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Three-stage service network design in rail-road networks with demand and capacity uncertainty

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Abstract

This paper addresses the service network design (SND) problem in a rail-road network with demand and capacity uncertainty from the perspective of a logistics service provider (LSP) in a synchromodal transport setting. Based on consultations with LSPs, we propose a three-stage model that includes an initial stage to book capacity, an intermediate stage to update capacity decisions with partial information in the form of improved demand forecasts, and a third stage with complete information for capacity updates, recourse actions and routing decisions. Stochasticity is included by means of a scenario generation approach which results in a scenario tree. The impact of replanning rail capacity once when complete information is available, and twice with both partial and complete information, is compared against the case without replanning on a set of theoretical instances with a full factorial design. Results indicate that replanning once when complete information is available yields large cost savings and increases the share of rail transport. Replanning is more advantageous with cheaper train services, networks with more transhipment options, more rail capacity, and higher levels of demand uncertainty. Introducing an additional replanning stage, with partial information, yields diminishing returns, though savings increase with the amount of uncertainty that is resolved at the time of replanning.

Keywords: synchromodal transport, rail transport, service network design, stochasticity, capacity planning

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Declarations

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability Statement

This study only uses synthetic data sets generated by the authors. The data generation process is described in the article. The actual data sets are available from the authors upon request.

1 Introduction

In 2022, road transport accounted for 78% of continental freight transport in the EU, marking a consistent increase over the past decade (Eurostat, 2024). The high reliance on road freight transport causes various externalities, including greenhouse gas (GHG) emissions, congestion, road degradation and accidents. To address the growing freight transport demand while alleviating these externalities, more efficient transport solutions are needed (European Environment Agency, 2023). One of the proposed solutions is a modal shift from road transport to more sustainable high-capacity transport modes such as rail and inland waterways, for instance with the use of intermodal transport. Intermodal transport can be defined as transport with multiple transport modes in which goods remain in the same loading unit (Crainic & Kim, 2007). In addition to being more sustainable, high-capacity transport modes can be cheaper than trucks over long distances (Hanssen et al., 2012; Janic, 2007). However, their main drawbacks are lower flexibility when faced with unexpected events and the need for pre- and end-haulage (Demir et al., 2016). In the case of trains, the lower flexibility is due to fixed schedules and transport capacity which is harder to adapt in the short term. When faced with unexpected events such as last-minute arrivals of new orders, it is easier to send additional trucks than an additional train.

Logistics service providers (LSPs) receive transport orders from multiple clients and usually do not possess all the vehicles required to ship those orders. Instead, they resort to third parties such as rail operators that provide transport services. Capacity on high-capacity transport modes is typically booked in advance, making it more challenging to secure additional capacity in the short term compared to trucks. A main challenge is that at the time of booking capacity the exact transport demand is still unknown due to short lead times of incoming transport orders, leading to demand uncertainty. This demand uncertainty is a major hindrance to the implementation of intermodal transport (Delbart et al., 2021). Apart from demand uncertainty, an additional source of uncertainty is the available rail transport capacity on the medium and short term since, over time, other LSPs may buy capacity on the same rail transport services, reducing the remaining available capacity. Synchromodal transport attempts to cope with uncertainty. It is an extension of intermodal transport that includes real-time re-routing and a-modal booking (Ambra et al., 2019). This paper aims to assist rail capacity planning decisions in a rail-road network under uncertainty from the perspective of an LSP. It focusses on long term capacity decisions in a synchromodal context and is based on a real-life case of an LSP operating in Europe.

We propose a model that addresses a service network design (SND) problem from the perspective of an LSP in a synchromodal transport setting with two types of uncertainty: stochastic demand and stochastic capacity. While stochastic demand is commonly accounted for in SND research, studies that account for stochastic capacity are scarce (Delbart et al., 2021). We refer to Section 2 for more details on studied uncertainties in existing literature. In SND problems with stochastic demand, the aim is to select transport services based on the estimated demand to route freight through those services. Transport services can be set up with both owned vehicles and vehicles from third parties and, though our model only considers the latter, it can easily be adapted to include both. In an intermodal setting, the amount of capacity is expressed in container slots. SND problems with stochastic demand are typically modelled with two stages in academic literature to account for the different timing of the service selection and routing decisions (Bai et al., 2014; Crainic et al., 2011; Elbert et al., 2020; Meng et al., 2015; Zhao, Xue, et al., 2018). The service network is set up while demand is still uncertain in the first stage, which will be several weeks to several months before demand is known in reality. When designing the service network, the services on which to book capacity as well as the number of container slots to book are determined. The second stage takes place when the demand has materialised, at which point recourse actions are taken and freight is routed on the selected services. The most common recourse action in literature is to buy additional trucking capacity at a higher cost if the scheduled capacity on intermodal services is too low to ship all orders (Elbert et al., 2020), while capacity on intermodal services remains unchanged. In reality, LSPs do update their initial capacity decisions but, since complete demand materialises shortly before shipping (e.g., a week or a few days), the remaining available capacity on intermodal services might be too expensive or insufficient to perform large updates at that point. Consequently, LSPs do not wait until complete demand information is available before updating their capacity decisions in practice. For instance, the LSP we consulted updates its capacity plan a first time when a more accurate demand forecast is available and a second time with complete information. Therefore, the main purpose of this paper is to provide a more realistic model that can better support LSPs in their real-life operations, potentially stimulating a modal shift towards rail transport. To achieve this, we introduce a three-stage model with an intermediate stage that accounts for updates made with partial information in the form of more accurate demand forecasts.

The contributions of this paper are as follows. First, in contrast to classical two-stage SND models, we are the first to introduce capacity replanning at a later stage, with the ability to both purchase new capacity and cancel previously bought capacity on train services. Moreover, a second replanning stage is accounted for during which capacity decisions are updated based on partial information. Existing two-stage models do not update the initially-booked amounts of capacity, whereas capacity decisions are updated twice in our model: once with partial information and once with perfect information. Second, a mathematical formulation and solution method are presented to solve realistic-sized instances of the model. Third, we demonstrate the benefits of revising capacity once when complete information is available, and an additional time with partial information. Finally, this paper contributes to the scarce body of literature on SND problems with capacity uncertainty, and it combines this with stochastic demand.

Section 2 presents a review of the relevant literature. The proposed model is outlined in Section 3, which includes a description of the research problem and how stochasticity is included in the model. Section 4 describes the solution approach and contains the mathematical formulation. Section 5 provides an overview of our mathematical experiments, which includes information on the input parameters, tested instances and factorial design. Results are discussed in Section 6. In Section 7, we offer insights and draw conclusions based on our findings.

2 Related literature

This paper introduces a SND model in a rail-road network with stochastic demand and capacity. Existing research demonstrates that including uncertainty in SND problems leads to lower costs and solutions that provide more flexibility (Lium et al., 2009). The focus of our model is on selecting services through which orders are routed. Therefore, we review papers that treat stochastic SND problems, especially with uncertain demand or capacity, and that focus on the selection of services and routing of freight. Stochastic SND problems applied to intermodal transport are a growing field of research, with the majority of studies published in the past decade (Delbart et al., 2021; Elbert et al., 2020). For more detailed reviews on multimodal, intermodal and synchromodal transportation, we refer to the review of Elbert et al. (2020) on tactical network planning and design and the review by Delbart et al. (2021) that focusses on uncertainties.

Table 1 provides an overview of the literature. Our search led to a total of 23 papers. 13 papers do not specify the considered transport mode, of which ten include variable service schedules, which means that the schedules are established during the planning phase as part of the decision-making process. In contrast, eight out of the ten papers that specify the transport modes contain fixed service schedules that are outside the planner's control. Capacity of transport services is limited in all papers that consider fixed service schedules. However, literature that focusses on variable service schedules considers services with both limited and unlimited capacity. In cases of unlimited capacity, it is assumed that there is a cost per unit associated with utilizing the services. When capacity is limited, the papers by Crainic et al. (2011) and Wang et al. (2019) consider that a fixed cost is incurred to purchase a service with multiple units of capacity, whereas all other papers incur a cost per unit. Wang and Wallace (2016) consider both options.

Table 1 Literature on stochastic SND problems in an intermodal context

Reference	Transport modes	Stochasticity			Service schedules	Transport capacity	Time window constraints	Recourse actions	Approach
		Demand	Transport time	Capacity					
Lium et al. (2009)	Unspecified	X			Variable	Unlimited	Hard	Ad hoc capacity increase	Two-stage stochastic programming
Puettmann and Stadtler (2010)	Road, ship	X			Fixed	Limited	Hard	Ad hoc capacity increase	Mixed integer linear programming
Hoff et al. (2010)	Unspecified	X			Variable	Unlimited	Hard	Ad hoc capacity increase	Two-stage stochastic programming
Crainic et al. (2011)	Unspecified	X			Fixed	Limited	Hard	Ad hoc capacity increase	Two-stage stochastic programming
Bai et al. (2014)	Unspecified	X			Variable	Unlimited	Hard	Ad hoc capacity increase and rerouting	Two-stage stochastic programming
Meng et al. (2015)	Barge, rail, road	X			Fixed	Limited	Hard	Ad hoc capacity increase	Two-stage stochastic programming
Demir et al. (2016)	Barge, rail, road	X	X		Fixed	Limited	Soft	Ad hoc capacity increase	Chance-constrained mixed integer linear programming
Wang and Wallace (2016)	Unspecified	X			Fixed	Limited	Hard	Ad hoc capacity increase and selling excess capacity	Two-stage stochastic programming
Layeb et al. (2018)	Barge, rail, road	X	X		Fixed	Limited	Soft		Simulation optimisation
Sun, Hrušovský, et al. (2018)	Rail, road		X	X	Fixed	Rail: limited Road: unlimited	Soft		Fuzzy chance-constrained mixed integer programming
Sun, Zhang, et al. (2018)	Rail, road			X	Fixed	Limited	Not applicable		Fuzzy chance-constrained mixed integer programming
Zhao, Liu, et al. (2018)	Rail, ship	X	X + transfer time		Variable	Limited	Soft		Two-stage chance-constrained programming
Zhao, Xue, et al. (2018)	Rail, ship	X	X + transfer time		Fixed	Limited	Soft		Chance-constrained mixed integer programming
Hewitt et al. (2019)	Unspecified	X			Variable	Unlimited	Hard	Ad hoc capacity increase	Two-stage stochastic programming
Wang and Qi (2019)	Unspecified	X			Variable	Limited	Hard	Ad hoc capacity increase	Two-stage robust programming
Wang et al. (2019)	Unspecified	X			Variable	Limited	Hard	Ad hoc capacity increase	Two-stage stochastic programming
Hewitt et al. (2019)	Unspecified	X			Variable	Limited	Hard	As hoc capacity increase	Two-stage stochastic programming
Lanza et al. (2021)	Unspecified		X		Fixed	Limited	Soft		Two-stage stochastic programming
Müller et al. (2021b)	Rail	X			Variable	Limited	Hard	Ad hoc capacity increase and rerouting	Two-stage stochastic programming
Müller et al. (2021a)	Rail, road		X		Fixed	Limited	Soft	Ad hoc capacity booking on the next service	Two-stage stochastic programming
Xiang et al. (2022)	Unspecified	X			Variable	Unlimited	Hard	Ad hoc capacity increase	Two-stage robust programming
Zang et al. (2023)	Unspecified	X			Variable	Unlimited	Hard	Ad hoc capacity increase	Two-stage robust programming with chance constraints
Zhang et al. (2024)	Unspecified	X			Variable	Unlimited	Hard	Ad hoc capacity increase	Two-stage robust programming
This study	Rail, road	X		X	Fixed	Limited	Hard	Ad hoc capacity increase and updating capacity decisions	Three-stage stochastic programming

Concerning stochastic parameters, demand uncertainty is the most studied type with 19 out of the 23 papers, either alone or in combination with stochastic transportation times. Conversely, stochastic capacity is included in two studies (Sun, Hrušovský, et al., 2018; Sun, Zhang, et al., 2018). Moreover, there are no studies that simultaneously include stochastic demand and capacity in an intermodal setting. 17 out of the 23 reviewed papers address a stochastic SND problem with a two-stage model. In 14 of those, capacity decisions from the first-stage remain fixed in the last stage, at which point either recourse actions are taken or a penalty cost is incurred for late deliveries. Only the studies by Bai et al. (2014), Wang and Wallace (2016) and Müller et al. (2021b) perform changes to the initially booked capacity in the second stage. Bai et al. (2014) allow previously booked vehicles to take other routes, though the total capacity remains identical. In addition to rerouting, Müller et al. (2021b) also include purchasing additional capacity on train services, albeit at the same price as outsourcing. Wang and Wallace (2016) consider the possibility to sell excess capacity on the spot market. Out of the papers that do not employ a two-stage model, four of them employ mixed-integer programming and one employs simulation optimisation.

Time window constraints can either be hard or soft. Hard constraints mean that late deliveries are not allowed, while soft constraints allow for late deliveries. All studies without stochastic travel times include hard time constraints, which necessitates recourse actions in case the demand exceeds the available transport capacity. The most common recourse action is to consider an external source of unlimited capacity at a high cost, called ad hoc capacity increase. This is often in the form of trucks and can be seen as outsourcing. In contrast, studies with stochastic transportation times cannot guarantee on-time deliveries and therefore include penalty costs for late deliveries, negating the need for recourse actions. Only the paper from Demir et al. (2016) includes both penalty costs and outsourcing, while Müller et al. (2021a) consider that remaining capacity on later services is automatically booked. In addition to penalty costs, five out of seven papers that include stochastic transportation times impose chance constraints that limit the probability of late deliveries.

