinatorial optimization problem under uncertainty. The objective function is the minimization of weekly expected cost, which includes barge (fuel) costs, trucking costs and penalties for postponing containers. Note that the penalty term is not an actual cost, we define it artificially to overcome the problem of leaving all containers postponed, which empirically led to excessive trucking costs. In the mathematical model, the first stage decision variables (X_k^t) determine if terminal k will be called on day $t \in T_w$, where T_w is the set of days at week w. The second stage variables determine whether an order i will be handled by a truck (Y_i^ω) or postponed (P_i^ω) when ω days of delay occurs (i.e. delay scenarios).

The probability of scenarios are represented by p_i^ω, implying ω days of delay for order i. There are three different cases characterizing the calculation of p_i^ω: (i) For the orders that are expected to arrive during week w (i.e. $a_i \in T_w$), p_i^ω are characterized entirely by the probability mass function of the container arrival process. (ii) The containers that *were* expected to arrive previous week $w-1$ (i.e. $a_i < min\{T_w\}$) may have already arrived. (ii) The containers that *were* expected to arrive previous week $w-1$ (i.e. $a_i < min\{T_w\}$) have not arrived, and thus a delay of $min\{T_w\} - a_i$ days has already been observed. Hence, for those containers conditional probabilities are calculated illustrated by the following example:

Consider an example, where we are at the start of day $t = 7$*, and a plan is being made for days* $\{7, 8, \ldots, 13\}$*. Further assume that the probability mass function for the delays are as follows:*

$$P(w) = \begin{cases} 0.4, & w = 0 \\ 0.3, & w = 1 \\ 0.2, & w = 2 \\ 0.1, & w = 3 \end{cases}$$

$Case$ (i) $a_i = 8$. *Since we have no additional information, the delay scenarios are identical to the assumed probability mass function. The container will arrive at days 8,9,10 or 11 with probabilities 0.4, 0.3, 0.2 and 0.1 respectively.*

$Case$ (ii) $a_i = 5$ (so the container was expected to arrive previous week) *and the container has actually arrived at time* 6*, so the delay is 1.*

$$p_i^\omega = \begin{cases} 1, & w = 1 \\ 0, & otherwise \end{cases}$$

$Case$ (iii) $a_i = 5$ (so the container was expected to arrive previous week) *and the container has not arrived until day 7.*

$$p_i^\omega = \begin{cases} 0, & w = 0 \\ 0, & w = 1 \\ 0.67, & w = 2 \\ 0.33, & w = 3 \end{cases}$$

As a result, the problem is dynamic due to new orders arriving after the decision moment, and due to the information at hand from previous week. The notation and the mathematical formulation are provided below.

Notation		
Sets		
W	:	Set of weeks for the whole year, $w \in \{1, \ldots, 52\}$
N	:	Set of nodes, $\{0\}$ for inland terminal, other terminals in the port $\in \{1, 2, \ldots, \lvert N-1 \rvert\}$
T_w	:	Set of upcoming days to plan for a given week w, $[(w-1)T + 1, \ldots, wT]$
I_w	:	Set of all orders *already* received at the start of week w. $I_w = I_w^{I,P} \cup I_w^{I,T} \cup I_w^{E,P} \cup I_w^{E,T}$
$I_w^{I,P}$	:	Set of import orders that can be postponed to next week, i.e. $b_i > max\{T_w\}$.
$I_w^{I,T}$	:	Set of import orders that cannot be postponed to next week, i.e. $b_i \le max\{T_w\}$.
$I_w^{E,P}$	:	Set of export orders that can be postponed to next week, i.e. $b_i > max\{T_w\}$.
$I_w^{E,T}$	:	Set of export orders that cannot be postponed to next week, i.e. $b_i \le max\{T_w\}$
Ω	:	The set of possible delay scenarios for a container arrival (in days) w.r.t to the expected arrival day, $\omega \in \{0, 1, 2, \ldots, \lvert\Omega\rvert - 1\}$
Decision Variables		
X_k^t	:	Decision variable representing barge calls, 1 if a call is made at node k at time t, $k \in N$, $t \in T_w$
Y_i^ω	:	Decision variable representing trucking, 1 if trucking is used for container i given a delay of ω, $i \in I_w^{I,T} \cup I_w^{E,T}, \omega \in \Omega$
P_i^ω	:	Decision variable representing postponed orders, 1 if order i is left for the next week, given a delay of ω, $i \in I_w^{I,P} \cup I_w^{E,P}, \omega \in \Omega$.
Parameters		
T	:	Planning horizon
p_i^ω	:	Probability that a container arrival i is delayed by ω days, $\omega \in \{0, 1, 2, \ldots, \lvert\Omega\rvert - 1\}$. If the scheduled arrival of a container was previous week, p_i^ω represents the conditional probability based on the information that it has arrived or delayed already.
a_i	:	The expected arrival day of order i
b_i	:	The due date of order i
o_i	:	The origin node of order i, $o_i \in N$
d_i	:	The destination node of order i, $d_i \in N$
C^B	:	The marginal cost of a call at a terminal
C^T	:	The cost of trucking per container
C^P	:	The penalty for postponing a container
σ_k	:	Weight of a node, which can be interpreted as congestion in the port: With an increased value of σ_k, the number of calls that can be made within 24 h decreases, $0 < \sigma_k < 1$ for $k > 0$, $\sigma_k = 1$ for $k = 0$, $k \in N$
Δ	:	1 if the barge made a call in inland terminal just before the planning horizon starts (i.e. at time $\min\{T_w\} - 1$). Used to link barge's last position in previous week with first position in current week w.

$$Minimize \quad C^B \sum_{t\in T_w}\sum_{k\in N} X_k^t + C^T \sum_{i\in\{I_w^{I,T}\cup I_w^{E,T}\}}\sum_{\forall\omega\in\Omega} p_i^\omega Y_i^\omega + C^P \sum_{i\in\{I_w^{I,P}\cup I_w^{E,P}\}}\sum_{\forall\omega\in\Omega} p_i^\omega P_i^\omega$$

Subject to:

$$\sum_{t=max\{min\{T_w\},a_i+\omega\}}^{b_i-1} X_{o_i}^t + Y_i^\omega \geq 1 \qquad ,\forall i\in I_w^{I,T},\forall\omega\in\Omega \tag{1}$$

$$\sum_{t=max\{min\{T_w\},a_i+\omega+1\}}^{b_i} X_{d_i}^t + Y_i^\omega \geq 1 \qquad ,\forall i\in I_w^{E,T},\forall\omega\in\Omega \tag{2}$$

$$\sum_{t=max\{min\{T_w\},a_i+\omega\}}^{max\{T_w\}} X_{o_i}^t + P_i^\omega \geq 1 \qquad ,\forall i\in I_w^{I,P},\forall\omega\in\Omega \tag{3}$$

$$\sum_{t=max\{min\{T_w\},a_i+\omega+1\}}^{max\{T_w\}} X_{d_i}^t + P_i^\omega \geq 1 \qquad ,\forall i\in I_w^{E,P},\forall\omega\in\Omega \tag{4}$$

$$\sum_{k\in N} \sigma_k X_k^t \leq 1 \qquad ,\forall t\in T_w \tag{5}$$

$$X_0^t + X_0^{t-1} = 1 \qquad ,\forall t\in T_w, t > min\{T_w\} \tag{6}$$

$$X_0^{min\{T_w\}} = 1-\Delta \tag{7}$$

$$X_k^t \in \{0,1\} \qquad ,\forall k\in N,\forall t\in T_w \tag{8}$$

$$0\leq Y_i^\omega \leq 1 \qquad ,\forall i\in\{I_w^{I,T}\cup I_w^{E,T}\},\forall\omega\in\Omega \tag{9}$$

$$0\leq P_i^\omega \leq 1 \qquad ,\forall i\in\{I_w^{I,P}\cup I_w^{E,P}\},\forall\omega\in\Omega \tag{10}$$

