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Service Level, Financial and Environmental Optimization of Collaborative Transportation

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Abstract. Less than truckload (LTL) is an important type of road-based transportation. By collaborating with several LTL Canadian shippers and carriers shipping to the United States, we propose new mechanisms that can be readily implemented in order to improve their financial performance while being significantly more sustainable in terms of their transportation activities. By sharing information and capacity about origins and destinations, one can benefit from consolidation opportunities given by the open and interconnected economy. We show that a collaborative approach between several shipping companies offers important potential benefits. We propose the use of an LTL hub whose role is to develop partnerships with other companies and synchronize shipments to common customer locations. Because different objectives are intertwined, we developed three operational collaborative schemes with different optimization objectives. The first one focuses on shipping and timing costs. The second one is only based on minimizing the distance traveled. The third one is based on a more comprehensive function of shipping and timing costs and distance traveled. The results of our computational experiments demonstrate that collaboration can lead to significant cost reductions and distance savings, without deteriorating the service level.

Keywords. Collaborative transportation, routing, environment, optimization, less than truckload, logistics.

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1 Introduction

Road transportation of freight plays a central role in modern manufacturing industries. In many cases, trucking continue to be the dominant mode of transportation even across borders, such as the case of Canada and the United States. In 2014, 44.4% ($179 billion) of exports and 69.1% ($192 billion) of imports were transported by trucks between Canada and the United States, representing 54.5% of overall trade between these two countries, and 42.7% of all Canadian trade [22].

Road transportation can be split in two types of shipping: truckload (TL) and less than truckload (LTL). TL shipping is the most advantageous option in terms of cost and service quality. It consists of a fully or partially loaded truck going to a single destination at a fixed price [21]. TL shipping does not require multiple pickups and deliveries compared to LTL. TL freight is also priced significantly lower per unit. On the other hand, LTL shipping is appropriate for the shippers who do not have a big cargo and do not want to pay the entire truck cost [17]. Since it needs more loading and unloading operations and often a visit to a consolidation center, LTL transportation can be slower and more costly per unit.

There are three common ways for carriers to charge for LTL shipments. Depending on their specializations, their activity areas (types of products transported) and their partnerships with clients, they can use *weight* pricing, *pallet position* pricing or *linear feet* pricing. An LTL pricing grid essentially presents the price charged to travel from the distribution center to a given location (one single delivery) depending on the quantity (expressed in weight, pallets or linear feet) and the type of product shipped. Typically, the marginal delivery cost decreases as the number of units in the shipment increases.

LTL pricing grids advantage carriers because there are no financial benefits for shippers to manage and synchronize more effectively their expeditions throughout several destinations. Even if they dispatch to close destinations, they are generally charged separately. Some carriers accept as one single shipping (at a better rate) two different loads for destinations which are close together. This is called multi-drop LTL and associated rates are generally negotiated through special contracts. In this case, carriers may charge a fee for each additional drop. Hence, multi-drop LTL decreases costs and the number of non-synchronized movements that cause significant economic and environmental losses. Unfortunately, this option is not frequently used by freight shippers and carriers.

This paper is positioned within the field of collaborative transportation management, which includes shippers and carriers collaboration. They are often considered independently due to their perspectives and benefits for each side. Carrier collaboration seems to be more studied in the literature [24]. [5] assess the potential benefit of this horizontal cooperation between carriers in a large empirical study in Europe. The objective is the minimization of total transportation costs based on distance [7] and it is often formulated as a pickup and delivery problem with time-windows [20, 4, 13]. Since there are several carriers serving a set of shippers, there will be a global profit from sharing their infrastructure and maximizing vehicle loading [14]. [1] study carrier alliances in the liner shipping and determine side payments that align decisions of carriers within the coalition. [3] and [23] present a carrier collaboration in which requests are optimally shared. [15] study a problem in which a TL carrier receives requests from shippers and decides upon using his vehicles or outsourcing the request. [25] consider a carrier collaboration network with multiple LTL carriers and vehicle types in the e-commerce logistics system.

Shipper collaboration, on the other hand, considers only a single carrier and focuses on finding optimal routing decisions for different shippers, minimizing the distance [9]. Shippers may benefit by establishing a private community in which they share information [12]. These benefits come from the ability to use advanced information on available capacity to better use the spot market. There are two main variants of this problem. The first one arises with large-scale shippers having enough volume to fill a truck and collaborating with other shippers to guarantee back-hauls for the carrier [24]. Since the price paid includes all the implicit truck-repositioning costs such as returning to its distribution center (potentially empty), the shipper can negotiate significant discounts by guaranteeing that the carrier will have back-haul cargo [8]. The second variant arises with shippers making occasional small shipments who collaborate with other shippers by consolidating their cargo to share a single line-haul in order to pay a price closer to that of a TL. To obtain savings, the origin and destination of shipments must be reasonably close. This is the context in which this paper is positioned. Ergun et al. [8, 9] address a shipper collaboration problem in which fixed schedules are used to reduce dead-hauling cost by making repeatable continuous movements. Frisk et al. [10] study the collaboration among eight lumber shippers in forest transportation to obtain one-way TL shipments. [12] study three types of collaborative transportation: when only shippers collaborate, only carriers collaborate, and both shippers and carriers collaborate. The collaborative networks are assumed to operate as a spot market. The utilization of transportation hubs with collaboration is studied in [11] in which several shippers use a network of transportation hubs in many-to-many markets.

In the LTL context, Audy et al. [2] present a case study of four Canadian furniture manufacturers. The authors design a cost-allocation scheme and provide a sensitivity analysis on the savings needed to convince manufacturers for joining the coalition. Cruijssen et al. [6] study the case of Dutch groceries in which shipper collaboration is facilitated by a logistics service provider. Consolidation of orders results in savings due to more efficient routes. [26] compare two levels of collaboration in a market characterized by randomly arriving loads with delivery deadlines. Consolidation levels are determined through simulation. [24] address the coalition formation among small shippers in a transportation market characterized by uncertain demands using a game theoretical approach. They show that shippers always benefit from the collaboration.

Most of the existing literature focuses on gains or cost sharing among partners, and some on distance minimization. We take a more encompassing approach, assessing not only costs or distances, but also service levels in the sense that we evaluate transportation operations and departure timing as well. Moreover, our analyses allow us to provide important insights on greenhouse gas (GHS) emissions. To the best of our knowledge, this study is the first of its kind to propose the use of a centralized distribution center (hub) to satisfy shipping requests.

We have partnered with three Canadian companies from the province of Québec operating in the same industrial park and having many LTL shipments to the United States. Based on this collaboration, we propose the use of a hub for shippers to improve their financial performance and their sustainable activities when distributing their products, without deteriorating service levels. This will be achieved by developing partnerships with other companies who share common client locations and by synchronizing their shipments. This also allows decreasing traffic in the industrial park for picking up freight. The main contributions of this paper are then twofold. First, we present different collaborative schemes to consolidate compatible shipments from different partners in order to benefit from cost savings. Our second contribution is to evaluate GHS emission reduction resulting from this partnership.

The remainder of the paper is organized as follows. In Section 2 we formally describe the problem and define its particularities. Section 3 presents three collaborative scheme with shipper collaboration. It also introduces three mathematical models considering a set of given optimization decisions and parameters. Section 4 presents a branch-and-cut algorithm and an adaptive large neighborhood search developed and adapted to solve all three scenarios. Computational experiments are detailed in Section 5, and our conclusions follow in Section 6.

2 Problem description

Whether in a cooperative environment between shippers and carriers or not, the problem remains to optimally plan the pickups schedule for a set of transportation requests. The consolidation of LTL shipments is defined on a directed graph $G = (\mathcal{V}, \mathcal{A})$ such that $\mathcal{V} = \{0, \ldots, n\}$ is the set of nodes, $\mathcal{A} = \{(i, j) : i, j \in \mathcal{V}\}$ is the set of arcs between nodes. Node 0 is the depot of the carrier. A cost (distance) c_{ij} for each arc (i, j) is determined.

