Breaking Truck Dominance in Supply Chains: Proactive Freight Consolidation and Modal Split Transport

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Abstract

Environmental concerns and a shortage of truck drivers motivate a paradigm shift in truck-dominated supply chains. To alleviate the pressure on truck transport, one can consolidate freight with other companies. Freight consolidation can be facilitated by third-party logistics service providers, who combine shipments that require delivery to the same destination on the same day. More gains can be realized through "proactive freight consolidation", by proactively synchronizing the timing of shipments prior to placing orders. This is facilitated by a joint replenishment policy. The truck intensity of supply chains can be further reduced by shifting freight from road towards alternative transport modes, such as train. Modal split transport combines two complementary transport modes by using both modes in parallel. We analyze how proactive freight consolidation can be combined with modal split transport. We propose a heuristic that combines a can-order joint replenishment policy to consolidate freight orders proactively via truck, with a tailored base-surge policy to coordinate shipments via train. We develop a lower bound on the optimal cost to validate our heuristic. By comparing the truck usage and cost performance of our policy against alternative replenishment strategies, we show how the combination of proactive freight consolidation and modal split transport can shift freight towards alternative transport modes, without negatively impacting costs or service.

Keywords: Horizontal collaboration, Multi-modal transportation, Joint replenishment, Dual sourcing, Sustainable supply chains

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1. Introduction

In today's supply chains, most freight is transported via road, one of the most polluting transport modes (Ritchie, 2020). As both the amount of freight transportation *and* the share of road transport are projected to increase, so will the negative impact of congestion, air pollution, and greenhouse gas (GHG) emissions (European Environment Agency, 2021). While other sectors report steady declines in GHG emissions since 1990, the transportation sector struggles to decarbonize (European Environment Agency, 2021). The transportation sector is urged to rethink truck-dominated supply chains to achieve the ambitious targets to combat climate change, such as, e.g., Europe's promise in the Green Deal to become climate neutral by 2050.

In addition to the environmental harm caused by truck transport, there is a dire shortage of truck drivers. Although this is not new (McKinnon et al., 2016), the problem did become worse recently (Kirby, 2022). According to estimates of the American Trucking Associations (2021), the shortage of truck drivers in the United States reached an all-time high of 80,000 drivers in 2021. Similar figures are reported in the European Union (Arnold and Vladkov, 2021). Among others, this shortage of truck drivers has led to fuel pumps running dry in the United States and Great Britain in the summer of 2021, which disrupted a large part of their economies (Bair, 2021; Gross, 2021). The prospects are not bright either, as the sector suffers from increased ageing. The average age of a truck driver in Europe is 44 years, and 46 years in the United States (Kirby, 2022). The shortage in truck drivers, which is projected to increase in the coming years, urges immediate action. Measures to make the job of truck driver more appealing will not suffice. Supply chains will have to decrease their reliance on truck transport.

Two solutions are often brought forward to reduce the use of truck transport in today's supply chains. Firstly, the available capacity of truck transport can be used more efficiently by consolidating freight, and by collaborating with different – even competing – companies at the same level of the supply chain, known as horizontal collaboration (Ferrell et al., 2020). Secondly, more freight volume can be shipped with alternative transport modes, such as train. Yet, the lower flexibility of rail transport both in terms of shipment quantities and departure schedules, hampers an entire "modal shift" towards this environmentally friendly mode (Dong et al., 2018b). The solution lies in smartly combining inflexible (but sustainable) rail transport with flexible (albeit unsustainable) truck delivery, referred to as modal split transport (MST) by Dong et al. (2018b). Still, companies often lack scale to make this (partly) modal shift economically viable. As trucks are only used to cover a small portion of a company's total shipment volume, their load factor may be lower under

MST. This is where freight consolidation can offer a solution, thereby achieving the required scale and load factors under MST.

In this paper, we consider a supply chain in which a number of companies, closely located to each other, replenish their (upstream) orders from their suppliers who are also located in the same vicinity of each other. Transportation between the suppliers and the receivers can be done by truck or train, and orders of different companies can be consolidated. By appealing to a logistics service provider (LSP), companies already commit to some form of freight consolidation. LSPs try to bundle orders of different companies that require delivery to the same area on the same day. This practice, known as "groupage", aims to increase the load factor, thereby lowering transportation costs and GHG emissions (McKinnon, 2004). Yet, under this kind of collaboration the replenishment process of each company remains optimized individually, and bundling opportunities are identified *a posteriori*. We therefore refer to this form of groupage as *reactive consolidation*.

More gains can be achieved by optimizing the replenishment process holistically, thereby minimizing the supply chain cost over all collaborating companies and identifying consolidation opportunities proactively (Vanovermeire et al., 2014). Under such *proactive consolidation*, a company can, for example, advance a particular order to benefit from a consolidation opportunity with another company. The resulting increase in inventory holding costs can then be compensated by reduced transportation costs. A real-life example is given by the collaboration between UCB and Baxter, two global health care companies. The company Tri-Vizor acts as a neutral "orchestrator" and synchronizes the replenishment flows of both companies between Belgium and Romania. The consolidated flows are assigned to a transportation company, resulting in higher load factors and lower transportation costs. Moreover, the scale created due to the collaboration allowed to use rail transport in a cost-efficient way (Boute et al., 2011). In this case, proactive consolidation was carried out at the initiative of the collaborating companies (i.e., UCB and Baxter), and facilitated by a neutral orchestrator (i.e., Tri-Vizor). Alternatively, proactive consolidation can also be initiated by the LSP who then acts as a neutral trustee, provided that shippers are flexible in the timing of their inventory replenishments.

Proactive consolidation implies the synchronization of the companies' replenishment processes. In the inventory literature, this is known as the joint replenishment problem (JRP). The JRP considers the coordination of the replenishment of products that share a joint order cost, such that inventory and order costs of all products are minimized. JRP policies can be used to facilitate freight consolidation when the same transport mode is used for different companies (Tinoco et al., 2017; Vanvuchelen et al., 2020).

To combine the use of rail with road transport, dual transport mode policies can be adopted. Dong et al. (2018b) present a tailored base-surge (TBS) dual-mode policy that splits the freight volumes between road and rail transport. The proposed policy ships a constant volume via train at a fixed time interval, while a period dependent base-stock policy is used for truck transport with a base-stock level that is dependent on the time until the next train arrives.

To the best of our knowledge, no policies exist that orchestrate the replenishment of different companies proactively using two parallel transport modes. As both the dual mode and the JRP are intractable, the optimal replenishment policy for this *dual-mode JRP* is intricate, if not impossible, to derive. We therefore resort to a heuristic, proactive consolidation policy that allows parallel shipments using two complementary transport modes. We coin our proposed policy the *joint TBS policy*. It combines a TBS policy that ships constant volumes on rail per company and uses a period dependent can-order policy to coordinate truck transport. We propose a heuristic search procedure that decomposes the problem per company, and that solves the single-company problems sequentially until convergence of the best policy parameters. To benchmark our joint TBS policy, we develop a lower bound on the optimal dual-mode JRP policy, and report a gap of around 10%. This is in line with other JRP policies that make use of a single transport mode, thereby validating our approach for joining replenishments in a multi-modal setting. A numerical experiment demonstrates how MST and proactive freight consolidation can reduce truck usage by shipping more volume per truck and/or shifting more freight towards rail transport. We also show how the combination of MST with proactive consolidation can shift freight towards alternative transport modes, without negatively impacting costs or service. As rail transport has a much higher efficiency in terms of emissions per tonne-kilometer compared to heavy goods vehicles (European Environment Agency, 2022), we thus demonstrate how logistics can be decarbonized in a cost-efficient way. Although we focus our attention on rail transport (inspired by Europe's push to drastically increase the share of rail freight transportation (Chapuis et al., 2022)), we note that our model and insights remain valid when considering alternative transport modes, such as inland waterways.

