



## A share-first-plan-second policy for efficient cooperation in a multi-modal transportation corridor

Albert H. Schrottenboer <sup>a</sup>, Paul Buijs <sup>b\*</sup>, Gerlach van der Heide <sup>b</sup>, Tim Phoa <sup>b</sup>, Onur A. Kilic <sup>b</sup>

<sup>a</sup> Operations, Planning, Accounting, and Control Group, School of Industrial Engineering, Eindhoven University of Technology

<sup>b</sup> Department of Operations, Faculty of Economics and Business, University of Groningen

Article history: received 23-07-2023, accepted 04-12-2023, published 29-12-2023

**Abstract** – Cooperation in transportation networks has been a cornerstone of policies towards more sustainable transportation, aiming to improve the modal split and increase the fill rates of transportation resources. Effective cooperation between transportation firms requires some form of joint planning, which is often challenging to implement from an IT perspective and difficult to sustain due to the reliance on advanced planning software. In this paper, we present a simple but effective policy for cooperative transportation that does not require a complex joint optimization of operations. In this share-first-plan-second policy, cooperating firms first develop a cyclic schedule for a fleet of shared transportation resources and then assign their shipments to the transportation resources in real time. The policy performs nearly as well as a jointly optimized planning of operations while not requiring advanced IT systems and planning software. Finally, the share-first-plan-second policy exhibits robustness against deviations from planned transport operations, enhancing its practical applicability.

**Keywords:** Horizontal collaboration; sustainability; multimodal transportation; physical internet; network design

### 1. Introduction

Dedicated logistics services and just-in-time delivery requirements have fragmented logistics flows and have placed enormous pressure on transportation firms (Sarraj et al., 2014a), inadvertently advancing the use of road-freight transportation over transport by rail or waterways. Individual transportation firms often face an imbalanced flow of goods, which causes underutilized transportation resources. Cooperation between transportation firms may (partly) resolve this imbalance, yet, cooperation is difficult to arrange, tough to adapt, and hard to scale (Ballot et al., 2014; Pan et al., 2019). It involves selecting the right partners, making extensive agreements about the resources that are to be shared, and dividing the costs and benefits associated with the cooperation. Changes in the flows of goods or the composition of the collaborating transportation firms may necessitate redoing those agreements. On top of that, planning transportation services and assigning shipments is already a complex optimization problem. This complexity increases substantially when considering practical factors of multiple individual transportation firms, such as stochasticity, irrationality, and information sharing. Our focus is, therefore, to investigate how and when simple cooperative strategies can achieve a similar performance as is promised by complex collaboration strategies.

In this paper, we present an approach to cooperation between transportation firms that eradicates the need for solving the often intractable optimization problems related to the complete joint planning of all shared transportation resources. Instead of scheduling each shipment between origin and destination on a shared fleet of transportation resources, we advocate the sharing of those resources while abstracting from scheduling all the shipments on these transportation resources. That is, the shared fleet will be scheduled cyclically, based on expected demands, as is common in public transport planning. The assignment of shipments to transportation

resources is done in real-time, on a first-come, first-serve basis, and independently from the planning of the transportation resources. We refer to our approach of collaboration as the share-first-plan-second policy. Due to the regularity and predictability of this policy, we expect it to be a means for improving the modal split (i.e., by advancing the use of barges or trains over the use of trucks) and fill rates—and hence reduce the environmental impact of the transportation sector (Jonkeren et al., 2011; Truschkin & Elbert, 2013; Norlund & Gribkovskaia, 2015).

To test our policy, we consider a multi-modal multi-firm scheduling problem between major hubs in a transportation network. Specifically, we provide a Mixed Integer Programming (MIP) model that mimics current practice by simultaneously planning transportation services and assigning shipments to those services. By considering multiple firms that ship between the same origin and destination hub, we provide two benchmarks to our share-first-plan-second policy. First, we provide the optimal multi-modal scheduling solution for each firm individually, resembling a fully competitive environment where firms do not share any resources. Second, we provide the optimal multi-modal multi-firm scheduling solution where all firms share all their transportation resources and schedule all the shipments jointly, resembling a fully optimized collaborative setting that is very hard to realize in practice.

We compare our share-first-plan-second policy with both the competitive and optimized collaborative benchmark in a stochastic environment. We first solve the deterministic multi-modal, multi-firm scheduling problem for both the competitive and optimized collaborative settings based on expected demand and afterward observe disruptions to this planning. That is, transportation resources may arrive too early or too late, shipments may have higher or lower quantities, and they may be released for transportation earlier or later than expected. Whereas the share-first-plan-second policy assigns shipments after disturbance on a first-come, first-serve basis, the competitive and optimized collaborative benchmark asks for reoptimization of their (joint) transportation plans. Our comparison yields three notable insights. First, fragmenting transport services across different firms, a characteristic of the competitive setting, leads to low sustainability in transport operations. Second, implementing relatively simple cooperative strategies can yield many benefits compared to such competitive settings. Our share-first-plan-second policy outperforms the competitive setting in terms of the modal-split and fill rates of the transportation resources while performing close to the optimized collaborative setting. Third, the share-first-plan-second policy is robust among all considered parameters, rendering it attractive for practitioners by providing reliable predictability of freight stream operations for logistics service providers, shippers, and consumers.

The remainder of this paper is organized as follows. In Section 2, we give a brief literature overview on developments aimed at improving the resource efficiency of freight transportation. In Section 3, we give a description of our multi-firm, multi-modal corridor, and in Section 4, we describe how the competitive setting, the optimized collaborative setting, and the share-first-plan-second policy work on this corridor. Details on the set-up of the simulation study are provided in Section 5. The results of the simulation study are presented in Section 6. We conclude and provide directions for further research in Section 7.

## 2. Literature review

We position our study in parallel with the significant advances in the vehicle routing literature, which has primarily concentrated on formal optimization methods. We refer interested readers to the excellent review by Gansterer and Hartl (2018) on this topic. Our work contributes to another stream of literature, focusing on more pragmatic, rule-based solution approaches. These approaches, although less explored, are crucial for addressing the real-time, dynamic complexities inherent in practical scenarios.

Our ideas for the share-first-plan-second policy build on insights from Physical Internet research (Montreuil, 2011). The term Physical Internet originates from an analogy between sending physical objects through a transportation network and sending digital information via the internet (Sarraj et al., 2014b). When sending an e-mail, the sender focuses on writing the content of the email and not on planning how the information in the e-mail will be delivered to its recipients. The sender relies on standardized protocols of the digital internet to route all information through a vast network of hubs. The Physical Internet envisions a similar system for sending physical objects (Montreuil et al., 2010; Ballot et al., 2014). Instead of using contracted transportation services and specifying routes and modes of transportation in advance, companies sending physical objects simply specify a destination and delivery time window and then trust the system to arrange the transportation. Seamlessly connected transportation firms exchange requests for transportation or share transport and storage capacity to reduce costs

and safeguard the environment (Irannezhad et al., 2018; Van der Heide et al., 2018). In the Physical Internet, objects potentially move via multiple hubs from origin to destination and can be (re-)combined with other objects at every hub along the way.