A planning horizon $\mathcal{T} = \{1, \ldots, H\}$ is given, expressed in days. A set of homogeneous vehicles $\mathcal{K} = \{1, \ldots, m\}$ is available with a capacity $\mathcal{Q}$ expressed in linear feet. Each node $i = \{1, \ldots, n\}$ represents a transportation request with a demand of q_i units at time r_i, such that $1 \leq r_i \leq H$. Without loss of generality, we use the number of pallets as the demand unit, knowing that a pallet has a 4x4 feet dimension. A transportation request has to be entirely satisfied in one pickup and in a time window $[r_i^-, r_i^+]$ such that $r_i^- < r_i < r_i^+$. For each order i, we define a non-negative parameter δ_i^t for $t \neq r_i$ which imposes a penalty if order i is not picked up at r_i. As each node represents a distinct order, many nodes could have the same origin, meaning that a customer can have an independent demand for each period in $\mathcal{T}$. We define the customer set without the depot as $\mathcal{V}' = \mathcal{V} \backslash \{0\}$.

The cost structure is in linear feet up to the capacity of the vehicle, say, $\mathcal{Q} = 53$ feet. Demand is expressed in 4x4 feet pallets that could be arranged side-by-side. Thus, one or two pallets require 4 feet, three and four pallets require 8 feet and so on. For $q \leq 26$ pallets, the number of feet required in the truck is $4\lceil \frac{q}{2} \rceil$ and there are in fact only 13 usable sections in a 53 feet truck. We denote $l \in \mathcal{L}$ all possible price interval numbers associated to the number of used sections. For all intervals $l \in \mathcal{L}$, we define a specific shipping cost α_l.

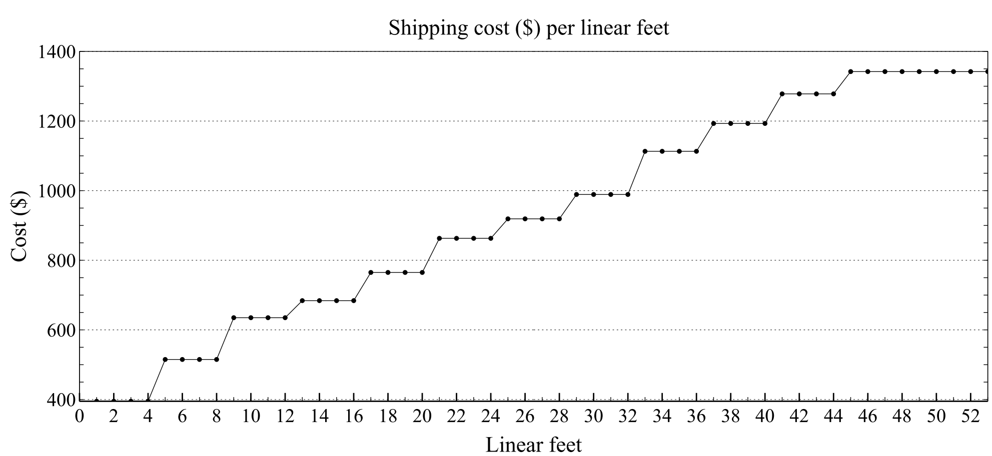

Figure 1: Shipping cost as a function of the number of linear feet used for a given destination

Carriers have their own shipping cost functions depending on the destination and the number of used linear feet. For almost all U.S. destinations, these functions have similar shape but different heights for each state. Figure 1 shows a generic shipping function used in our research, obtained from our partners for a given destination, starting from Quebec City. We see an increasing staircase form where the steps correspond to each used section in the vehicle (the price of $l = 12$ is the same of $l = 13$). The price of using 1, 2 or 3 feet is the same as using 4 linear feet in the truck as only 4x4 feet pallets are considered. After 45 linear feet, the price is constant, as the shipment is considered as a TL.

3 Collaborative schemes models

To model a collaborative scheme, we develop a mathematical framework that optimizes three different objectives, or criteria, in order to evaluate the quality of a collaborative transportation solution:

1. the total shipment cost,
2. the total cost of delayed/advanced requests (timing cost), and
3. the total distance for a carrier to pick up all requests.

The travelled distance is computed in order to evaluate the sustainable impact in terms of greenhouse gas emissions. Each function aims at minimizing a criterion, or a combination of criteria. We name these collaborative schemes CS1, CS2 and CS3. With collaboration and consolidation, all shippers will be visited by the same carrier in order to reduce their total shipping costs and improve their sustainability by reducing truck flows.

Collaborative scheme CS1: This first collaborative scheme focuses on timing and shipping costs, ignoring the total distance to cover all requests. The model will determine the best combination of requests per route and period. We then apply a TSP algorithm in order to find the best route for each used vehicle.

We define binary variables y_i^{kt} equal to 1 if request i is assigned to vehicle k in period t, zero otherwise. Variables y_i^{kt} and associated penalties δ_i^t are defined only for $t \in [r_i^-, r_i^+]$. In order to simplify the formulation, let $\mathcal{T}_i = [r_i^-, r_i^+]$ be the set of all possible periods to pickup request i. We define integer variables p_k^t indicating the number of pairs of pallets assigned to vehicle k in period t. Finally, we define binary variables z_l^{kt} equal to 1 if the price interval l is associated to trip k, 0 otherwise. Model for CS1 is the following:

$$\text{(CS1)} \min \sum_{i\in\mathcal{V}'}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}_i} \delta_i^t y_i^{kt} + \sum_{l\in\mathcal{L}}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}} \alpha_l z_l^{kt} \tag{1}$$

subject to:

$$\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}_i} y_i^{kt} = 1 \quad \forall i \in \mathcal{V}', \tag{2}$$

$$p_k^t \geq \sum_{i\in\mathcal{V}'|t\in\mathcal{T}_i} \frac{q_i y_i^{kt}}{2} \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, \tag{3}$$

$$\sum_{l\in\mathcal{L}} l z_l^{kt} = p_k^t \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, \tag{4}$$

$$z_l^{kt} \in \{0,1\} \quad \forall l \in \mathcal{L}, t \in \mathcal{T}, k \in \mathcal{K}, \tag{5}$$

$$y_i^{kt} \in \{0,1\} \quad \forall i \in \mathcal{V}', t \in \mathcal{T}_i, k \in \mathcal{K}, \tag{6}$$

$$p_k^t \geq 0 \textit{ and integer} \quad \forall t \in \mathcal{T}, k \in \mathcal{K}. \tag{7}$$

The objective function (1) minimizes the total timing and shipping cost. Constraints (2) force all nodes to be visited exactly once. Constraints (3) compute the total number of side-by-side pallets in the vehicle and set variables p_k^t accordingly. The summation is over the quantities q_i that can be shipped within periods $[r_i^-, r_i^+]$. Constraints (4) use the pair of pallets number to compute the number of used linear feet and set the price interval. Constraints (5), (6) and (7) define the nature of variables.

It is possible to strengthen constraints (3) by giving a valid upper bound to p_k^t:

$$p_k^t \leq \sum_{i\in\mathcal{V}'|t\in\mathcal{T}_i} \frac{q_i y_i^{kt}}{2} + 1 \quad \forall t \in \mathcal{T}, k \in \mathcal{K}. \tag{8}$$

Without this valid upper bound on the variable, all solutions with an integer value greater than the upper bound become non-optimal feasible solutions.