In the next section, we position our work in the literature. Afterwards, we formally introduce the dual-mode JRP and our proposed joint TBS policy that combines proactive consolidation and dual-mode transport. In Section 4 we describe the decomposition method to optimize the parameters of our joint TBS policy, and we derive a lower bound on the optimal dual-mode JRP policy in Section 5. We show the impact of our joint TBS policy on truck usage and costs in a numerical experiment in Section 6. Section 7 concludes this paper. Appendix A provides an overview of the notation used throughout the paper.

2. Positioning in the literature

This paper contributes to the literature on both multi-modal transportation and collaborative shipping. Coined as a key to design efficient and sustainable supply chains, multi-modality has received ample attention over the last years. Bontekoning et al. (2004), SteadieSeifi et al. (2014), and Ambra et al. (2019) provide extensive reviews. Most research on multi-modal transport does not consider the inventory dynamics that arise due to transport mode decisions. Yet, the impact of multi-modal transportation on the entire supply chain should be taken into account, as choosing a cost-efficient transport mode can increase costs elsewhere in the supply chain, such as for example in inventories (Dong et al., 2018a).

Literature on collaborative shipping is well-established and covers many topics including collaborative vehicle routing, the selection of collaborating actors, gain and cost sharing between collaborating companies, and many more. Extensive reviews are provided by Cruijssen et al. (2007), Verdonck et al. (2013), Gansterer and Hartl (2018), and Pan et al. (2019). Similar to the literature on multi-modal transportation, few articles approach collaborative shipping from an inventory perspective, studying how inventory replenishment cycles between collaborating companies can be synchronized. Tinoco et al. (2017) and Vanvuchelen et al. (2020) focus on collaborative shipping by modelling the problem as a JRP (e.g., Tinoco et al. (2017) study gain and cost sharing allocation under collaborative shipping facilitated by a can-order joint replenishment policy).

The joint consideration of multi-modal transportation and collaborative shipping is mostly studied through the development of collaborative, multi-modal supply chain networks. Groothedde et al. (2005), for example, design and implement a collaborative, multi-modal hub network to distribute fast moving consumer goods in the Netherlands. Kreutzberger (2010) identifies and compares different collaborative networks in terms of network costs. Other articles assume a given multi-modal network, and optimize collaborative freight flows in this network. Van Heeswijk et al. (2018), for example, use an arc-expansion procedure to optimize intermodal (potentially bundled) routes of given orders. Pan et al. (2013) pool the flows of two multi-modal supply chains using mixed integer linear programming with the goal of minimizing CO_2 emissions. Yet, while there is an abundance of articles that consider the design of multi-modal networks and the optimization of collaborative flows, the decision-making of the different companies in these networks (i.e., the orders placed in the networks) is often assumed to be given.

We contribute to the literature by studying ordering policies in collaborative, multi-modal supply chains. The combination of multi-modal and collaborative shipping introduces a new, complex inventory problem for which we propose a novel heuristic and lower bound. The technique proposed to optimize the parameters of our heuristic ordering policy extends existing optimization techniques. Our lower bound is used to validate our heuristic, but can additionally serve to benchmark future policies. By combining multi-modal and collaborative shipping, we demonstrate how the cost efficiency of MST can be improved through proactive freight consolidation.

3. Replenishment strategies for the dual-mode joint replenishment problem

We consider a periodic review inventory model, where inventory can be replenished using truck transport and/or rail transport, and a set of companies $\mathcal{N} = \{1, ..., N\}$. Each company places orders to minimize its holding, shortage, and order (transport) costs. We assume that $\mathcal{N}$ contains companies in close proximity to each other, with the origin and destination of their shipments in the same vicinity, such that it allows possible consolidation of freight. We refer to Creemers et al. (2017) to identify companies with their origin and destination in the same vicinity. Every period (e.g., a day), each company places orders after having observed its respective inventory position. Orders by truck can be placed every period, while a train only runs every T periods. Orders are consolidated in the same shipment if they are placed at the same moment in time using the same transport mode.

We assume that each company's order quantity shipped via rail is constant during the entire planning horizon. As a result, the total volume shipped by rail remains constant and can be reserved at the rail operator (Dong et al., 2018b). The volumes shipped by truck, in contrast, can vary over time. We do not impose a capacity limit to the truck capacity, although the model could be extended accordingly (at the expense of increased model complexity). As such, rail transport is used for the constant "base" demand, whereas trucks are used to cover "surge" demand. The sequence of events is as follows: first, inventory is replenished; then, demand is satisfied; finally, an order is placed. Orders shipped by trucks can be placed every period, whereas shipments by rail can only be placed every T periods. Orders placed by truck at the end of period t replenish inventory at the start of period $t + 1$.

Let K denote the transport cost to ship a (consolidated) order by truck, and $\tilde{K}$ the transport cost to ship a (consolidated) order by train. K ($\tilde{K}$) can be interpreted as the cost to ship a container from origin to destination via truck (train), containing orders from one or more companies. In the JRP literature, these costs are referred to as "major" order costs, as they are shared amongst all companies joining the order on the specific transport mode. We assume $\tilde{K} < K$, similar to other articles, e.g., Bouchery and Fransoo (2015). The negative externalities associated with truck transport (e.g., emissions, noise, congestion, accidents) further motivate this cost difference. Note that, if $\tilde{K} \geq K$, from an economic cost perspective it would never be beneficial to make use of train transport.

In addition to the (potentially shared) major order cost, a company-specific order cost k_i is incurred per company i that takes part in the order. This fixed cost reflects the cost of handling and loading, and is referred to as the "minor" order cost in JRP literature. Daily demand is assumed to be Poisson distributed with a demand rate λ_i for company i. Demand that cannot be met immediately, is backlogged (such that negative inventory positions are possible). At the end of each period, we incur a holding cost h per unit in inventory, and a shortage cost p per unit backlog.

With a set of $\mathcal{N}$ companies and two available transport modes, we can distinguish four different replenishment strategies (see also Table 1): (1) Each company decides individually on its replenishment orders, only making use of truck transport. When orders coincide, they can be reactively consolidated. (2) The set of $\mathcal{N}$ companies decide holistically on their replenishment, thereby proactively consolidating their orders, and only make use of truck transport. (3) Each company replenishes individually, making use of both train and truck transport (MST). (4) The companies make use of MST, and proactively synchronize their truck replenishment. In what follows, we describe the policies that can be used in each of the four replenishment strategies.

3.1. Reactive consolidation using trucks only

Under this replenishment strategy, each company optimizes its replenishment individually using only road transport. A third-party logistics provider consolidates shipments placed in the same period. With fixed transportation costs and backordering, it is well-known that an (s, S) policy minimizes the cost of each company individually (Arrow et al., 1951). In this setting, each company i has its respective reorder point s_i and order-up-to level S_i. Whenever the inventory position of a company i is at or below its reorder point s_i, an order is placed to replenish the inventory position to the order-up-to level S_i. If multiple companies order (coincidentally) at the same point in time, consolidation is possible, and the major fixed transportation cost K is incurred only once.

	Reactive Consolidation	Proactive Consolidation
Truck only	(s, S) policy per company $i \in \mathcal{N}$ (Arrow et al., 1951)	Can-order JRP policy (Balintfy, 1964) Periodic JRP policy (Atkins and Iyogun, 1988; Viswanathan, 1997)
Modal Split	TBS policy per company $i \in \mathcal{N}$ (Dong and Transchel, 2020)	Joint TBS policy (Presented in this paper)

Table 1: Framework in which different strategies for the dual-mode JRP can be positioned. For proactive consolidation with MST, we provide a new *joint TBS policy* and a heuristic search procedure to find policy parameters.