Academic research on the Physical Internet roughly falls into four threads: conceptual research, establishing its main principles; assessment research, evaluating its effects on, e.g., resource-efficiency; design research, proposing network design methodologies and technical blueprints; and validation research, studying the adoption of the Physical Internet via case studies and pilots (Pan et al., 2017; Sternberg & Norrman, 2017; Treiblmaier et al., 2016; Ambra et al., 2019). Drawing on insights from the conceptual, assessment, and design research threads, this paper contributes to the literature by proposing an alternative, multi-modal PI network design (i.e., our share-first-plan-second policy) that is inspired by the planning and scheduling of public transportation (Guihaire & Hao, 2008; Ibarra-Rojas et al., 2015). In network designs proposed in prior Physical Internet research, transportation resources are shared, and the routing and assignment decisions are made in real-time. For example, trucks can determine autonomously and in real-time which load to transport next or how to re-position based on distributed intelligence (Hakimi et al., 2012; Sarraj et al., 2014a). Several large-scale simulation studies provide evidence suggesting that Physical Internet network design can outperform current practice in, for example, the French fast-moving consumer goods sector (Ballot et al., 2012; Hakimi et al., 2012; Sarraj et al., 2014a; Fazili et al., 2017), and full truckload transportation in the province of Quebec, Canada (Hakimi et al., 2015). Instead of such approaches, with local intelligence at the vehicle level (Lafkihi et al., 2019), our share-first-plan-second policy schedules a fleet shared transportation resources at a network level and then allows for decentralized decision-making regarding the assignment of shipments to those transportation resources.

While our study finds its roots in the Physical Internet research, it bears resemblance to approaches proposed in the broader transportation research literature. Approaches in this domain often leverage agent-based simulation techniques for detailed micro-level decision-making in multi-actor systems, as exemplified by, for example, Roorda et al. (2010). Few of those approaches consider a multi-modal setting. Di Febbraro et al. (2016) forms a notable exception. They propose a modeling framework for cooperative transportation oriented towards a distributed and cooperative optimization process involving negotiation among multiple actors. More recently, Zhang et al. (2022) developed an approach that echoes our aim for more sustainable transport operations while concentrating on strategic collaborative planning among carriers. Compared to these approaches, our share-first-plan-second policy emphasizes simplicity, real-time adaptability, and operational flexibility.

### 3. System description

We consider a transportation corridor that appears in almost any supply chain consisting of two major logistics hubs (e.g., two major ports) and their hinterlands. Multi-modal transportation services on this corridor are offered by—potentially competing—transportation firms. We study three settings that reflect how those firms can plan their transportation services on the corridor, and how they cope with disruptions to their planning.

The first setting closely resembles current practice. It addresses a situation where firms plan their transportation services independently. Relying on demand forecasts, each firm plans all its transportation services to minimize its own costs. We call this the competitive setting. The second setting resembles how firms could collaborate by sharing their transportation resources. Using aggregated demand forecasts, they plan their transportation services jointly. While joint optimization would result in the most efficient transportation services, optimized collaborative plans are notoriously hard to compute, which may cause cooperation initiatives to fail in practice. We, therefore use this optimized collaborative setting mainly as a benchmark for the best-case scenario. The third setting makes use of our share-first-plan-second policy that does not require the hard computations used in the optimized collaborative setting. It schedules transportation services to depart and arrive cyclically, and in real-time, it assigns shipments to these services on a first-come, first-served basis. We note that for networks with more than two logistical hubs, the scheduling of transportation services can be done based on the relative demand between distinct origin-destination pairs.

As disturbances to a transportation plan are inevitable in practice, we adopt a recourse policy that describes how transportation firms cope with disruptions to their plans. This recourse policy is especially relevant for the competitive and optimized collaborative setting and less for the share-first-plan-second setting since, in the latter, no predetermined assignment of goods to transportation services is present before any disruption occurs.

To clearly describe each of the above-described settings, we first introduce the multimodal transportation system upon which each setting acts. Then, we formulate a mixed-integer-programming model (MIP) for determining a transportation planning, i.e., when the transportation modes depart and which shipments are assigned to them. This MIP will be utilized in the competitive and optimized collaborative setting, on which we will elaborate in Section 4. There, we also explain the dynamics of the share-first-plan-second policy.

### 3.1 Multimodal transportation system

A graphical overview of the transportation corridor is presented in Figure 1. It is a stylized setting consisting of two nodes  $A$  and  $E$ . The problem consists of shipping batches of containers, denoted by  $\mathcal{K}$ , through this corridor. Although each container has its destination location in the hinterland of one of the two hubs, we solely model the planning between the hubs  $A$  and  $E$  and ignore the transportation to the final destinations. This is motivated by the observation that there is typically no multi-modal option for this final stage of the delivery.

Each batch  $k \in \mathcal{K}$  is characterized by its origin-destination pair  $a \in \mathcal{A} := \{(A, E), (E, A)\}$ , volume in the number of containers  $Q^k$ , release time  $R^k$ , and delivery deadline  $D^k$ . For convenience, we refer to  $R^k - D^k$  as the delivery time (i.e., the available time for transportation). The length of the planning horizon is denoted by  $T$ , i.e., all shipments should be made within the interval  $[0, T]$ . With  $A(k)$  we refer to the origin-destination pair that corresponds to batch  $k$ .

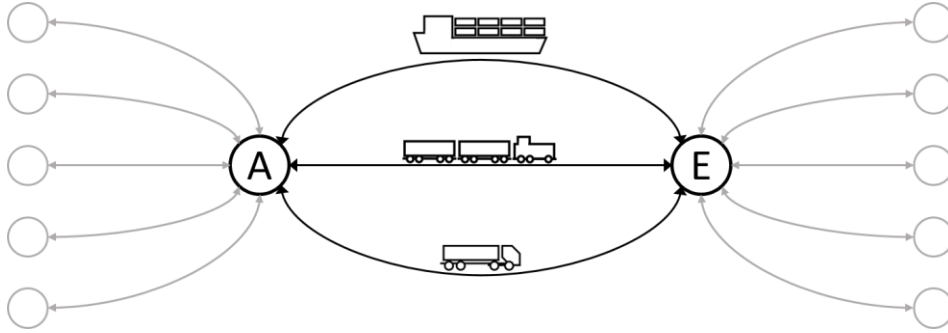


Figure 1. The two-hub transportation corridor where barges, trains, and trucks run back and forth between hubs  $A$  and  $E$  (derived from Behdani et al., 2016)

To transport the containers between the hubs, the transportation firms deploy barges ( $B$ ), trains ( $R$ ), and trucks ( $V$ ) in both directions, and we collectively denote this as the set of transportation modes  $\mathcal{M} = \{V, B, R\}$ . With each transportation mode  $m \in \mathcal{M}$ , we associate a limited capacity for containers  $U_m$  and a transportation time  $T_m$  between hubs  $A$  and  $E$  that is symmetric.

We consider  $F$  transportation firms, denoted by the set  $\mathcal{F} = \{1, \dots, F\}$ , that need to transport batches of containers over the corridor. Each transportation firm  $f \in \mathcal{F}$  is responsible for the shipment of a subset of batches  $\mathcal{K}^f \subseteq \mathcal{K}$  that are mutually exclusive and collectively exhaustive. Each firm has, at both hubs, a set of barges  $\mathcal{L}_B^{fa} = \{1, \dots, L_B^{fa}\}$  and a set of trains  $\mathcal{L}_R^{fa} = \{1, \dots, L_R^{fa}\}$  available to ship batches of containers in direction  $a \in \mathcal{A}$ . We impose that the number of scheduled services in both directions ( $A - E$  and  $E - A$ ) should be equal; otherwise the fleet could become imbalanced in the long-term.

We assume an unlimited amount of trucks to be available whenever needed, and that the transit times of trucks are shorter than the delivery time of any batch. This implies that if a firm is not able to ship a (part of a) batch by train or barge within the available delivery time, it can always opt for transportation by truck. Finally, we assume that batches can be split among different transportation services, but containers cannot be split.

