Service level, cost and environmental optimization of collaborative transportation

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Abstract

Less than truckload is an important type of road-based transportation. Based on real data and on a collaboration with industry, we show that a collaborative approach between companies offers important benefits. We propose to develop partnerships between shipping companies and to synchronize their shipments. Four operational collaborative schemes with different objectives are developed. The first one focuses on minimizing shipping costs for shippers. The second and third ones minimize the carrier's costs and the environmental cost, respectively. The fourth one is a combination of all three. The results of our computational experiments demonstrate that collaboration lead to significant cost reductions.

Keywords: collaborative transportation, routing, greenhouse gas, optimization, less than truckload, logistics.

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 (Transport Canada, 2014).

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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 (Toptal and Bingöl, 2011). 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 (Özkaya et al., 2010). Since it needs more loading and unloading operations and often a visit to a consolidation center, LTL transportation is generally 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. This pricing grid includes several implicit costs such as distance-based components (fuel, maintenance, tolls, etc) and temporal-based components (equipment depreciation, salary, etc). Knowing the distance and the time to a destination, economies of scale arise because all the items in a shipment share the fixed cost of the vehicle utilization (Daganzo, 2005; Tsao and Lu, 2012). Thus the fixed components from an origin-destination route are paid for each vehicle used.

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 (Yilmaz and Savasaneril, 2012). Cruijssen et al. (2007) 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 and it is often formulated as a pickup and delivery problem with time-windows (Savelsbergh and Sol, 1995; Cordeau et al., 2007; Krajewska et al., 2008; Dai and Chen, 2009). Since there are several carriers serving a set of shippers, there will be a global profit from sharing their infrastructure and maximizing vehicle loading (Liu et al., 2010a). Agarwal and Ergun (2010) study carrier alliances in the liner shipping and determine side payments that align decisions of carriers within the coalition. Berger and Bierwirth (2010) and Wang and Kopfer (2014) present a carrier collaboration in which requests are optimally shared. Liu et al. (2010b) study a problem in which a TL carrier receives requests from shippers and decides upon using his vehicles or outsourcing the request. Zhang et al. (2017) consider a carrier collaboration network for the e-commerce logistics system with multiple LTL carriers and vehicle types.

Shipper collaboration, on the other hand, considers only a single carrier and focuses on finding optimal routing decisions for different shippers, minimizing the distance (Ergun et al., 2007b). Shippers may benefit by establishing a private community in which they share information (Kale et al., 2007). 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 (Yilmaz and Savasaneril, 2012). 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 (Ergun et al., 2007a). 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. (2007a,b) address a shipper collaboration problem in which fixed schedules are used to reduce dead-hauling cost by making repeatable continuous movements. Frisk et al. (2010) study the collaboration among eight lumber shippers in forest transportation to obtain one-way TL shipments. Kale et al. (2007) 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 Groothedde et al. (2005) in which several shippers use a network of transportation hubs in many-to-many markets.

In the LTL context, Audy et al. (2011) 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. (2010) 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. Zhou et al. (2011) compare two levels of collaboration in a market characterized by randomly arriving loads with delivery deadlines. Consolidation levels are determined through simulation. Yilmaz and Savasaneril (2012) 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. Estrada-Romeu and Robusté (2015) present a methodology to identify when freight consolidation strategies are cost-efficient. Shipments are assigned based on proximity and cost criteria and improved with a tabu search algorithm.

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. Cost impacts for shippers and carrier are studied in order to design balanced scenarios.

Moreover, not only costs and time influence shipping decisions. Transportation activities account for 27% of the total global CO_2 emission, and among them the top CO_2 producer is road transportation (78.8% of all transportation emissions) (Bektaş et al., 2016). Other types of emissions, such as methane (CH_4) and nitrous oxide (N_2O), are also important greenhouse gases (GHGs), and are accounted for in what is called CO_2 equivalent (CO_2e) emissions (MERN, 2014). A recent but growing body of research focuses in green logistics activities (Demir et al., 2012). Recent developments in this area include Demir et al. (2011), Dekker et al. (2012), Erdoğan and Miller-Hooks (2012) and Lin et al. (2014). Incorporating fuel consumption models into classical routing is a way of explicitly accounting for emissions in the route planning, in what is called Pollution-Routing Problems (Bektaş and Laporte, 2011; Demir et al., 2014).