In our model, it is assumed that transport services are offered by third parties and schedules are therefore outside the LSP's control, which is why train service schedules are fixed and the available amount of capacity that can be bought decreases over time. In line with the concept of synchromodality and most previous work, we assume that LSPs can choose the amount of capacity they book on each service instead of an all-or-nothing approach. Our study considers hard time window constraints and an unlimited number of trucks available in the short term. Since trucks cannot be booked in advance in our model, they are identical to ad hoc capacity increases as a recourse action, similar to existing papers. However, the last stage of our model allows changes to previously booked capacity in the form of new bookings and cancellations in addition to ad hoc capacity increases, which differs from existing two-stage models. As such, capacity decisions can be taken at three different stages in our model compared to only the first stage in existing two-stage models.

3 Model description

This study focuses on an SND problem from the perspective of an LSP with trains and trucks as transport modes. Two sources of stochasticity are considered: demand and rail capacity. Our SND model covers two types of decisions, namely the selection of transport services and the routing of transport orders through those services. Service selection decisions are made at three different points in time before the transport execution (as illustrated in Fig. 1), and additional capacity may be booked or cancelled based on new information in each stage. Routing decisions are only made once when all demand is known, which is in the third stage. The first stage takes place well in advance, for instance six months or more before the transport execution. At this stage, a high number of slots is available on train services and there is a high degree of demand uncertainty. The second stage occurs when more information is available on the state of the market, for instance one month in advance, which results in less uncertainty regarding demand. However, the remaining number of slots available for booking may be lower due to bookings from other companies on the same train services. At this stage, the LSP determines the amount of additional capacity to book on each train service, and previously booked capacity from the first stage may be cancelled with a partial refund. The third stage takes place a few days before the transport execution when all orders are known. At this stage, additional train slots may still be booked, but at a higher cost than in the second stage. Similarly to the second stage, previously booked train slots can be cancelled, but the refunded amount is lower as it is more difficult for the train operator to find additional customers in the short term. On top of train services, our model assumes that additional capacity is always available in the short term at a higher cost in the form of trucks.

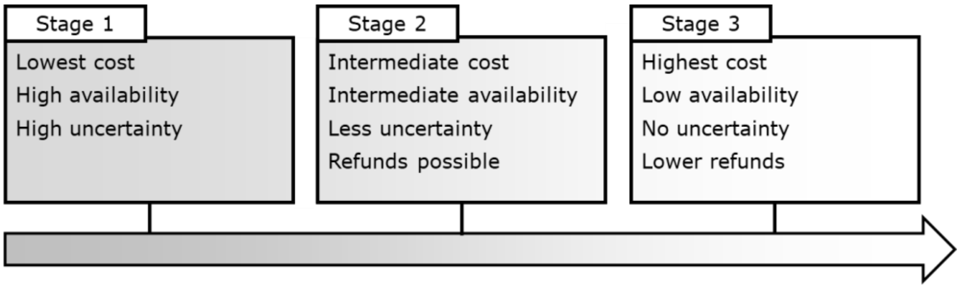

Fig. 1 Three decision-making stages

The proposed model aims to determine the amount of capacity to book at each stage such that the costs of delivering transport orders in time are minimised. The included costs are the costs of booked train services at each stage and the trucking costs, minus refunds for cancellations of previously booked train services. Naturally, it is possible to add more replanning stages. The reason for only considering three stages is to investigate whether there is a significant benefit to replanning more than once. In addition, the real-life LSP that this case is based on updates their capacity decisions twice.

3.1 Network

Fig. 2 illustrates an example of the considered rail-road intermodal network. The nodes are train terminals and train services are offered on the arcs. A train service is a scheduled train from a third party that can visit multiple terminals, has limited capacity, and follows a fixed schedule. A part of a service between two consecutive terminals is called a connection. At each visited terminal, loading units (e.g. containers) can be loaded or unloaded. The train operator can add or remove wagons at terminals, such that the capacity of a train service varies over different connections. In line with the principle of synchromodal transport, it is assumed that LSPs may book capacity separately on each connection of a service. Additionally, transport orders can be split and delivered through different services. Other companies can book capacity on the same train services, which reduces the available capacity on the market over time. Capacity reductions in the second and third stages are stochastic and depend on the market state, which is determined by the total demand of transport services in the market including other LSPs. In a market state with high demand, other LSPs are likely to order more slots on the train services, driving up their prices and reducing the amount of capacity available. It is assumed that the increase in price is fixed for each market state. In addition to train services, direct trucking services with unlimited capacity are available between all terminals, which are faster and more expensive than trains. Due to their higher flexibility, it is assumed that their cost is independent of the time of booking. Hence, they are only booked in the short term.

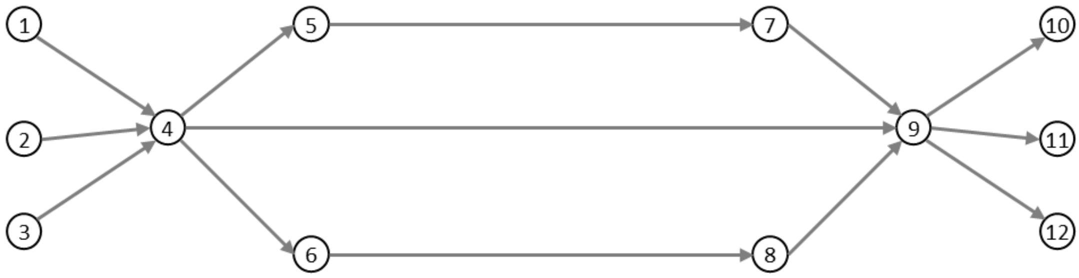

Fig. 2 Example of a rail-road intermodal network

Containers can be switched between trucks and trains or between two train services at train terminals. In that case, a transhipment cost is incurred per handled container. Because of the short delivery deadlines, time-dependent storage costs are omitted. To account for differences between terminal's prices and handling speeds, the cost per transhipped container and the transhipment time can vary between terminals.

3.2 Modelling stochasticity

The considered problem contains stochastic demand volumes and stochastic capacity reductions, which are assumed to follow known probability distributions. Accounting for every possible realisation of demand volume and capacity reduction would result in a dataset that is too large to be solved with exact methods (Shapiro, 2003). Therefore, scenarios are generated in which values of the stochastic parameters are sampled from their distributions. To resolve this issue, scenarios are generated in which values of the stochastic parameters are sampled from their distributions, resulting in a deterministic problem with a limited number of discrete scenarios (Li & Grossmann, 2021). In two-stage stochastic programming, it is assumed that the uncertainty is resolved after the first stage, resulting in complete information when making decisions in the second stage. If decisions are taken at several points in time without complete information, this results in multi-stage models. At each stage, decisions are made with the available information at that time. Since there are multiple decision-making stages, the result is a scenario tree as illustrated in Fig. 3. Scenario trees are a common approach to include stochasticity and are employed by Lium et al. (2009), Bai et al. (2014) and Hoff et al. (2010) among others.

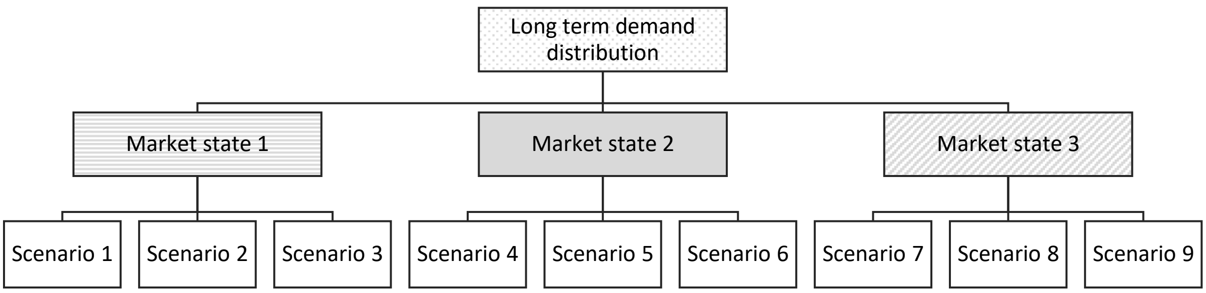

Fig. 3 Example of a scenario tree with three market states and nine third-stage scenarios

In each instance consisting of a single scenario tree, multiple scenarios are generated, e.g. 200, each representing a one-week time period with their own set of transport orders and capacity reductions. During the optimisation, the objective is to minimise the total (or average) cost over all those scenarios. The more samples are included, the more accurately the samples follow their underlying distribution. However, this comes at a trade-off of larger problem sizes that take longer to solve. Therefore, in- and out-of-sample stability is tested as described in Appendix A.

Demand takes the form of customer orders, which have an origin and a destination, a release and due time, and an order size, all of which are stochastic. It is assumed that the distribution of the total weekly demand volume of the LSP is known in the first stage. In the second stage, additional information becomes available about the total demand in the market, which indicates whether the current market state is one of low, medium, or high demand. This information leads to more accurate distributions with a different mean and lower standard deviation compared to the first-stage distribution. We here assume that a "higher" market state leads to a larger average demand that we will face. We assume that for every potential market state in the second stage, the LSP can estimate a demand distribution. In our modelling framework, this distribution can be of any type. The probabilities of each market state may differ, and the first-stage demand distribution is the weighted sum of the second-stage distributions. Fig. 4 illustrates an example in which three triangular distributions for the weekly demand volume are considered that represent market states with low, medium and high demand, which have an average demand of respectively 80%, 100% and 120% of the global average demand. The probability of a market state is 25% for low and high demand, and 50% for medium demand. Demand materialises in the third stage and is expressed in number of containers to be transported. The demand volume is generated from the corresponding second-stage distributions, resulting in respectively 25%, 50%, and 25% of the total scenarios in low, medium, and high demand market states. After generating the weekly demand volume in each scenario, it is split into individual orders, to which time windows and origin-destination pairs are assigned as described in Section 5 on the experimental setup.

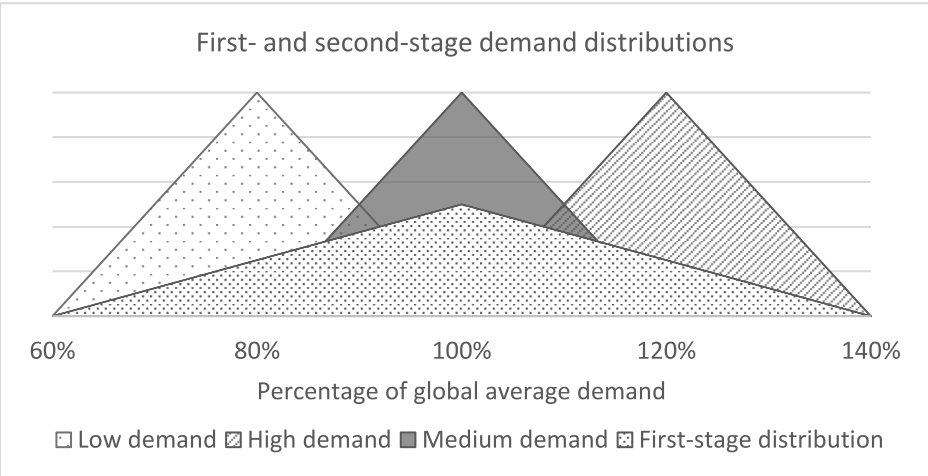

Fig. 4 An example of probability density functions of the demand at the first stage and second stage

Train capacity decreases over time are modelled in a similar manner as the demand volume, since the amount of capacity that is booked by other companies is assumed to be correlated with the total demand in the market. In the first stage, the available capacity of each service is known and at its maximum. In the second stage, the capacity on each train service decreases by a fixed percentage of the initial amount based on the market state, with a "higher" market state leading to a larger reduction. Capacity decreases in the third stage follow probability distributions with different means across market states as illustrated in Fig. 5, with again larger (average) reductions for "higher" market states. As a result, the average demand and average capacity reductions that we face are correlated, in the sense that they both depend on the market state. For more details on the respective values used in our experiments, we refer to Section 5.1. Prices of train services evolve over time depending on the market state, with higher prices in high-demand market states. Our model may accommodate both fixed and stochastic price increases similarly to capacity decreases.

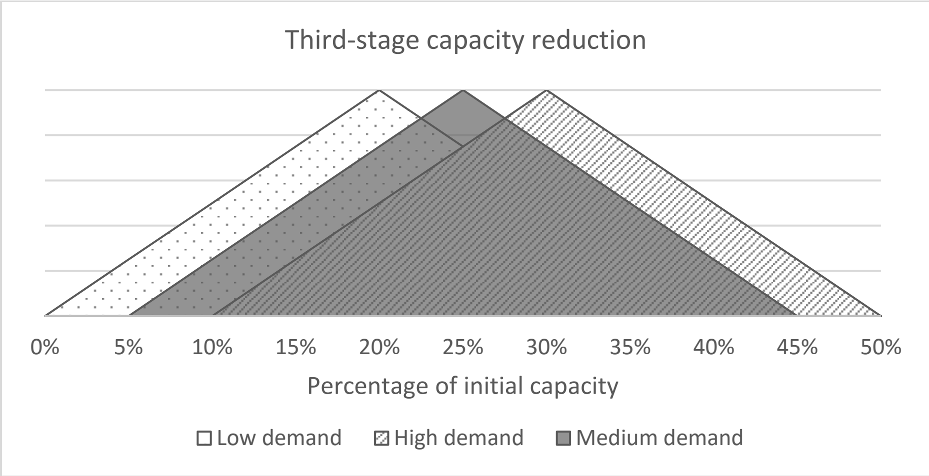

Fig. 5 An example of potential distributions of third-stage capacity-reductions in each market state

4 Mathematical model

The three-stage model is formulated as a single-objective integer linear programming problem that minimises costs and is solved with an exact solver. As mentioned in Section 3, stochasticity is included by generating multiple scenarios in which values of the stochastic parameters are sampled from probability distributions. As a result, we define a deterministic model which minimizes the total costs over all scenarios. Dividing this total cost by the number of scenarios, will lead to (an approximation of) the expect cost of our decision problem. As the values of the stochastic parameters are realized at different points in time (e.g., the market state in stage two, the exact demand level in stage three), this leads to a scenario tree in which for example multiple scenarios are related to the same market state (in stage two), but have a different demand level (in stage three). To determine the optimal decisions in each stage, a mathematical model is developed which minimises the total cost over all scenarios.