3.2. Proactive consolidation using trucks only

The classical JRP considers the replenishment of N products that minimizes the total costs (i.e., holding, shortage, and order costs) over all products. By interpreting the N products as N companies, JRP policies can be used to facilitate proactive consolidation of orders of N companies (Tinoco et al., 2017; Vanvuchelen et al., 2020). JRP policies reduce the transportation costs by proactively synchronizing the companies' replenishment, thereby sharing the major order cost. The optimal JRP policy can be obtained through dynamic programming. Yet, the computational requirements quickly grow with the number of companies. Although methods have been proposed to reduce the computational complexity (e.g., Creemers and Boute, 2022), calculating the optimal policy remains intractable, and even impossible, for problems with more than two companies.

The intractability of the optimal policy poses the need for well-performing heuristics that coordinate orders, and are easy to compute. Under a can-order policy, introduced by Balintfy (1964), an order is placed to lift a company's inventory position up to its order-up-to level S_i when the inventory position of a company i hits its reorder level s_i. Other companies $j \in \mathcal{N} \setminus \{i\}$ join the order up to their respective order-up-to level S_j if their inventory position is at or below their can-order level c_j. An alternative JRP heuristic is the periodic $P(s, S)$ JRP policy, which places orders at fixed periodic intervals (Viswanathan, 1997). Every replenishment interval, the inventory position of each company i is checked, and raised up to its respective S_i when the inventory position is at or below its respective s_i.

3.3. Modal split transport and reactive consolidation

When each company individually optimizes its dual-mode replenishment, a third-party logistics provider can consolidate orders on both transport modes if possible. Dong et al. (2018b) use an inventory replenishment heuristic from the dual sourcing literature to determine the modal split for a single company. They apply the tailored base-surge (TBS) policy by shipping constant volumes via train every T periods, and by using a dynamic base-stock policy for road transport in which the base-stock level depends on the time until the next train arrives. Dong and Transchel (2020) show that the total cost (holding, shortage, and order) per period is convex in the delivery quantity shipped using rail. They exploit this observation to optimize their MST policy using a binary search method. Policy iteration is used to identify the optimal trucking policy for each delivery quantity shipped using rail, after which the total system (i.e., train and truck) is evaluated. Dong and Transchel (2020) characterize the optimal road replenishment policy (in the presence of a periodic fixed rail quantity) as a base-stock policy for which the base-stock level is higher if it still takes a longer time for the next train to arrive.

3.4. Modal split transport and proactive consolidation on truck transport

To the best of our knowledge, no policy exists that considers the combination of dual-mode transport and proactive consolidation. We therefore propose a new policy, and use a heuristic search procedure to find policy parameters. Our heuristic policy (the optimal policy is intractable) combines a TBS policy with a can-order policy. We coin it the *joint TBS policy*. Each company i ships a fixed volume via train every T periods, denoted Q_i. A time dependent can-order policy coordinates orders placed by truck transport. The can-order policy is time dependent in the sense that its parameters depend on the time until the next train arrives, denoted by $\theta = 0, 1, ..., T-1$.

For each company, the reorder point s_i^θ, can-order level c_i^θ, and order-up-to level S_i^θ are thus dependent on θ. We define $\boldsymbol{s}_i = (s_i^0, s_i^1, ..., s_i^{T-1})$, $\boldsymbol{c}_i = (c_i^0, c_i^1, ..., s_i^{T-1})$, and $\boldsymbol{S}_i = (S_i^0, S_i^1, ..., S_i^{T-1})$ as the can-order policy parameters that govern the truck transports of company i depending on the time until the next train arrival [1]. Combined with each company's rail quantity Q_i, the total number of policy parameters for N companies is $(3 \times T \times N) + N$. As the number of companies N grows, the optimization of the policy parameters becomes computationally intractable, and heuristic solution methods are required. In the next section, we propose a heuristic to optimize the policy parameters of the joint TBS policy.

[1] Throughout the paper, we adopt boldface notation for vectors with components corresponding to $\theta = 0, 1, ..., T-1$.

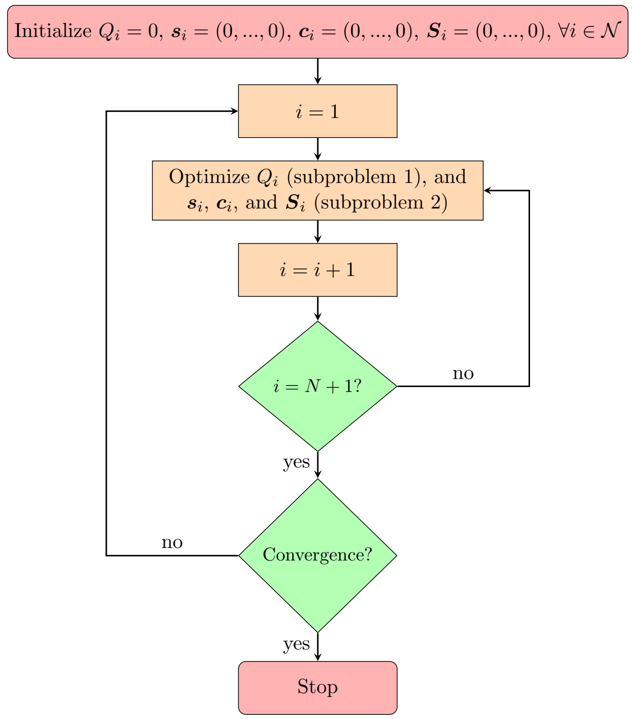

Figure 1: Flowchart to describe the different steps to optimize the joint TBS policy.

4. Parameter optimization of the joint TBS policy

We propose a decomposition algorithm to optimize the parameter set $\{Q_i, \boldsymbol{s}_i, \boldsymbol{c}_i, \boldsymbol{S}_i\}, \forall i \in \mathcal{N}$. The algorithm has three hierarchical levels. The master problem iterates over all companies i, and calculates their respective policy parameters, until the global policy over all companies converges. To identify the policy parameters for company i, we optimize Q_i through a binary search. We refer to this as subproblem 1. Given Q_i, we optimize $\{\boldsymbol{s}_i, \boldsymbol{c}_i, \boldsymbol{S}_i\}$. We refer to this as subproblem 2. In what follows, we describe these optimizations in more detail. Figure 1 provides a flowchart that describes the high-level working of our algorithm. To demonstrate the dynamics, we illustrate with the following example.

Example *We consider $N = 3$ companies with a Poisson demand of resp. $\lambda_1 = 2; \lambda_2 = 3; \lambda_3 = 4$. Holding and shortage costs are equal to $h = 1$ and $p = 2$. The minor order cost is the same for all companies, $k_i = 3$, while the major order cost for truck transport is $K = 33$, and the major order cost for rail transport is $\tilde{K} = 8$. A train runs every $T = 3$ periods.*

4.1. Master problem: sequentially iterate over all companies until convergence

We decompose the dual-mode JRP by sequentially optimizing the policy parameters for each company i until the global policy (over all companies $i \in \mathcal{N}$) converges. To acknowledge the interdependence between the replenishment processes of the companies, we use the concept of discount replenishment opportunities. Discount replenishment opportunities for company i arise when another company $j \in \mathcal{N} \setminus i$ initiates an order, such that company i can join the order while only incurring its minor order cost k_i (Silver, 1974; Federgruen et al., 1984). This implies that another company (i.e., the company that initiated the order) pays the major order cost. By estimating the occurrence of discount replenishment opportunities with a stochastic process, the multi-company problem can be decomposed, without sacrificing the relationship between the order processes of the collaborating companies. As the discount replenishment opportunities depend on the other companies' replenishment policies (as we will discuss in Section 4.3), we iterate until the policy parameters converge. All policy parameters are initialized to 0: $Q_i = 0$, $\boldsymbol{s}_i = (0, ..., 0)$, $\boldsymbol{c}_i = (0, ..., 0)$, $\boldsymbol{S}_i = (0, ..., 0)$, $\forall i \in \mathcal{N}$.