We have partnered with three Canadian manufacturing companies in 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 to develop partnerships with other companies who share common client locations and by synchronizing their shipments. Most shippers form the park use different carrier companies, generating several invoices split among different carriers. We propose the use of a single hub from one of the carriers, for shippers to improve their financial performance and their sustainable activities when distributing their products. This also allows for decreased 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 GHG emission reductions 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 four shipping collaborative scheme. It also introduces four 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 four 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 $\mathcal{V} = \{0, \dots, n\}$ 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 distance (km) c_{ij} for each arc (i, j) is determined from the real road network. A planning horizon $\mathcal{T} = \{1, \dots, H\}$ is given, expressed in days. A set of homogeneous vehicles $\mathcal{K} = \{1, \dots, m\}$ is available with a capacity $\mathcal{Q}$ expressed in linear feet. Each node $i = \{1, \dots, n\}$ 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.

A collaborative approach involving a single carrier requires us to consider some costs incurred by each stakeholder. First, we consider the variable cost as a distance-based one (fuel, maintenance, tolls, etc). Let V be the variable cost in \$/km for a 53 feet long vehicle. A fixed cost F is considered and corresponds to the use of a vehicle on the network (driver salary, inspection, vehicles depreciation, etc). Finally, an external variable component is also considered. This relates to the environmental cost E corresponding to GHGs cost per kilometer run.

Most of these costs are embeded within the carrier's shipping cost functions which depend 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

This section presents four collaborative schemes (CS). The first three minimize a part of

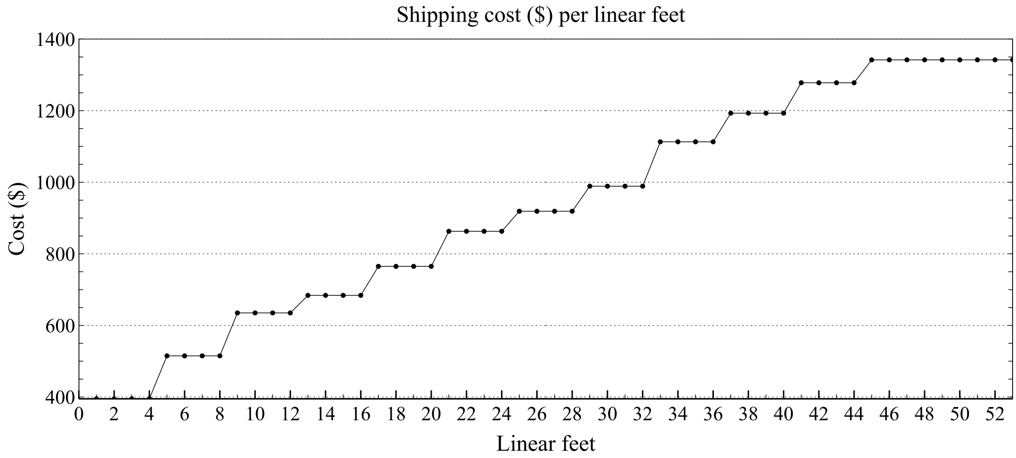

Figure 1: Shipping cost as a function of the number of linear feet used for a given destination

a complete collaborative strategy, given the different perspectives of each stakeholder. The last CS includes all cost components (shipper, carrier and external cost components). We develop a mathematical framework that optimizes five different criteria in order to evaluate the quality of a collaborative transportation solution:

1. the shipment cost (α_l),
2. the cost of delayed/advanced requests (δ_i^t),
3. variable costs of the carrier (V),
4. fixed operational costs (F),
5. environmental cost (E).

Each of the four schemes described below aim at minimizing a criterion, or a combination of criteria. We name these collaborative schemes CS1, CS2, CS3 and CS4. With collaboration, 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 to minimize the cost of shippers.

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. The selected carrier is given by the instance. 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:

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

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

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

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

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

$$0 \leq p_k^t \leq 13 \textit{ and integer} \quad \forall t \in \mathcal{T}, k \in \mathcal{K}. \tag{7}$$

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 vehicle k 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 number of pair of pallets to compute the 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.

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

Having the y_i^{kt} variables which assign requests i to vehicle k, we then apply a TSP algorithm in order to find the best route for each selected vehicle. This corresponds to a cluster-first-route-second strategy. The TSP algorithm used is a classical integer linear program for routing the corresponding subset of nodes, and solved by branch-and-cut using CPLEX as the integer programming solver.