It is assumed that the following information is available when solving the model: In the first stage, information is available on the probabilities of each market state and their corresponding demand and capacity reduction distributions. In the second stage, additional information is available on the current market state. In the third stage, complete information is available. In addition to the generated scenarios, the mathematical model requires all feasible paths per transport order as an input, where a path is a set of consecutive train and truck connections through which containers can be transported on time from their origin to their destination. Section 4.1 explains how the paths are generated. The mathematical formulation is provided in Section 4.2.

4.1 Path generation

Different orders have different origins, destinations and time windows. As such, different orders will have different paths. We assume that time windows for order release and due times are discrete rather than continuous, resulting in a limited number of possible time windows. However, travel times remain continuous, which prevents the loss of solution quality that occurs when discretising time into fixed intervals (Boland et al., 2019). Before the optimisation phase, the feasible paths of all orders of each scenario are generated. The feasible paths of an order are generated recursively as shown in Algorithm 1 and discussed below.

Algorithm 1: Path-generation pseudocode

```
Input:   path p = ∅, set of completed paths P = ∅, all train connections c with origin c.terminal.start,
destination c.terminal.end, departure time c.time.start and arrival time c.time.arrival, all terminals y
Output: All feasible paths

For each order with origin g, destination b, release time l, due time d
    Add origin terminal g to path p
    Extend_partial_path(p)
End for
Return the list of all completed paths P

Function Extend_partial_path(p)
    If number of terminals in p < number of terminals in network
        If last terminal in p = origin terminal g
            For all train connections c
                If g = c.terminal.start AND c.time.departure ≥ l AND c.time.arrival ≤ d
                    Add c to p
                    If c.terminal.end = b
                        Add p to completed paths list : P = P ∪ {p}
                    Else
                        Extend_partial_path(p)
                    Remove c from p
                End if
            End for
            For all terminals y
                If g ≠ y AND d ≥ arrival time of truck connection from g to y
                    Add truck connection from g to y to p
                    If y = b
                        Add p to completed paths list : P = P ∪ {p}
                    Else
                        Extend_partial_path(p)
                    Remove c from p
                End if
            End for
        Else
            For all train connections c
                If last terminal in p = c.terminal.start AND c.time.departure ≥ time of
                last arrival in p AND c.time.arrival ≤ d AND c.terminal.end is not visited
                in p
                    Add c to p
                    If c.terminal.end = b
                        Add p to completed paths list : P = P ∪ {p}
                    Else
                        Extend_partial_path(p)
                    Remove c from p
                End if
            If last connection in p is a train connection
                For all terminals y
                    If y is not in p AND arrival time of truck connection from last
                    terminal to y ≤ d
                        Add truck connection from last terminal to y to p
                        If y = b
                            Add p to completed paths list : P = P ∪ {p}
```

```
53              Else
54                  Extend_partial_path(p)
55              Remove c from p
56            End if
57          End for
58        End if
59      End if
60    End if
61  Return the list of all completed paths P
```

The inputs of the path generation algorithm are the potential origin-destination pairs, the terminal locations, the list of train connections, transhipment times, and the combinations of order release and due times. Concerning the train connections, information is needed on the departure and arrival terminals, and the departure and arrival times. As trucks can travel directly between all terminals, all terminal pairs form a truck connection. In contrast to train connections, truck connections can depart at any time and are characterised solely by their origin-destination and travel time. The amount of capacity on each connection and the order sizes are not considered in the path generation phase, as the capacity decisions are part of the optimisation phase. In the path generation phase, an order is simply defined as a unique combination of an origin-destination pair and a release and due time. Paths are generated separately for each of those orders.

For each order, the first step is to create a new empty path which departs from the order's origin terminal (1-4). The uncompleted path is then extended with the depth-first recursive function "Extend_partial_path" on line 7 in the pseudocode. This function searches for new train and truck connections to add as long as the path visits fewer terminals than the total number of terminals in the network (9). Starting with an empty path that only contains the origin terminal, each train connection is evaluated on line (10). If the connection's origin terminal matches the order's origin, and the connection's departure and arrival times are feasible, the train connection is added to the path (11-12). If the order destination is reached by adding that connection, the path is added to a list of complete paths (13-14), after which the last connection is removed and the search for a new feasible connection continues. If the added connection does not end at the order's destination, the function "Extend_partial_path" is called again and the search for a second connection begins (15-16). After the feasible train connections to add to the empty path are exhausted, the search continues with truck connections. Truck connections to all terminals are evaluated (20). If the terminal is reached before the order's due time the truck connections is added to the empty path. Similarly to the train connections, if the order destination is reached by adding a truck connection, the path is added to the list of completed paths, after which the last connection is removed and the search continues (23-24). If the destination is not reached by adding a truck connection, the function "Extend_partial_path" is called to search for a second connection to add (25-26).

Paths that contain at least one connection are expanded similarly to empty paths. However, the search should account for the last location in the path, and all previously visited terminals to prevent visiting the same terminal twice. Therefore, while evaluating train connections, a condition is imposed that only connections which arrive in an unvisited terminal can be added (31-32). This condition is on top of the time window constraints and the constraint that the new connection must depart from the last location in the path. If a new train connection is added, it is again evaluated whether the order destination is reached, in which case the path is added to the completed paths, the last connection is removed, and the search continues (36-37). If the destination is not reached, the search for an additional connection starts (38-39). After evaluating all train connections, the truck connections are evaluated. Differently from the case with an empty path, new conditions are imposed upon paths that contain at least one connection. Only truck connections towards unvisited terminals may be added and a truck connection can only be added if the previous connection in the path was on a train (42-44). The latter condition prevents consecutive truck connections, since there would be no benefit over a single direct truck connection between the same origin and destination. The same steps are followed when adding truck connections as with train connections (46-50). After exhausting the search over all train and truck connections for a given path, the last connection in that path is removed and the search continues where it left off (17, 27, 40, 51).

To speed up the process of generating paths, a constraint is included which ensures that, from the second visited terminal on a path, only terminals which are closer to the destination than the current terminal can be visited. Preliminary tests indicate that there seems to be no impact on the obtained solutions in the networks tested in this study. However, in other networks, this constraint can be either removed or relaxed to allow visiting terminals farther away from the destination by a limited amount.

4.2 Mathematical formulation

This section presents the mathematical formulation of the integer programming problem for the three-stage model. It is based on the path-based network design formulation from Crainic (2000).

Sets

C	Set of train connections (index c)
I	Set of market states in the second-stage (index i)
J^i	Set of third-stage scenarios for market state $i \in I$ (index j)
$R_{i,j}$	Set of orders of market state $i \in I$ and third-stage scenario $j \in J^i$ (index r)
$A_{i,j,r}$	Set of paths of order $r \in R_{i,j}$ in market state $i \in I$ and third-stage scenario $j \in J^i$ (index a)

Parameters

g_c	Initial price per train slot on connection $c \in C$
p_i^m	Price multiplier of train slots in the second stage in market state $i \in I$
p_i^s	Price multiplier of train slots in the third stage in market state $i \in I$
z_i^m	Refund rate of train slots in the second stage in market state $i \in I$
z_i^s	Refund rate of train slots in the third stage in market state $i \in I$
u_c	Capacity of train connection $c \in C$ in the first stage
$w_{i,c}^m$	Capacity reduction of train connection $c \in C$ in the second stage in market state $i \in I$
$w_{i,j,c}^s$	Capacity reduction of train connection $c \in C$ in third-stage scenario $j \in J^i$ of market state $i \in I$
$k_{i,j,r,a}$	Trucking and transhipment cost of path $a \in A_{i,j,r}$ of order $r \in R_{i,j}$ in third-stage scenario $j \in J^i$ of market state $i \in I$

$h_{i,j,c,r,a}$ Binary parameter equal to 1 if train connection $c \in C$ is included in path $a \in A_{i,j,r}$ of order $r \in R_{i,j}$ in third-stage scenario $j \in J^i$ of market state $i \in I$ and equal to 0 otherwise

$o_{i,j,r}$ Order size in number of containers of order $r \in R_{i,j}$ in third-stage scenario $j \in J^i$ of market state $i \in I$

Decision variables

S_c^l Number of train slots booked on connection $c \in C$ in the first stage

$S_{i,c}^m$ Number of train slots booked on connection $c \in C$ in the second-stage in market state $i \in I$

$S_{i,j,c}^s$ Number of train slots booked on connection $c \in C$ in third-stage scenario $j \in J^i$ of market state $i \in I$

$Q_{i,c}^m$ Number of train slots cancelled on connection $c \in C$ in the second-stage in market state $i \in I$

$Q_{i,j,c}^s$ Number of train slots cancelled on connection $c \in C$ in third-stage scenario $j \in J^i$ of market state $i \in I$

$X_{i,j,r,a}$ Number of containers routed on path $a \in A_{i,j,r}$ of order $r \in R_{i,j}$ in third-stage scenario $j \in J^i$ of market state $i \in I$

Auxiliary variables

$B_{i,c}^m$ Binary variable equal to 0 if the remaining number of slots on connection $c \in C$ in the second-stage in market state $i \in I$ are lower than the capacity reduction $w_{i,c}^m$ and equal to 1 otherwise. If it is equal to 0, no additional slots can be booked on this connection in the second stage in this market state. Binary variable equal to 1 if there are remaining slots available on connection $c \in C$ in the second-stage in market state $i \in I$, and equal to 0 otherwise. Slots are available if the initial capacity u_c minus the number of slots booked in the first stage S_c^l is greater than the second-stage capacity reduction w_{ic}^m. Additional slots on connections in the second stage S_c^m can only be booked if $B_{i,c}^m$ is equal to 1.

$B_{i,j,c}^s$ Binary variable equal to 1 if there are remaining slots available on connection $c \in C$ in the third-stage scenario $j \in J^i$ of market state $i \in I$, and equal to 0 otherwise. Slots are available if the initial capacity u_c plus the number of cancelled slots in the second stage $Q_{i,c}^m$, minus the number of slots booked in the first two stages S_c^l and $S_{i,c}^m$ is greater than the sum of the capacity reductions in the second and third stages $w_{i,c}^m$ and $w_{i,c}^s$. Additional slots on connections in the third stage $S_{i,j,c}^s$ can only be booked if $B_{i,j,c}^s$ is equal to 1.

Objective function

$$\min \sum_{i \in I} \sum_{j \in J^i} \left(\sum_{c \in C} ((S_c^l + S_{i,c}^m\, p_i^m + S_{i,j,c}^s\, p_i^s - Q_c^m\, z_i^m - Q_{i,j,c}^s\, z_i^s)\, g_c) + \sum_{r \in R_{i,j}} \sum_{a \in A_{i,j,r}} (X_{i,j,r,a}\, k_{i,j,r,a}) \right) \quad (1)$$

Capacity constraints

First stage:

$$S_c^l \leq u_c \qquad \forall\, c \in C \quad (2)$$

Second stage:

$$S_c^l - Q_{i,c}^m \geq 0 \qquad \forall\, c \in C, i \in I \quad (3)$$

$$S_c^l + S_{i,c}^m + w_{i,c}^m\, B_{i,c}^m \leq u_c \qquad \forall\, c \in C, i \in I \quad (4)$$

$$\left(u_c - w_{i,c}^m\right) B_{i,c}^m - S_{i,c}^m \geq 0 \qquad \forall\, c \in C, i \in I \quad (5)$$

Third stage:

$$S_c^l + S_{i,c}^m - Q_{i,c}^m - Q_{i,j,c}^s \geq 0 \qquad \forall\, c \in C, i \in I, j \in J^i \quad (6)$$

$$S_c^l + S_{i,c}^m + S_{i,j,c}^s - Q_{i,c}^m + (w_{i,c}^m + w_{i,j,c}^s)\, B_{i,j,c}^s \leq u_c \qquad \forall\, c \in C, i \in I, j \in J^i \quad (7)$$

$$\left(u_c - w_{i,c}^m - w_{i,j,c}^s\right) B_{i,j,c}^s - S_{i,j,c}^s \geq 0 \qquad \forall\, c \in C, i \in I, j \in J^i \quad (8)$$

Flow constraints

$$S_c^l + S_{i,c}^m + S_{i,j,c}^s - Q_{i,c}^m - Q_{i,j,c}^s - \sum_r^{R_{i,j}} \sum_a^{A_{i,j,r}} (X_{i,j,r,a}\, h_{i,j,c,r,a}) \geq 0 \qquad \forall\, c \in C, i \in I, j \in J^i \quad (9)$$

$$\sum_a^{A_{i,j,r}} X_{i,j,r,a} = o_{i,j,r} \qquad \forall\, i \in I, j \in J^i, r \in R_{i,j} \quad (10)$$

Domain constraints

$$X_{i,j,r,a}, S_c^l, S_{i,c}^m, S_{i,j,c}^s, Q_{i,c}^m, Q_{i,j,c}^s \in \mathbb{Z}_0^+ \qquad \forall\, c \in C, i \in I, j \in J^i, r \in R_{i,j}, a \in A_{i,j,r} \quad (11)$$

$$B_{i,c}^m, B_{i,j,c}^s \in \{0,1\} \qquad \forall\, c \in C, i \in I, j \in J^i \quad (12)$$

The objective function (1) minimises the total cost over all scenarios, which are comprised of transhipment costs, trucking costs and the costs of train slots in all three stages minus refunds for cancellations. Constraint (2) limits the number of train slots that can be booked in the first stage on each connection to the available capacity. Constraint (3) ensures that the number of slots cancelled in the second stage does not exceed the number of previously booked slots.