Shipping containers comes at a cost per container  $C_m$ , for  $m \in \mathcal{M}$ . As trucks have capacity 1,  $C_V$  can be interpreted as the fixed costs per truck used. The goal is then to find a planning, adhering to the setting-specific constraints, which minimizes the sum of shipping costs. For each setting, we will detail this in the next section.

### 3.2 Mixed Integer Programming model formulation

We solve the planning problem using a mixed integer programming model. It is defined for a single firm that minimizes transportation costs, given its set of transportation resources and batches of containers. This requires solving a planning problem that consists of two parts that are solved jointly. First, we devise a schedule for each mode of transportation with the available transportation capacities, thereby specifying a set of transportation services. Second, we assign the containers of each batch to one or more transportation services such that all the delivery deadlines are met. This problem can be modeled and solved as a MIP, inspired upon the work of Behdani et al. (2016).

Let  $x_\ell^k$  be a non-negative integer variable that represents how much volume of batch  $k$  is transported by transportation service  $\ell \in \mathcal{L}_m^{fa}$  of mode  $m \in \{B, R\}$  in direction  $a \in \mathcal{A}$ . Consequently, let  $y_\ell$  be binary variable that denotes whether transportation service  $\ell \in \mathcal{L}_m^{fa}$  is used and let  $d_\ell^k$  be a binary variable that denotes if a part of batch  $k \in \mathcal{K}$  is delivered by service  $\ell \in \mathcal{L}_m^{fa}$ . Finally, let the departure time of each service  $\ell \in \mathcal{L}_m^{fa}$  be modeled by the continuous non-negative variable  $t_{ml}^a$ .

The transportation planning for firm  $f$  is then obtained by solving the following MIP:

$$z(f) = \min \sum_{k \in \mathcal{K}} \sum_{a \in \mathcal{H}} \sum_{m \in \{B, R\}} \sum_{\ell \in \mathcal{L}_m^{fa}} C_m x_\ell^k + C_v \sum_{k \in \mathcal{K}} \left[ Q^k - \sum_{m \in \{B, R\}} \sum_{a \in \mathcal{A}} \sum_{\ell \in \mathcal{L}_m^{fa}} x_\ell^k \right] \quad (1)$$

$$\text{s.t.} \quad \sum_{k \in \mathcal{K}} x_\ell^k \leq U_m y_\ell \quad \forall m \in \{B, R\}, a \in \mathcal{A}, \ell \in \mathcal{L}_m^{fa} \quad (2)$$

$$Q^k - \sum_{m \in \{B, R\}} \sum_{a \in \mathcal{A}} \sum_{\ell \in \mathcal{L}_m^{fa}} x_\ell^k \geq 0, \quad \forall k \in \mathcal{K} \quad (3)$$

$$x_\ell^k \leq M d_\ell^k \quad \forall k \in \mathcal{K}, m \in \{B, R\}, a \in \mathcal{A}, \ell \in \mathcal{L}_m^{fa} \quad (4)$$

$$t_\ell \geq R^k - M(1 - d_\ell^k) \quad \forall k \in \mathcal{K}, m \in \{B, R\}, a \in \mathcal{A}, \ell \in \mathcal{L}_m^{fa} \quad (5)$$

$$D^k \geq t_\ell + T_m - M(1 - d_\ell^k) \quad \forall k \in \mathcal{K}, m \in \{B, R\}, a \in \mathcal{A}, \ell \in \mathcal{L}_m^{fa} \quad (6)$$

$$\sum_{\ell \in \mathcal{L}_m^{f(A,E)}} y_\ell - \sum_{\ell \in \mathcal{L}_m^{f(E,A)}} y_\ell = 0 \quad \forall m \in \{B, R\} \quad (7)$$

$$\sum_{\ell \in \mathcal{L}_m^{fa}} y_\ell \leq L_m^{fa} \quad \forall a \in \mathcal{A}, m \in \{B, R\} \quad (8)$$

$$x_\ell^k \in \mathbb{N}_{\geq 0} \quad \forall k \in \mathcal{K}, m \in \{B, R\}, a \in \mathcal{A}, \ell \in \mathcal{L}_m^{fa} \quad (9)$$

$$t_\ell \geq 0 \quad \forall m \in \{B, R\}, a \in \mathcal{A}, \ell \in \mathcal{L}_m^{fa} \quad (10)$$

$$y_\ell \in \{0, 1\} \quad \forall m \in \{B, R\}, a \in \mathcal{A}, \ell \in \mathcal{L}_m^{fa} \quad (11)$$

$$d_\ell^k \in \{0, 1\} \quad \forall k \in \mathcal{K}, m \in \{B, R\}, a \in \mathcal{A}, \ell \in \mathcal{L}_m^{fa} \quad (12)$$

The Objective (1) sums the transportation costs of the barges and the trains used (first part) and the costs of the trucks used. Constraints (2) ensure that the capacities of each transportation service  $\ell \in \mathcal{L}_m^{fa}$ , for each mode  $m$  (trains and barges) on each arc  $a \in \mathcal{A}$ , are respected. To ensure that the volume transported by trucks is non-negative, Constraints (3) state that, for each batch, the volume transported by barge or train should not exceed the demand. Constraints (4) state that if any part of batch  $k$  is transported by service  $l$ ,  $d_l^k$  should equal 1. Here  $M$  is a big enough number. Constraints (5) state that if any part of batch  $k$  is transported with transportation service  $\ell$ , this service cannot leave before the batch has arrived at its origin. Note that the variable  $d_l^k$  could be replaced by a summation over the  $x_l^k$  variables, but this will weaken the formulation as it might lead to a lower LP relaxation. The delivery deadlines are modeled by Constraints (6). For every transportation mode, the number of services from  $A$  to  $E$  should equal the number of services from  $E$  to  $A$ , which is modeled by Constraints (7). Constraints (8) state that for every mode, the total number of services should be less than or equal to the maximum number of services. Finally, Constraints (9)-(12) model the domain of the variables.

The above MIP formulation can be solved with a commercial off-the-shelf solver such as CPLEX or Gurobi. Depending on the setting, it will be put to work on transportation corridors with one or multiple firms, be it competitors or cooperators. We discuss this in detail in Section 4.

## 4. Implementation

We now describe how the competitive setting, the optimized collaborative setting, and the share-first-plan-second policy work on the multi-modal transportation corridor as described in Section 3. We first describe how we obtain the transportation plans for the competitive and optimized collaborative setting using the MIP formulation in Section 3. We also detail how the share-first-plan-second policy plans transportation resources and assigns shipments. Afterward, we discuss how each of the three settings deals with disturbances to the initial plan, which is particularly relevant for the competitive and optimized collaborative setting.

### 4.1. Planning policies of the three settings

In the *competitive setting*, we model the situation where transportation firms act individually. Indeed, by solving the above MIP for each firm  $f$  separately, we get the solution for the competitive setting, and the resulting objective equals  $\sum_{f \in \mathcal{F}} z(f)$ .

In the optimized collaborative setting, we model the situation where the transportation plan is optimized for all firms jointly. It reflects the situation where firms are willing to share all information and transportation resources, and carry out the plan and execution of their shipments in full coordination. From a modeling point of view, this boils down to aggregating all batches and transportation resources. Let  $\hat{f}$  be a artificial firm with  $\mathcal{L}_m^{\hat{f},a} = \cup_{f \in \mathcal{F}} \mathcal{L}_m^{fa}$  for all  $a \in \mathcal{A}$  and  $m \in \{B, R\}$ , and  $\mathcal{K}^{\hat{f}} = \mathcal{K}$ . Then the optimized collaborative setting equals solving  $z(\hat{f})$ . Note that  $\sum_{f \in \mathcal{F}} z(f) - z(\hat{f}) > 0$  expresses the gains that are obtained when firms are collaborating completely, which we expect to increase if more firms start to collaborate.