The objective function minimizes the expected sum of barge costs, trucking costs and penalty costs. The barge costs represent the marginal cost of making an additional call at a container terminal in a given port visit, and only depend on the decision of the operator. Trucking costs are direct costs of hiring an external truck operator, while penalty costs are introduced to avoid myopic solutions. Both trucking costs and penalty costs depend on the delay scenario. Note that the number of trips between the inland terminal and the port is fixed due to alternating schedule of the barge, and thus associated sailing costs (i.e. the cost of long hauls between the port and the inland terminal) are excluded. The optimization is subject to the following constraints.

(1) Each import container i with a due date within the planning horizon (i.e. $b_i \leq max\{T_w\}$), must be picked up by a barge from node o_i earliest when the container is ready (i.e. at $a_i+\omega$) and latest one day before the due date (the sailing time from the port to the inland terminal takes 1 day), or it must be trucked. Note that pick up by barge can be only be done at a time t within planning horizon (i.e. $t\in T_w$).

(2) Each export container i with a due date within the planning horizon (i.e. $b_i \leq max\{T_w\}$), must be delivered to node d_i by barge earliest one day after it arrives at the inland terminal (i.e. at $a_i+\omega+1$ because the sailing time from the inland terminal to the port takes 1 day) and latest at the due date b_i, or it must be trucked. Note that delivery by barge can be only be done at a time t within the planning horizon (i.e. $t\in T_w$).

(3) Each import container i with a due date beyond the planning horizon (i.e. $b_i > max\{T_w\}$), must be picked up from node o_i earliest when the container is ready (i.e. at $a_i+\omega$) and latest at time $max\{T_w\}$, or it must be postponed (Trucking is unnecessary since there is a chance of pick up by barge next week). Note that pick up by barge can be only be done at a time t within the planning horizon (i.e. $t\in T_w$)

(4) Each export container i with a due date beyond the planning horizon (i.e. $b_i > max\{T_w\}$), must be delivered to node d_i by barge earliest one day after it arrives at the inland terminal (i.e. at $a_i+\omega+1$) and latest at time $max\{T_w\}$, or it must be postponed (Trucking is unnecessary since there is a chance of delivery by barge next week). Note that delivery by barge can be only be done at a time t within the planning horizon (i.e. $t\in T_w$).

(5) The total duration in the port cannot be exceeded.

(6) The barge has to alternate between port and inland terminal in consecutive days.

(7) Linking of the barge call in the first day of the planning horizon with the last day of the previous week.

(8) Binary variables for barge calls.

(9)–(10) Continuous variables for trucking and postponing a container to next week. By nature these variables are binary, but for computational efficiency they are introduced as continuous variables between 0 and 1.

Our model differs from the classical 2-stage stochastic MIP programs, where Sample Average Approximation (SAA) is employed on a sample of generated scenarios. In such models, due to the interaction between stochastic variables, each scenario involves one realization for each random variable. In our approach, because we have verified that capacity can be safely ignored for the purposes of our study, whether a container i is picked-up or barged has no effect on a container j; container j will be picked up by barge as long as there is a barge call within the feasible pick-up windows. This allows us to isolate random variable (i.e. arrival delay) of a container i from that of container j, and treat the associated second-stage decisions individually. This also means that we can optimally solve the two-stage stochastic programming formulation, i.e. we do not introduce a sampling bias because there is no sampling.

4.2. Simulation of weekly activities

When the MIP is solved for I_w, the rotation plan of the barge is finalized. However, it is possible that new orders may arrive throughout the week that were unknown, represented by $\hat{I}_w$. Based on the rotation plan, the actual realizations take place for all orders, $I_w \cup \hat{I}_w$. There are four main steps of the simulation:

1. *Arrival of new transport orders*: In addition to I_w (i.e. the set of already received orders at the start of each week), new orders ($\hat{I}_w$) are received after the plan is made (For the computational study, the dates on which the orders are received are taken from the real dataset).
2. *Actual arrival of containers*: For the set of all orders $I_w \cup \hat{I}_w$ (already received and new), actual container arrivals are generated based on the probability mass function of the container arrival process.
3. *Handling of containers*: For the set of all orders, based on the planned barge calls and the actual arrivals, the actual handling of the container is determined, which refers to whether the container will be transported by barge, the container will be trucked, or the container will be postponed. For an import container i, if starting from the day the container *actually* arrived ($\hat{a}_i$) until the due date ($b_i - 1$) there is at least one call at the terminal at which the container has arrived, then the container is transported by barge (i.e. if Constraint (1) in the model is satisfied considering the actual arrival instead of the expected arrival). Else, if there is no barge call during the feasible time windows and the due date of the order is within week w, the order has to be trucked. Else, if there is no barge call but the due date of the order is in week $w + 1$ or later, the order is postponed and will be re-planned in the next week (See Fig. 4). Note that the handling of containers are determined in the exact same way in the MIP. Given the barge plan, if for a container i and delay w, the container is trucked ($Y_i^{\omega} = 1$) or postponed ($P_i^{\omega} = 1$), in simulation stage the same occurs. Instead of using the 2nd stage decision variables in MIP, this step is implemented due to the new transport orders. Since new orders were not known before the barge plan is made, there were no associated 2nd stage decision variables in the MIP. As a result, the handling of such orders are determined in this step.