Constraints (4) and (5) ensure that slots can only be booked on connections in the second stage on which capacity remains available. On each rail connection, u_c stands for the total capacity that is offered by the rail operator, while the capacity reduction $w_{i,c}^m$ is the external demand for that capacity coming from other companies. The condition that capacity remains available is satisfied if the initial capacity u_c is greater than the sum of the capacity reduction $w_{i,c}^m$ and the first stage bookings S_c^l on that connection. If that is the case, the number of slots booked in the second stage $S_{i,c}^m$ can be greater than zero, but at most equal to the remaining capacity, which in turn requires that the binary variable $B_{i,c}^m$ is equal to 1. In the event that the sum of the capacity reduction and the number of slots booked in the first stage exceeds the initial capacity, $B_{i,c}^m$ is forced to 0. As a result, $S_{i,c}^m$ is forced to 0, i.e., no slots can be booked in the second stage.

Constraints (6) to (8) are equivalent to constraints (3) to (5) for the third stage. Regarding flow constraints, constraint (9) ensures that the total flow on each train connection does not exceed the number of booked train slots. For each order, constraint (10) sets the sum of flows on all paths of that order equal to the order's size. In domain constraint (11), the number of booked and cancelled slots as well as the flow of each order on each path are set as positive integers. Domain constraint (12) sets the variables that prevent new bookings on a connection when the sum of previously booked slots and capacity reductions are larger than the initial capacity as binary.

In Section 6, the potential benefit of our three-stage model is analysed by comparing it to a two-stage model with capacity updates in the second stage, a two-stage model without updates and a model with perfect information. The two-stage model with capacity updates is obtained by fixing the decisions variables for the number of slots booked ($S_{i,c}^{m}$) and cancelled ($C_{i,c}^{m}$) in the second stage to zero. For the two-stage model without updates, the equivalent decision variables for the third stage ($S_{i,j,c}^{s}$ and $C_{i,j,c}^{s}$) are set to zero as well. For the model with perfect information, as the name implies, we assume that we know the realizations of all stochastic parameters already when making decisions at the first stage, and hence optimal decisions can be taken at once, without the need for replanning. A straightforward way to obtain the total costs corresponding to such a setting would be to individually and independently solve a simplified single-scenario model for each of the sampled scenarios, and sum the costs. However, we take a different approach, allowing us to solve our multi-scenario model a single time. Basically, we solve the mathematical model described in Section 4.2, but we fix all second-stage decision variables ($S_{i,c}^{m}, Q_{i,c}^{m}$) to zero and we set the refund rate in the third stage (z_i^s) to one, allowing for each scenario to cancel any first-stage bookings which are not required for this scenario with a full refund.

5 Experimental setup

The impact of replanning is evaluated on a set of theoretical instances. To this end, three models are compared: (1) a two-stage model without replanning rail capacity, which is similar to typical models found in existing literature, (2) a two-stage model that updates capacity decisions in the last stage when perfect information is available, and (3) the three-stage model with two replanning stages. A further comparison is made against a model with perfect information. With perfect information, it is assumed that complete information on the market states and the demand, which includes origin-destination pairs, time windows and volumes of all orders, is available in the first stage. The case with perfect information, albeit unachievable, returns a lower bound on costs. It serves as a benchmark that indicates the maximum potential cost savings that can be achieved through improved capacity planning. The cost surplus compared to perfect information can also be seen as the cost of uncertainty. With all four models, rail capacity is purchased in the first stage while truck service bookings and routing decisions are performed in the third stage. Only the three-stage model updates rail capacity in the second stage, whereas all models apart from the one without replanning update rail capacity in the third stage. With perfect information, it is assumed that the third-stage refund rate is 100%.

The objective of our experiments is twofold: first, the aim is to evaluate the performance improvement by updating the capacity planning, both once (in the last stage) and twice (at the final and an additional intermediate stage). Second, we want to identify which factors influence the potential performance improvement gained through replanning. To evaluate the performance of the different models, we employ the cost per container, averaged over all scenarios. In addition, since synchromodal transport aims to facilitate the modal switch, the share of rail transport is considered as well, which is measured as the distance travelled on trains divided by the total travelled distance by all containers.

Experiments are run on a supercomputer with Xeon Gold 6140 CPUs at 2.3 GHz and Xeon Gold 6240 CPUs at 2.6 GHz. To solve the mathematical model, we apply CPLEX 22.1.0. To speed up the optimisation, the domain constraints for the integer decision variables are relaxed to continuous variables. The terminating criterion is set at an optimality gap of 0.5%.

The remainder of this section describes which test instances are employed and is further divided into three parts: Section 5.1 presents the input parameters that remain constant over all instances, and Section 5.2 explains the factorial design to evaluate the impact of multiple factors on the performance of the different tested models.

5.1 Constant input parameters

The impact of several input parameters on the model outputs is investigated with a factorial design, which is further detailed in Section 5.2. Multiple instances are performed for each factor level combination. Each instance considers three market states: one with a low, one with a medium and one with a high demand market state with respective probabilities of 25%, 50% and 25%. The total number of third-stage scenarios per instance is 200, which is sufficient to achieve in- and out-of-sample stability. The performed stability tests are described in Appendix A. The input parameters that remain constant over all instances are listed in Table 2. For each of the 200 scenarios per instance, all stochastic parameters are independently drawn from their distribution (e.g., demand level, third-stage capacity reduction). Although any planning horizon can be considered for our problem and model, the considered planning horizon is one week, which is chosen such that it is short enough to have complete demand information in the last stage for the entire duration.

Table 2 Constant parameter values over all instances

Parameter	Value
Probability of each market state	▪ Low demand: 25% ▪ Medium demand: 50% ▪ High demand: 25%
Planning horizon	1 week
Average demand	360 containers
Train speed	50 kph
Truck speed	60 kph
Trucking cost per km	€1.60
Terminal operation cost per unit	€40
Transhipment time	2 hours
Order size	Triangular distribution with minimum 5, maximum 25 and mode 15 containers
Release time	Discrete uniform distribution with minimum 0, maximum 120 and intervals of 6 hours
Time between release and due time	Discrete uniform distribution with minimum 48, maximum 72 and intervals of 6 hours
Second-stage capacity reduction in % of initial capacity	▪ Low demand: 5% ▪ Medium demand: 15% ▪ High demand: 25%
Third-stage capacity reduction in % of initial capacity	Triangular distributions with the following parameter values: ▪ Low demand: minimum 0%, maximum 40% and mode 20% ▪ Medium demand: minimum 5%, maximum 45% and mode 25% ▪ High demand: minimum 10%, maximum 50% and mode 30%
Second-stage train slot price increase	▪ Low demand: 0% ▪ Medium demand: 2.5% ▪ High demand: 5%
Third-stage train slot price increase	▪ Low demand: 0% ▪ Medium demand: 5% ▪ High demand: 20%
Train slot refund rate	▪ Second stage: 90% of the first-stage price ▪ Third stage: 50% of the first-stage price

One of the investigated factors in the factorial design is the network, with three considered rail-road networks that contain a varying number of rail connections. However, the terminals in each network are identical. The distances between terminals are comparable to those in existing freight corridors in Europe, such as the Rhine-Alpine corridor and the corridor between Belgium and Poland. Origin and destination terminals are located around 900 km apart, while terminals around the origins and destinations are more clustered. According to the European Court of Auditors, while the average speed of freight trains is low in the EU, some corridors such as the Rhine-Alpine corridor reach speeds of 50 km/h, which is close to the average speed of trucks of 60 km/h (European Court of Auditors, 2016). After confirming these numbers with rail operators, truck and train speeds are fixed at respectively 60 and 50 km/h. Trucking costs per km are set at €1,60, whereas fares for train slots per km in the first stage are set between 65% and 85% of that amount. Increases in train slot prices for scenarios with low, average and high demand respectively amount to 0%, 2.5% and 5% in the second stage and 0%, 5% and 20% in the third stage. The amount refunded when cancelling slots is 90% of the first-stage price when cancelled in the second stage and 50% when cancelled in the third stage, irrespective of the time at which the slots were booked. A terminal operation cost of €40 is incurred per container for each loading and unloading operation on trains and when switching between vehicles. Terminal operations take 2 hours, which is the time trains spend at each intermediate terminal.

The planning horizon is one week (from Monday till Sunday) with an average weekly demand of 360 containers. The demand volume in each scenario is generated from the corresponding second-stage distribution, after which the containers are split into transport orders of different sizes. Order sizes follow a triangular distribution with minimum five, maximum 25 and modus 15 containers, although order sizes are lower if fewer containers remain. As is the case with demand volume, the model is compatible with any theoretical distribution for order sizes. An origin-destination pair and time windows are then randomly assigned to each order. We consider a limited number of origin terminals and destination terminals, with each combination having the same probability of being assigned to an order. In reality, customer origins and destinations are not on intermodal terminals themselves. Therefore, a transhipment cost is also incurred for loading and unloading trains at origin and destination terminals. It is assumed that distances between the customer locations and terminals are sufficiently small that there are no large differences in trucking costs for the extra distance between direct trucking and trucking to the terminal.

Regarding time windows, each order is assigned a release time and a due time. Release times indicate the time at which containers become available for transport. Due times are the latest allowed delivery times. Release times are possible from Monday till Friday at midnight. A discrete uniform distribution is employed between zero and 120 hours (Friday at 24:00) with increments of six hours, although a continuous distribution would also work. This discretization is done with the fixed train departure times in mind, since small differences in release times have no impact on the available transport options of orders if they have to wait for the same train. Due times are uniformly distributed between two and three days (48 and 72 hours) after release times and in steps of six hours as well. The values obtained from the distribution of due times indicate the amount of time available from the release time onwards. If orders have a due time that is later than the chosen time horizon, e.g. an order with a due time past Sunday and a time horizon of one week, the order can be shipped using capacity of the services at the start of the week. Doing so ensures that the model accounts for orders from a previous week which have yet to be shipped and take up transport capacity, which avoids the need for a warm-up period. Furthermore, it is assumed that there are no train departures on Sunday. Consequently, an additional day (24 hours) is added to due times that are later than Sunday (i.e. due times above 144 hours).

The average amount of train slots available in the first stage from each origin to each destination terminal is identical in all networks. These train slots are divided over the services such that the number of slots that depart from each origin and arrive at each destination terminal is identical. In addition, train departure times are selected such that the departing slots are evenly spread out over the week. The first departure is set on Monday at 10:00 to provide a margin for orders to be transported to the terminal by truck and loaded onto the train. It is assumed that the latest possible release time accepted by the LSP is on Friday at 24:00. As an example, Table 3 displays the departure times of each train in one of the investigated networks that contains 5 train services, with three weekly departures each, which have a combined weekly capacity of 540 containers (i.e., 150% of the average demand).

Table 3 Train capacities and departure times in network 3

Train service	Train capacity in containers	1st departure	2nd departure	3rd departure
1	20	Monday 10:00	Wednesday 07:00	Friday 04:00
2	20	Tuesday 01:00	Wednesday 22:00	Friday 19:00
3	60	Tuesday 16:00	Thursday 13:00	Saturday 10:00
4	40	Monday 16:00	Wednesday 13:00	Friday 10:00
5	40	Tuesday 07:00	Thursday 04:00	Saturday 01:00

In the second stage, capacity on each train connection is reduced by a fixed amount depending on the market state. The reductions are respectively 5%, 15% and 25% of the total capacity for the low, medium and high demand market states. Further capacity reductions in the third stage follow a triangular distribution with minimum 5%, maximum 45% and modus 25% of the total capacity. In market states with respectively a low and high demand, these reductions are 5% lower and higher compared to the market state with medium demand. This is done to reflect the capacity requirements from other LSPs as a result of the total transport demand in the market.

5.2 Factorial design

A full factorial experiment is performed to identify which factors have the greatest impact on the potential solution improvement of the three-stage model over a two-stage model. The tested factors and their factor levels are shown in Table 4. There are a total of 405 factor level combinations (3x3x5x3x3), for each of which 10 instances are run with a different random seed, resulting in 4050 instances (405x10). For each instance, the terminating criterion is an optimality gap of 0.5%. Note that scenarios are identical and contain the same random values in comparisons between the different models, i.e., each model is tested on the same 4050 instances.

Table 4 Factorial design

Factor	Factor levels
Network	1 - 2 - 3
Train capacity/demand ratio	120% - 150% - 180%
Train/truck cost ratio	65% - 70% - 75% - 80% - 85%
Width of demand volume distributions	20% - 40% - 60%
Difference between market state demand volumes	10% - 20% - 30%

Three networks are considered, each with a different number of train services and connections. The networks are shown in Fig. 6. Terminals are represented by a dot and the arcs are railways on which train services are provided. Each train service has three departures per week. The three leftmost terminals are origins and the rightmost terminals are destinations. The different train services in each network determine how many transhipment options are available.