In addition, this mathematical formulation presents some symmetry problems. There are many identical solutions with different vehicle assignments. This can adversely affect the computational performance. To break the symmetry of vehicles, we add constraints (9) to force the model to use vehicles with lower indices first.

$$y_i^{(k-1)t} \geq y_i^{kt} \quad \forall i \in \mathcal{V}', t \in \mathcal{T}_i, k \in \mathcal{K}\backslash\{1\}. \tag{9}$$

Collaborative scheme CS2: In the second collaborative scheme, we only minimize the total distance travelled to visit all shippers. Knowing the minimum distance will enable the analysis of the impact of the delay or advancement and shipping cost from the other schemes.

The formulation for CS2 is a multi-period VRP. It minimizes the distance to visit all nodes and pick up all shipments. This formulation neglects the timing and the shipping costs that will be computed a posteriori. We define binary variables x_{ij}^{kt} equal to 1 if arc $(i, j) \in \mathcal{A}$ is used by the vehicle k in period $t \in \mathcal{T}_i \cap \mathcal{T}_j$, zero otherwise. Model CS2 is defined as follows:

$$\text{(CS2)} \ \min \sum_{(i,j)\in\mathcal{A}} c_{ij} \sum_{k\in\mathcal{K}} \sum_{t\in\mathcal{T}_i\cap\mathcal{T}_j} x_{ij}^{kt} \tag{10}$$

subject to (2), (6), (9), and to:

$$\sum_{j\in\mathcal{V}} x_{ij}^{kt} = \sum_{j\in\mathcal{V}} x_{ji}^{kt} \quad \forall i \in \mathcal{V}', t \in \mathcal{T}_i \cap \mathcal{T}_i, k \in \mathcal{K}, \tag{11}$$

$$\sum_{j\in\mathcal{V}'|t\in\mathcal{T}_j} x_{0j}^{kt} \leq 1 \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, \tag{12}$$

$$\sum_{i\in\mathcal{V}'|t\in\mathcal{T}_i} x_{i0}^{kt} \leq 1 \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, \tag{13}$$

$$\sum_{i\in\mathcal{V}|t\in\mathcal{T}_i} x_{ij}^{kt} = y_j^{kt} \quad \forall j \in \mathcal{V}', t \in \mathcal{T}_j, k \in \mathcal{K}, \tag{14}$$

$$\sum_{i \in S} \sum_{j \in S} x_{ij}^{kt} \leq |S| - r(S) \quad \forall S \subseteq \mathcal{V}', |S| > 2, t \in \mathcal{T}_i \cap \mathcal{T}_j, k \in \mathcal{K}, \tag{15}$$

$$x_{ij}^{kt} \in \{0, 1\} \quad \forall i, j \in \mathcal{V} : i \neq j, t \in \mathcal{T}_i \cap \mathcal{T}_j, k \in \mathcal{K}. \tag{16}$$

The objective function (10) minimizes the total distance to visit all shippers. Constraints (11) maintain the flow equilibrium at each node. Constraints (12) and (13) impose at most one trip per vehicle per day. Constraints (14) makes the link between routing variables x_{ij}^{kt} and visiting variables y_j^{kt}. Constraints (15) are the rounded-up capacity inequalities which eliminate all subtour possibilities and ensure that the capacity of the vehicle is respected. The capacity check is made with the function $r(S) = \left\lceil \frac{2 \sum_{j \in S} q_j}{Q} \right\rceil$. These constraints are added dynamically through a branch-and-cut framework. Constraints (16) define the nature of variables.

Collaborative scheme CS3: The third collaborative scheme combines all aspects: distance, timing and shipping costs. The model for CS3 is the combination of those of CS1 and CS2. We keep all the routing formulation and we add to it the shipping variables z_l^{kt} and p_k^t and their corresponding constraints. The objective function becomes:

$$\text{(CS3) min} \sum_{(i,j) \in \mathcal{A}} c_{ij} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}_i \cap \mathcal{T}_j} x_{ij}^{kt} + \sum_{i \in \mathcal{V}'} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}_i} \delta_i^t y_i^{kt} + \sum_{l \in \mathcal{L}} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \alpha_l z_l^{kt} \tag{17}$$

Subject to (2)–(9) and (11)–(16).

Table 1 summarizes the objectives of each collaborative scheme model.

Table 1: Objective function per collaborative scheme

Costs	Distance $\sum_{(i,j) \in \mathcal{A}} c_{ij} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}_i \cap \mathcal{T}_j} x_{ij}^{kt}$	Timing penalty $\sum_{i \in \mathcal{V}'} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}_i} \delta_i^t y_i^{kt}$	Shipping $\sum_{l \in \mathcal{L}} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \alpha_l z_l^{kt}$
CS1		✓	✓
CS2	✓		
CS3	✓	✓	✓

4 Solution methods

This section presents two solution methods to solve all three collaborative schemes presented in Sections 3. The first approach uses mathematical programming and the second one is based on a heuristic method with local search.

4.1 Branch-and-cut algorithm

All models can be solved by feeding them directly into an integer linear programming solver by branch-and-bound if the number of rounded capacity inequalities (15) is not excessive. However, for realistic size instances, e.g., 30 or 40 nodes, as is the case of our partners, the number of rounded capacity constraints (15) is too large to allow full enumeration and these must be dynamically generated throughout the search process. The exact algorithm we use is a branch-and-cut scheme in which rounded capacity inequalities constraints are generated and added into the program whenever they are found to be violated. It works as follows. At a generic node of the search tree, a linear program containing the model with a subset of the subtour elimination constraints and relaxed integrality constraints is solved, a search for violated inequalities is performed, and some of these are added to the current program which is then reoptimized. This process is reiterated until a feasible or dominated solution is reached, or until there are no more cuts to be added. At this point, branching on a fractional variable occurs. We provide a sketch of the branch-and-cut scheme in Algorithm 1.

4.2 Adaptive large neighborhood search

We present an implementation of an ALNS heuristic for our problem, based on Ropke and Pisinger [19]. The ALNS is composed of a set of destruction and reconstruction heuristics in order to find better solutions at each iteration, according to the simulated annealing principle. One of the strengths of the ALNS is the capacity to adapt its search,

Algorithm 1 Branch-and-cut algorithm

Subproblem solution: Solve the LP relaxation of the current node
Termination check:
if there are no more nodes to evaluate **then**
    Stop
else
    Select one node from the branch-and-cut tree
end if
while solution of the current LP relaxation contains subtours **do**
    Identify connected components with CVRPSEP [16]
    Add violated subtour elimination constraints
end while
if the solution of the current LP relaxation is integer **then**
    Go to the termination check
else
    Branching: branch on one of the fractional variables
    Go to the termination check
end if

by choosing different heuristics with different instances. Since we have different objective functions, this method seems well tailored for the problems at hand.

An initial solution can be considered to speed up the search and the convergence. We have implemented a fast sequential insertion heuristic, which performs a greedy search for the best insertion for one request at a time.

The ALNS selects one of many destroy and repair operators at each iteration. We have implemented four destroy and two repair operators. Each destroy operators removes a set of requests ranged between $0.1|\mathcal{V}'|$ and $0.4|\mathcal{V}'|$. Our first destroy operator is a random removal in which we remove random requests from the existing routes. The second one is a cluster removal in which we select an initial request as a seed and select the closest requests from this seed, up to the given number. The third operator is a worst removal in which we select the requests which have the most important impact on the current objective function. The last one is a larger removal operation based on the period of requests. We select a random period and remove, up to the given number, requests within this period.

Thus, after each removed request, the objective value is recalculated. Our repair operators include a greedy parallel insertion and a k-regret heuristic [18].

Each operator is selected with a probability that depends on its past performance and a simulated annealing acceptance criterion is used. The mechanism and parameters remain the same for each collaborative scheme model. The only difference is how to calculate the value of the objective function. We accept a worse solution s' given the current solution s with probability $e^{(f(s')-f(s))/T}$ where $T > 0$ is the temperature and $f(s)$ is the objective function value. We use a cooling rate ϕ to adjust the temperature T at each iteration. After every 100 iterations, the weight of each operator is updated according to its past performance. Initially, all the operators have the same weight. Our sop criterion is a maximal number of iterations. A sketch of our ALNS is provided in Algorithm 2 and for further details we refer to Ropke and Pisinger [19].