Example (ctd.) *We first optimize the policy parameters of company* 1*. Solving subproblem 1 (cf. the solution procedure discussed infra in Section 4.2) reveals that* $Q_1 = 5$ *is optimal, and the optimization in subproblem 2 (cf. the solution procedure discussed infra in Section 4.3) leads to* $\boldsymbol{s}_1 = (-7, -4, -2)$*,* $\boldsymbol{c}_1 = (-1, 1, 2)$*, and* $\boldsymbol{S}_1 = (1, 3, 5)$*. Given the policy parameter values of company* 1*, we optimize the policy parameters for company* 2*, and obtain* $Q_2 = 8$*,* $\boldsymbol{s}_2 = (-11, -5, -2)$*,* $\boldsymbol{c}_2 = (-3, 1, 3)$*, and* $\boldsymbol{S}_2 = (0, 3, 5)$*. Given the policy parameters for company* 1 *and* 2*, we find that* $Q_3 = 10$ *and* $\boldsymbol{s}_3 = (-13, -5, -2)$*,* $\boldsymbol{c}_3 = (-2, 2, 5)$*, and* $\boldsymbol{S}_3 = (1, 4, 8)$ *minimizes the costs for company* 3*. As the policies of company* 2 *and* 3 *affect the discount replenishment opportunities for company* 1*, we re-optimize the policy parameters of company* 1*, yielding* $Q_1 = 5$ *and* $\boldsymbol{s}_1 = (-8, -4, -3)$*,* $\boldsymbol{c}_1 = (-2, 0, 2)$*, and* $\boldsymbol{S}_1 = (1, 3, 4)$*. We repeat for company* 2 *and find* $Q_2 = 8$*, and* $\boldsymbol{s}_2 = (-11, -5, -3)$*,* $\boldsymbol{c}_2 = (-3, 0, 3)$*, and* $\boldsymbol{S}_2 = (-1, 3, 5)$*. Similarly, we find* $Q_3 = 10$ *and* $\boldsymbol{s}_3 = (-12, -4, -2)$*,* $\boldsymbol{c}_3 = (-2, 2, 5)$*, and* $\boldsymbol{S}_3 = (1, 5, 8)$*. Given the updated policy parameter values, we perform a new iteration and find that the optimization yields the exact same policy parameter values for company* 1*,* 2*, and* 3*. The algorithm stops after three iterations.*

4.2. Subproblem 1: optimize the rail quantity for company i

We use a binary search to optimize the quantity to be shipped via rail, Q_i, similar to the method of Dong and Transchel (2020). For this, we rely on the conjecture that the costs for company i are convex in Q_i, when the can-order policy governing truck transports is optimized given Q_i (we cannot make theoretical claims but extensive numerical tests confirm our conjecture). The binary search finds the value for Q_i in $[q_{min} = 1; q_{max} = \lambda_i T]$ for which the convex cost function is minimal. Note that a value higher than $\lambda_i T$ would lead to an infinite amount of inventory buildup (and associated costs) in the long run. The binary search splits the search space in two parts, and evaluates Q_i adjacent to the split, i.e., $Q'_i = \lceil (q_{min} + q_{max})/2 \rceil$ and $Q''_i = Q'_i - 1$. For each of these two values of Q_i, we optimize $\{\boldsymbol{s}_i, \boldsymbol{c}_i, \boldsymbol{S}_i\}$, cf. Subproblem 2 described in Section 4.3, and evaluate their average cost performance (in an exact way using Markov chain analysis). If Q''_i yields the lowest costs, the search space is adjusted by changing $q_{max} = Q''_i$; if Q'_i yields the lowest costs, the search space is adjusted by changing $q_{min} = Q'_i$. A new iteration starts until $q_{min} = q_{max}$, at which point we have identified the value of Q_i that minimizes the costs for company i.

Example (ctd.) *To illustrate the binary search procedure, we consider the optimization of* Q_1 *in the first iteration of the master problem. The initial search space for* Q_1 *is* $[1; 2 \times 3 = 6]$*, such that* $Q'_1 = \lceil (1 + 6)/2 \rceil = 4$ *and* $Q''_1 = 3$*. After calculating the best can-order policy parameters for both values of* Q_1 *(see Section 4.3), their respective costs (obtained through Markov chain analysis) are* 7.01 *for* $Q_1 = 4$ *and* 7.96 *for* $Q_1 = 3$*. This reduces the search space to* $[4; 6]$*, in which we evaluate* $Q'_1 = \lceil (4 + 6)/2 \rceil = 5$ *and* $Q''_1 = 4$*, yielding a cost of respectively* 6.25 *for* $Q_1 = 5$ *and* 7.01 *for* $Q_1 = 4$*. This reduces the search space to* $[5; 6]$ *in which we obtain a cost of* 6.48 *for* $Q_1 = 6$ *and* 6.25 *for* $Q_1 = 5$*. At this point, we find that the value of* $Q_1 = 5$ *yields the lowest cost for company* 1.

4.3. Subproblem 2: optimize the can-order policy parameters for company i, given Q_i

In subproblem 2, we decompose the multi-company problem into N single-company problems. For each company i, we optimize the can-order policy parameters, given its order quantity shipped by rail (Q_i; obtained in subproblem 1), and given the can-order policies of all other companies $j \in \mathcal{N} \setminus \{i\}$. To mimic the orders that are initiated by other companies $j \in \mathcal{N} \setminus \{i\}$, we use so-called "discount replenishment opportunities" (Silver, 1974; Federgruen et al., 1984). This entails that, if a discount replenishment opportunity arises, company i can join a "virtual" order of another company, and only incurs its minor order cost k_i. Discount replenishment opportunities allow us to recapture some of the interdependencies between orders of different companies that were lost by decomposing the multi-company problem into single-company problems.

The discount replenishment opportunities can be estimated by a stochastic process. In absence of any rail deliveries, Johansen and Melchiors (2003) suggest to model discount replenishment opportunities by a Bernouilli process characterised by the parameter μ_i, representing the probability that at least one company $j \in \mathcal{N} \setminus \{i\}$ places an order. The latter can be expressed in terms of β_j, the fraction of ordering moments where company j initiates an order,

$$\mu_i = 1 - \Pi_{j \in \mathcal{N} \setminus i}(1 - \beta_j), \tag{1}$$

where β_j depends on the can-order policy parameters of company j. They can be calculated by analyzing the steady state distribution of the corresponding Markov chain, i.e., β_j is the sum of the steady-state probabilities of states where company j has an inventory position of s_j or smaller.

Assuming that the arrivals of discount replenishment opportunities for company i are memoryless and independent of the order process of company i (as in Johansen and Melchiors, 2003), the optimization of the can-order policy for company i can be obtained through dynamic programming (Zheng (1994) has shown that the optimal policy for a company for which discount replenishment opportunities occur is indeed a can-order policy). The state of the corresponding Markov decision process (MDP) is defined by (y_t, ϕ_t), with y_t the inventory position of company i in period t, and $\phi_t = 1$ if there is a discount replenishment opportunity for company i in period t (and $\phi_t = 0$ otherwise). Both the demand process, characterized by λ_i, and the probability of discount replenishment opportunities, characterized by μ_i, determine the transition probabilities of the MDP. Solving this MDP using traditional dynamic programming methods such as value iteration allows to derive the cost-minimizing can-order policy parameters, s_i, c_i, and S_i.