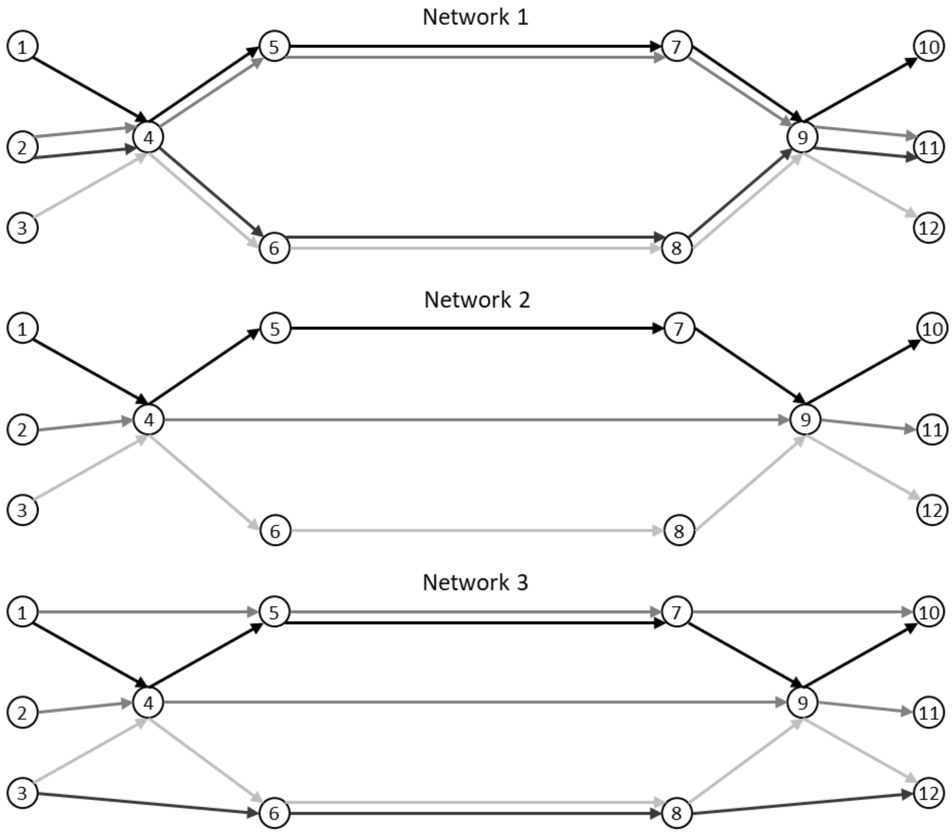

Fig. 6 Train networks and their train services. Each train service has three weekly departures and contains multiple connections between two consecutive terminals

The second factor in Table 4 determines the amount of train capacity, which is expressed in number of slots. The total number of available train slots in the first stage across all train services throughout the planning horizon varies between 120% and 180% of the average total demand, which equals 360 containers. This factor is included because we expect that with the decrease in amount of capacity left on the market over time, the advantage of performing an earlier update of the booked train capacity might increase since the risk of running out of capacity by delaying the decision is higher.

The train/truck cost ratio determines the train slot prices. A ratio of 65% means that a first-stage train slot costs 65% of the cost of a truck travelling the same distance. It is expected that the rail share decreases as this ratio increases.

Demand volume is generated from symmetric triangular distributions. The following two factors relating to demand uncertainty are analysed in the factorial experiment:

- The width of the second-stage triangular distributions from which demand volume is generated (denoted "width" in short).
- The difference between the average demand volumes in the different market states (denoted "difference" in short).

Both factors are expressed as a percentage of the average demand. A larger width of the triangular distribution reduces the value of the information obtained in the second stage, whereas a larger difference in average demand between market states increases it. This is visualised in Fig. 7. When the difference between average demand volumes increases, differences in demand volume between market states increase. Therefore, so does the value of knowing the current market state. For this reason, it is expected that the three-stage model performs relatively better compared to the two-stage model at larger differences. In contrast, an increased width of the demand distributions would mean that the market state would less accurately predict the demand. As such, the three-stage model is expected to have a smaller advantage over the two-stage model.

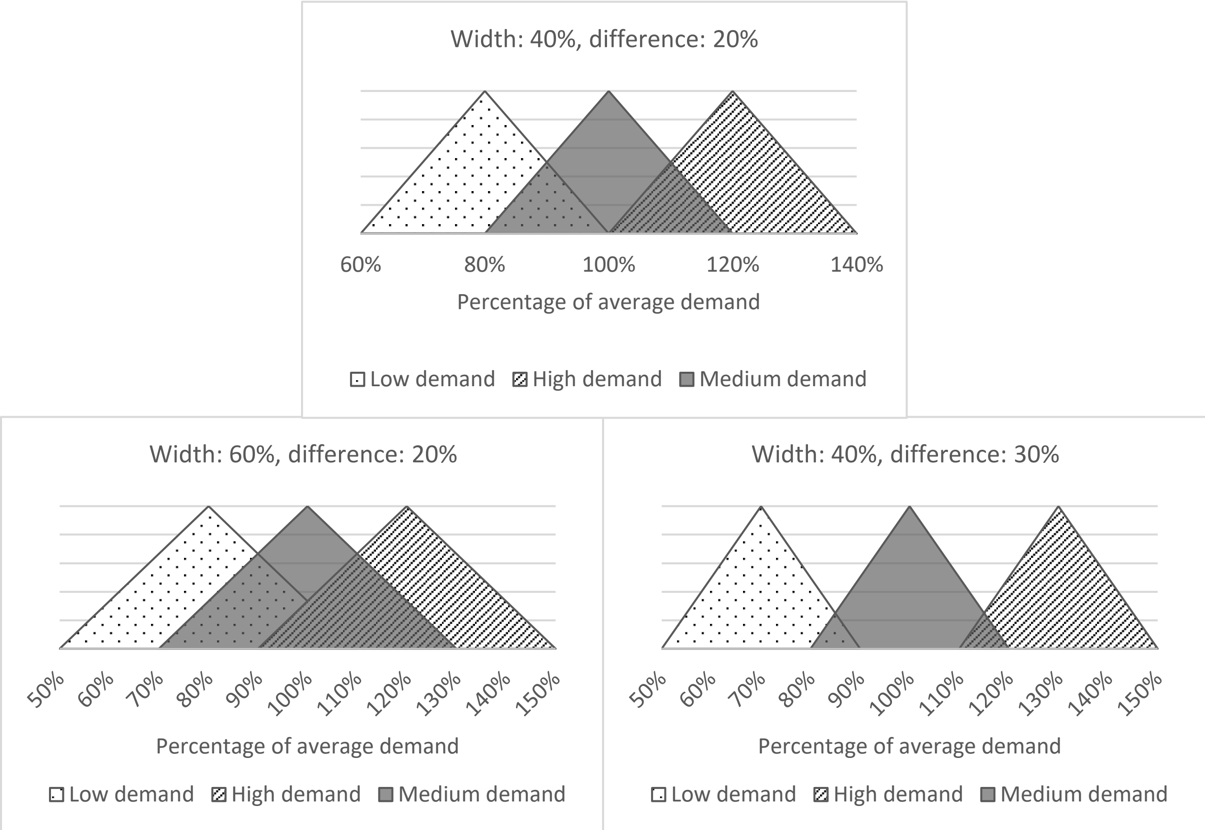

Fig. 7 Demand volume distributions with varying triangular distribution widths and differences in the average demand volume between market states

6 Experimental results and discussion

This section discusses the results of our experiments, focusing on the effect of the five factors introduced in Section 5. First, an analysis of variance is performed to identify which factors have a significant effect on the total cost for the three-stage model. Once these significant factors have been determined, their impact on the performance difference between the models is analysed. The ANOVA results of the three-stage model are illustrated in Appendix B. All main effects apart from the width of the demand distributions are significant. Regarding interaction effects, the following combinations are significant: network and train capacity, network and train/truck cost ratio, train capacity and train/truck cost ratio, train/truck cost ratio and the difference in average demand volume between market states, train/truck cost ratio and the width of demand volume distributions and finally the difference between and the width of the demand volume distributions. In the remainder of this section, results are discussed in order from the factor with the largest to smallest effect on costs in the three-stage model.

6.1 Impact of the train/truck cost ratio

Fig. 8 to 10 compare the four different models for different values of the train/truck cost ratio: (1) a two-stage model without replanning rail capacity (no updates), (2) a two-stage model that updates capacity decisions in the last stage when perfect information is available (2 stages), (3) the three-stage model with two replanning stages (3 stages), and a model with perfect information (perfect info). Fig. 8 illustrates the average cost per container, taken as the average total cost divided by the average demand over each instance's 200 scenarios, for each model with varying train/truck cost ratios. Fig. 9 depicts the relative additional cost incurred compared to the total cost with perfect information (percentage increase with the cost of perfect information as base). The rail shares at varying train slot prices in the different models are shown in Fig. 10. The cost of train services has the largest impact on both total costs and the share of rail transport, with higher train service prices naturally leading to higher costs and lower rail shares across all models. Based on average performance, we see that the three-stage model outperforms the two-stage models while the model without updates comes in last. This holds for every train/truck cost ratio, although the differences are smaller as this ratio increases. Results clearly indicate that capacity updates lead to considerable improvements. At a train/truck cost ratio of 65%, rail shares are 10% higher and the costs of uncertainty are respectively 42% and 51% lower for the two- and three-stage models compared to the model without updates (Fig. 9 and Fig. 10). Even at a high train/truck cost ratio of 85%, the costs of uncertainty remain at least 17.5% lower. Differences between the two- and three-stage models with capacity updates are relatively small, but increase at lower train/truck costs. Therefore, updating capacity multiple times leads to diminishing returns. Differences in total cost between all models decrease as the train/truck cost ratio increases, which indicates that improved capacity planning is more beneficial when the costs of train services are lower compared to trucks.

The share of rail transport experiences a sharp decline when the train/truck cost ratio exceeds 75%, dropping by 40% as the cost ratio increases from 75% to 85%. At high cost ratios, the three-stage model still outperforms the two-stage models in terms of costs, though it should be evaluated whether the increased effort of replanning outweighs the cost savings. To illustrate, consider an LSP that ships 100 containers a day. At a train/truck cost ratio of 75%, going from one capacity update to two leads to a savings of approximately 0.3%, which amounts to over €140.000 per year (Fig. 8). At a train/truck cost ratio of 85%, these savings drop to €13.000 per year. Due to the small differences observed at high train costs, the subsequent analyses focus on the results obtained with train/truck cost ratios of 65% and 75%.

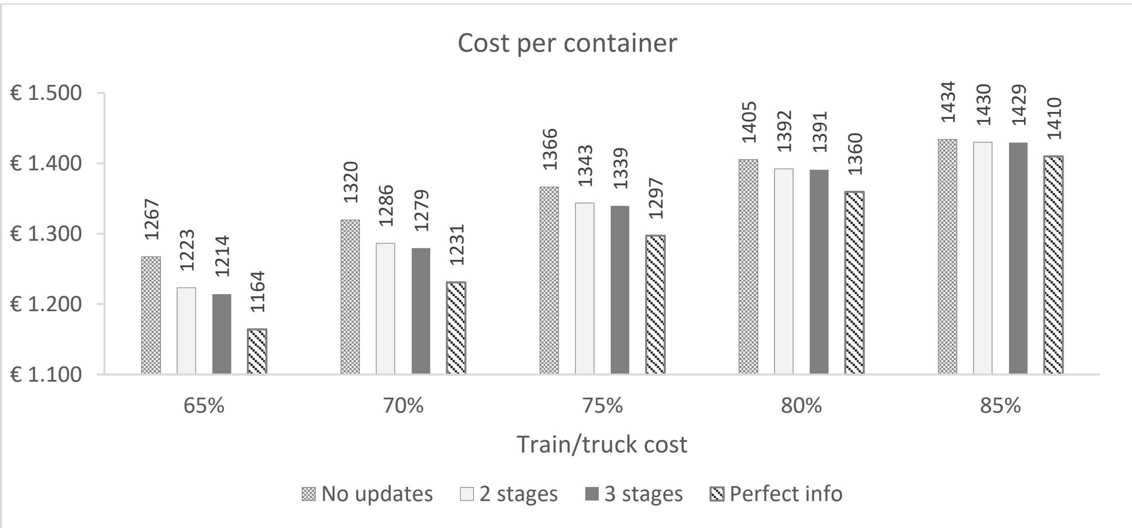

Fig. 8 Average costs per container with each model at varying train/truck cost ratios

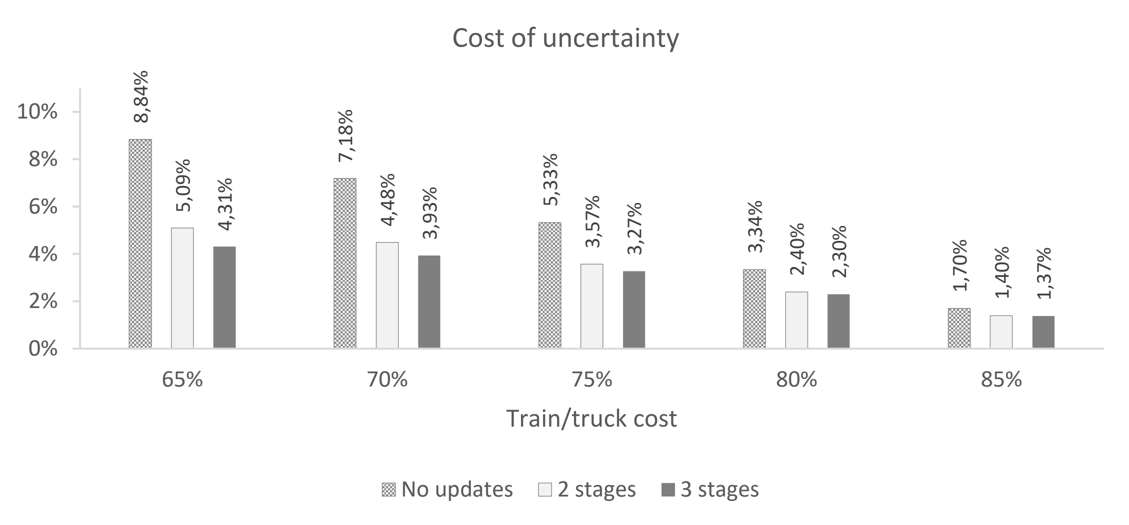

Fig. 9 Cost of uncertainty at varying train/truck cost ratios (relative to perfect information)