In the share-first-plan-second policy, the planning of transportation services is done separately from the assignment of containers to those services. The transportation services are planned by distributing all available transportation resources (of all the firms) uniformly over the time horizon. In scenarios where demand is fluctuating or non-homogeneous, an improved approach could involve tailoring the distribution of transportation services to align with expected demand patterns. However, under our study's assumption of stable or sufficiently large demand, a homogeneous distribution of transportation services over time is deemed adequate. Containers are assigned to the transportation service based on a first-come, first-serve basis. In practice a buffer is needed between the moment one decides to assign a shipment and the actual loading of the shipment to allow for the scheduling of processes at the logistics hub. While such processes are outside the scope of this paper, we will consider disruptions to the release time of shipments (i.e., when goods become available), the departure time of transportation services, and the volume of shipped goods.

## 4.2. Disruption management

Transportation systems are often subject to a variety of disruptions. Among others, the most common disruptions are: (1) a delay in the planned transportation services, (2) a delay or advance in the release times of batches due to third-party services upstream in the network, and (3) a batch size that differs from what was anticipated.

In our context, these disturbances may cause pre-determined transportation plans to become infeasible in four different ways. First, if a train or barge departs later than scheduled, the assigned containers may exceed their delivery deadline. Second, if some batches of containers arrive late at the originating hub, the scheduled transportation service may already have left the hub. Third, if some batches of containers arrive early at the originating hub, it may become feasible to assign them to an earlier service. Fourth, when a batch size is larger than anticipated, the capacity of the transportation service may be exceeded.

To resolve any issue that may result from a disruption, firms can take recourse actions of different forms. For the competitive and optimized collaborative setting, we use the following approach to integrate disruptions and recourse actions in our analysis. An initial transportation plan is created before any disruption has occurred. Then, before execution of that plan, all disruptions are revealed for the entire planning horizon at once, and the initial plan is revised accordingly. Note that the share-first-plan-second policy does not require any recourse actions to be taken because the containers of the batches are assigned in real-time on a first-come, first-serve basis.

We model those recourse actions for the competitive and optimized collaborative settings as follows:

1. We consider the batches in chronological order of their revealed release time.
2. We check whether there is space on a transportation service that is less expensive than the service currently assigned. Notice that if (part of) the batch was assigned to a now infeasible transportation mode, it is treated as if the current mode of transportation is by truck, which is the most expensive transportation mode.
3. If no less expensive service is available, and the original assignment is feasible, we guarantee an assignment that is at most as expensive.
4. After all the recourse actions are applied, an updated transportation plan is obtained for each individual firm and the resulting costs per firm can be calculated.

The assumption of knowledge about disruptions is evidently not realistic, as disruptions are often revealed over time. However, it allows the competitive and optimized collaborative settings to take the best recourse actions possible, and hence does not provide an undue advantage to the share-first-plan-second policy.

## 5. Experimental design

The aim of the numerical analysis is to assess the performance of our proposed share-first-plan-second policy compared to the optimized collaborative and competitive settings for a wide variety of system characteristics. We will do this by means of a simulation study extending the approach taken in Behdani et al. (2016).

### 5.1 Parameter Values for the simulation study

The parameters defining the system are comprised of (1) the transportation costs and times for each mode as well as their capacities, (2) the set of batches of containers and their destination, volume, release time, and delivery deadline, and (3) the set of transportation firms in the market, their capacities with respect to transportation modes, and the allocation of batches to each transportation firm.

First, the per container transportation costs equal 45, 60, and 90 euros per container for shipping by barge, train, or truck, respectively. Transportation times of the trains and barges equal 11 and 6 hours, respectively. The capacity of a train equals 110 containers and a barge can carry 40 containers. Trucks ship a single container and always arrive on time at the destination location.

Second, the number of batches  $|\mathcal{K}^f|$  is equal for each transportation firm  $f \in \mathcal{F}$ . The release time  $R^k$  is a uniformly drawn integer between 0 and  $T$ . The volume  $Q^k$  of a batch (in number of containers) as well as the

delivery deadlines  $D^k$  are drawn from a uniform distribution of which the interval is varied in our simulation study, i.e.,  $Q^k \sim U(10, Q^{\max})$  and  $D^k \sim U(D^{\min}, D^{\max})$ .

Third, the number of transportation firms  $|\mathcal{F}|$ , and the number of barges and trains they have available, are varied in our simulation study. The batches of containers are equally divided (at random) among the transportation firms.

In our simulation experiments, we consider disturbances on the size of the batches, the release times of batches, and the departure times of scheduled transportation services. Those parameters are modeled as follows. We define batch sizes as  $Q^k = \bar{Q}^k p_Q \phi$ , release times as  $R^k = \bar{R}^k + p_R \rho$ , and departure times as  $t = \bar{t} + p_t \tau$ . Here,  $\bar{R}^k, \bar{Q}^k$  and  $\bar{t}$  are nominal values on which the initial transportation planning is based,  $p_Q, p_R$  and  $p_t$  are Bernoulli distributed, and  $\phi, \rho$  and  $\tau$  are uniformly distributed.

We performed a full factorial Monte-Carlo Simulation over a set of parameter values as described in Table 1. We varied the maximum batch size, the length of the time horizon, the minimum and maximum delivery time and the so-called stochastic and stakeholder scenarios. All denoted parameter values represent the flow in a single direction in our network. As we consider two directions in our network (from  $A$  to  $E$  and vice versa), the problem is in fact twice as large as the parameter values in Table 1 suggest.

Table 1. The considered values regarding parameters describing the setting.

Parameter	Interpretation	Considered Values
$D^{\min}$	Minimum delivery time	{12,18}
$D^{\max}$	Maximum delivery time	{20,36}
$T$	Time horizon	{168,120,72}
$Q^{\max}$	The maximum batch size (minimum = 10)	{30,35,40,45,50}
Stochastic scenario	The considered stochastic settings, see Table 2.	{1,2}
Stakeholder scenario	Describes the number of firms, batches, barges and trains, see Table 3	{1,2,3,4,5,6,7,8,9}

In the stochastic scenario(s), the parameter values corresponding to the modeling of the disturbances are clustered, see Table 2. We consider two stochastic scenarios, one with relatively small variance and one with relatively large variance.

The parameters corresponding to the number of transportation firms, the number of transportation modes of each firm, and the number of batches are clustered in stakeholder scenarios, see Table 3. We consider three different scenarios, indicated by “HIGH”, “MEDIUM”, and “LOW”. These indicate having a relatively high, medium, or low number of batches of containers to be transported. This impacts the so-called coverage ratio (see Table 4) which is the maximum fraction of containers that could be transported by barge and train if all planning restrictions are ignored. Combined with the time horizon length it determines the expected intensity of the use of transportation modes in the network. The total number of transportation services of all the firms is equal for each scenario. In addition, the total number of containers to be shipped is kept constant for each scenario. This enables a fair comparison of the effect of the number of firms on performance.

## 5.2 Logic of a single simulation experiment

For each combination of parameter values presented in Table 1, 24 demand scenarios are sampled for the complete planning horizon. For each of the 24 demand scenarios, we assess the share-first-plan-second against the competitive and optimized collaborative settings. Then, for each demand scenario, we draw 200 stochastic demand scenarios and apply the recourse actions as described in Section 3. This procedure results in 4800 cost estimations for the three settings, for each of the 1080 combinations of parameter values.



Table 2. Composition of the stochastic scenarios.