Collaborative scheme CS2: In the second collaborative scheme, we minimize the carrier's costs. These costs include a distance-based component and a vehicle-based component over a fixed horizon, typically a few days.

The formulation for CS2 corresponds to a multi-period VRP with time-windows. It minimizes the total variable costs per kilometer traveled and the total fixed cost per vehicle used. 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:

$$\text{(CS2)} \min V\left(\sum_{(i,j)\in\mathcal{A}} c_{ij} \sum_{k\in\mathcal{K}} \sum_{t\in\mathcal{T}_i\cap\mathcal{T}_j} x_{ij}^{kt}\right) + F\left(\sum_{j\in\mathcal{V}'}\sum_{k\in\mathcal{K}}\sum_{t\in\mathcal{T}_i\cap\mathcal{T}_j} x_{0j}^{kt}\right) \tag{10}$$

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 variable and fixed costs. A fixed cost is computed for each arc leaving the depot (node 0). 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 minimizes the environmental cost, computing the equivalent monetary cost of all emissions generated for each kilometer traveled, while neglecting all direct costs associated the carrier and the shippers. Transport Canada (2014) estimates that a 53' long truck consumes in average 46.9 liters per 100 kilometers. In average, the GHG emission is estimated to 0.00279 ton per liter of fuel used. This report has estimated the Québec GHG financial cost as 16.45\$/ton. Finally, from these data, we can compute the GHG cost per kilometer as $E = 0.0215$ \$/km. Since the minimization of GHG's cost corresponds to minimizing the total distance, the CS4 formulation corresponds to:

$$\text{(CS3) min } E \left(\sum_{(i,j) \in \mathcal{A}} c_{ij} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}_i \cap \mathcal{T}_j} x_{ij}^{kt} \right) \tag{17}$$

subject to (11)–(16).

Collaborative scheme CS4: The fourth collaborative scheme combines all aspects: shippers, carrier and external cost. The model for CS4 is the combination of CS1, CS2 and CS3. It combines the routing formulation, shipping variables z_l^{kt} and p_k^t and their corresponding constraints. The objective function becomes:

$$\begin{aligned} \text{(CS4) min } & \sum_{i \in \mathcal{V}'} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}_i} \delta_i^t y_i^{kt} + \sum_{l \in \mathcal{L}} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} \alpha_l z_l^{kt} \\ & + (E+V) \left(\sum_{(i,j) \in \mathcal{A}} c_{ij} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}_i \cap \mathcal{T}_j} x_{ij}^{kt} \right) + F \left(\sum_{j \in \mathcal{V}'} \sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}_i \cap \mathcal{T}_j} x_{0j}^{kt} \right) \end{aligned} \tag{18}$$

subject to (2)–(9) and (11)–(16).

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

One of the most promising solution technique to solve a capacited vehicle routing problem (or similar problems) is the branch-and-cut, in which valid linear inequalities are used as cutting planes to strengthen a linear programming relaxation at each node of a branch-and-bound tree (Lysgaard et al., 2004; Semet et al., 2014). Hence, branch-and-cut provides the power and proved convergence of branch-and-bound and adds cutting planes dynamically to some nodes of the tree to help prune it, improve its dual bound, and forbid infeasible solutions. In the case of VRPs, the number of subtour elimination constraints are exponential, and creating them all a priori is prohibitive. These constraints are then relaxed and only added to the program when needed. We briefly explain this procedure below.

For realistic size instances, the exponential number of rounded capacity constraints (15) makes a full enumeration difficult. We use a branch-and-cut routine in which rounded capacity inequalities constraints are added whenever they are found to be violated. At a generic node of the search tree, chosen by CPLEX default search strategy, a linear program containing the model with a subset of already added 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 search is performed on the subset of nodes associated with a partial solution (a route of a given vehicle on a given day), and a network flow algorithm is used to identify whether these nodes are connected or if there are disjoint components. We refer to Lysgaard et al. (2004) for more details about the separation of the capacity inequalities heuristics. We provide a sketch of the branch-and-cut scheme in Algorithm 1.

4.2. Adaptive large neighborhood search

The mathematical formulations of our four collaborative schemes are combinatorial problems with many integer variables, which are very difficult to solve. In order to find good quality solutions for realistic size of instances, we propose an implementation of an ALNS heuristic framework that will work for all collaborative schemes. An ALNS based heuristic 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 (Ropke and Pisinger, 2006). One of the strengths of the ALNS is the capacity to adapt its search, by choosing different heuristics with different instances or objectives. 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.