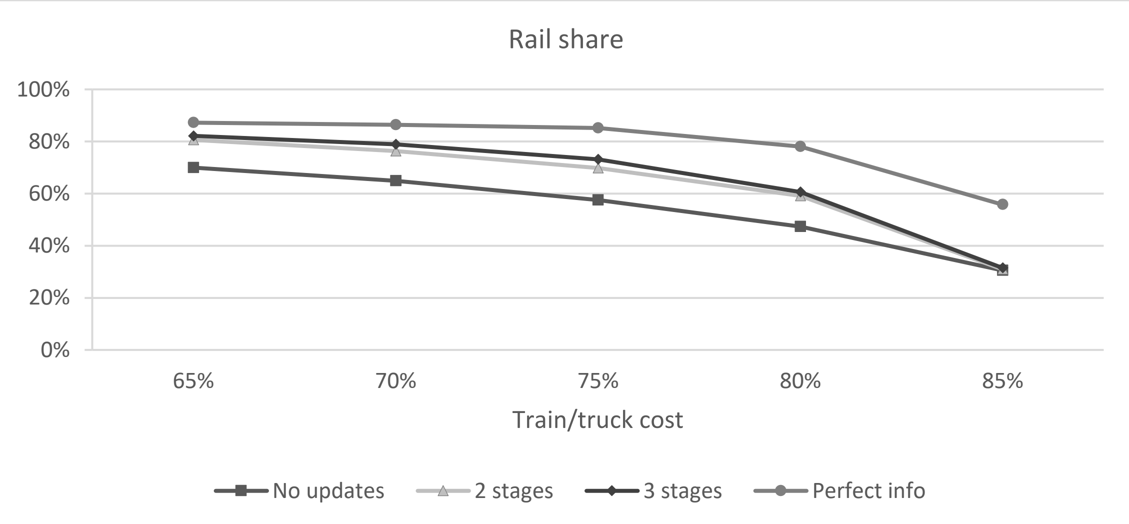

Fig. 10 Rail shares at varying train/truck cost ratios

6.2 Impact of the network

The train service offering in the network has the second largest impact on total costs. Average costs per container in the three networks are displayed in Fig. 11. Fig. 12 depicts the cost of uncertainty in the three studied networks. The shares of rail transport in the three networks at varying train slot prices are illustrated in Fig. 13. As can be seen in Fig. 11 and Fig. 13, the highest costs and lowest rail shares are observed in Network 1, which is the network with the fewest rail options for the long-haul. In contrast, Network 3, which has the most rail options, has the lowest costs and highest rail shares. The different train services in the networks carry different costs. For instance, the extra long-haul connection in Network 2 compared to Network 1 follows a more direct route, which decreases costs and travel times. Similarly, the additional train services in the third network offer more direct routes between the origin and destination terminals. Therefore, the networks differ in both the number of train services and their costs. Considering this, we conclude that having more direct rail routes and transhipment options encourages a modal shift.

The cost of uncertainty illustrated in Fig. 12 reveals that introducing a single replanning stage can lead to considerable savings of over 3%. Further savings from a second replanning stage are smaller at around 0.7%, and are the highest in the third network. Savings from both a single and two replanning stages are the lowest in the first network, which indicates that replanning enables to make better use of the increased number of rail options. The larger cost of uncertainty across all models in the third network could also suggest that planning under stochastic conditions is more challenging in networks with more options, even though the overall costs are lower.

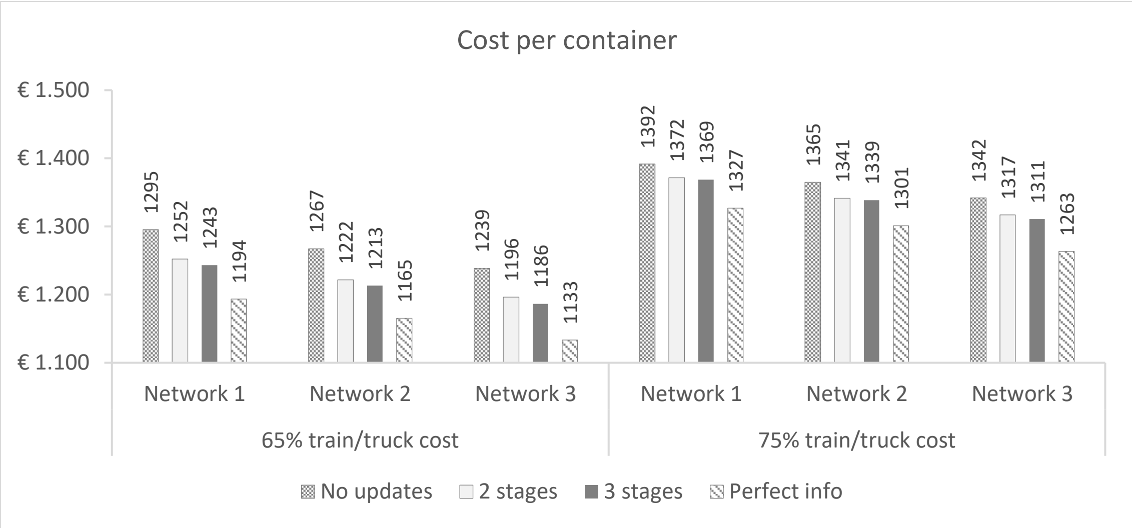

Fig. 11 Average costs per container with each model in the different networks

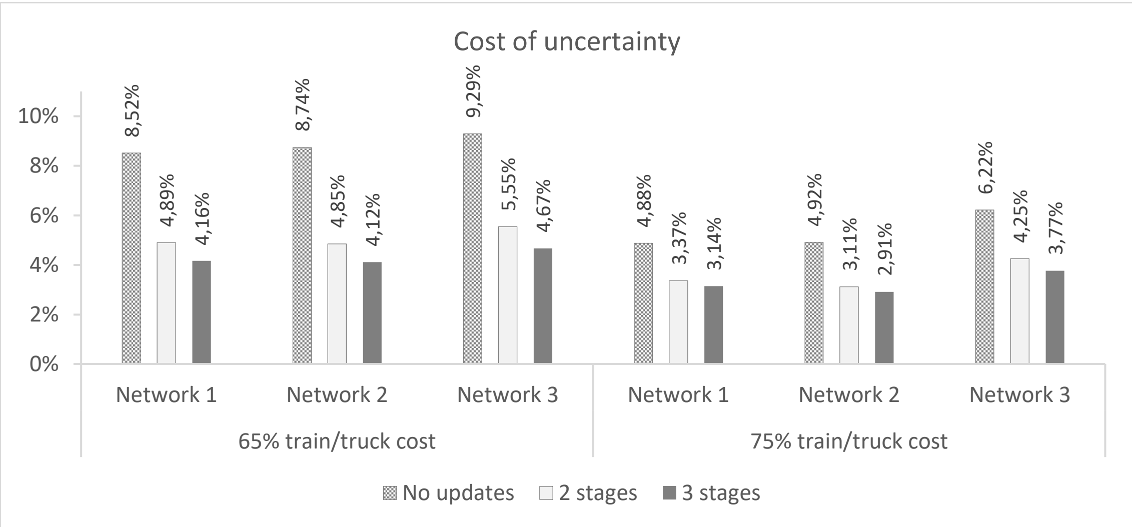

Fig. 12 Cost of uncertainty in the different networks (relative to perfect information)

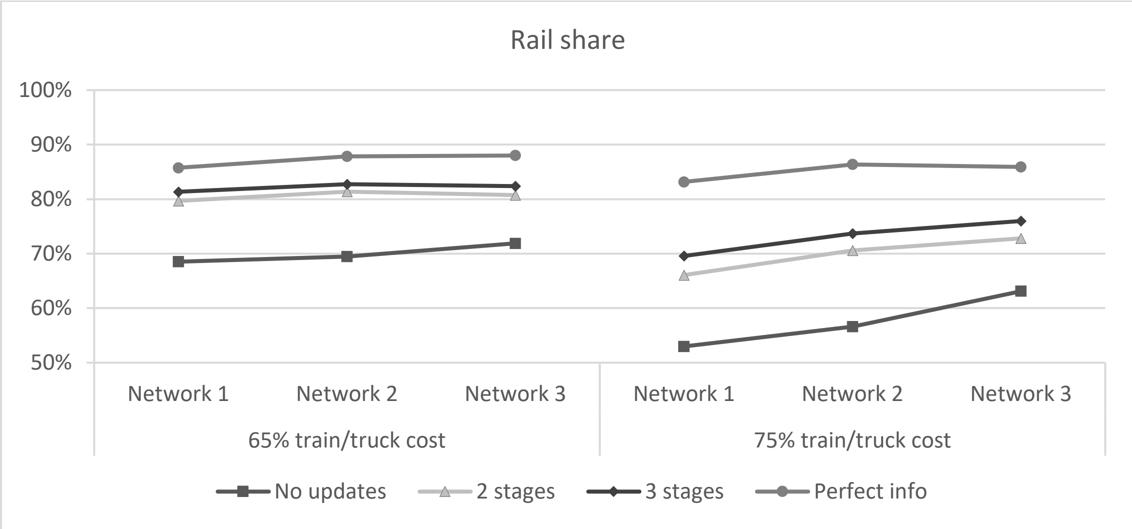

Fig. 13 Rail shares in the different networks

6.3 Impact of the available train capacity

In this section, the impact of available train capacity on the performance improvement from replanning is analysed. Because the amount of capacity left on the market decreases over time, it might be more advantageous to perform earlier updates if the risk of running out of capacity is high (i.e., capacity is more restrictive). Fig. 14 illustrates the average costs per container at initial train capacities between 120% and 180% of the average demand and Fig. 15 depicts the relative cost increase of the applied models compared to perfect information. Total costs decrease as capacity increases with all applied models. Moreover, the reduction in cost of uncertainty from a single replanning stage increases with the amount of capacity, while the savings from a second replanning stage remain constant. Therefore, it becomes more beneficial to update capacity decisions when more capacity is available on the market. The amount of capacity has no effect on the rail share without replanning (Fig. 16). However, with at least one replanning stage, the rail shares increase at higher capacity levels. As such, the ability to book more capacity after the demand has materialised leads to significant improvements.

Fig. 17 illustrates the average number of train slots that are booked and cancelled in each stage. Note that only the models with capacity updates obtain refunds for cancellations. For the model without capacity updates, the cancellations only indicate how many of the bought slots are unused. The results reveal that fewer slots are booked in the first stage, with more bookings in the second and especially third stages as the amount of capacity available on the market increases. The three-stage model results in more overall cancellations, though fewer cancellations are made in the third stage compared to the model with a single replanning stage. Although perfect demand information is unavailable in the second stage, the higher refund rate accounts for the equal or greater number of cancellations at that point compared to the third stage. As the capacity on the market increases, the number of cancellations decreases as well because more capacity is bought in later stages, when more demand information is available. However, the number of cancellations varies far less than the number of new bookings across different capacity levels. Since train slots are more expensive in the later stages, the cost reduction is not as large as the rail share improvement. Nevertheless, it does indicate that the LSP is willing to pay a higher price for capacity when demand uncertainty is lower and that further savings can be achieved if capacity is readily available. This highlights the importance of maintaining strong relationships with carriers, which supply transport capacity to LSPs, as they play an important role in managing uncertainty. Thus, if current suppliers offer little flexibility in altering the amount of booked capacity on short notice, it might be worthwhile to explore new supplier options.