Scenario	$\phi$	$P(p_Q = 1)$	$\rho$	$P(p_R = 1)$	$\tau$	$P(p_t = 1)$
1	$U(0.75,1.25)$	0.50	$U(-4,10)$	0.50	$U(0,10)$	0.25
2	$U(0.50,1.50)$	0.50	$U(-10,20)$	0.50	$U(0,20)$	0.25

Table 3. Composition of the stakeholder scenarios.

Scenario (cat)	$K$	$F$	# Barges	# Trains
1 (HIGH)	40	3	8	4
2 (MED)	36	3	8	4
3 (LOW)	32	3	8	4
4 (HIGH)	20	6	4	2
5 (MED)	18	6	4	2
6 (LOW)	16	6	4	2
7 (HIGH)	10	12	2	1
8 (MED)	9	12	2	1
9 (LOW)	8	12	2	1

### 5.3 Performance measures

The share-first-plan-second policy aims to enhance the economic and environmental sustainability of the transportation corridor. We assess its performance using two key metrics: total transportation costs per container and the modal split. The modal split, reflecting the distribution of cargo across different transportation modes, serves as an indicator of environmental impact. Given that trucks have a higher CO2 emission compared to barges and trains, minimizing truck usage is crucial for environmental sustainability. Consequently, the proportion of containers transported by truck is a critical measure of the modal split and, by extension, the policy’s environmental effectiveness.

## 6. Results

This section presents the results of our simulation study. We obtain results for different parameter combinations reflecting situations varying from low to high capacity and demand, and with various degrees of uncertainty of the main planning problem determinants, such as release times and deadlines. We thereby mimic a variety of real-world situations. We will focus on four relations between parameters that strongly influence the performance of the share-first-plan-second policy and the competitive and fully optimized collaborative settings.

### 6.1 The impact of varying batch sizes and varying number of transportation firms

Figure 2 shows the impact of varying batch sizes categorized for the number of firms in the system. It presents the average increase of the per container transportation cost of the share-first-plan-second policy and the competitive setting, relative to the optimized collaborative setting.

Two relations can be observed in Figure 2. First, the relative performance of the competitive setting worsens for increasing number of transportation firms in the system. This is caused by the tailored (and probably clustered) transportation planning arising in the competitive setting, as the total number of transportation services in each experiment is equal and the number of batches to be transported is proportional to the number of transportation firms. By contrast, the share-first-plan-second policy remains very robust for increasing batch sizes, i.e., no significant differences are observed for an increasing number of firms. Second, the competitive approach becomes relatively better for increasing batch sizes, i.e., the average cost increase per transported container decreases. This can be explained by the nature of the problem itself; for larger batch sizes, it is more likely that transportation services are completely filled with a single batch (or a few), thereby simplifying the initial planning problem.

Table 4. Expected coverage rates for each stakeholder scenario (HIGH, MED, LOW) and each value of  $Q^{\max}$ .

Stakeholder scenario cat.	$Q^{\max} = 30$	$Q^{\max} = 35$	$Q^{\max} = 40$	$Q^{\max} = 45$	$Q^{\max} = 50$
(HIGH)	0.95	0.84	0.76	0.69	0.63
(MED)	1.05	0.94	0.84	0.77	0.70
(LOW)	1.19	1.05	0.95	0.86	0.79

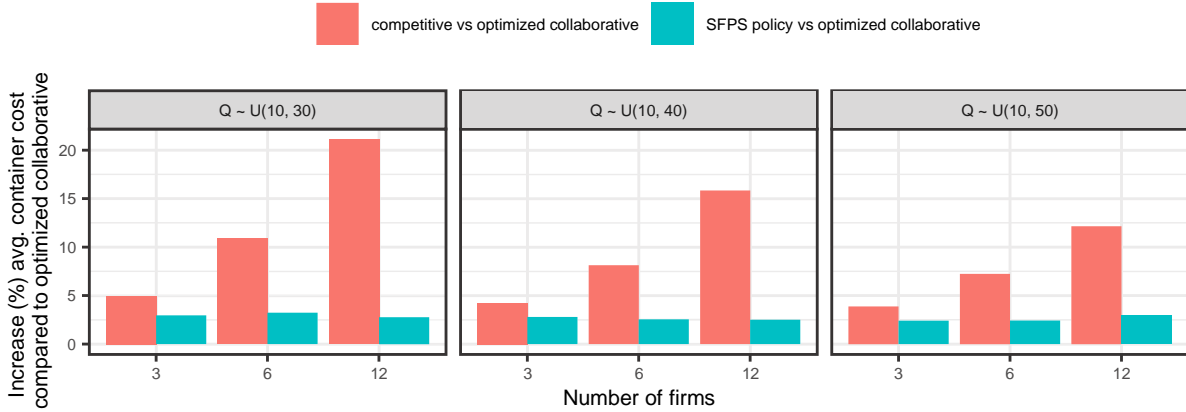


Figure 2. The average cost per shipped container relative to the performance of the fully optimized collaborative setting, for the competitive setting and the share-first-plan-second policy. We consider different distributions of the batch size  $Q$  and categorize the results per number of firms in the system. The results are averaged for all experiments with stochastic scenario 1, the time horizon length equal to 120 h, the stakeholder category equal to “MED”, and with delivery times between 12 and 36 h.

The effect of varying batch sizes, categorized for the number of firms, on the modal split is denoted in Figure 3. It shows that the share-first-plan-second policy performs robust relative to the competitive setting for both an increasing number of firms and increasing batch sizes. The increase in the proportion of containers transported by trucks can be explained by the capacity of other modes in the system is considered constant.

In line with the results from Figure 2, the proportion of containers shipped by truck increases when more containers need to be shipped through the network, and the relative difference between the number of trucks in the competitive and optimized collaborative setting decreases for increasing batch sizes. The difference between the share-first-plan-second policy and the optimized collaborative setting is more or less constant (in absolute values) for the different experiments, i.e., its efficiency seems to equal the optimized collaborative setting plus some absolute premium.

## 6.2 The impact of the length of the time horizon and the relative number of batches

Figure 4 shows the effect of varying the relative number of batches (“LOW”, “MED”, or “HIGH”) and the number of firms, categorized per time horizon length, on the average cost per shipped container for the share-first-plan-second policy and the competitive setting, compared to the optimized collaborative setting.

Several effects are visible in Figure 4. First, a longer time horizon increases the difficulty of the initial planning problem, especially when there are a lot of firms that each have a relatively low number of transportation resources. This causes more severe relative cost increases of the competitive setting when the length of the time horizon is increased, i.e., notice the upward trend of the competitive settings in all the individual bar charts. The share-first-plan-second policy is slightly outperformed by the competitive setting when there are three firms, relatively large demand, and short time horizons (72 h). Here, the initial planning problem is relatively simple and transportation services by individual firms are likely to be scheduled over the time horizon rather homogeneously. Again, the

share-first-plan-second policy performs robustly compared to the optimized collaborative setting, with the average increased transportation costs per container within 5% for all considered scenarios.