We have implemented four destroy and two repair operators. The heuristic selects one of many destroy and repair operators at each iteration. Each destroy operators removes a

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 (Lysgaard, 2003)
    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

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 (for all four objective functions). The last one is a removal operation based on the period of requests. We select a random period and remove, up to the given number, requests within this period. Our repair operators include a greedy parallel insertion and a k-regret heuristic (Potvin and Rousseau, 1993). Thus, after each removed request, the objective value is recalculated.

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 stop 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 (2006).

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 experimentations are based on a collaboration with three canadian manufacturer and carriers shipping to the United States. 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 are 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 with 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 which allow to compute all possible distances. 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 request i: $q_i \in \{1, \ldots, 3\}$ 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.

The shipping cost function, as depicted in Figure 1, is provided by a carrier partner for a generic destination and will be used for all instances. We use a variable cost (V) per kilometer of 2\$ and a vehicle utilization fixed cost (F) of 50\$. The environmental cost (E), as presented in collaborative scheme CS3 is 0.0215\$/km. The timing cost (δ_i^t) of advancing a request is 50\$ per day and 100\$ for delaying it.

5.2. Benchmark scenarios

This section presents two benchmark solutions reproducing the current behavior of the network without collaboration. 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. Note that these scenarios have no interaction with other algorithms from Section 3 and they are presented here only as comparison with the results from a collaboration perspective. 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. Visits are done at their 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 $\sum_{i \in \mathcal{V}'} 2c_{i\tau_i}$.

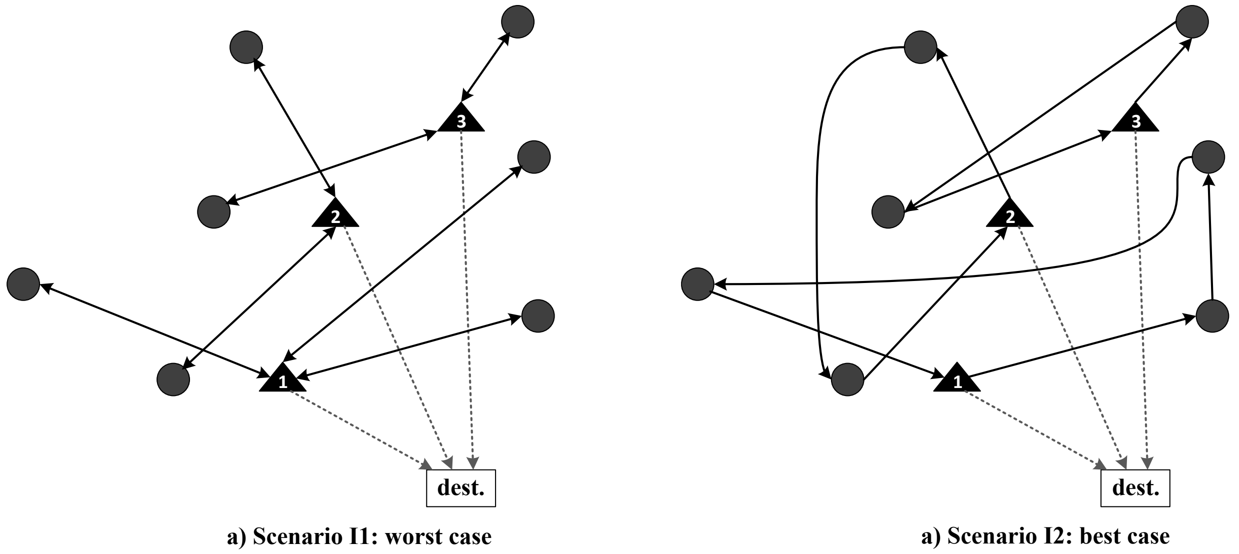

Figure 2: Two initial routing scenarios

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 requests in the same period r_i for the same carrier as long as the vehicle capacity is respected. This scenario is illustrated in 2b). 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

In this section, 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. For collaborative schemes CS1 to CS4, Table 1 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*) as obtained by CPLEX. 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 1256.9 seconds on average. For collaborative scheme CS2, minimizing the carrier's cost, Table 1 shows that the problem is difficult to solve. It yields an average gap of 47.7% for instances *f1*, 62.3% for *f2* and 65.0% for *f3.* In total, 24 out of 30 instances reached the maximum allotted time. Collaborative scheme CS3 with the environmental cost leads to very similar results because the mathematical model is similar. The total average gap of CS3 is 60.2%. Model CS4 provided more optimal solutions than CS2 and CS3 for a total of 12 optimal solutions. The total average gap is 8.8% for all instance groups. The average gap of *f1* instances is 3.7%, 11.6% for *f2* instances and 11.2% for *f3*.