Algorithm 2 Adaptive large neighborhood search

Create an initial solution S;
$S^* \leftarrow S$, set T;
Initiate probability ρ^d for destroy operators and ρ^i for repair operators;
while stop criterion is not met **do**
    Select a number of picks $1 \leq q \leq n$;
    Select removal and insertion operators using ρ^d and ρ^i;
    Apply operators on S to obtain S';
    if $f(S') < f(S)$ **then**
        $S \leftarrow S'$;
        if $f(S') < f(S^*)$ **then**
            $S^* \leftarrow S'$;
        end if
    end if
    if $f(S') \geq f(S)$ **then**
        $S \leftarrow S'$ according to simulated annealing criterion;
    end if
    Update ρ^d and ρ^i;
    $T = \phi \cdot T$
end while
return S^*.

5 Computational experiments

In this section, we provide details on the implementation, benchmark instances, and describe the results of extensive computational experiments. The description of the generated instances is presented in Section 5.1. We presents two benchmark approximations for scenarios without collaboration in Section 5.2. This is followed by the results and analysis of the computational experiments in Section 5.3 and a GHS emissions analysis is presented in Section 5.4.

All the formulations described in Section 3 and the algorithms described in Sections 4 are implemented in C++. We use IBM CPLEX Concert Technology 12.6 as the branch-and-bound solver. All computations were executed on machines equipped with two Intel Westmere EP X5650 six-core processors running at 2.667 GHz, and with 16 GB of RAM running the Scientific Linux 6.3. All algorithms were given a time limit of 10 800 seconds and a maximum of 50 000 iterations for ALNS.

5.1 Instances generation

An instance consists of n requests, associated to different shippers. Since we were given access to a set of 42 companies spread within four industrial parks around Québec City, we can randomly associate an order to one of them. We also have access to ten carriers, with their distribution center locations. The pickup time r_i of request i is in the range $[1, H = 5]$. The number of requests per instance $n \in \{10, 20, \ldots, 100\}$, for a total of ten different sizes. We create three groups of instances: *f1*, *f2* and *f3*. The difference between them lies in the number of pallets per order: $q_i \in \{1, \ldots, 3\}$ for *f1*, $q_i \in \{2, \ldots, 6\}$ for *f2* and $q_i \in \{3, \ldots, 9\}$ for *f3*, uniformly distributed. We have one instance per combination for a total of 30 instances.

5.2 Benchmark and worst case solutions

This section presents two benchmark solutions reproducing the current behavior of the network without collaboration. It also presents the results of extensive computational experiments of all our algorithms for all 30 instances. We start our analysis by evaluating the performance of our models in terms of optimality gap and CPU time, and we compare the results to those of the ALNS algorithm.

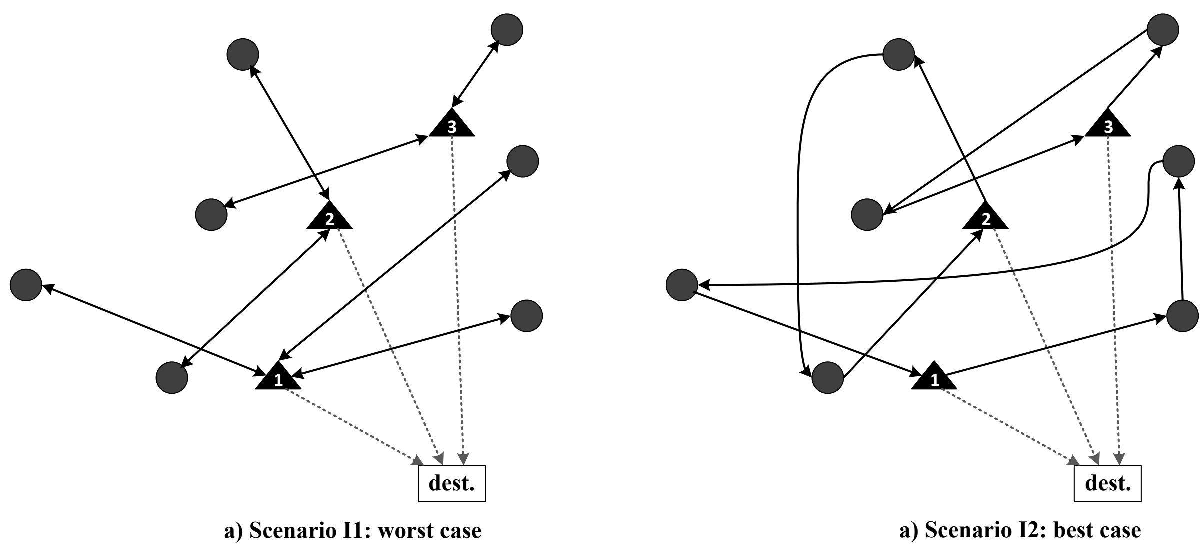

Figure 2: Two initial routing scenarios

Without collaboration and consolidation of shipment requests, each shipper node is visited by its initial carrier. In this case, the total LTL shipping cost of the system is easily determined as the sum of all individual shipping costs. The distance traveled for the pickup of all requests is more complex to be determined because carrier operations are not totally known as they visit several shippers when they are picking up orders for LTL shipping. This led us to elaborate two different initial scenarios. Initial scenario I1 consists of the worst possible case, whereas initial scenario I2 is the best possible case without collaboration. These are described next and depicted in Figure 2.

Scenario I1: Round trips (worst case)

In the first scenario we suppose that each request is picked up by a round trip performed by its carrier. It is the worst-case scenario in which the distance will be the largest. This situation is shown in Figure 2a) with three carriers (represented by triangles) and seven shipper requests (circles). All shippers are visited at their desired period r_i, before departing to their common destination (dest.) by their initial carrier. The visit is done at the requested period and no timing penalty is incurred, meaning that the multi-period perspective is not relevant. For each visit i performed by their initial carrier from his depot, say τ_i, we know the distance $c_{i\tau_i}$. The total distance will be the sum of all round trips, computed as $\sum_{i\in\mathcal{V}'} 2c_{i\tau_i}$.

Scenario I2: Sequence of visits per carrier and day (best case)

The first scenario (I1) neglects the possibility for the carrier to consolidate its visits within a day. In the second initial scenario (I2), we group all visits in the same period r_i for the same carrier as long as the vehicle capacity is respected. This scenario is illustrated in 2b). Each request from the same shipper still keeps its initial assigned carrier. It is possible to determine the best sequence of visits for each resulting group by solving a well-known TSP. The solution will be composed of small clusters and the computational time will be negligible. Recall that I2 does not consider the consolidation aspect and each request is charged at full price. The timing penalty is still zero since everything is picked up at the requested period.

5.3 Computational experiments

For collaborative schemes CS1, CS2 and CS3, Table 2 presents the upper bound (UP), the lower bound (LB), the optimality gap in percentage, and the running time for the three groups of instances (*f1*, *f2* and *f3*). There is one instance per row. We observe that collaborative scheme CS1, focusing on timing and shipping costs, solves all instances of groups *f1, f2* and *f3* to optimality within 782 seconds on average. For collaborative scheme CS2, Table 2 shows that the problem is difficult to solve. It yields an average gap of 43.24% for instances *f1*, 37.20% for *f2* and 32.07% for *f3*. In total, 24 out of 30 instances reached the maximum allotted time. Model CS3 provided more optimal solutions than CS2 for a total of nine optimal solutions. The total average gap is 11.83% for all instance groups. The average gap of *f1* instances is 10.35%, 13.45% for *f2* instances and 11.68% for *f3*.