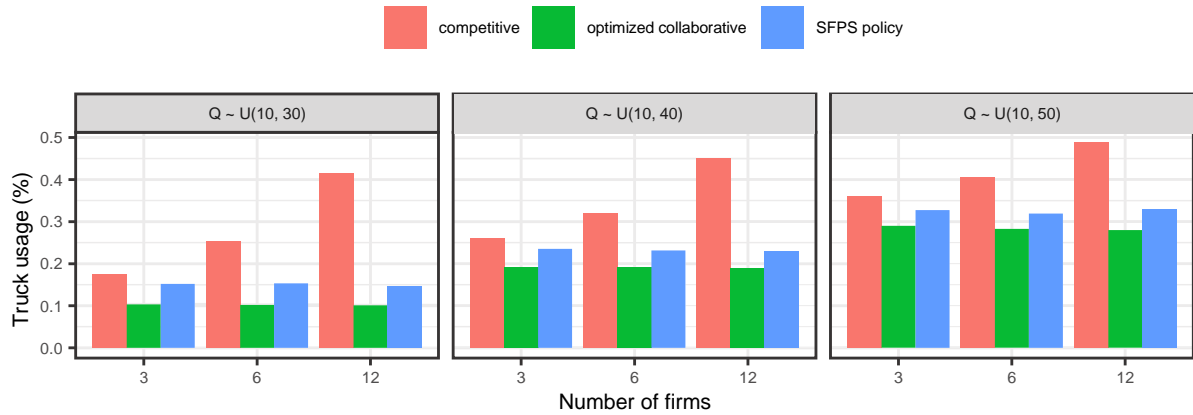


Figure 3. The proportion of trucks used for the competitive setting and share-first-plan-second policy compared to the optimized collaborative setting for different distributions of the batch size  $Q$  and categorized per number of firms. Presented results are averaged for all experiments with stochastic scenario 1, the time horizon length equal to 120 h, the stakeholder category equal to “MED”, and with delivery times between 12 and 36 h.

### 6.3 The impact of the width of the delivery times on the modal split

Figure 5 presents the impact of varying the delivery time distribution, categorized per time horizon length, on the modal split of the three settings. Looking into the effect of the time horizon length for the different delivery deadline distributions, we observe that truck usage increases when time horizons become longer, which is in line with the previous results. Furthermore, the truck usage seems to decrease among the delivery deadlines clockwise, starting at the left top bar chart. Regarding the share-first-plan-second policy, two results stand out. First, it performs comparable to the optimized collaborative setting when delivery times are between 18 and 20, indicating that homogeneous network characteristics may suit a share-first-plan-second policy particularly well. Second, for larger time windows, the differences between different time horizon lengths become smaller. Thereby, we confirm the results presented by Van Riessen et al. (2015) and, more surprisingly, show that structured delivery deadlines are beneficial for the relative performance of the share-first-plan-second policy. The reason for this is that more structured deadlines imply there are fewer planning options as there are fewer shipments with wide time windows, which complicates the fully optimized collaborative setting.

### 6.4 The robustness of the share-first-plan-second policy

In Figure 6, we provide the density functions of the proportion of containers shipped by truck for two particular simulation experiments. All parameter values, except the intensity of disturbances (i.e., the stochastic scenario), are equal in both experiments. The density plots on the left represent the stochastic scenario with low variance (Scenario 1) and the density plots on the right represent the high variance (Scenario 2).

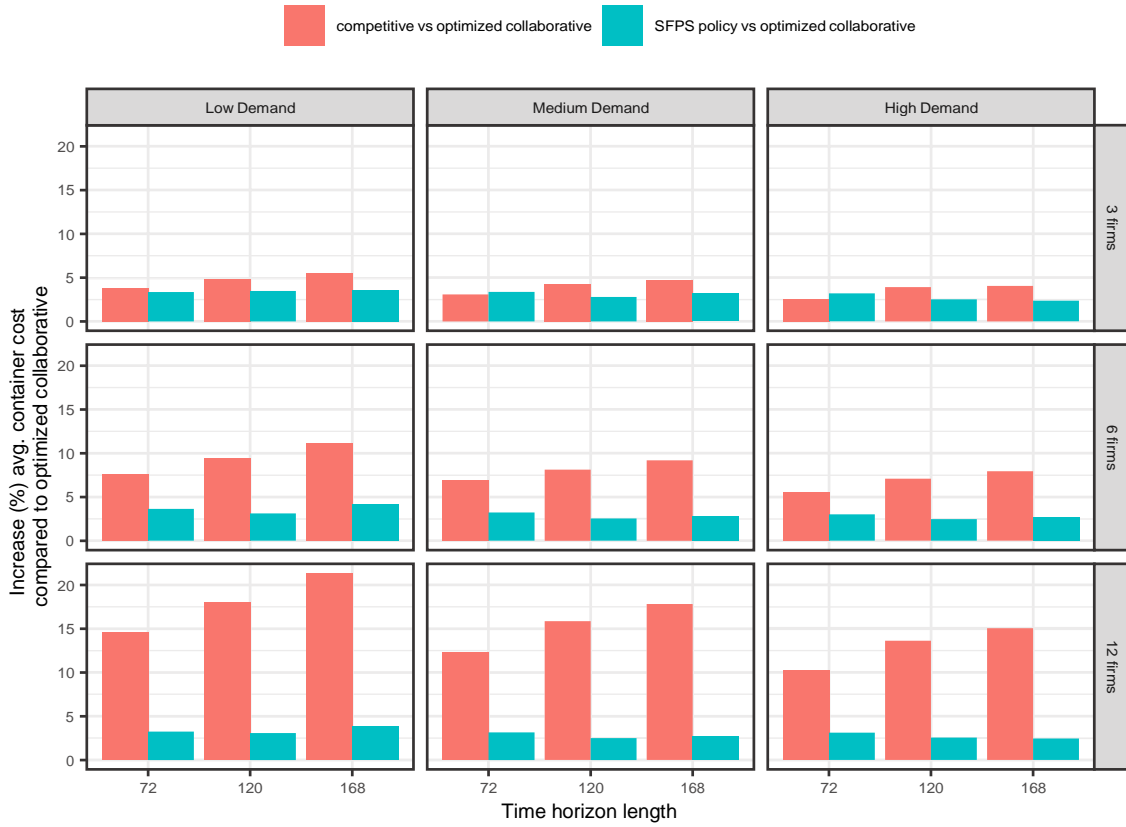


Figure 4. The average cost per shipped container for the competitive setting and share-first-plan-second policy compared to the optimized collaborative setting for different relative number of batches and different number of firms, categorized per time horizon length. Presented results are average for all experiments with stochastic scenario 1, delivery deadlines between 12 and 36 h, and batch sizes between 10 and 40 containers.

Note that the density plots of the share-first-plan-second policy are slightly more compact (i.e., steeper) than those of the competitive and optimized collaborative setting. This underscores the policy’s operational stability with limited variability. We also studied the costs associated with the shown densities, as presented in Figure 7. It is evident that the share-first-plan-second policy closely matches the performance of the optimized collaborative setting. Detailed analysis shows that there are even a few cases where the share-first-plan-second policy outperforms the optimized collaborative setting.

## 7. Conclusions

In this paper, we present a simple but efficient policy for cooperation among transportation firms in a multi-modal transportation corridor. In the proposed share-first-plan-second policy, cooperating firms first develop a cyclic schedule for a fleet of shared transportation resources and then assign their shipments to the transportation resources in real-time. We compare this policy to settings where firms manage the network either competitively or fully optimize their operations collaboratively. The competitive setting resembles current practice in transportation, where firms often schedule their transportation services in consultation with their customers, and independent from other transportation firms. The optimized collaborative setting, where all transportation firms are willing to plan and execute their shipments together, serves as a benchmark for the overall performance of the transportation network.