In Table 2, we compare the ALNS, which is adapted for each formulation, with the four model upper bounds. We present the solution of the ALNS, the upper bound (UB), and the difference in percentage ($\Delta(\%)$) between the ALNS solution and the upper bounds. A positive difference indicates that the solution of the heuristic is better than that of the model. Model of CS1 is the only one to perform equally or marginally better than ALNS for the three groups of instances. The average difference shows that the solution from this model is 0.1% better than the heuristic. Regarding CS2, ALNS provides for almost all cases better results than the mathematical programming techniques. The average difference for group *f1* is 39.9% in favor of ALNS, 47.2% in *f2* and 41.8% in *f3*. These results make sense given the poor results provided by the upper bound models CS2. ALNS for model CS3 performs even better since the objective function only includes one element (environmental cost). For groups *f1*, *f2* and *f3*, ALNS provides better solutions with an average difference of 60.3%, 68.7% and 60.4%, respectively. ALNS is also able to improve solutions for collaborative scheme CS4 with a total average of 7.2% of improvement from the mathematical formulation.

Since the heuristic method can provide better solutions on average for all four formulations and for instances with more than 20 requests, we will analyze the cost breakdown from the solution obtained from the heuristic. This is done in Table 3 in which the average results for all groups are presented. In order to make a comparison with the two initial scenarios without collaboration (I1 and I2) presented in Section 5.2, we extracted the resulting fixed, variable, environment and shipping costs from these two scenarios. Note that the shipping cost is the same for both initial scenarios without collaboration. There are no timing penalties with I1 and I2.

In Table 3, the first column shows initial scenarios and collaborative schemes. The second column shows the type of cost. The next three columns present the average partial cost for each group of instances, followed by the total average and the total cost. The cells in gray color represent the cost part taken into account in the optimization process for each collaboration method. We recall that these solutions have not been proved optimal and are subject to improvement. The fix cost of scenario I1 is very high and constant for each group of instances because we assume round trips to pickup all requests. Scenario I2, in which we plan a tour for each carrier, greatly improves I1 in terms of fix, variable and environmental costs by making more reliable routes without collaboration. The variable and environmental costs, reflecting the distance, are reduced by 42.5% with I2.

When we compare collaborative scheme CS1 with initial scenarios, we see an improvement of 58.6% in the total shipper cost (shipping + timing penalties) from 29 371.5$ to 11

Table 1: Performance of collaborative scheme models in terms of optimality gap and running time