In Table 3, we compare the ALNS, which is adapted for each formulation, with the three model upper bounds. We present the solution of the ALNS, the upper bound (UB), and the difference in percentage between the ALNS solution and the upper bounds (Diff.). A positive difference indicates that the solution of collaborative scheme model is better than that of the heuristic. Model CS1 is the only one to perform equally or marginally better than ALNS for the three groups of instances. The average difference for the three groups is 0.18%. Regarding CS2, ALNS provides for almost all cases better results than the mathematical programming techniques. The average difference for group *f1* is -33.65% in favor of ALNS, -32.96% in *f2* and -28.05% in *f3*. These results make sense given the poor results provided by the upper bound models CS2 and CS3. ALNS with the third objective function also gives a better solution than collaborative scheme model CS3 for all three groups of instances. For groups *f1*, *f2* and *f3*, ALNS provides better solutions with an average difference of -8.06%, -8.56% and -8.74% respectively.

Since the metaheuristic method can consistently provide better solutions on average for the three formulations, we will analyze the cost breakdown from the solution obtained from this method. This is presented in Table 4. Column *I1 - Dist.* presents the distance for scenario I1 (round trips), and column *I2 - Dist.* presents the distance for scenario I2 (sequence of visits per carrier per day). The third column presents the shipping cost for both scenarios, since they are the same. The other columns present for CS1, for CS2 and for CS3 the distance, the timing cost and the shipping cost. We give the average results for each group and a total average in the last row. The cells in gray color represent the part taken into account in the total column of each collaborative scheme. We recall that these solutions have not been proved optimal and are subject to improvement.

Table 2: Performance of collaborative scheme models in terms of optimality gap and running time

Instance	CS1				CS2				CS3			
	UB	LB	Gap (%)	Time (s)	UB	LB	Gap (%)	Time (s)	UB	LB	Gap (%)	Time (s)
f1-10	2142	2142	0.00	0	147	147	0.00	0	2348	2348	0.00	0
f1-20	3341	3341	0.00	0	184	184	0.00	28	3630	3630	0.00	1
f1-30	4563	4563	0.00	0	261	219	16.09	10800	4962	4962	0.00	35
f1-40	4969	4969	0.00	0	352	218	38.07	10800	5470	5470	0.00	152
f1-50	5659	5659	0.00	0	547	225	58.93	10800	6176	6176	0.00	127
f1-60	6682	6682	0.00	0	554	210	62.18	10800	7223	7119	1.44	10800
f1-70	8357	8357	0.00	3	613	208	66.07	10800	11764	8192	30.37	10800
f1-80	8139	8139	0.00	1	722	340	52.89	10800	9740	8296	14.82	10800
f1-90	10104	10104	0.00	3	802	253	68.45	10800	13717	10038	26.82	10800
f1-100	10808	10808	0.00	5	948	288	69.67	10800	15588	10898	30.09	10800
Average	**6476**	**6476**	**0.00**	**1**	**513**	**229**	**43.24**	**8643**	**8062**	**6713**	**10.35**	**5432**
f2-10	2906	2906	0.00	0	119	119	0.00	0	3045	3045	0.00	1
f2-20	4562	4562	0.00	0	177	177	0.00	15	4780	4780	0.00	2
f2-30	7606	7606	0.00	16	301	245	18.60	10800	8033	7645	4.83	10800
f2-40	8988	8988	0.00	65	561	344	38.68	10800	9781	8939	8.61	10800
f2-50	11083	11083	0.00	21	703	379	46.09	10800	13181	10939	17.01	10800
f2-60	13403	13403	0.00	44	878	427	51.38	10800	18237	13339	26.86	10800
f2-70	14680	14680	0.00	358	956	457	52.15	10800	18533	14560	21.44	10800
f2-80	17946	17946	0.00	580	1063	577	45.68	10800	22466	18050	19.66	10800
f2-90	18786	18786	0.00	1241	1129	529	53.12	10800	22461	18628	17.07	10800
f2-100	20481	20481	0.00	347	1339	451	66.32	10800	25146	20356	19.05	10800
Average	**12044**	**12044**	**0.00**	**267**	**723**	**371**	**37.20**	**8642**	**14566**	**12028**	**13.45**	**8640**
f3-10	4244	4244	0.00	0	168	168	0.00	0	4504	4504	0.00	0
f3-20	7350	7350	0.00	0	281	281	0.00	255	7758	7758	0.00	19
f3-30	10094	10094	0.00	45	293	287	1.96	10800	11247	9965	11.40	10800
f3-40	13467	13467	0.00	70	327	290	11.24	10800	14419	13234	8.22	10800
f3-50	17140	17140	0.00	1447	737	387	47.49	10800	19550	16966	13.22	10800
f3-60	18959	18959	0.00	552	995	483	51.45	10800	22542	18850	16.38	10800
f3-70	21872	21872	0.00	169	1267	685	45.94	10800	26824	22224	17.15	10800
f3-80	25216	25216	0.00	999	1304	577	55.73	10800	31085	25332	18.51	10800
f3-90	29048	29048	0.00	6684	1428	627	56.09	10800	35328	29148	17.49	10800
f3-100	31466	31452	0.05	10800	1635	804	50.83	10800	37164	31810	14.41	10800
Average	**17886**	**17884**	**0.00**	**2077**	**844**	**459**	**32.07**	**8666**	**21042**	**17979**	**11.68**	**8642**
Total average	**12135**	**12135**	**0.00**	**782**	**693**	**353**	**37.50**	**8650**	**14557**	**12240**	**11.83**	**7571**

Table 3: ALNS performance against the collaborative scheme models

Instance	CS1			CS2			CS3		
	ALNS	UB	Diff. (%)	ALNS	UB	Diff. (%)	ALNS	UB	Diff. (%)
f1−10	2162	2142	0.93	147	147	0.00	2348	2348	0.00
f1−20	3341	3341	0.00	184	184	0.00	3683	3630	1.46
f1−30	4563	4563	0.00	257	261	−1.53	4962	4962	0.00
f1−40	4969	4969	0.00	284	352	−19.32	5470	5470	0.00
f1−50	5659	5659	0.00	294	547	−46.25	6176	6176	0.00
f1−60	6682	6682	0.00	276	554	−50.18	7223	7223	0.00
f1−70	8357	8357	0.00	315	613	−48.61	8932	11764	−24.07
f1−80	8139	8139	0.00	390	722	−45.98	8784	9740	−9.82
f1−90	10104	10104	0.00	313	802	−60.97	10750	13717	−21.63
f1−100	10808	10808	0.00	345	948	−63.61	11454	15588	−26.52
Average	**6478**	**6476**	**0.09**	**281**	**513**	**−33.65**	**6978**	**8062**	**−8.06**
f2−10	3027	2906	4.16	119	119	0.00	3403	3045	11.76
f2−20	4562	4562	0.00	177	177	0.00	4780	4780	0.00
f2−30	7606	7606	0.00	277	301	−7.97	8029	8033	−0.05
f2−40	8988	8988	0.00	361	561	−35.65	9524	9781	−2.63
f2−50	11083	11083	0.00	398	703	−43.39	11688	13181	−11.33
f2−60	13403	13403	0.00	527	878	−39.98	14168	18237	−22.31
f2−70	14680	14680	0.00	492	956	−48.54	15450	18533	−16.64
f2−80	17946	17946	0.00	615	1063	−42.14	18769	22466	−16.46
f2−90	18786	18786	0.00	584	1129	−48.27	19676	22461	−12.40
f2−100	20481	20481	0.00	486	1339	−63.70	21237	25146	−15.55
Average	**12056**	**12044**	**0.42**	**404**	**723**	**−32.96**	**12672**	**14566**	**−8.56**
f3−10	4244	4244	0.00	168	168	0.00	4504	4504	0.00
f3−20	7350	7350	0.00	285	281	1.42	7758	7758	0.00
f3−30	10105	10094	0.11	293	293	0.00	10608	11247	−5.68
f3−40	13467	13467	0.00	324	327	−0.92	14034	14419	−2.67
f3−50	17174	17140	0.20	421	737	−42.88	17830	19550	−8.80
f3−60	18959	18959	0.00	512	995	−48.54	19661	22542	−12.78
f3−70	21872	21872	0.00	754	1267	−40.49	22887	26824	−14.68
f3−80	25216	25216	0.00	652	1304	−50.00	26148	31085	−15.88
f3−90	29048	29048	0.00	662	1428	−53.64	30064	35328	−14.90
f3−100	31466	31466	0.00	892	1635	−45.44	32683	37164	−12.06
Average	**17890**	**17886**	**0.03**	**496**	**844**	**−28.05**	**18618**	**21042**	**−8.74**
Total average	**12142**	**12135**	**0.18**	**393**	**693**	**−31.55**	**12756**	**14557**	**−8.45**