In the presence of rail replenishment, the parameters of the can-order policy additionally depend on the time until the next train arrival. As a result, the probability of the occurrence of a discount replenishment opportunity depends on the time until the next train arrival $\theta = 0, 1, ..., T-1$. The discount replenishment opportunities for company i are driven by T different Bernouilli processes with parameters μ_i^θ, denoting the probability that a discount replenishment opportunity occurs for company i when a train arrives in θ periods. Each parameter μ_i^θ is calculated using Eq. (1), with β_j^θ the fraction of time at which company j initiates an order in a state in which a train arrives in θ periods. Then, given a value of Q_i, the cost-minimizing policy of company i can be obtained by modelling it as an MDP with states (y_t, ϕ_t, θ_t), and by solving it with value (or policy) iteration. The transition probabilities of this MDP are dictated by the demand process λ_i, the probability of discount replenishment opportunities μ_i^θ, and the quantity shipped via rail Q_i.

Example (ctd.) *We illustrate the optimization of the can-order policy for company* 3*, given* $Q_1 = 5$, $\boldsymbol{s}_1 = (-7, -4, -2)$, $\boldsymbol{c}_1 = (-1, 1, 2)$, $\boldsymbol{S}_1 = (1, 3, 5)$, $Q_2 = 8$, $\boldsymbol{s}_2 = (-11, -5, -2)$, $\boldsymbol{c}_2 = (-3, 1, 3)$, *and* $\boldsymbol{S}_2 = (0, 3, 5)$*. The steady state distributions of the policies for company* 1 *and* 2 *are obtained by modelling these can-order policies as a Markov chain. Adding the steady state probabilities of states where companies 1 and 2 have an inventory position of s_j^θ or below at $\theta = 0, 1, ..., T-1$ leads to $\boldsymbol{\beta}_1 = (0.0123, 0.0385, 0.0806)$ and $\boldsymbol{\beta}_2 = (0.0017, 0.0297, 0.0638)$. The probability of a discount replenishment opportunity for company 3 at the different train epochs is then given by $\mu_3^\theta = 1 - \Pi_{j \in \mathcal{N} \setminus \{3\}}(1-\beta_j^\theta)$, leading to $\boldsymbol{\mu}_3 = (0.0140, 0.0671, 0.1393)$. These probabilities determine the transition probabilities of the MDP with states (y_t, ϕ_t, θ_t), together with the demand rate λ_3 and the rail quantity Q_3. With $Q_3 = 10$ (as obtained after solving subproblem 1), we solve this MDP using value iteration. By analyzing the optimal actions in each state, we find that $\boldsymbol{s}_3 = (-13, -5, -2)$, $\boldsymbol{c}_3 = (-2, 2, 5)$, and $\boldsymbol{S}_3 = (1, 4, 8)$.*

5. A lower bound on the optimal dual-mode joint replenishment policy

To evaluate the performance of our *joint TBS* policy, we benchmark it against a lower bound that we derive on the long run average cost per period of the optimal dual-mode JRP policy. Our lower bound extends the one derived by Atkins and Iyogun (1988) for the single-mode JRP to a dual transport mode setting. We compare our lower bound against the proposed joint TBS policy in a numerical experiment.

5.1. Derivation of the lower bound

Atkins and Iyogun (1988) and Viswanathan (2007) show how the lower bound on the long run average cost per period of the optimal single-mode JRP policy can be found by allocating a portion of the major order cost to each company. Let $\mathcal{X}_t = \{x_1, x_2, ..., x_N\}$ be order quantities for the set of companies $\mathcal{N}$ in a given period t. Assuming a major order cost K and minor order costs k_i, the total order costs over all companies $\forall i \in \mathcal{N}$ incurred by ordering $\mathcal{X}_t$ are:

$$K\delta(\sum_{i \in \mathcal{N}} x_i) + \sum_{i \in \mathcal{N}} k_i \delta(x_i),$$

with $\delta(\xi) = 1$ if $\xi > 0$ and $\delta(\xi) = 0$ otherwise.

Suppose we allocate the shared order cost K to the N companies with weights α_i, such that $\alpha_i K$ is allocated to company $i \in \mathcal{N}$ with $0 \leq \alpha_i \leq 1$, $\forall i \in \mathcal{N}$ and $\sum_{i \in \mathcal{N}} \alpha_i = 1$. Then, the total order costs over these N problems incurred by ordering $\mathcal{X}_t$ are equal to:

$$\sum_{i \in \mathcal{N}} (\alpha_i K + k_i)\delta(x_i).$$

As $\delta(\sum_{i\in\mathcal{N}} x_i) \geq \sum_{i\in\mathcal{N}} \alpha_i \delta(x_i)$ for any feasible α_i, we know that:

$$K\delta(\sum_{i\in\mathcal{N}} x_i) + \sum_{i\in\mathcal{N}} k_i\delta(x_i) \geq \sum_{i\in\mathcal{N}} (\alpha_i K + k_i)\delta(x_i).$$

As neither holding nor shortage costs are affected by allocating the major order cost K to different companies, the lower bound on the long run average cost per period of the optimal JRP policy is thus given by $\sum_{i\in\mathcal{N}} C_i(\alpha_i)$, with $C_i(\alpha_i)$ the long run average cost per period of the optimal policy for the single-company problem with a fixed order cost $\alpha_i K + k_i$. This result holds for any choice of allocation α_i as long as $0 \leq \alpha_i \leq 1$, $\forall i \in \mathcal{N}$ and $\sum_{i\in\mathcal{N}} \alpha_i = 1$. The optimal lower bound is obtained by the values α_i, $\forall i \in \mathcal{N}$, such that $\sum_{i\in\mathcal{N}} C_i(\alpha_i)$ is maximized. Viswanathan (2007) provides an algorithm to find these optimal weights in the single-mode JRP.

Using the same technique of allocating the major order cost, we develop a lower bound for the dual-mode JRP considered in this paper. Let α_i be the portion of the major truck transportation cost K allocated to company $i \in \mathcal{N}$, with $0 \leq \alpha_i \leq 1$, $\forall i \in \mathcal{N}$ and $\sum_{i\in\mathcal{N}} \alpha_i = 1$. Define $C_i(\alpha_i)$ as the long run average cost per period (consisting of holding, shortage, and truck transportation costs) of the optimal policy for the single-company dual-mode problem with a fixed truck transportation cost of $\alpha_i K + k_i$. We assume that an order will be placed by train every T periods (if not, the lower bound for the single-mode JRP can be used). Then the lower bound on the long run average cost per period of the optimal dual-mode JRP policy is given by:

$$\sum_{i\in\mathcal{N}} C_i(\alpha_i) + \frac{\tilde{K}}{T}.$$

The question remains how to find α_i such that the lower bound $\sum_{i\in\mathcal{N}} C_i(\alpha_i)$ is maximized. Given a certain set of weights for which $\sum_{i\in\mathcal{N}} \alpha_i < 1$, the sensible thing to do is to increase α_i with a small number Δ_α for company i that orders the most trucks per period on average. This will induce the largest increase in $\sum_{i\in\mathcal{N}} C_i(\alpha_i)$, resulting in a tighter lower bound. Therefore, we propose the following method for allocating the major order cost. We start with $\alpha_i = 0$, $\forall i \in \mathcal{N}$, and calculate the optimal dual-mode ordering policy for each company i individually using a binary search method (similar to Section 4.2). Next, we derive the steady state distribution (i.e., the probability of being in a particular state, following a certain policy) of the optimal MST policy for each company. Then, the company i with the largest probability mass of steady state probabilities in which a truck order is placed (i.e., at or below its respective reorder level) is identified, its α_i

is increased slightly by adding Δ_α, and its optimal MST policy is recalculated. Increasing the allocated fixed truck transportation cost reduces the number of trucks ordered. Therefore, we again identify company i that orders most trucks per period, increase its α_i with Δ_α, and recalculate its optimal MST policy. We repeat this procedure until $\sum_{i \in \mathcal{N}} \alpha_i = 1$.