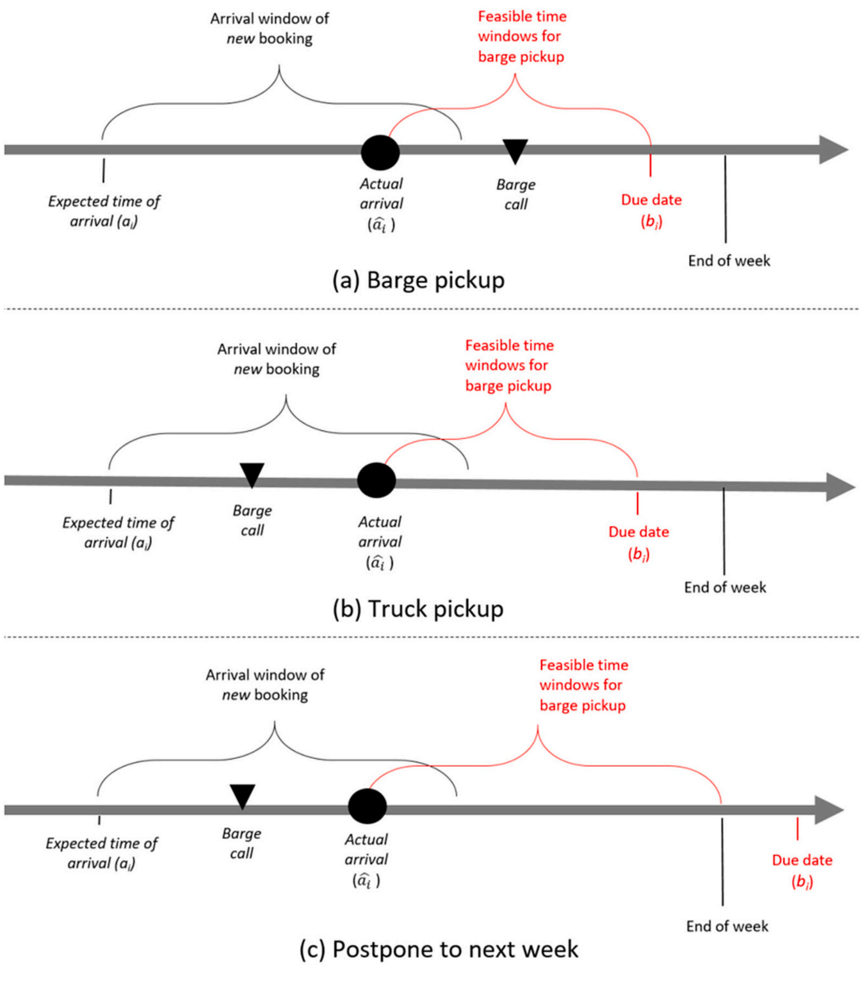

Fig. 4. An illustration of possible handlings for an example order. (a) Container picked up by barge as planned, (b) Due to a delay of container arrival, the container has to be trucked since the due date is within the current week, (c) Due to a delay of container arrival, the container is postponed to next week since the due date is in next week.

4. Finally, actual costs are computed based on barge call costs and trucking (Note that the penalty costs of postponing containers are excluded here, as they are artificial means to avoid myopic solutions, not real costs). Barge call costs depend entirely on the weekly rotation plan and equals to C^B (unit cost per call) multiplied with the number of calls made. Trucking costs are equal to C^T (unit trucking costs) multiplied by the number of containers trucked (which may be an already received order or new order). I_{w+1} is updated based on I_w, $\hat{I}_w$, and actual container handlings. So I_{w+1} consists of the orders in $I_w \cup \hat{I}_w$ that are not trucked or barged.

5. Computational experiment and results

In this part we discuss the computational experiment that shows the effect of uncertainty and dynamism on transportation costs and modal split. First in Section 5.1 we discuss the setup of the computational experiment, which consists of solving the instances that are characterized by the problem parameters. Next in Section 5.2, we discuss the results of the experiment and the insights gained.

5.1. Setup

The computational experiment is carried out on an order set that is formed by the real data of an inland terminal located in the Netherlands from 2016. Raw data taken from the company are cleaned and filtered as described in Appendix A. The total number of orders is 45 335. The number of total weekly orders ranges between 284 and 1150, with an average of 872 and standard deviation of 163. Among these 45 335 orders, the booking dates of the orders of the inland terminal are compared with the arrival dates of the corresponding containers, and 27 180 were known before the time of decision making at the start of the week, which accounts for 60%. In other words, at each iteration just before solving the weekly problem, 60% of the orders that are expected to arrive were already known and thus could be included in planning. The bookings of the remaining 40% arrived during the week after the barge plan is already determined and thus could not be considered while planning. Naturally, simulation is executed for all the containers that were expected to arrive, either already received or new. This shows the extent of limited information in the dynamic environment.

There are 20 terminals in total, including the inland terminal. Trucking cost, C^T, is assumed to be 250 Euros per container, determined in consultation with the practitioners (Note that throughout the rest of the paper, all cost terms are in Euros). Each instance uses the same order set and is characterized by four parameters that are of interest: uncertainty in container arrivals, penalty cost C^P, the weight of terminals σ_k and barge cost C^B. Each parameter takes on a value from the predetermined set of discrete values for analysis.

1. There are 4 uncertainty levels in container arrivals represented by 4 discrete probability mass functions, where p^ω is the probability that the container is delayed by ω number of days. To the best of our knowledge, there are no published data on the uncertainty of container arrivals. These probability distributions are determined based on the historical reliability of shipping lines in recent years (See SeaIntel (2018)). Further specification of the probabilities are determined by consulting the practitioners and based on our judgment (See Table 2).
During simulation, actual delays are generated randomly and same delays are used in a given uncertainty scenario for a fair comparison among instances.

Table 2
Probability mass function for each uncertainty level.

Scenario	p^0	p^1	p^2
Deterministic	1	0	0
Low uncertainty	0.9	0.08	0.02
Average uncertainty	0.60	0.30	0.10
High uncertainty	0.3334	0.3333	0.3333

2. There are 3 levels of penalty cost values, C^P for the overall run: $75, 100, 125$. This range is determined based on the initial test runs, where a wider range $[0, 250]$ with increments of 25 was used. In these test runs, above the penalty value 25, the differences in total cost were minor, and the best costs seemed to be observed in the range $[75, 125]$. Therefore, for brevity, we report the range $75, 100, 125$ in this paper. However, one important observation was that there is a sharp decrease from the penalty value of 0 to 25. To have a detailed look, we made an additional run where the set of penalty values is $\{0, 1, 2, ..25\}$ and barge cost is 200. We discuss the findings in detail in Section 5.2.3.
3. There are 5 levels of maximum number of calls per visit, limited to the set $\{3, 4, 5, 6, 7\}$ based on current practice. We set σ_k values to the reciprocals of these numbers.
4. There are 3 different levels for barge cost decided in consultation with practitioners, $C^B \in \{50, 200, 350\}$. When we consulted the practitioners about the fuel cost of an additional call in the port, the original number given was 200 with a margin of 50 euros. We extended this number to 50 at minimum and 350 at maximum for the sensitivity analysis. Quantifying the marginal cost of a barge call and assigning a fixed cost is not straightforward and unrealistic due to varying distances between the terminals. Therefore, multiple values are tested to see the effect of barge cost for sensitivity analysis.

In the end, the computational experiment mainly consists of running the overall procedure for each of the 180 instances characterized by these four parameters. The observations in the overall run later necessitated two additional runs for specific reasons: First to test the impact of penalty values in detail, and second to test the impact of the length of planning horizon, T, which turned out to give valuable insights on the concept of dynamism and the limited information while decision making. These additional runs are discussed in Section 5.2 in detail.

The solution algorithm is coded in C and the stochastic MIP was solved by invoking Gurobi 8.1 from C. The runs are executed on an Intel® Core™ i7 - 6700HQ with 2.60 GHz processor and 8 GB of RAM. The data cleaning and preparation of order set was made in R following the procedure in Appendix A. The order set and the generated random numbers for delays are then written to a text file and loaded to C for each run, which is provided with this paper. The execution times of the instances are summarized in Table 3. Although each instance involved solving the stochastic MIP for 52 times with 522 new orders per each week on average (Note that these are the orders already known and accounts for around 60% of the 872 weekly average), we did not observe dimensionality problems. This is mainly due to the simplified modeling of the problem without time space network and capacity considerations. We did not observe significant differences in execution times among different levels of the four parameters.