Table 4: Benchmark solutions and cost breakdown (distance, timing and shipping costs)

	I1	I2		ALNS M1			ALNS M2			ALNS M3		
Instance	Dist. (km)	Dist. (km)	Ship. ($)	Dist. (km)	Timing ($)	Ship. ($)	Dist. (km)	Timing ($)	Ship. ($)	Dist. (km)	Timing ($)	Ship. ($)
f1-10	360	261	4430	245	100	2062	147	1100	2023	206	200	1942
f1-20	790	515	8860	408	600	2741	184	1600	2712	260	700	2723
f1-30	886	624	13170	632	400	4163	257	2800	4003	399	400	4163
f1-40	1230	817	17360	851	0	4969	284	3300	4561	501	0	4969
f1-50	2014	1031	21310	1109	0	5659	294	4200	5219	515	100	5561
f1-60	2042	837	25980	1148	100	6582	276	5200	6561	541	100	6582
f1-70	2102	1241	30650	1390	100	8257	315	7100	7988	575	100	8257
f1-80	2538	1309	34360	1493	300	7839	390	8600	8385	645	300	7839
f1-90	3264	1499	39510	1685	200	9904	313	9000	10209	644	300	9806
f1-100	3398	1852	43100	1927	200	10608	345	8500	10672	646	200	10608
Average	**1862**	**999**	**23873**	**1089**	**200**	**6278**	**281**	**5140**	**6233**	**493**	**240**	**6245**
f2-10	280	158	5150	209	400	2627	119	700	2712	186	600	2617
f2-20	456	369	10420	346	600	3962	177	1900	3962	218	600	3962
f2-30	1096	643	16650	623	400	7206	277	2600	7509	423	400	7206
f2-40	1598	758	21200	865	300	8688	361	4400	8672	536	300	8688
f2-50	1760	1085	26830	1087	700	10383	398	4700	10587	605	700	10383
f2-60	2030	1107	32580	1293	400	13003	527	5100	13743	765	400	13003
f2-70	2212	1372	37010	1358	500	14180	492	7400	14384	746	400	14304
f2-80	2560	1346	43960	1782	500	17446	615	9100	17977	823	500	17446
f2-90	2914	1593	47790	1822	500	18286	584	8600	19006	885	200	18591
f2-100	3102	1629	52220	1586	500	19981	486	7300	20741	756	500	19981
Average	**1801**	**1006**	**29381**	**1097**	**480**	**11576**	**404**	**5180**	**11929**	**594**	**460**	**11618**
f3-10	208	204	6637	276	0	4244	168	1200	3797	260	0	4244
f3-20	646	425	13125	451	200	7150	285	2100	7245	408	200	7150
f3-30	1080	741	19213	739	100	10005	293	2500	10170	479	200	9929
f3-40	1432	933	25455	738	400	13067	324	3700	14208	567	400	13067
f3-50	1530	1182	32521	938	300	16874	421	4600	17318	656	300	16874
f3-60	2084	1128	37624	1320	400	18559	512	5300	19259	702	400	18559
f3-70	2306	1535	43745	1771	400	21472	754	7100	22603	1015	400	21472
f3-80	2928	1578	50061	1558	300	24916	652	6600	26570	932	300	24916
f3-90	3168	1823	57202	1809	300	28748	662	8100	29247	986	200	28878
f3-100	2822	1936	63021	2136	600	30866	892	9800	32256	1217	600	30866
Average	**1820**	**1149**	**34860**	**1174**	**300**	**17590**	**496**	**5100**	**18267**	**722**	**300**	**17596**
Total average	**1828**	**1051**	**29371**	**1120**	**327**	**11815**	**393**	**5140**	**12143**	**603**	**333**	**11820**

In order to make a systematic comparison of solution methods in terms of distance, timing and shipping costs, we compare them with the scenario I1. First, we compare I1 against scenario I2. We can assert that scenario I2 is 42.22% better in terms of distance for group *f1*, 41.86% for group *f2* and 32.44% for group *f3*. In total, we observe that the naive construction heuristic I2 provides solutions 38.84% better than those from scenario I1.

When we compare collaborative scheme CS1 with scenario I1, we see an improvement of 57.82% in the total cost (shipping + timing penalties) from 29 371$ to 12 142$. The timing penalty cost is relatively small at 327$. The greatest difference comes from instances from group *f1*, where we see an improvement of 69.63% in the total cost. Even if CS1 does not focus on distance minimization, the distance reduces from 1828 km in I1 to 1120 km in CS1, an improvement of 35.12%. Note that we apply a TSP algorithm on each CS1 resulting route in order to obtain the best sequence.

Model CS2, which focuses only on distance minimization, gives a total average of 393 km, a significant improvement of 73.72% from I1. We note that the average distance between each group increases. Since the number of requests per instance is the same from a group to another, but the average number of pallets per request increases, it makes senses that the distances increase because more trips are needed. The average number of requests per route will be bigger in *f1* and reduces the distance. Even with an average of 6 pallets per request in *f3* (capacity of 26 in the vehicle), we can improve the distance from scenario I1 by 66.58%. In return, we see a huge increase of the timing penalties for each instance groups. However, in total average, the combination of timing and shipping costs still gives an average saving of 40.98% (timing penalty of 5 140$ and shipping cost of 12 143$).

As expected, CS3 gives very similar results in terms of costs to CS1. In total average, the total cost is 12 153$ (timing penalty 333$ + shipping 11 820$). In comparison with I1, it represents an improvement of 57.67%. The total average distance of CS3 is 603 km. An improvement of 60.09% from I1, and of 46.16% from CS1. The benefit of adding distance minimization to the objective function is now fully justified. Just like CS1 and CS2, these improvements tend to decrease slightly when the average number of pallets increases in the instances.

Our results show that there is an important difference between CS1 and CS3 in terms of distance with equivalent timing and shipping costs. This shows that there are a number of possible combinations yielding the same timing and shipping costs but these combinations do not necessarily incur the same distances. Compared to CS1, which does not minimize the distance, CS3 focuses on finding good trade offs in terms of distance and costs. The value of this collaborative scheme resides in its capacity to find adequate sequences at a good cost.

5.4 Potential reductions in greenhouse gas emissions

In this section we study potential reductions in GHG emissions that can be obtained by employing our solutions.

Using data obtained from [22], we assume that each heavy duty truck used for activities described in this paper consumes 48.1 L/100 km, and that each liter of diesel produces 2.61 kg of CO_2. Using these figures and the data provided in Table 4, we are able to assess potential reductions by using our consolidation methods.