We note that the choice of Δ_α determines the strength of the lower bound: a low Δ_α yields a tighter lower bound. This comes at the cost of a higher computation time, however, as a new policy is calculated $1/\Delta_\alpha$ times to obtain the lower bound. We numerically tested the effect of Δ_α on the strength of the lower bound, and found decreasing marginal gains by reducing Δ_α. In our numerical experiments, starting from $\Delta_\alpha = 0.3$, reducing Δ_α only yielded negligible improvement.

5.2. Validation of the lower bound and the joint TBS policy

We set up a numerical experiment to compare the joint TBS policy against our lower bound. A tighter gap indicates both a good performance of our policy, as well as a tight lower bound to the optimal policy. We consider 27 four-company settings with varying demands, and consider different values of p, k, K, and $\tilde{K}$ (see Table 2). The pair (k, K) is set to (3,33), (5,30), and (5,15) in different settings, reflecting a ratio $k/(K-k)$ of 0.10, 0.25, and 0.50, similar to the numerical experiment in Federgruen et al. (1984). The major train transportation cost $\tilde{K}$ is set to represent a ratio $\tilde{K}/K$ of approximately 0.25, 0.50, and 0.75. The holding cost h is equal to 1 in every setting. To reflect different service levels, the shortage cost p is set to 2, 5, and 10. In all settings, different companies have their own Poisson demand rates $\lambda_i = \{2, 3, 4, 5\}$ to reflect different sized companies. Lastly, we assume that the number of periods between two train runs is set to $T = 3$ in all settings.

For each of these 27 instances, we find that the relative difference in cost performance between the joint TBS policy and our lower bound, calculated with $\Delta_\alpha = 0.01$, is around 10%. These cost differences have the same order of magnitude as the cost differences between the can-order policy[2] and the optimal lower bound for the single-mode JRP, proposed by Viswanathan (2007). This validates our joint TBS policy and parameter optimization.

[2]We considered both the periodic review can-order and the $P(s, S)$ policy. Although they have comparable performance (with a difference of no more than 3% over all instances), the can-order policy outperformed the $P(s, S)$ policy in all settings considered, and is therefore used to report performance gaps. The can-order policy was calculated by decomposing the problem per company, and by optimizing the subproblem using full enumeration while evaluating the global problem using simulation. This was repeated for each company until no improvement in policy performance was found. The $P(s, S)$ policy was calculated by choosing a replenishment interval τ from the set $\mathcal{T} = \{1, 2, ..\}$, and optimizing s_i and S_i for each company $i \in \mathcal{N}$ given τ using the algorithm of Zheng and Federgruen (1991). Starting from $\tau = 1$, the replenishment interval was increased until no improvement in policy performance was found.

Setting	p	k	K	$\tilde{K}$	Cost performance gap joint TBS policy with our lower bound	 can-order policy with optimal lower bound
1	2	3	33	8	12.9080 %	**8.2503 %**
2	2	3	33	17	11.6073 %	**8.2503 %**
3	2	3	33	25	10.713 %	**8.2503 %**
4	2	5	30	8	10.5730 %	**7.8938 %**
5	2	5	30	15	9.8086 %	**7.8938 %**
6	2	5	30	23	9.0970 %	**7.8938 %**
7	2	5	15	4	8.3474 %	**8.1631 %**
8	2	5	15	8	**7.9744 %**	8.1631 %
9	2	5	15	11	**7.6961 %**	8.1631 %
10	5	3	33	8	13.9990 %	**10.8194 %**
11	5	3	33	17	12.8302 %	**10.8194 %**
12	5	3	33	25	11.9170 %	**10.8194 %**
13	5	5	30	8	11.7436 %	**10.6238 %**
14	5	5	30	15	10.7699 %	**10.6238 %**
15	5	5	30	23	**10.0990 %**	10.6238 %
16	5	5	15	4	**8.8467 %**	8.9839 %
17	5	5	15	8	**8.4964 %**	8.9839 %
18	5	5	15	11	**8.2519 %**	8.9839 %
19	10	3	33	8	13.862 %	**11.8951 %**
20	10	3	33	17	12.8300 %	**11.8951 %**
21	10	3	33	25	12.0345 %	**11.8951 %**
22	10	5	30	8	**11.4988 %**	11.7094 %
23	10	5	30	15	**10.8490 %**	11.7094 %
24	10	5	30	23	**10.2049 %**	11.7094 %
25	10	5	15	4	**8.7065 %**	9.3490 %
26	10	5	15	8	**8.3693 %**	9.3490 %
27	10	5	15	11	**8.1591 %**	9.3490 %

Table 2: A numerical experiment with 27 settings is set up in which $h = 1$, $\lambda_i = \{2, 3, 4, 5\}$, and $T = 3$ in all settings. The experiment reveals that the cost performance gap between the joint TBS policy and the lower bound on the optimal dual-mode JRP policy is around 10%. This is in line with the gap between the can-order policy and the optimal lower bound in a single-mode JRP setting, developed by Viswanathan (2007). The boldface indicates the lowest of the two.

6. Numerical analysis of proactive consolidation and modal split transport

Now that we have introduced (and validated) a heuristic policy to combine proactive freight consolidation and modal split transport, we can numerically analyze their impact on the use of truck transport (i.e., how often a truck is ordered and how much volume is put on trucks), as well as on total transportation costs. To do so, we compare the different replenishment strategies outlined in Table 1, that is, (1) only truck transport and reactive freight consolidation; (2) only truck transport with proactive freight consolidation; (3) modal split transport with reactive consolidation; and (4) modal split transport with proactive consolidation. For truck transport only with reactive consolidation, we optimize the periodic (s, S) policy of each company individually using the algorithm of Zheng and Federgruen (1991). If multiple companies place an order by truck in the same period, the truck transport is shared, and the fixed order cost K is only incurred once. For truck transport with proactive bundling, we optimize a periodic review can-order policy (see footnote 2 for the description on its optimization in Section 5.2). For MST and reactive consolidation, we optimize

Replenishment strategy	Average number of orders by truck per period	Average number of units per order by truck	Average number of units per order by train
Truck only & Reactive Consolidation	0.6059	23.2902	0
Truck only & Proactive Consolidation	0.4044	35.2962	0
MST & Reactive Consolidation	0.2231	9.7110	35.7778
MST & Proactive Consolidation	0.2145	14.6132	33.0000

Table 3: The average number of orders by truck per period, the average number of units per order by truck, and the average number of units per order by train over all 27 settings (see Table 2) for each of the four replenishment strategies (see Table 1). We observe that both MST and proactive consolidation reduce truck usage. Whereas the former shifts more freight towards rail transport, the latter ships more volume per truck order.

the modal split for each company individually using the approach of Dong and Transchel (2020). Orders placed by truck or train in the same period are consolidated, such that their fixed order cost is incurred only once. For MST and proactive consolidation, we optimize the joint TBS policy using the procedure outlined in Section 4. The optimized policies are evaluated by simulating 10 times a horizon of 1 million periods, and using a warm-up of 10,000 periods.