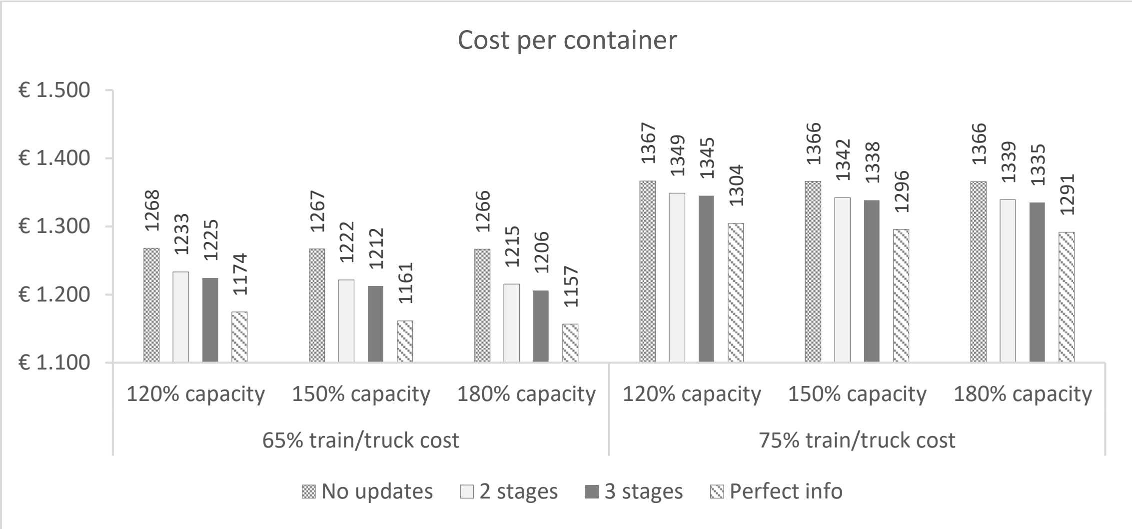

Fig. 14 Average costs per container with each model at varying amounts of train capacity

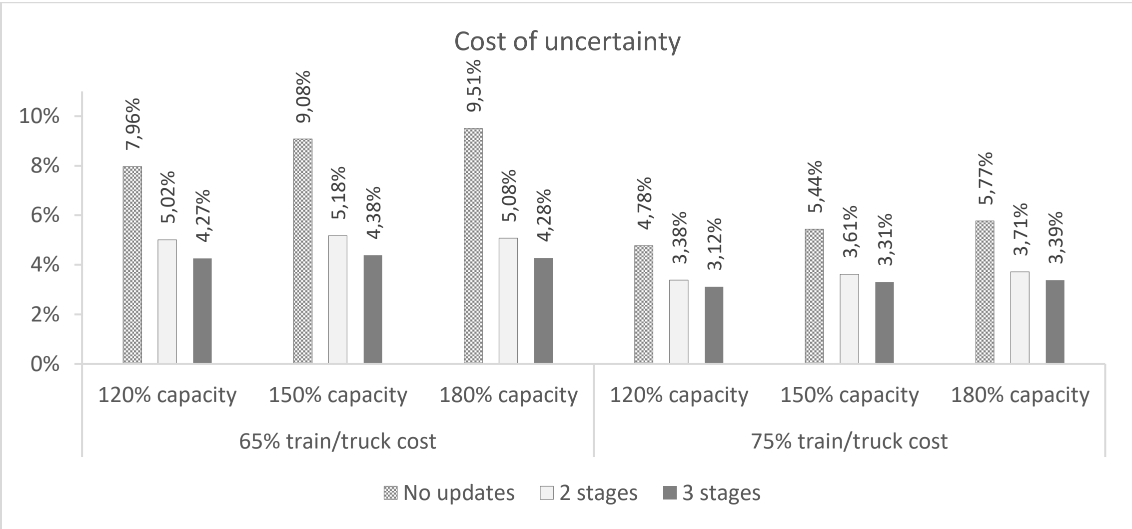

Fig. 15 Cost of uncertainty at varying amounts of train capacity

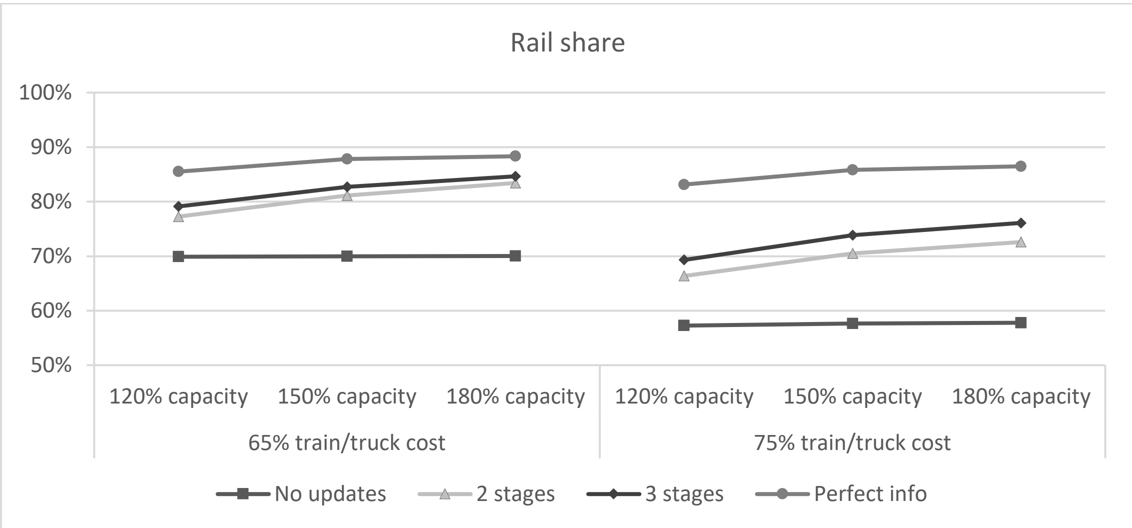

Fig. 16 Rail shares at varying amounts of train capacity

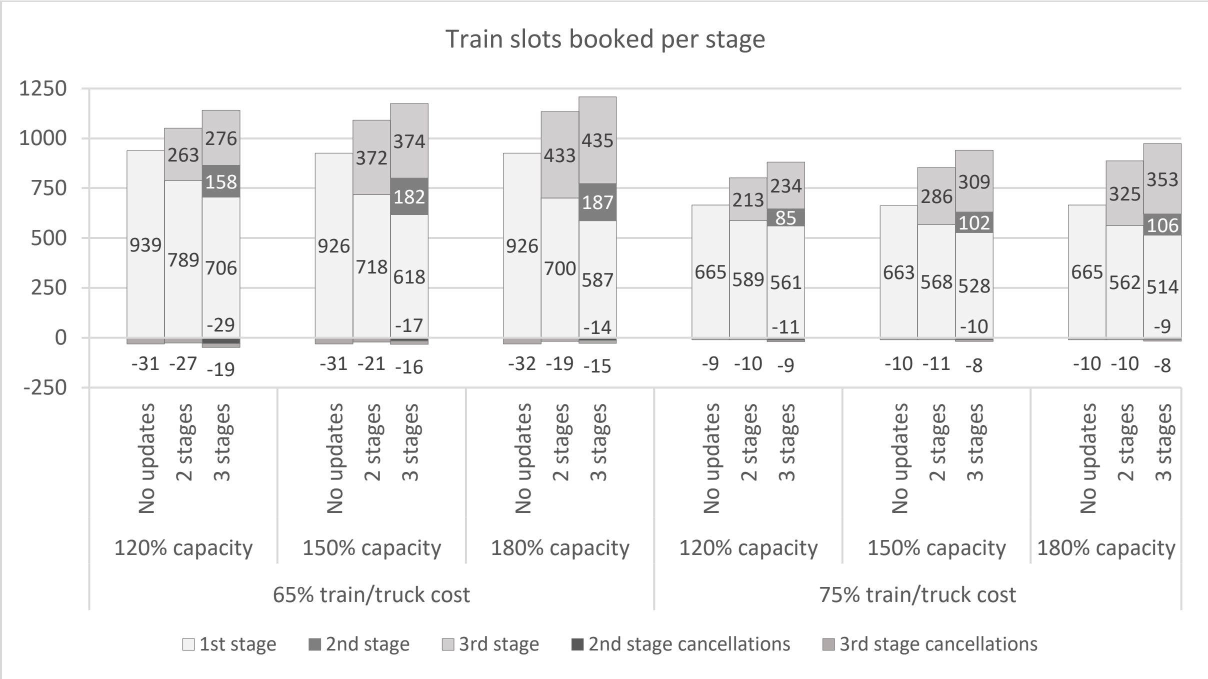

Fig. 17 Average number of train slots booked and cancelled per stage at varying train capacities with the model without capacity updates, the two-stage model and the three-stage model. Note that train slots can only be booked in the first stage with the model without updates, and only in the first and third stages with the two-stage model (as discussed in the final paragraph of Section 4.2)

6.4 Impact of the average demand volume difference between market states

Of the two investigated stochastic parameters, the demand volume difference between market states has a larger impact on total costs than the difference within market states. That being said, the variation between market states has a larger impact on the width of the first-stage distribution compared to the variation within market states. As the demand volume difference between market states increases, and therefore the uncertainty before the second stage, the average cost per container increases and the rail share decreases significantly without replanning (Fig. 18 and Fig. 19). Introducing a single replanning stage improves capacity planning at higher levels of uncertainty, as is observed by the larger difference in cost of uncertainty compared to the case without replanning (Fig. 20). However, there remains a clear increase in cost of uncertainty and decrease in rail share. With a second replanning stage, in which capacity can be updated immediately when the market state is known, the impact of larger demand volume differences between market states is greatly diminished. Both the cost of uncertainty and the rail share remain almost level, even at higher amounts of uncertainty. The lower impact when replanning with partial information is explained by the fact that the demand volume difference between market states is a source of uncertainty that is resolved in the second stage. As such, we conclude that the benefit of an additional update to the capacity planning increases with the demand volume variation that can be observed before replanning.

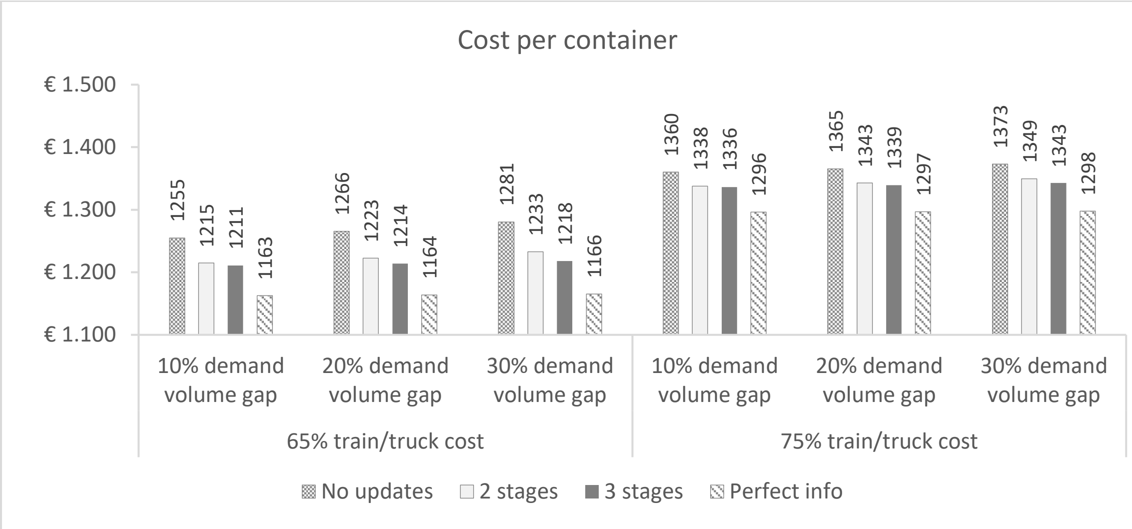

Fig. 18 Average costs per container with each model at varying demand volume differences between market states at train/truck cost ratios of 65% and 75%

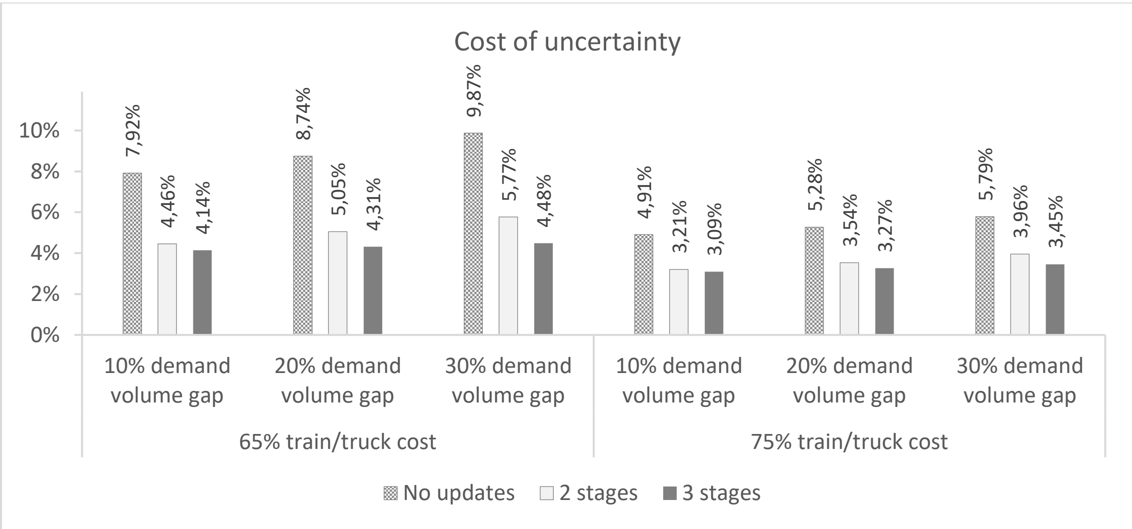

Fig. 19 Cost of uncertainty at varying demand volume differences between market states

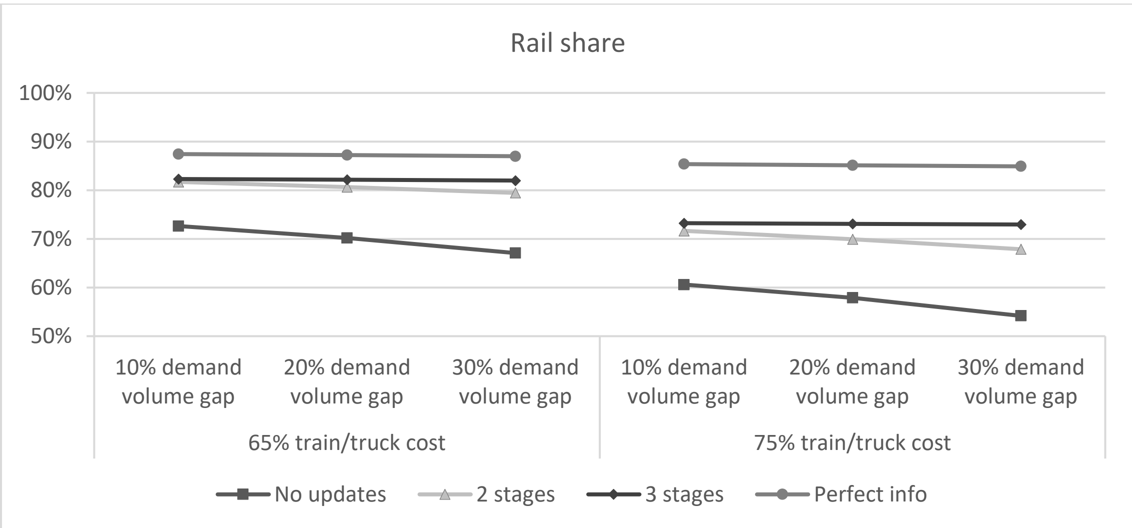

Fig. 20 Rail shares at varying demand volume differences between market states

6.5 Impact of capacity updates with partial information

This section examines the cost savings achieved by implementing capacity updates with perfect information. To this end, the two-stage model with capacity updates and the three stage model are compared. The aim of this analysis is to identify in which cases it makes the most sense to implement a second replanning stage. Table 5 illustrates the average reductions in cost per container and the reduction in cost of uncertainty between the two- and three-stage models at each factor level. Since the results presented in Section 6.1 indicate that cost differences between models decrease at higher train/truck cost ratios, the results in Table 5 are gathered at a train/truck cost ratio of 65%.