First, we show that the worst case scenario I1 and the optimized best case I2 produce significantly different emission levels. We depict in Figure 3 the savings in emissions and the number of tonnes of CO_2 saved over the course of a year (assuming 250 days of operations under the same circumstances). The figure shows that over the course of a year, up to 554 tons of CO_2 could be saved simply by grouping pickups, even without the consolidation proposed in this paper. This shows that carrier behavior can have major impact on their fuel comsumption and thus GHG emissions.

Comparing the potential savings from the three proposals (CS1, CS2 and CS3) against the initial solution, our analysis is depicted in Figures 4, 5, and 6.

Figure 4 shows the results of collaborative scheme CS1, focusing on timing and shipping

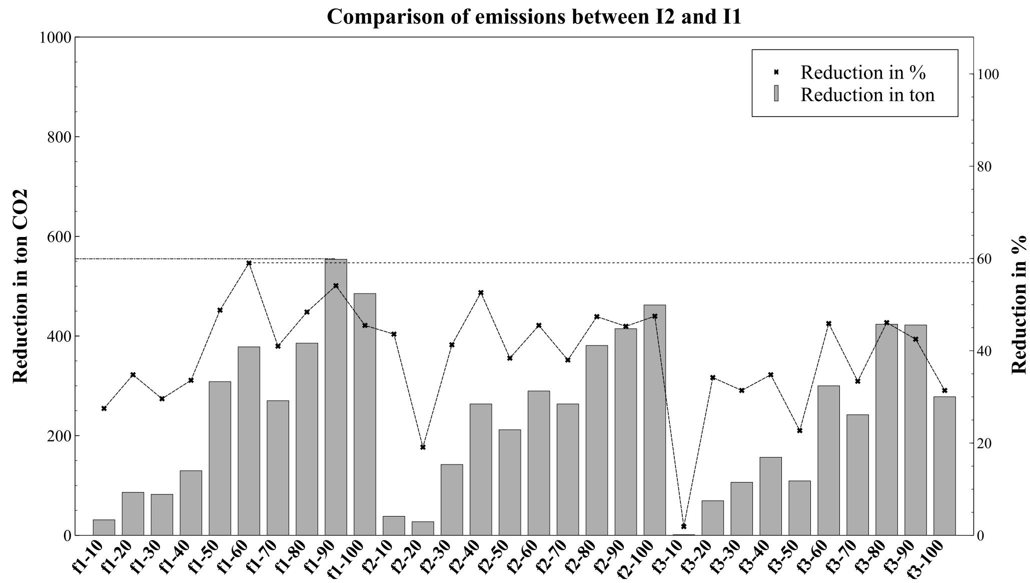

Figure 3: Emissions saving in tons and percentage – comparison between I2 and I1

costs only. Even if this case does not consider the pickup distance traversed by the trucks in optimization process, it is still able to save up to 243 tons of CO_2 per year on average for instances of group *f1*, with requests containing from 10 to 100 pallets. Even the case of group *f2*, the one yielding the smallest savings, the reduction in CO_2 emission is significant, averaging 220 tons per year, representing 37% less than the initial scenario I1.

When our proposed collaborative scheme CS2 is considered, it becomes evident that these savings can be significantly higher, going from 69% for group *f3* up to 81% for group *f1*, reducing emissions of CO_2 by 497 tons per year on average for this group. These are shown in Figure 5. Finally, an all encompassing collaborative scheme considering distance, timing and shipping costs also shows important savings achieving 68% and 430 tons of CO_2 on average per year for instances of group *f1* (Figure 6).

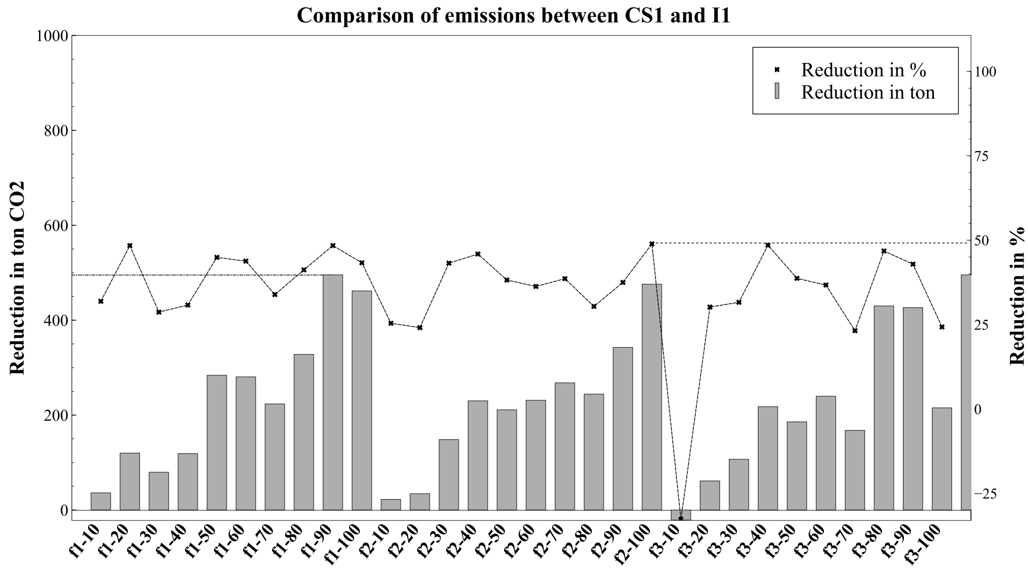

Figure 4: Emissions saving in tons and percentage – comparison between CS1 and I1

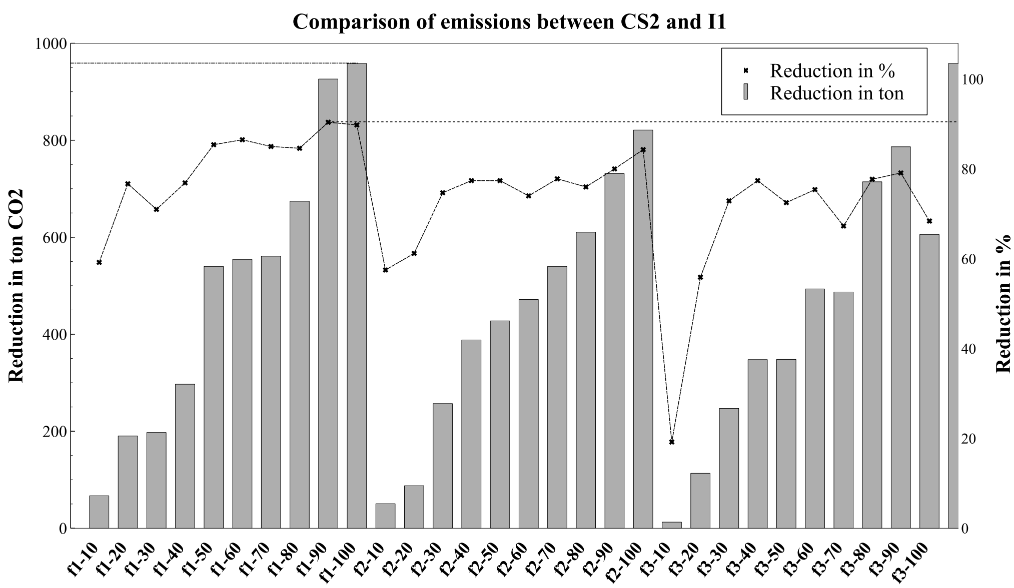

Figure 5: Emissions saving in tons and percentage – comparison between CS2 and I1