Table 3
Summary of execution time of each instance in seconds.

Average	Minimum	Maximum
44.55	31.44	66.11

5.2. Results

In this section, we will discuss the impact of uncertainty in container arrivals, the impact of the maximum number of calls in a port visit, the impact of penalty values used to avoid myopic solutions, the impact of dynamism and the impact of barge costs on total costs and modal split. We also validate the findings in the presence of barge capacity.

Our focus here is on results obtained using the simulation model represented in Fig. 3. This simulation model uses the stochastic program developed in Section 4.1 to solve a weekly planning problem, and Appendix B investigates this stochastic program in isolation, i.e. without the bigger simulation context.

5.2.1. Impact of uncertain container delays

The computational results show that uncertain container delays have a significant impact in total costs and the modal split (i.e. number of containers trucked) as observed in practice. We observe that the costs and trucking increase in parallel with the increase in the uncertainty of container arrivals. Depending on the instance and scenario, the increase in costs go as high as 53% while the trucking increases by 55%.

The impact of adding uncertain delays compared to the deterministic case is illustrated in Table 4. For each instance, the percentage change compared to the deterministic case is calculated in pairwise manner and summarized in Table 4.

Table 4
Impact of uncertainty in container arrivals on total cost and number of containers trucked for the overall run (Maximum number of calls per visit $\in [3,7]$, $C^P \in \{75,100,125\}$, $C^B \in \{50,200,350\}$).

Uncertainty level	% Change in total cost wrt deterministic case			% Change in number of containers trucked wrt deterministic case			Average cost	Average % trucking
	Min	Max	Average	Min	Max	Average		
Deterministic	0	0	0	0	0	0	3 371 849	28.0
Low	3.4	6.1	5.1	3.6	7.0	5.4	3 538 172	29.4
Average	14.0	27.0	20.3	14.5	27.7	21.7	4 039 082	33.9
High	27.8	53.7	40.4	29.4	55.2	43.3	4 690 857	39.6

The modal split in Table 5 is of interest as it depicts the ratio of trucking needed even if all containers are meant to be carried by barges. We observe that the uncertainty has a big impact on modal split; on average, overall, 32.7% of total containers had to be trucked to comply with time requirements even if barge transport is much cheaper. When the uncertainty in container arrival is the highest and the maximum number of calls that can be made in one visit is the smallest (i.e. equal to 3), 47.9% of the containers have to be trucked. It should be noted that in the dataset we used, for 6.2% of the containers, the expected arrival date is the same day as the due date (i.e. $a_i = b_i$), which means it is impossible to use a barge for these containers even if there is no delay in container arrival since the trip from/to the port takes 1 day violating the due date requirement.

Table 5
Summary of percentage of containers trucked for different uncertainty levels in container arrival in overall run (Maximum number of calls per visit $\in [3,7]$, $C^P \in \{75,100,125\}$, $C^B \in \{50,200,350\}$).

Uncertainty Level	Minimum	Maximum	Average
Deterministic	21.72	37.00	27.96
Low	23.05	38.47	29.43
Average	27.53	42.90	33.86
High	33.71	47.92	39.61

5.2.2. Impact of maximum number of calls made at a port visit

One important determinant on modal split turns out to be the number of terminals that can be visited. The impact of the number of calls per visit can be seen in Table 6. The table shows that increasing the maximum number of calls per visit has a significant impact, which underlines the negative effect of waiting times in the port. The maximum number of calls per visit is directly linked with the barge congestion, which is currently one of the biggest problems in practice in the Port of Rotterdam (Gumuskaya et al., 2020; van der Horst and de Langen, 2008). Due to the barge congestion and increased waiting times, barge operators can make less number of calls per visit, the effect of which we see here. On average, we observe that one additional call decreases the trucking by 6.09% to 1.89% in magnitude.

Table 6
Percentage of containers trucked for different values of maximum number of calls per visit in overall run (Four uncertainty levels, $C^P \in \{75, 100, 125\}$, $C^B \in \{50, 200, 350\}$).

Maximum number of calls per visit	Minimum	Maximum	Average	Difference in average trucking with an additional call
3	36.84	47.91	41.43	6.09
4	30.43	42.29	35.34	4
5	26.38	38.37	31.34	2.66
6	23.69	35.93	28.68	1.89
7	21.72	34.35	26.79	–

5.2.3. Impact of penalty values for postponing

The penalty for postponing a container has a dampened effect with increasing values. When the penalty is increased within the range close to 0, it has a sharp decreasing effect in total cost by avoiding myopic behavior. However, this effect becomes marginal with increased values and then stabilizes. To have a more detailed look, an additional run is made for C^P taking integer values from 0 to 25, and $C^B = 200$ as can be seen in Fig. 5.

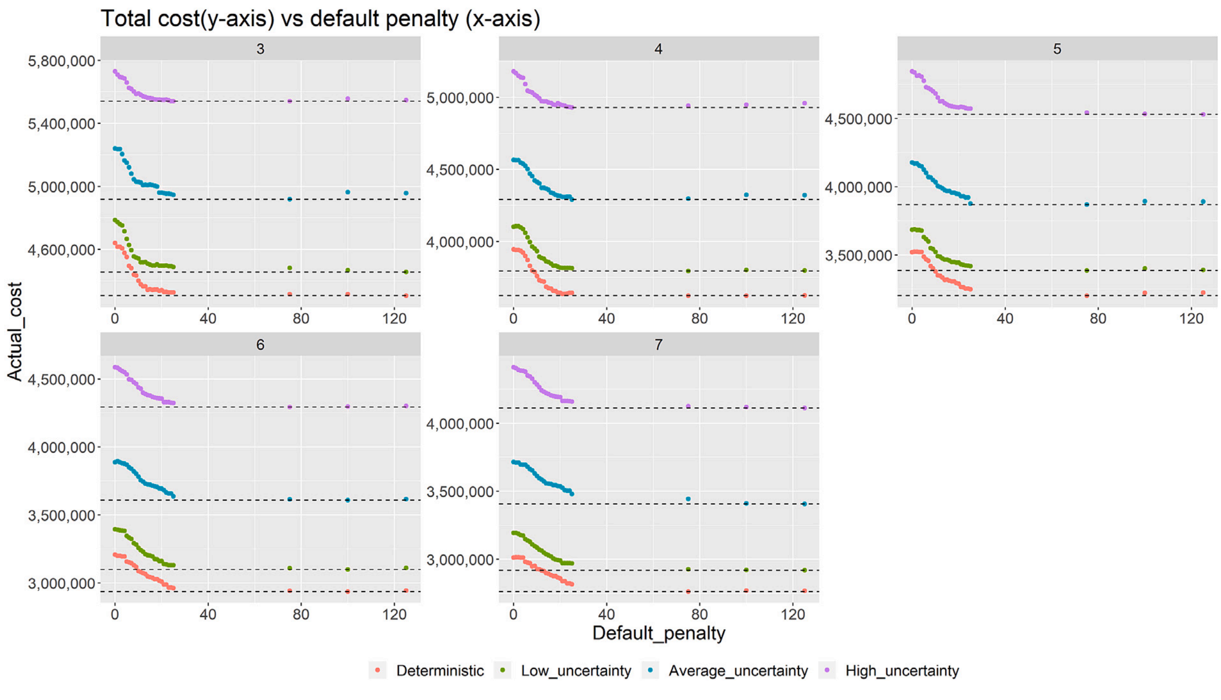

Fig. 5. The impact of default penalty on total costs for C^B=200 depicted for different values of maximum number of calls per port visit.