Table 3 reports the average number of (joint) orders by truck per period, the average number of units per order by truck, and the average number of units per order by train following each of the four replenishment strategies for the 27 numerical settings outlined in Table 2. Compared to only using trucks with reactive consolidation (the currently most adopted practice by LSPs), we observe how proactive consolidation, MST, or a combination of both reduces the number of orders placed by truck. Proactive consolidation using only trucks achieves this through increased freight consolidation, as can be seen by the higher volume ordered by truck. It is noteworthy to observe the lower volumes ordered per truck under both MST strategies. In those cases, a "base" volume is shipped per train, and truck transport is only used to cover the remaining "surge" demand. Interestingly, the volumes shipped per order by rail are in general higher under reactive consolidation than under proactive consolidation. This is due to the fact that truck transport is relatively cheaper under proactive consolidation because it shares the fixed transportation cost more often. This entails that, under MST, more volume is shipped via truck when collaborating proactively compared to reactively, meaning that proactive consolidation stimulates higher truck loads under MST. Lastly, we note that the average number of trucks shipped per period does not differ much between reactive and proactive consolidation using MST. Yet, proactive consolidation using MST manages to reduce the truck intensity slightly when compared to reactive consolidation using MST.

To visually compare the order processes between the four replenishment strategies, we provide an excerpt of 100 periods (i.e., the first 100 periods following the 10,000 warm-up periods) in the

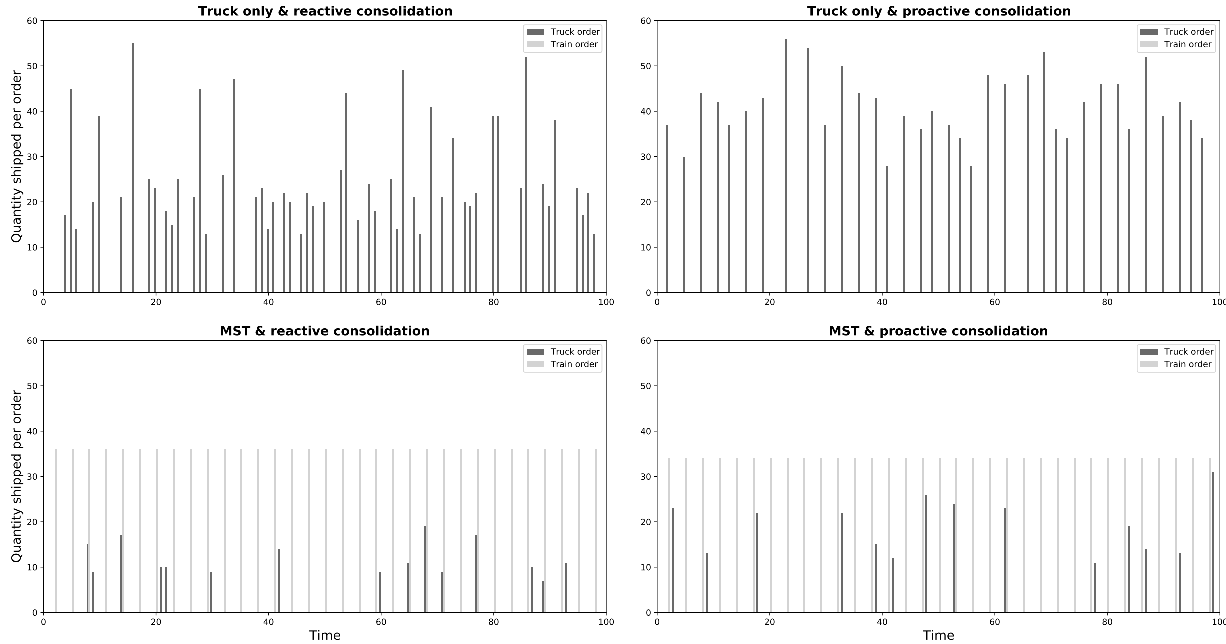

Figure 2: Excerpt of 100 simulation periods (the first 100 periods following the 10,000 warm-up periods) of the order process related to each of the four replenishment strategies defined in Table 1, for numerical setting 1 (see Table 2). In each subplot, the x-axis represents the time and the y-axis represents the order quantity on a specific transport mode. Dark and light grey bars represent orders via truck and train respectively. We can visually observe the decrease in truck usage due to proactive consolidation and modal split transport.

simulation experiment of setting 1 (see Table 2) in Figure 2. The x- and y-axis represent time and volume shipped by a specific transport mode, respectively. The dark and light gray bars represent orders shipped per truck and train, respectively. We can visually confirm the decrease in number of trucks when bundling proactively or using MST, compared to reactive consolidation using trucks only. Furthermore, we verify the increase in quantities shipped per truck when shifting from reactive to proactive consolidation. Lastly, we observe that, when using only trucks, the variance in order sizes is larger when bundling reactively, compared to proactive consolidation. Analyzing the other experiments, we observe that this is the case in 21 out of 27 settings. This could have benefits in practice as the prospect of more stable orders may allow carriers to organize their operations more efficiently.

We note that the reduction in truck usage under MST will entail a large reduction in GHG emissions. It is estimated that rail freight transportation emits on average 82% less gCO_2 per tonne-kilometer, well-to-wheel, compared to transportation via heavy goods vehicles (European Environment Agency, 2022). The question remains whether this strong reduction in GHG emissions is also cost efficient.

					Gains compared to reactive consolidation using trucks only		
Setting	p	k	K	$\tilde{K}$	Truck only & proactive consolidation	MST & reactive consolidation	MST & proactive consolidation
1	2	3	33	8	29.4480% (± 0.0890%)	26.7206% (± 0.1435%)	**32.6750%** (± 0.1585%)
2	2	3	33	17	**29.4480%** (± 0.0890%)	20.2427% (± 0.1581%)	26.2565% (± 0.1073%)
3	2	3	33	25	**29.4480%** (± 0.0890%)	14.5425% (± 0.1397%)	20.5036% (± 0.0834%)
4	2	5	30	8	25.3737% (± 0.0910%)	20.3239% (± 0.1266%)	**25.4715%** (± 0.1324%)
5	2	5	30	15	**25.3737%** (± 0.0910%)	15.2513% (± 0.1193%)	20.4114% (± 0.1272%)
6	2	5	30	23	**25.3737%** (± 0.0910%)	9.4423% (± 0.1224%)	14.5967% (± 0.1010%)
7	2	5	15	4	**15.8646%** (± 0.0737%)	9.4628% (± 0.0935%)	13.8949% (± 0.0783%)
8	2	5	15	8	**15.8646%** (± 0.0737%)	5.6442% (± 0.0822%)	10.0614% (± 0.0665%)
9	2	5	15	11	**15.8646%** (± 0.0737%)	2.7455% (± 0.1116%)	7.2037% (± 0.0768%)
10	5	3	33	8	25.3669% (± 0.1140%)	23.6900% (± 0.1266%)	**29.0555%** (± 0.1207%)
11	5	3	33	17	**25.3669%** (± 0.1140%)	18.0399% (± 0.0922%)	23.3816% (± 0.1096%)
12	5	3	33	25	**25.3669%** (± 0.1140%)	12.9612% (± 0.0916%)	18.3577% (± 0.1195%)
13	5	5	30	8	21.5248% (± 0.1058%)	18.2871% (± 0.1391%)	**23.0223%** (± 0.1007%)
14	5	5	30	15	**21.5248%** (± 0.1058%)	13.8467% (± 0.0739%)	18.5876% (± 0.1050%)
15	5	5	30	23	**21.5248%** (± 0.1058%)	8.7733% (± 0.0807%)	13.4910% (± 0.0737%)
16	5	5	15	4	**13.3146%** (± 0.0610%)	8.7338% (± 0.0740%)	12.2453% (± 0.0842%)
17	5	5	15	8	**13.3146%** (± 0.0610%)	5.4053% (± 0.0928%)	8.9525% (± 0.0765%)
18	5	5	15	11	**13.3146%** (± 0.0610%)	2.9736% (± 0.1242%)	6.4823% (0.0705%)
19	10	3	33	8	22.3624% (± 0.1330%)	21.9332% (± 0.1673%)	**26.6710%** (± 0.1550%)
20	10	3	33	17	**22.3624%** (± 0.1330%)	16.5974% (± 0.1157%)	21.3621% (± 0.1089%)
21	10	3	33	25	**22.3624%** (± 0.1330%)	11.9165% (± 0.1390%)	16.6439% (± 0.1223%)
22	10	5	30	8	18.7435% (± 0.1080%)	16.9544% (± 0.0986%)	**21.0087%** (± 0.1160%)
23	10	5	30	15	**18.7435%** (± 0.1080%)	12.8128% (± 0.1098%)	16.8759% (± 0.1095%)
24	10	5	30	23	**18.7435%** (± 0.1080%)	8.0830% (± 0.1005%)	12.1400% (± 0.0810%)
25	10	5	15	4	**11.5362%** (± 0.0788%)	8.0124% (± 0.0912%)	11.0083% (± 0.0727%)
26	10	5	15	8	**11.5362%** (± 0.0788%)	4.9702% (± 0.0882%)	8.0063% (± 0.0996%)
27	10	5	15	11	**11.5362%** (± 0.0788%)	2.6990% (± 0.0956%)	5.7310% (± 0.1048%)
Average					20.3927%	12.6320%	17.1888%