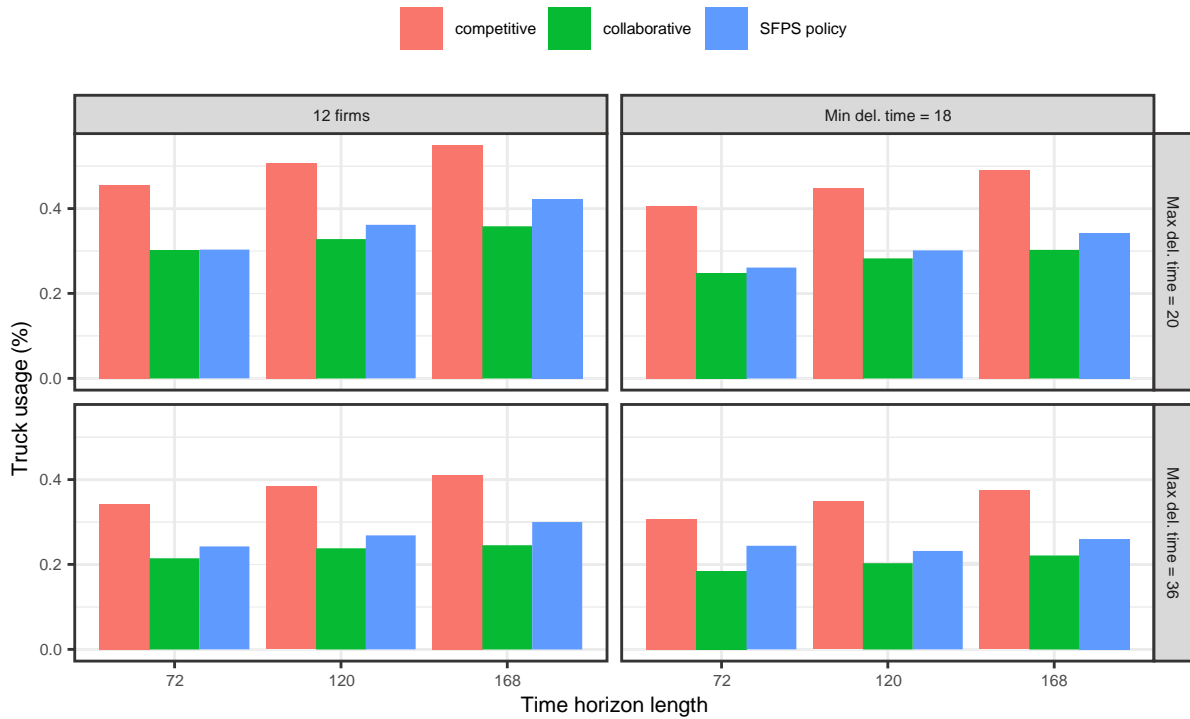


Figure 5: The percentage truck use for the three transportation policies for different delivery time distributions, categorized per time horizon length. Presented results are averaged for all experiments with stochastic scenario 1, number of firms equal to 6, the number of batches equal to “MED”, and batch sizes between 10 and 40 containers.

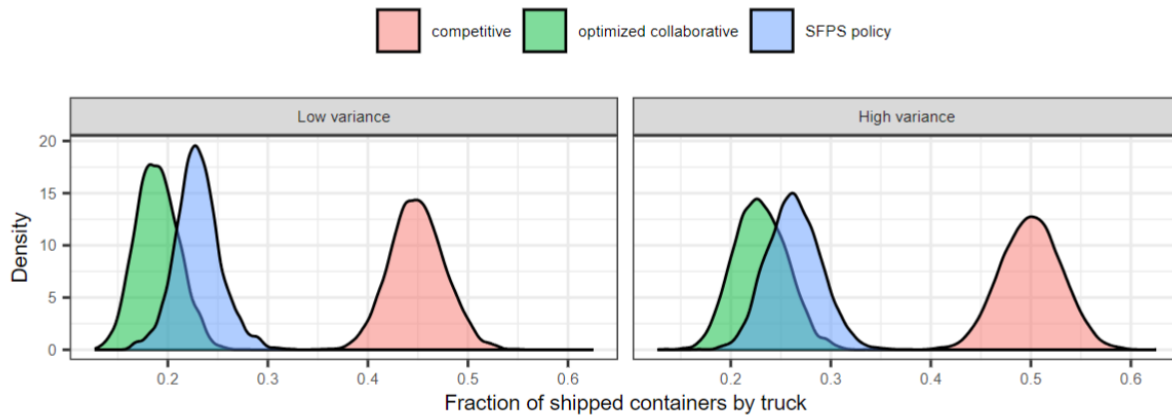


Figure 6: Empirical density of the proportion of shipments sent by truck for both stochastic scenarios for the three transportation policies. Higher proportions imply less use of barges and trains and thus worse environmental performance. Results are obtained from the two experiments (both stochastic scenarios) with 12 firms, batch sizes distributed between 10 and 40, time horizon length equal to 120, the relative number of batches equal to “MED”, and delivery times between 12 and 36 h.

The performance of the share-first-plan-second policy, in terms of cost and environmental impact, is tested in the context of a stylized transportation corridor, where multiple transportation firms need to ship containers between two hubs by means of train, barge, or truck. In the optimized collaborative setting and the competitive setting, the transportation plans indicate which containers are shipped along which transportation service at which time. After this plan is devised, disturbances occur and recourse actions are undertaken to recover from infeasible planning. The proposed share-first-plan-second policy separates the scheduling of transportation services from the

assignment of containers to those services. The transportation services are scheduled based on expected demand, and containers are assigned to services in a first-come, first-serve manner. Results indicate that the share-first-plan-second policy not only clearly outperforms the competitive setting but also closely rivals the performance of the fully optimized collaborative setting. Moreover, the share-first-plan-second policy is very robust against deviations from planned transport operations.

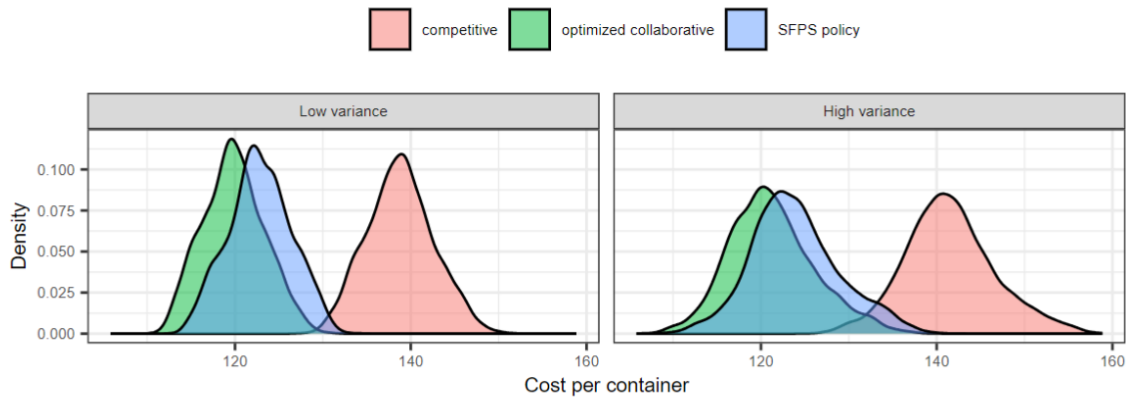


Figure 7: Empirical density of the average container cost for both stochastic scenarios for the three transportation policies. Results are obtained from the two experiments (both stochastic scenarios) with 12 firms, batch sizes distributed between 10 and 40, time horizon length equal to 120, the relative number of batches equal to “MED”, and delivery times between 12 and 36 h.