5.2.4. Impact of dynamism and limited information of orders

The impact of dynamism and decision making with limited information is recognized by academia (Pillac et al., 2013; van Riessen et al., 2016). In this paper, by default we take the dynamism into account in our solution approach. To test the extent of the impact of dynamism quantitatively, we made additional runs for this purpose where we kept $C^B = 200$ and $C^P = 125$. In this additional run, we do two things: First, we make a distinction of two cases, limited information and complete information cases. In the original setup, the barge operator is only aware of the order set I_w, while during the simulation stage all orders $I_w \cup \hat{I}_w$ (i.e. already received and new) incur costs. This corresponds to the limited information. In the complete information case, we assume that all the orders $(I_w \cup \hat{I}_w)$ are known by the barge operator, and thus can be included in MIP while barge planning. Note that in both cases, the actual arrivals are subject to uncertainty based on the scenario. Table 7 shows that the additional information has a significant impact on costs and modal split depending on the uncertainty. It is the highest (22.65% on trucking) when the uncertainty is the lowest (i.e. deterministic case), and the lowest (9.22% on trucking) when the uncertainty is the highest. This emphasizes how the *quality* of information is important: when the uncertainty in container arrival is the highest, the quality of information is lowest (because it is subject to uncertainty) and the impact *that* additional information is at hand while decision making, is lower.

Table 7
Impact of limited information on total costs and on trucking for the instance: Maximum number of calls per visit $\in [3,7]$, $C^P = 125$, $C^B = 200$ for four uncertainty levels.

Scenario	Total cost			% of containers trucked		
	Complete information	Limited information	%Change	Complete Information	Limited information	%Change
Deterministic	2 796 000	3 373 110	20.64	22.78	27.94	22.65
Low uncertainty	2 996 800	3 526 280	17.67	24.56	29.30	19.30
Average uncertainty	3 584 720	4 033 800	12.53	29.77	33.81	13.55
High uncertainty	4 300 570	4 679 500	8.81	36.16	39.49	9.22

Second, we used 14 different planning horizons ($T \in \{1, 2, \dots, 14\}$) for 20 instances ($C^B = 200, C^P = 125$, four uncertainty levels and max number of port visits $\in \{3, 4, ..7\}$)) to test the impact of planning horizon. The results show that the minimum cost occurs when $T = 3$ (13 out of 20 instances), $T = 4$ (4 out of 20 instances) and $T = 5$ (3 out of 20 instances). Interestingly, planning horizon does not have a monotonic effect on total costs (See Fig. 6). We believe that this is due to the trade-off between amount of information available and far-sightedness: By having a shorter planning horizon, the fraction of orders known prior to the decision making moment increases. For example, when $T = 7$, the percentage of orders known is approximately 60%, while it is 90% when $T = 2$. On the other hand, by having a shorter horizon there is a risk of having myopic solutions.

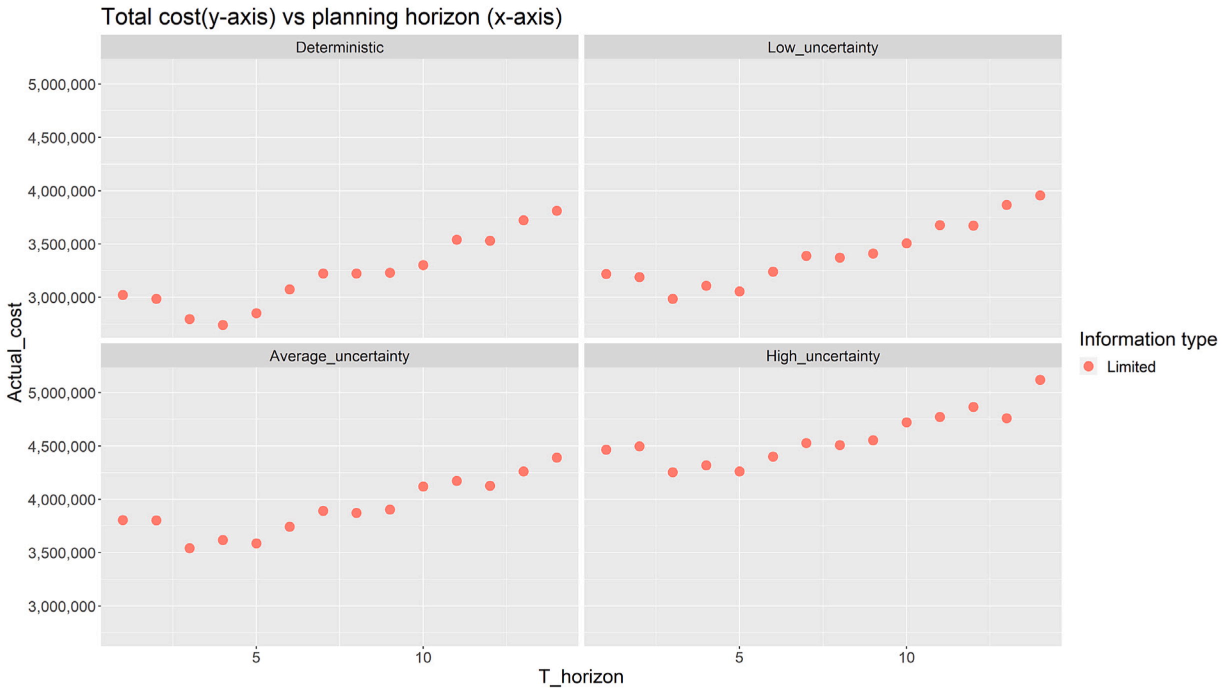

Fig. 6. The impact of planning horizons and complete information for C^B=200, $C^P = 125$, max number of calls at a port visit =5 depicted for four uncertainty levels.

5.2.5. *Impact of barge cost*

Barge cost, C^B, is mainly kept as a parameter for sensitivity analysis. From Table 8 we can see that the impact of barge cost on modal split is marginal, while the total costs increase with C^B as expected. Therefore, we can conclude that the specified value of C^B does not have much effect on the characteristics of the solution, i.e. the decisions made.

Table 8
Impact of barge cost C^B on total costs and percentage of trucking in overall run (Maximum number of calls per visit $\in [3,7]$, $C^P \in \{75, 100, 125\}$, four uncertainty levels).

C^B	Total cost			% of containers trucked		
	Min	Max	Average	Min	Max	Average
50	2 528 550	5 447 150	3 742 713	21.72	47.91	32.64
200	2 762 550	5 556 400	3 908 679	21.98	47.91	32.69
350	2 994 100	5 665 100	4 078 578	22.31	47.91	32.82

5.2.6. Impact of barge capacity

In this section, we check if the major findings of the uncapacitated case hold for the capacitated case by making additional runs. To involve capacity, Step 3 of the simulation stage is modified as follows:

- *Handling of containers in the capacitated version*: Firstly, all of the orders (i.e. already received before the planning stage and new orders after planning) are ordered based on their due dates in an ascending order to prioritize the orders with urgency. Starting from the most urgent order to the least, the handling of a container is determined following the same logic in the uncapacitated case, and in addition barge capacity is imposed. In other words, for each container i, we check if there is a feasible barge call within the feasible pick-up windows. If there are such possibilities, the container is picked up at the earliest opportunity provided that there is space in the barge. If not, the order is postponed or trucked as usual. This allocation scheme also fits to the current practice.