Table 4: Gains of different replenishment strategies compared to reactive consolidation using trucks only in 27 numerical settings in which $h = 1$, $\lambda_i = \{2, 3, 4, 5\}$, and $T = 3$ in all settings. Gains are calculated as the relative difference between the long run average cost per period of reactive consolidation using trucks only, and the other replenishment strategies, respectively. The figures in bold represent the highest gains in each setting. 95% confidence intervals are added between brackets. We can observe the gains that proactive consolidation, modal split transport, or a combination of both has on the cost performance. While proactive consolidation using only trucks is the cheapest in most settings, cost-efficient modal split policies can be found by using proactive consolidation, if the train transportation cost is sufficiently low.

Table 4 reports the relative cost difference of all companies under the different replenishment strategies compared to the situation without proactive consolidation and without MST in each of the 27 numerical settings. For a complete picture, 95% confidence intervals are also provided, even though they are very narrow due to the long simulation runtimes. The numbers in bold represent the highest gains in each of the settings.

We observe that combining MST and proactive consolidation decreases costs on average by 17.19% compared to reactive consolidation using only trucks. Proactive consolidation seems to be important to make multi-modal ordering policies more cost-efficient. MST policies with reactive consolidation only save on average 12.63% compared to reactive consolidation using only trucks. We observe that proactive consolidation using trucks only is often the best strategy in terms of costs, reporting an average gain of 20.39% compared to reactive consolidation using only trucks. Still, if the train transportation cost is sufficiently low (e.g., $\tilde{K}/K = 0.25$), cost-competitive MST policies can be found by consolidating proactively.

A deeper analysis into the drivers of the cost efficiency of proactive consolidation and MST reveals more gains of proactive consolidation for higher values of the major trucking order cost K compared to the minor order cost k, and lower values of the shortage cost p (lower target service levels). The gains of MST strongly depend on the ratio between the rail and truck transport cost $\tilde{K}/K$: if rail transport is cheap compared to truck transport, the gains of MST are high. Yet, even in settings with low $\tilde{K}/K$, proactive consolidation is needed to make MST policies cost-competitive. It thus seems that proactive consolidation can be key to further induce a modal shift to decarbonize logistics in a cost-efficient manner.

7. Conclusion

In this paper we analyze the potential of proactive freight consolidation and modal split transport to reduce the dominant usage of (polluting) truck transport. Whereas the former reduces truck intensity by synchronizing orders of collaborating companies, thereby increasing the number of consolidation opportunities, the latter reduces the use of trucks by shipping more freight via alternative transport modes, such as rail transport. Proactive consolidation and MST can be facilitated by respectively joint replenishment and dual sourcing policies. To combine proactive consolidation with MST, we propose a heuristic policy that combines a tailored base-surge (dual sourcing) policy and a can-order (joint replenishment) policy. To optimize our policy, we develop a heuristic algorithm that decomposes the problem per company and solves the single-company problems sequentially until convergence. To validate our policy (optimization), we derive a lower bound on the optimal policy and present a gap of around 10% in several numerical settings. This is in line with other well-performing joint replenishment policies reported in a single-mode setting.

A numerical experiment reveals how proactive freight consolidation and MST impact truck usage and cost performance. By combining MST with proactive consolidation, we can obtain a further reduction in truck usage compared to traditional groupage, without negatively impacting total costs. Demonstrating how a modal shift can positively impact costs, may induce a "mental shift" towards collaborative, multi-modal supply chains. Especially taking into account increasing truck transport prices, and an increasing governmental pressure towards alternative transport modes, (collaborative) multi-modal transportation becomes a viable alternative compared to traditional trucking. Still, there are some issues to be resolved to allow for better collaboration which in turn can lead to profitable multi-modality, such as anti-trust compliance, adequate gain and cost sharing mechanisms, and the need for a neutral orchestrator.

Our model could be further extended by adding capacity constraints on both transport modes. Although our current insights will continue to hold, it could lead to an explicit additional quantification of the load factors of both trucks and trains. Likewise, the stringent assumption of fixed order quantities by rail imposed per company could be relaxed in favor of a fixed order quantity over all companies. That way, the collaborating companies decide on a total rail quantity and allocate this among each other depending on their inventory position. This could entail a pooling effect that may further promote a modal shift. The resulting problem, however, requires the optimal allocation of rail capacity for each possible combination of companies' inventory levels, in addition to determining the total rail capacity reserved for the collaborating companies. This is a new project on its own, subject for future research.

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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

Data will be made available on request.

Appendix A. Overview of the notation used

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MST	Modal Split Transport
JRP	Joint Replenishment Problem
TBS	Tailored Base-Surge
$\mathcal{N}$	Set of collaborating companies
N	Number of collaborating companies
T	Number of periods between two consecutive train runs
t	Current period
K	Fixed (major) transport cost to ship an order by truck
$\tilde{K}$	Fixed (major) transport cost to ship an order by train
k_i	Fixed (minor) transport cost when company i ships an order
λ_i	Poisson demand rate for company i
h	Holding cost per unit in inventory, per period
p	Shortage cost per unit backlog, per period
Q_i	Volume that company i ships per train every T periods
θ_t	Number of periods until the next train arrives at time t
s_i^θ	Reorder point of company i if a train arrives in θ periods
c_i^θ	Can-order level of company i if a train arrives in θ periods
S_i^θ	Order-up-to level of company i if a train arrives in θ periods
y_t	Inventory position of a company at time t
ϕ_t	1 if there is a discount replenishment opportunity at time t, 0 otherwise
μ_i^θ	Probability that a discount replenishment arises occurs for company i when a train arrives in θ periods
β_i^θ	Fraction of time at which company i initiates an order in a state in which a train arrives in θ periods
α_i	Portion of the fixed truck transport cost that is allocated to company i
$C_i(\alpha_i)$	Long-run average cost per period of the optimal policy for the single-company problem with a fixed order cost $\alpha_i K + k_i$
Δ_α	Step size used to allocate the fixed transportation cost
τ	Replenishment interval of the $P(s, S)$ policy
$\mathcal{T}$	Set of possible replenishment intervals of the $P(s, S)$ policy

Table A.5: Overview of the notation and abbreviations used in this paper, in order of appearance.

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