This paper confirms findings from prior research suggesting that cooperative transportation planning provides clear economic and environmental benefits compared to settings where individual transportation firms plan their services in isolation (Ballot et al., 2012; Behdani et al., 2016; Pan et al., 2017; Sarraj et al., 2014b). Our main aim was to study if simple cooperative policies could perform well compared to the joint optimization policies more commonly proposed in the academic literature (Gansterer & Hartl, 2018). The rationale is that simple policies could overcome some of the barriers and implementation issues identified with cooperation based on joint optimization (Pan et al., 2019). Compared to recent advances in decentralized policies for cooperative multi-modal transportation (Di Febbraro et al., 2016; Zhang et al., 2022) the share-first-plan-second policy proposed in this paper emphasizes simplicity, real-time adaptability, and operational flexibility. We believe that our results provide some indications that simple cooperative policies could perform well in practice.

The opportunities for further research are numerous. First, the underlying transportation corridor could be extended into a multi-hub network, for which a similar analysis can be performed. In larger and more complex transportation networks, our simple share-first-plan-second approach may yield even better performance. However, determining transportation service frequencies ex-ante would become more challenging and hence forms an interesting future research direction. A hybrid approach, with scheduled transportation services along major routes and real-time, decentralized planning in less dense areas of the network may be a way forward.

A second opportunity for future research would be to consider a stakeholder view on cooperative transportation planning. While our overall findings indicate that the share-first-plan-second policy provides clear performance benefits, individual stakeholders in the transportation network may be worse off. This limitation could potentially impede the adoption of our approach. In response, one could, for instance, incorporate gain sharing models (Krajewska et al., 2008) or explore the effect of multiple joint ventures of firms within the competitive setting, or even within the optimized collaborative setting, where multiple joint ventures share information only within the venture they are part of.

## References

- Ambra, T., Caris, A., & Macharis, C. (2019). Towards freight transport system unification: reviewing and combining the advancements in the physical internet and synchromodal transport research. *International Journal of Production Research*, 57(6), 1606-1623.
- Ballot, E., Gobet, O., & Montreuil, B. (2012). Physical internet enabled open hub network design for distributed networked operations. *Service orientation in holonic and multi-agent manufacturing control*, 279-292.
- Ballot, E., Montreuil, B., & Meller, R. D. (2014). *The physical internet*. La Documentation Française.
- Behdani, B., Fan, Y., Wiegman, B., & Zuidwijk, R. (2016). Multimodal schedule design for synchromodal freight transport systems. *European Journal of Transport and Infrastructure Research*, 16, 424-444.
- Di Febbraro, A., Sacco, N., & Saeednia, M. (2016). An agent-based framework for cooperative planning of intermodal freight transport chains. *Transportation Research Part C: Emerging Technologies*, 64, 72-85.
- Fazili, M., Venkatadri, U., Cyrus, P., & Tajbakhsh, M. (2017). Physical internet, conventional and hybrid logistic systems: a routing optimisation-based comparison using the eastern canada road network case study. *International Journal of Production Research*, 55, 2703-2730.
- Gansterer, M., & Hartl, R.F. (2018). Collaborative vehicle routing: a survey. *European Journal of Operational Research*, 268, 1-12.
- Guihaire, V., & Hao, J.K. (2008). Transit network design and scheduling: A global review. *Transportation Research Part A: Policy and Practice*, 42, 1251-1273.
- Hakimi, D., Montreuil, B., & Hajji, A. (2015). Simulating Physical Internet enabled hyperconnected semi-trailer transportation systems, in: *Proceedings of 2nd International Physical Internet Conference, Paris*.
- Hakimi, D., Montreuil, B., Sarraj, R., Ballot, E., & Pan, S. (2012). Simulating a Physical Internet enabled mobility web: The case of mass distribution in France, in: *9th International Conference on Modeling, Optimization & Simulation, Paris*.
- Ibarra-Rojas, O. J., Delgado, F., Giesen, R., & Muñoz, J. C. (2015). Planning, operation, and control of bus transport systems: A literature review. *Transportation Research Part B: Methodological*, 77, 38-75.
- Irannezhad, E., Prato, C.G., & Hickman, M. (2018). The effect of cooperation among shipping lines on transport costs and pollutant emissions. *Transportation Research Part D: Transport and Environment*, 65, 312-323.
- Jonkeren, O., Jourquin, B., & Rietveld, P. (2011). Modal-split effects of climate change: The effect of low water levels on the competitive position of inland waterway transport in the river Rhine area. *Transportation Research Part A: Policy and Practice*, 45, 1007-1019.
- Krajewska, M.A., Kopfer, H., Laporte, G., Ropke, S., & Zaccour, G. (2008). Horizontal cooperation among freight carriers: request allocation and profit sharing. *Journal of the Operational Research Society*, 59, 1483-1491.
- Lafkihi, M., Pan, S., & Ballot, E. (2020). Rule-based incentive mechanism design for a decentralised collaborative transport network. *International Journal of Production Research*, 58(24), 7382-7398.
- Montreuil, B. (2011). Toward a Physical Internet: Meeting the global logistics sustainability grand challenge. *Logistics Research*, 3, 71-87.
- Montreuil, B., Meller, R.D., & Ballot, E. (2010). Towards a Physical Internet: The impact on logistics facilities and material handling systems design and innovation. *Progress in Material Handling Research*, 305-327.
- Norlund, E.K., & Gribovskaja, I. (2015). Modal split in offshore supply network under the objective of emissions minimization. *Transportation Research Part D: Transport and Environment*, 35, 160-174.
- Pan, S., Ballot, E., Huang, G.Q., & Montreuil, B. (2017). Physical Internet and interconnected logistics services: Research and applications. *International Journal of Production Research*, 55, 2603-2609.
- Pan, S., Trentesaux, D., Ballot, E., & Huang, G.Q. (2019). Horizontal collaborative transport: survey of solutions and practical implementation issues. *International Journal of Production Research*, 57, 5340-5361.
- Roorda, M.J., Cavalcante, R., McCabe, S., & Kwan, H. (2010). A conceptual framework for agent-based modelling of logistics services. *Transportation Research Part E: Logistics and Transportation Review*, 46, 18-31.
- Sarraj, R., Ballot, E., Pan, S., Hakimi, D., & Montreuil, B. (2014a). Interconnected logistic networks and protocols: Simulation-based efficiency assessment. *International Journal of Production Research*, 52, 3185-3208.
- Sarraj, R., Ballot, E., Pan, S., & Montreuil, B. (2014b). Analogies between internet network and logistics service networks: Challenges involved in the interconnection. *Journal of Intelligent Manufacturing*, 25, 1207-1219.
- Sternberg, H., & Norrman, A. (2017). The Physical Internet—review, analysis and future research agenda. *International Journal of Physical Distribution & Logistics Management*, 47, 736-762.
- Treiblmaier, H., Mirkovski, K., & Lowry, P. (2016). Conceptualizing the Physical Internet: Literature review, implications and directions for future research, in: *11th CSCMP Annual European Research Seminar, Vienna*.
- Truschkin, E., & Elbert, R. (2013). Horizontal transshipment technologies as enablers of combined transport: Impact of transport policies on the modal split. *Transportation Research Part A: Policy and Practice*, 49, 91-109.
- Van der Heide, G., Buijs, P., Roodbergen, K.J., & Vis, I.F.A. (2018). Dynamic shipments of inventories in shared warehouse and transportation networks. *Transportation Research Part E: Logistics and Transportation Review*, 118, 240-257.

- Van Riessen, B., Negenborn, R., Lodewijks, G., & Dekker, R. (2015). Impact and relevance of transit disturbances on planning in intermodal container networks using disturbance cost analysis. *Maritime Economics & Logistics*, 17, 440–463.
- Zhang, Y., Heinold, A., Meisel, F., Negenborn, R.R., & Atasoy, B. (2022). Collaborative planning for intermodal transport with eco-label preferences. *Transportation Research Part D: Transport and Environment*, 112, 103470.