With this modification an additional run is made to see the impact of different barge capacities on total cost with respect to the main findings. Similar to the previous runs, barge cost C^B is 200, penalty cost C^P is 125 and $T = 7$. The results are depicted in Fig. 7. From the figure, we observe that in all cases the curve flattens above 100, and that above this capacity, the impact of barge capacity is very limited. Since a capacity of 100 containers is reasonable, this observation supports the approach taken in this paper of ignoring capacity for the purposes of investigating the impact of uncertainty and dynamism.

These results are in line with expectations: Barge capacity is much cheaper then trucking of containers (which is needed in case of capacity shortage), hence barge operators ought to choose barge capacities such that shortages are comparatively rare. As a consequence, ignoring the barge capacity in our study of the impact of uncertainty makes sense. In line with this, at the inland terminal that inspired this study monthly barge utilization peaks at around 70%. When checking the results with this in mind, we found that instances with peak monthly utilization between 65 and 75% occurred with barge capacities of 125 and 150. At these levels, the impact of capacity shortage on the insights derived in this paper are negligible, as observed in Fig. 7. When capacities are above 100, and especially when they are above 150, the uncertainty of container arrivals has a very substantial impact.

For barge capacities below 50, the impact of uncertain delays all but disappears. This makes sense, because even if arrivals are uncertain, a capacity of 50 containers can be filled completely most of the time, regardless of uncertain delays. But a setting with a vast shortage of capacity does not make business economic sense, as barge capacity is substantially cheaper than trucking: A barge operator faced with frequent capacity shortages will choose to operate a bigger barge in practice.

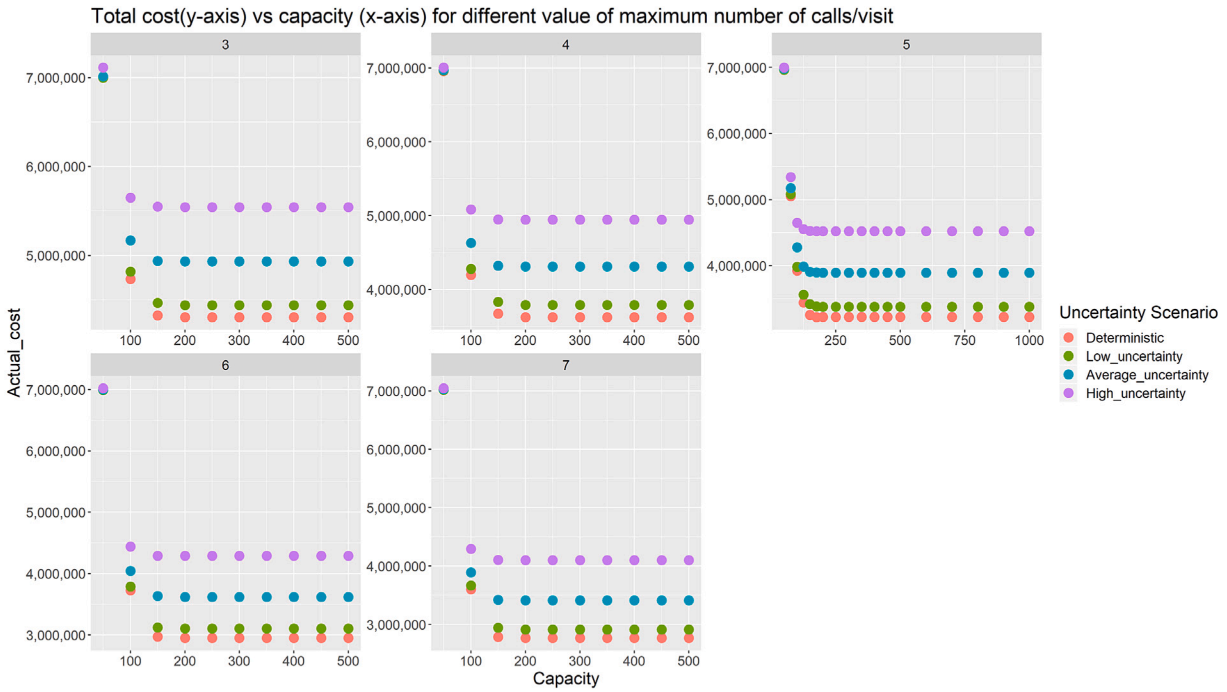

Fig. 7. The impact of barge capacity on total costs for $C^B = 200, C^P = 125, T = 7$ depicted for different values of maximum number of calls per port visit.

5.2.7. Discussion of results

The uncertainty in container arrivals and the maximum number of calls per visit have a strong impact on total cost and modal split. Although the figures for modal split deviate from the current modal split in the Port of Rotterdam (i.e. trucking 54%, barge 35% and rail 11%), the problem context is different. Here, we assume that all containers are aimed to be transported by barge. In reality barge connection may not be available or shippers may prefer trucking or railway transport over barges. The adverse effects of limited information due to dynamism compared to the hypothetical case of complete information are illustrated. Moreover, it is shown that there is a trade-off between amount of information prior to decision making and farsightedness among different values of planning horizons, and that 3 to 5 days yield the best results. We also show that the penalty for postponing a container, C^P has a positive effect in costs and modal split by avoiding myopic solutions. This effect diminishes with increasing values of C^P away from 0. Finally, the solutions seem to be robust with respect to C^B. Most of these observations can also be summarized altogether in Fig. 8, where the percentage of containers trucked (y-axis) is plotted against maximum number of calls per port visit (x-axis) in different plots for each barge cost (C^B). Penalty costs (C^P) are represented by different shapes (circle, triangle, square) and uncertainty in container arrivals by colors. Our experiments also show that the main findings of this paper continue to hold in the capacitated case, as long as capacities are in line with those seen in practice.