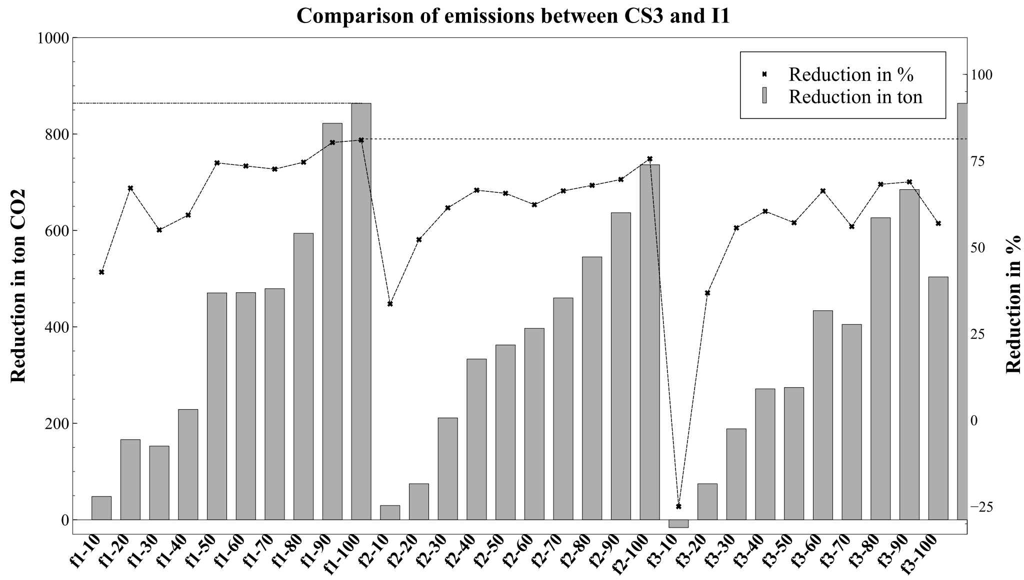

Figure 6: Emissions saving in tons and percentage – comparison between CS3 and I1

6 Conclusions

In this paper we have proposed an innovative solution for shipping companies having many partial shipments (LTL) to common locations. Via extensive computational experiments based on data collected from Canadian companies shipping to the US, we show that shippers can consolidate their cargo and negotiate better tariffs with carriers. This consolidation has many positive side effects. We have computed and estimated reductions in traffic and milage for the pickup of all requests, on financial savings for the long haul shipment, and on service level impacts of these activities. We showed that large benefits can be obtained with very few impact on the service level. From worst benchmark scenario, we show that milage reductions of up to 3053 km are possible when picking up to 100 orders in a week.

From a city logistics perspective, we have estimated a reduction in GHG emissions stemming from the aggregation of orders. Our analysis shows a potential reduction of 81% in GHG emissions for small orders (up to 3 pallets per request), and of 31% in large orders (up to 9 pallets per request). More importantly, we have shown based on a real-case collaboration that GHG emissions saving of up to 497 tons of CO_2 per year are possible, while at the same time decreasing shipping costs by up to 69%, whitout deteriorating the service level.

References

[1] R. Agarwal and Ö. Ergun. Network design and allocation mechanisms for carrier alliances in liner shipping. *Operations Research*, 58(6):1726–1742, 2010.

[2] J.-F. Audy, S. D'Amours, and L.-M. Rousseau. Cost allocation in the establishment of a collaborative transportation agreement - an application in the furniture industry. *Journal of the Operational Research Society*, 62(6):960–970, 2011.

[3] S. Berger and C. Bierwirth. Solutions to the request reassignment problem in collaborative carrier networks. *Transportation Research Part E: Logistics and Transportation Review*, 46(5):627–638, 2010.

[4] J.-F. Cordeau, G. Laporte, J.-Y. Potvin, and M. W. P. Savelsbergh. Transportation on demand. In C. Barnhart and G. Laporte, editors, *Handbooks in Operations Research and Management Science*, volume 14, pages 429–466. Elsevier, Montréal, 2007.

[5] F. Cruijssen, M. Cools, and W. Dullaert. Horizontal cooperation in logistics: opportunities and impediments. *Transportation Research Part E: Logistics and Transportation Review*, 43(2):129–142, 2007.

[6] F. Cruijssen, P. Borm, H. Fleuren, and H. Hamers. Supplier-initiated outsourcing: A methodology to exploit synergy in transportation. *European Journal of Operational Research*, 207(2):763–774, 2010.

[7] B. Dai and H. Chen. Mathematical model and solution approach for collaborative

logistics in less than truckload transportation. In *International Conference on Computers & Industrial Engineering, 2009*, pages 767–772. IEEE, 2009.

[8] Ö. Ergun, G. Kuyzu, and M. W. P. Savelsbergh. Reducing truckload transportation costs through collaboration. *Transportation Science*, 41(2):206–221, 2007.

[9] Ö. Ergun, G. Kuyzu, and M. W. P. Savelsbergh. Shipper collaboration. *Computers & Operations Research*, 34(6):1551–1560, 2007.

[10] M. Frisk, M. Göthe-Lundgren, K. Jörnsten, and M. Rönnqvist. Cost allocation in collaborative forest transportation. *European Journal of Operational Research*, 205 (2):448–458, 2010.

[11] B. Groothedde, C. Ruijgrok, and L. Tavasszy. Towards collaborative, intermodal hub networks: A case study in the fast moving consumer goods market. *Transportation Research Part E: Logistics and Transportation Review*, 41(6):567–583, 2005.

[12] R. Kale, P. T Evers, and M. E. Dresner. Analyzing private communities on internet-based collaborative transportation networks. *Transportation Research Part E: Logistics and Transportation Review*, 43(1):21–38, 2007.

[13] M. A. Krajewska, H. Kopfer, G. Laporte, S. Ropke, and G. Zaccour. Horizontal cooperation among freight carriers: request allocation and profit sharing. *Journal of the Operational Research Society*, 59(11):1483–1491, 2008.

[14] P. Liu, Y. Wu, and N. Xu. Allocating collaborative profit in less-than-truckload carrier alliance. *Journal of Service Science and Management*, 3(1):143–149, 2010.

[15] R. Liu, Z. Jiang, X. Liu, and F. Chen. Task selection and routing problems in collaborative truckload transportation. *Transportation Research Part E: Logistics and Transportation Review*, 46(6):1071–1085, 2010.

[16] J. Lysgaard. *CVRPSEP: A package of separation routines for the capacitated vehicle*

routing problem. Institut for Driftøkonomi og Logistik, Handelshøjskolen i Århus, 2003.

[17] E. Özkaya, P. Keskinocak, V. R. Joseph, and R. Weight. Estimating and benchmarking less-than-truckload market rates. *Transportation Research Part E: Logistics and Transportation Review*, 46(5):667–682, 2010.

[18] J.-Y. Potvin and J.-M. Rousseau. A parallel route building algorithm for the vehicle routing and scheduling problem with time windows. *European Journal of Operational Research*, 66(3):331–340, 1993.

[19] S. Ropke and D. Pisinger. An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. *Transportation Science*, 40(4):455–472, 2006.

[20] M. W. P. Savelsbergh and M. Sol. The general pickup and delivery problem. *Transportation Science*, 29(1):17–29, 1995.

[21] A. Toptal and S. O. Bingöl. Transportation pricing of a truckload carrier. *European Journal of Operational Research*, 214(3):559–567, 2011.

[22] Transport Canada. Transportation in Canada - Overview report. pages 1–99. TP-15296-F, 2014.

[23] X. Wang and H. Kopfer. Collaborative transportation planning of less-than-truckload freight. *OR Spectrum*, 36(2):357–380, 2014.

[24] O. Yilmaz and S. Savasaneril. Collaboration among small shippers in a transportation market. *European Journal of Operational Research*, 218(2):408–415, 2012.

[25] M. Zhang, S. Pratap, G. Q. Huang, and Z. Zhao. Optimal collaborative transportation service trading in B2B e-commerce logistics. *International Journal of Production Research*, , forthcoming, 2017.

[26] G. Zhou, Yer Van H., and L. Liang. Strategic alliance in freight consolidation. *Transportation Research Part E: Logistics and Transportation Review*, 47(1):18–29, 2011.