Table 5 Differences in average cost per container and cost of uncertainty between the two- and three-stage models across factor levels at a train/truck cost ratio of 65%

Network	**1**	**2**	**3**
Average cost reduction	0.70%	0.70%	0.83%
Reduction in cost of uncertainty	14.46%	14.50%	15.15%
Rail capacity	**120%**	**150%**	**180%**
Average cost reduction	0.71%	0.76%	0.76%
Reduction in cost of uncertainty	14.31%	14.71%	15.09%
Demand volume difference between market states	**10%**	**20%**	**30%**
Average cost reduction	0.31%	0.70%	1.22%
Reduction in cost of uncertainty	7.21%	14.58%	22.32%
Demand volume difference within market states	**20%**	**40%**	**60%**
Average cost reduction	0.75%	0.76%	0.72%
Reduction in cost of uncertainty	15.27%	14.93%	13.91%

The factor with the largest impact on cost reductions from our tests is the demand volume difference between market states. At a demand volume difference of 10%, a second capacity update reduces costs by 0.31% on average, which corresponds to a decrease in the cost of uncertainty of 7.21%. In comparison, at a demand volume difference between market states of 30%, the cost reduction increases to 1.22% and the corresponding cost of uncertainty decreases by 22.32%. This indicates that capacity updates with partial information become more beneficial in cases with higher demand volume uncertainty before the replanning stage. Conversely, demand volume differences within market states, which are a source of uncertainty that remains unresolved when information on the current market state becomes available, only have a minor impact on the cost differences between two and three-stage models.

The impact of the remaining factors is much smaller compared to the demand volume difference between market states. This is explained by the fact that the benefit of replanning with partial information depends on the amount of uncertainty that is resolved at the time of replanning. However, the information only becomes useful if recourse actions are available, such as available rail capacity on the market to book extra slots. As the rail capacity increases from 120% to 150% of the average demand, cost differences between models increase from 0.71% to 0.76%. At higher amounts of capacity, the cost difference remains identical. This might indicate that a minimum amount of capacity is needed to be able to make adjustments at the second stage, while additional capacity past this point no longer improves the cost savings from replanning.

The network has the second largest impact on cost differences between the two models. While there is little difference between the first two networks, cost reductions as a result of a second capacity update are the largest in the third network. The third network has the most rail- and transhipment options. As such, replanning with partial information is more beneficial in networks that provide more options for recourse actions.

To summarise, the benefit of a capacity update with partial information increases in cases with lower train/truck cost ratios, larger differences in demand volumes between market states and networks with more transhipment options. Higher amounts of available capacity have a positive effect up to a certain point, after which further capacity increases do not. In contrast, the amount of demand uncertainty that remains after capacity updates with partial information has no significant impact.

7 Conclusion

Stochastic SND problems applied to intermodal transport are a growing field of research. Regarding the considered types of uncertainty, existing studies include stochastic travel times and demand volume, whereas literature on capacity uncertainty is scarce. A common approach to solve SND problems is with two-stage models in which capacity decisions are performed in the first stage under uncertain information and remain fixed in the second stage, at which point recourse actions are performed with complete information (in the form of booking trucking capacity). In reality, LSPs update their transport capacity as new information becomes available. In this work, we propose a more realistic SND model in which initial capacity decisions are updated twice: once with partial and once with complete demand information. Included types of uncertainty are the demand volume and the amount of transport capacity that is available on the market.

The performance improvement of replanning rail capacity is investigated by comparing a two-stage SND model without replanning, a two-stage model with replanning, and a three-stage model with two replanning stages. Further comparisons are made against a model with perfect information, which serves as a lower bound for costs and gives insight into the added cost caused by uncertainty. In our analyses, introducing capacity updates in the last stage of two-stage models leads to a considerable cost improvement and further improvements are achieved by the three-stage model with its additional update. Although there are diminishing returns to the number of updates, two replanning stages always outperforms a single one in terms of cost and almost always in terms of rail share. Therefore, we conclude that replanning is effective in mitigating the impact of demand uncertainty, and additional replanning stages lead to diminishing returns in terms of cost savings.

Out of the investigated factors, the ratio of train to truck prices for the same distance has the largest impact on total costs. As the price of train services approaches the price of trucks, the modal shift from road to rail transport yields lower cost savings. As a result, the cost benefit of replanning diminishes at higher train service prices. The factor with the second largest impact on total costs is the number of available train services in the network. Networks with more direct train services lead to lower costs across all four models. Moreover, the cost advantage of replanning is the largest in the network with the most direct services and the most transhipment options. This suggests that models with replanning can make better use of the available options. Concerning the amount of available capacity on the market, higher amounts reduce the risk of running out of slots, which leads to lower costs in all models. Postponing bookings becomes more viable at higher capacity levels, leading to fewer bookings in the first stage and more in the second and third stages when applying replanning. This is in spite of their higher prices at later stages. However, the amount of capacity does not impact the cost difference between the two-stage model with replanning and the three-stage model. Our results reveal that the cost savings from a second replanning stage are quite low. As such, replanning is only worthwhile if sufficient information is available at the time of replanning. This is observed in our results by larger cost savings of the three-stage model when differences in average demand volume between market states increase. In cases where demand is highly volatile, it becomes more valuable to obtain accurate demand forecasts and update capacity. Overall, the three-stage model's performance over the two-stage model with replanning improves when train prices decrease, the network contains more transhipment options, and the partial information that is available when performing updates becomes more accurate. If the partial information is a good predictor of final demand, demand uncertainty during the initial booking has little impact on the rail share with the three-stage model as opposed to the two-stage model. At a train/truck cost ratio of over 75%, the three-stage model only performs marginally better in terms of cost and rail share than a two-stage model with replanning, especially in networks with few transhipment options and with smaller demand volume differences between market states.

An additional requirement of the three-stage model compared to two-stage models is that more data is needed. However, with the ongoing digitalization, we make the assumption that LSPs will have access to a greater amount of data in the future. Moreover, it is mainly for major customers that it is important to have accurate demand forecasts since they account for a larger share of the demand volume. The two-stage model only requires an estimation of the total demand distribution, whereas the three-stage model needs data for both the total demand distribution and the more accurate demand distributions obtained from improved demand forecasts. If part of the orders are known early and are a good predictor of the final demand, the time at which orders become known could be collected to set up the second-stage distributions. A downside of the three-stage model is its increased computational complexity compared to two-stage models. Since the aim of the model is to support tactical decisions rather operational ones, longer runtimes are permissible. In future research, heuristic approaches could be developed in order to apply the model to larger instances that may occur in practice.

To conclude, our results indicate that our model allows to improve the competitiveness of rail transport, thereby potentially nudging the industry towards achieving these political goals. Furthermore, also interesting to policy makers, our results indicate that having more, and more direct, rail routes and transhipment options encourages a modal shift, and that the rail/truck cost ratio has a large impact on the potential of rail transport.

Clearly, the results in this paper should be seen in the light of the assumption that the considered probability distributions are sufficiently close to the actual distributions in reality. However, we believe this is a fair assumption, as more and more data are becoming available such that, combined with the long-term expertise of the decision-maker, it becomes more realistic to get reliable estimates. Yet, an interesting avenue for future research would be to analyse the impact of potential errors in the assumed demand distributions, i.e., studying the impact on the results in case the actual distribution is different. Another future research opportunity is to explore more advanced scenario generation techniques, potentially allowing to also address even larger cases (e.g., larger networks).

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Appendix

Appendix A Stability tests

The considered SND problem is NP-hard (Crainic, 2000; Magnanti & Wong, 1984), which leads to long computing times as the instance size increases. Increasing the scenario tree size will achieve a closer approximation of the sampled probability distributions, but this comes at the trade-off of longer runtimes. Therefore, 10 scenario trees of 200 scenarios are generated per factor level combination to check for in-sample and out-of-sample stability similarly to Lium et al. (2009). Results of the stability tests across all models (no updates, two stages, three stages and perfect info) are presented in Table 6. To verify in-sample stability, the difference between the lowest and highest objective values over the 10 solutions are compared. If this difference is sufficiently small, in-sample stability is achieved. The maximum difference of 1.24% is deemed sufficiently small to achieve in-sample stability across all models. To verify out-of-sample stability, the 10 solutions of the factor level combination that produces the highest variation in objective value are applied to a large set of 10000 scenarios, which is assumed to represent the "true" distribution. Differences between the lowest and highest objective values are much lower compared to the in-sample stability tests, with a maximum of 0.18%. In addition, the average objective values differ by at most 0.05% between in-sample and out-of-sample stability tests, which indicates that 200 scenarios are sufficient to prevent overestimating the solution quality (Kaut & Wallace, 2007). Therefore we can conclude that out of-sample stability is achieved. Since we have validated in- and out-of-sample stability, results of each factor level combination in Section 6 are taken as the average over the 10 solutions obtained on scenario trees with 200 scenarios.

Table 6 Stability test results for each model.

Stability test		No updates	2 stages	3 stages	Perfect info
In-sample	Average cost per container	1283.27	1224.12	1210.35	1157.67
	Maximum difference	1.24%	0.73%	0.65%	0.43%
Out-of-sample	Average cost per container	1283.55	1224.18	1210.95	1157.81
	Maximum difference	0.04%	0.18%	0.17%	
Difference in cost per container between in- and out-of-sample tests		0.02%	0.01%	0.05%	0.01%

[a]The table contains the average cost per container and relative difference between the lowest and highest objective value over 10 solutions for in- and out-of-sample tests. The last row illustrates the relative difference in average cost per container between the in- and out-of-sample stability tests.

Appendix B ANOVA results of the three-stage model

An analysis of variance (ANOVA) is performed to identify which factors of our factorial design have a significant effect on the total cost for the three-stage model. The results of the ANOVA for the three-stage model are shown in Table 7. All main effects apart from the width of the demand distributions are significant. Regarding interaction effects, the following combinations are significant: network and train capacity, network and train/truck cost ratio, train capacity and train/truck cost ratio, train/truck cost ratio and the difference in average demand volume between market states, train/truck cost ratio and the width of demand volume distributions and finally the difference between and the width of the demand volume distributions.

Table 7 ANOVA results

Tests of Between-Subjects Effects

Dependent Variable: Cost per container

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	25986181.142a	404	64322.23	35929.75	<.001
Intercept	7.17E+09	1	7.17E+09	4.01E+09	<.001
Cost	23998575	4	5999644	3351341	<.001
Network	1815497	2	907748.7	507059.3	<.001
Capacity	67311.2	2	33655.6	18799.68	<.001
difference	19157.09	2	9578.546	5350.479	<.001
width	4715.839	2	2357.92	1317.11	<.001
Cost * Network	47281.59	8	5910.199	3301.378	<.001
Cost * Capacity	27260.44	8	3407.556	1903.426	<.001
Cost * difference	1963.179	8	245.397	137.076	<.001
Cost * width	1105.14	8	138.143	77.165	<.001
Network * Capacity	1462.995	4	365.749	204.304	<.001
Network * difference	419.81	4	104.953	58.625	<.001
Network * width	123.697	4	30.924	17.274	<.001

Capacity * difference	15.626	4	3.907	2.182	0.068
Capacity * width	45.017	4	11.254	6.286	<.001
difference* width	108.671	4	27.168	15.176	<.001
Cost * Network * Capacity	388.131	16	24.258	13.55	<.001
Cost * Network * difference	369.068	16	23.067	12.885	<.001
Cost * Network * width	12.327	16	0.77	0.43	0.975
Cost * Capacity * difference	39.843	16	2.49	1.391	0.136
Cost * Capacity * width	72.206	16	4.513	2.521	<.001
Cost * difference* width	40.512	16	2.532	1.414	0.125
Network * Capacity * difference	57.386	8	7.173	4.007	<.001
Network * Capacity * width	28.38	8	3.547	1.982	0.045
Network * difference* width	21.952	8	2.744	1.533	0.14
Capacity * difference* width	2.489	8	0.311	0.174	0.994
Cost * Network * Capacity * difference	35.539	32	1.111	0.62	0.953
Cost * Network * Capacity * width	18.059	32	0.564	0.315	1
Cost * Network * difference* width	16.255	32	0.508	0.284	1
Cost * Capacity * difference* width	6.777	32	0.212	0.118	1
Network * Capacity * difference* width	10.18	16	0.636	0.355	0.991
Cost * Network * Capacity * difference* width	19.352	64	0.302	0.169	1
Error	6525.359	3645	1.79		
Total	7.2E+09	4050			
Corrected Total	25992707	4049			

a. R Squared = 1.000 (Adjusted R Squared = 1.000)