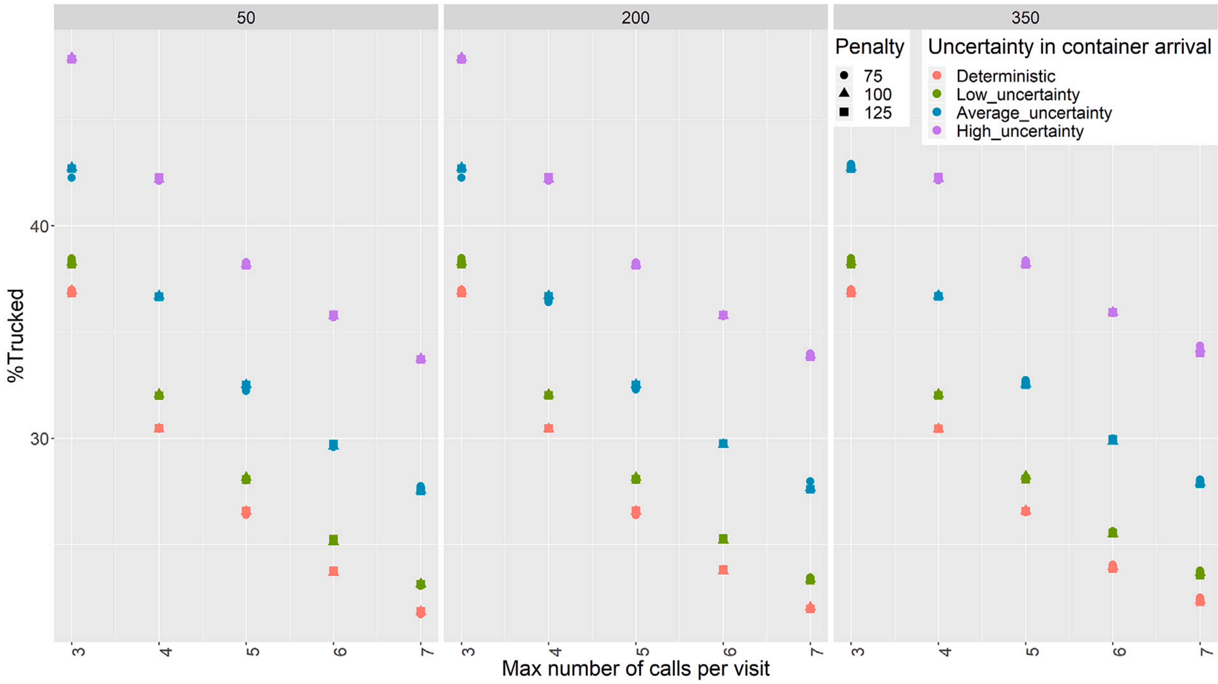

Fig. 8. Percentage of trucking vs. maximum number of calls per visit for the different barge cost values depicted in different plots.

6. Conclusion and further research

In this paper, we described a solution approach for planning barge trips between an inland terminal and multiple container terminals located in a seaport in order to quantify the effect of uncertainty in container arrivals on planning. To the best of our knowledge this has not been studied explicitly before. The solution procedure also takes into account the dynamism inherent in container transport, by incorporating the impact of receiving new bookings after the barge plan is made. The solution is applied on a real dataset of an inland terminal located in the Netherlands. From a methodological point of view, our study involves solving a two stage stochastic MIP, which has few examples in this domain. Moreover, a penalty for postponing containers is introduced.

The results show that the uncertain delays in container arrivals and the dynamism that leads to limited information while making decisions have a big impact on performance in terms of costs and modal split. This has certain implications: it draws attention to the impact of delays and uncertainty associated with deep sea vessel arrivals, which can be reduced, for example by better predictions or information exchange between the deep sea vessels and the barge operator. The significance of information sharing between the operator and the shipper is also emphasized: we showed that the limited availability of information during making decisions has a significant impact on performance. There is a big improvement potential without high investments; for instance, if the shipper shares the information of their prospective transport orders (i.e. complete information case), the number of containers trucked is decreased by up to 22%. We see that the fraction of information prior to decision making in practice is quite low (60% for a one week planning horizon). We also observe that the impact of having more information decreases when the quality of information is worse. In other words, when the uncertainty is higher, the actual time of container arrival is more stochastic, which helps less while decision making. An observation is that the maximum number of calls per visit has a significant impact, relating to the barge congestion problems. We show that one additional call made leads to an improvement in trucking by 6.09% to 1.89% in magnitude. This partly explains why the barge operators often change their rotation plans: to reduce waiting times and increase the number of calls they make. Using smaller but a higher number of barges could alleviate this problem, as it would be possible to visit a higher number of terminals in a given time period. For this, however, the increased fixed costs of having more barges must be justified. We also illustrate the trade-off in determining the planning horizon; a shorter horizon provides more information on the transport orders, while making the plans more myopic. More than half of the time, the best results are observed by planning ahead 3, while for the rest 4 or 5 days is optimal. This has a certain insight on the current practices: Container terminals oblige barge operators to send their call requests at least 2–3 days ahead, which seems to be in line with what is necessary on the barge operator side.

This study is intended to quantify the impact of uncertainty and dynamism rather than creating operational plans for real life. Future research can direct towards this purpose and incorporate constraints such as empty container repositioning, demurrage and detention costs and pre/end haul planning. By including these constraints, the impact of uncertainty and dynamism can be calculated more accurately, but it is unlikely that this will qualitatively alter the insights generated in this paper. Another research direction is to extend the model for employing larger fleets to offset the impact of uncertainty and dynamism. This analysis can provide insights on the trade-offs in determining fleet size. For a given total capacity, more barges may increase flexibility in planning as more calls can be made, but in the expense of increased fixed costs.

Acknowledgment

This work is part of the ISOLA project with project number 438-13-214, which is partly financed by the Dutch Research Council (NWO).

Appendix A. Data cleaning steps

See Table 9.

Table 9
The data cleaning and filtering steps executed to create the order dataset from the raw data of the inland terminal of the year 2016.

Step	# Rows left
Load raw data	52,488
Filter out bookings not in 2016	51,507
Filter out bookings with no origin and destination terminal	51,014
Assign Booking type to EXPORT or IMPORT, based on the full/empty condition of container in the main haul trip and type of modality	
Filter out is.na(Booking type)	50,810
Filter out the terminals in the right tail of 95% (Remaining number of terminals=20)	48,158
Replace Terminal names with Terminal numbers based on Booking type	
Assign Arrival times and Due times based on the Booking type and realizations	
Filter out is.na(Arrival time) or is.na(Due time)	48,149
Filter out unrealistic gaps between Due_time and Arrival_time (i.e. $0 \leq \text{gap} \leq 15$)	45,384
Filter out Arrival time not in 2016.	45,335
Merge week 201 653 with 201 701	
Create random number in 0–99 for each order	

Appendix B. The stochastic program

In this appendix, we investigate key measures relating to the ability of the stochastic programming approach to solve the weekly planning problem of Section 4.1.

Two measures to check in stochastic programs are VSS (Value of Stochastic Solution) and EVPI (Expected Value of Perfect Information). VSS refers to the difference between solving the stochastic problem (i.e. MIP in Section 4.1) and the mean value problem (i.e. solve a deterministic problem in which the random variables are set to their means). EVPI on the other hand refers to the difference between the stochastic problem and the case of perfect information (i.e. the random variables are subject to uncertainty, but the value of them are known with certainty). Calculating both VSS and EVPI are meaningful for comparing two solutions with the same problem parameters. However, in our case this is not readily applicable: A single change in week 0 cause a random chain-reaction effect for the following weeks. For this reason, we made an additional run, in which the weeks are solved in isolation. That is to say, for each week w and the same given set of orders, we solve the original stochastic problem, the mean value problem and the perfect information problem. We made this run for a subset of the parameters: $C^P = 125, C^B = 200$, maximum number of calls $\in \{3, \ldots, 7\}$, uncertainty scenario high. For each instance, we used 30 random realizations for each instance. We focus on the objective function presented in Section 4.1, i.e. we use the proxy costs for delaying the container until next week. The average deviations in percentages are given in Table 10. Also note that the original objective function value is reported, which includes the penalty for postponing containers.

Table 10
Summary of percentage deviations for VSS and EVPI for $C^P = 125, C^B = 200$, maximum number of calls $\in 3, \ldots, 7$, uncertainty scenario:high, 30 random realizations.

	Minimum	Maximum	Average
VSS	−2.07%	14.70%	2.51%
EVPI	0%	4.90%	0.55%

Looking at Table 10, we observe that solving the stochastic problem is useful in general, with a maximum of 14.7% and 2.51% on average. Perfect information on arrival delays, on the other hand, have a marginal improvement, which suggests that the dominating factor is the reduction of the pick-up windows due to the delays, and knowing the delays have a limited advantage.

References

Bai, R., Wallace, S.W., Li, J., Chong, A.Y.-L., 2014. Stochastic service network design with rerouting. Transp. Res. B 60, 50–65.

Bock, S., 2010. Real-time control of freight forwarder transportation networks by integrating multimodal transport chains. European J. Oper. Res. 200 (3), 733–746.

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 (2), 155–164. http://dx.doi.org/10.1016/j.compind.2012.06.003, UR: http://www.sciencedirect.com/science/article/pii/S0166361512001170. decision support for intermodal transport.

Bredström, D., Haugen, K., Olstad, A., Novotný, J., 2015. A mixed integer linear programming model applied in barge planning for omya. Oper. Res. Perspect. 2, 150–155. http://dx.doi.org/10.1016/j.orp.2015.07.002, URL: http://www.sciencedirect.com/science/article/pii/S2214716015000160.

Choong, S.T., Cole, M.H., Kutanoglu, E., 2002. Empty container management for intermodal transportation networks. Transp. Res. E 38 (6), 423–438. http://dx.doi.org/10.1016/S1366-5545(02)00018-2, URL: http://www.sciencedirect.com/science/article/pii/S1366554502000182.

Douma, A., Schutten, M., Schuur, P., 2009. Waiting profiles: An efficient protocol for enabling distributed planning of container barge rotations along terminals in the port of rotterdam. Transp. Res. C 17 (2), 133–148.

Dullaert, W., Zamparini, L., 2013. The impact of lead time reliability in freight transport: A logistics assessment of transport economics findings. Transp. Res. E 49 (1), 190–200. http://dx.doi.org/10.1016/j.tre.2012.08.005, http://www.sciencedirect.com/science/article/pii/S1366554512000804.

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. Transp. Res. C 89, 1–18. http://dx.doi.org/10.1016/j.trc.2018.01.012.

Feng, F., Pang, Y., Lodewijks, G., Li, W., 2017. Collaborative framework of an intelligent agent system for efficient logistics transport planning. Comput. Ind. Eng. 112, 551–567. http://dx.doi.org/10.1016/j.cie.2016.12.044, URL: http://www.sciencedirect.com/science/article/pii/S0360835216305228.

Gharehgozli, A., Zaerpour, N., 2018. Stacking outbound barge containers in an automated deep-sea terminal. European J. Oper. Res. 267 (3), 977–995. http://dx.doi.org/10.1016/j.ejor.2017.12.040, URL: http://www.sciencedirect.com/science/article/pii/S0377221717311748.

Gumuskaya, V., van Jaarsveld, W., Dijkman, R., Grefen, P., Veenstra, A., 2020. A framework for modelling and analysing coordination challenges in hinterland transport systems. Marit. Econ. Logist. 22, http://dx.doi.org/10.1057/s41278-019-00139-1, Accepted, Special Issue: Port-Hinterland Transport and Logistics - Emerging Trends and Frontier Research.

van der Horst, M., Kort, M., Kuipers, B., Geerlings, H., 2019. Coordination problems in container barging in the port of rotterdam: an institutional analysis. Transp. Plan. Technol. 42 (2), 187–199. http://dx.doi.org/10.1080/03081060.2019.1565164.

van der Horst, M., de Langen, P.W., 2008. Coordination in hinterland transport chains: a major challenge for the seaport community. Marit. Econ. Logist. 10 (1–2), 108–129.

Li, L., Negenborn, R.R., Schutter, B.D., 2015. Intermodal freight transport planning – a receding horizon control approach. Transp. Res. C 60, 77–95. http://dx.doi.org/10.1016/j.trc.2015.08.002, URL: http://www.sciencedirect.com/science/article/pii/S0968090X15002685.

Lium, A.-G., Crainic, T.G., Wallace, S.W., 2009. A study of demand stochasticity in service network design. Transp. Sci. 43 (2), 144–157.

Mes, M.R., Iacob, M.-E., 2016. Synchromodal transport planning at a logistics service provider. In: Logistics and Supply Chain Innovation. Springer, pp. 23–36.

Nabais, J., Negenborn, R., Benítez, R.C., Botto, M.A., 2015. Achieving transport modal split targets at intermodal freight hubs using a model predictive approach. Transp. Res. C 60, 278–297.

Notteboom, T.E., 2006. The time factor in liner shipping services. Marit. Econ. Logist. 8 (1), 19–39.

Parola, F., Risitano, M., Ferretti, M., Panetti, E., 2017. The drivers of port competitiveness: a critical review. Transp. Rev. 37 (1), 116–138. http://dx.doi.org/10.1080/01441647.2016.1231232.

Pillac, V., Gendreau, M., Guéret, C., Medaglia, A.L., 2013. A review of dynamic vehicle routing problems. European J. Oper. Res. 225 (1), 1–11.

Qu, W., Rezaei, J., Maknoon, Y., Tavasszy, L., 2019. Hinterland freight transportation replanning model under the framework of synchromodality. Transp. Res. E 131, 308–328. http://dx.doi.org/10.1016/j.tre.2019.09.014, URL: http://www.sciencedirect.com/science/article/pii/S1366554519301917.

van Riessen, B., Negenborn, R.R., Dekker, R., 2016. Real-time container transport planning with decision trees based on offline obtained optimal solutions. Decis. Support Syst. 89, 1–16.

van Riessen, B., Negenborn, R.R., Lodewijks, G., Dekker, R., 2015. Impact and relevance of transit disturbances on planning in intermodal container networks using disturbance cost analysis. Marit. Econ. Logist. 17 (4), 440–463.

Rivera, A.E., Mes, M.R., 2017. Anticipatory freight selection in intermodal long-haul round-trips. Transp. Res. E 105, 176–194.

SeaIntel, 2018. Global liner performance report. URL: http://www.seaintel.com/.

SteadieSeifi, M., Dellaert, N., Nuijten, W., Woensel, T.V., Raoufi, R., 2014. Multimodal freight transportation planning: A literature review. European J. Oper. Res. 233 (1), 1–15. http://dx.doi.org/10.1016/j.ejor.2013.06.055, URL: http://www.sciencedirect.com/science/article/pii/S0377221713005638.

Xu, Y., Cao, C., Jia, B., Zang, G., 2015. Model and algorithm for container allocation problem with random freight demands in synchromodal transportation. Math. Probl. Eng. 2015.

Zweers, B.G., Bhulai, S., Mei, R.D., 2020. Planning hinterland container transportation in congested deep-sea terminals. Flexible Serv. Manuf. J. 1–40.