	CS1				CS2				CS3				CS4			
	UB	**LB**	**GAP (%)**	**Time (s)**	**UB**	**LB**	**GAP (%)**	**Time (s)**	**UB**	**LB**	**GAP (%)**	**Time (s)**	**UB**	**LB**	**GAP (%)**	**Time (s)**
f1-10	2142.0	2142.0	0.0	0.0	398.0	398.0	0.0	1.0	3.2	3.2	0.0	1.0	2708.4	2708.4	0.0	0.0
f1-20	3341.0	3341.0	0.0	0.0	472.0	472.0	0.0	49.0	4.0	4.0	0.0	28.0	4075.2	4075.2	0.0	1.0
f1-30	4563.0	4563.0	0.0	1.0	674.0	674.0	0.0	1865.0	5.6	5.1	9.2	10800.0	5569.6	5569.6	0.0	22.0
f1-40	4969.0	4969.0	0.0	0.0	828.0	541.0	34.7	10800.0	8.0	4.0	49.1	10800.0	6231.8	6231.4	0.0	334.0
f1-50	5659.0	5659.0	0.0	0.0	998.0	430.3	56.9	10800.0	9.4	2.6	72.1	10800.0	6952.1	6952.1	0.0	53.0
f1-60	6682.0	6682.0	0.0	0.0	1238.0	460.3	62.8	10800.0	10.8	3.1	71.8	10800.0	8025.6	8024.9	0.0	1304.0
f1-70	8357.0	8357.0	0.0	11.0	1582.0	355.1	77.6	10800.0	12.7	2.2	82.6	10800.0	10091.3	9201.0	8.8	10800.0
f1-80	8139.0	8139.0	0.0	2.0	1830.0	355.3	80.6	10800.0	15.8	2.2	86.3	10800.0	10579.3	9205.7	13.0	10800.0
f1-90	10104.0	10104.0	0.0	2.0	2108.0	369.0	82.5	10800.0	16.2	2.5	84.4	10800.0	12111.7	11168.8	7.8	10800.0
f1-100	10808.0	10808.0	0.0	3.0	2020.0	353.7	82.5	10800.0	17.3	2.5	85.4	10800.0	13016.6	11990.8	7.9	10800.0
Average	**6476.4**	**6476.4**	**0.0**	**1.9**	**1214.8**	**440.9**	**47.7**	**7751.5**	**10.3**	**3.1**	**54.1**	**8642.9**	**7936.2**	**7512.8**	**3.7**	**4491.4**
f2-10	2906.0	2906.0	0.0	1.0	338.0	338.0	0.0	0.0	2.6	2.6	0.0	0.0	3287.0	3287.0	0.0	0.0
f2-20	4562.0	4562.0	0.0	0.0	504.0	504.0	0.0	19.0	3.8	3.8	0.0	7.0	5152.7	5152.7	0.0	0.0
f2-30	7606.0	7606.0	0.0	2.0	1060.0	538.5	49.2	10800.0	7.1	4.2	41.0	10800.0	8749.8	8748.9	0.0	5011.0
f2-40	8988.0	8988.0	0.0	14.0	1608.0	462.7	71.2	10800.0	13.2	3.4	73.9	10800.0	10421.5	10228.5	1.9	10800.0
f2-50	11083.0	11082.0	0.0	19.0	1946.0	453.3	76.7	10800.0	15.1	3.0	79.8	10800.0	13264.5	12106.5	8.7	10800.0
f2-60	13403.0	13401.7	0.0	33.0	2494.0	455.5	81.7	10800.0	19.7	2.6	87.0	10800.0	18460.8	14568.5	21.1	10800.0
f2-70	14680.0	14678.5	0.0	415.0	2432.0	456.9	81.2	10800.0	19.1	3.1	83.9	10800.0	17668.2	15689.8	11.2	10800.0
f2-80	17946.0	17944.2	0.0	206.0	2898.0	467.6	83.9	10800.0	24.3	3.1	87.4	10800.0	24717.8	19143.3	22.6	10800.0
f2-90	18786.0	18745.9	0.2	10800.0	3204.0	354.8	88.9	10800.0	25.9	2.5	90.5	10800.0	26136.6	19747.2	24.4	10800.0
f2-100	20481.0	20479.0	0.0	524.0	3340.0	341.4	89.8	10800.0	28.8	2.4	91.8	10800.0	29485.2	21795.5	26.1	10800.0
Average	**12044.1**	**12039.3**	**0.0**	**1201.4**	**1982.4**	**437.3**	**62.3**	**8641.9**	**16.0**	**3.1**	**63.5**	**8640.7**	**15734.4**	**13046.8**	**11.6**	**8061.1**
f3-10	4244.0	4244.0	0.0	0.0	486.0	486.0	0.0	1.0	3.6	3.6	0.0	1.0	4969.6	4969.6	0.0	0.0
f3-20	7350.0	7350.0	0.0	0.0	862.0	727.0	15.7	10800.0	6.0	5.5	8.2	10800.0	8474.8	8474.2	0.0	56.0
f3-30	10094.0	10093.0	0.0	43.0	1514.0	610.4	59.7	10800.0	7.8	4.4	43.8	10800.0	11382.0	11380.8	0.0	5511.0
f3-40	13467.0	13465.7	0.0	135.0	1776.0	659.0	62.9	10800.0	13.2	4.8	63.6	10800.0	15024.2	14703.2	2.1	10800.0
f3-50	17140.0	17138.3	0.0	693.0	2124.0	499.0	76.5	10800.0	15.8	3.5	78.2	10800.0	19526.5	18331.8	6.1	10800.0
f3-60	18959.0	18957.1	0.0	415.0	2572.0	557.5	78.3	10800.0	21.4	4.6	78.6	10800.0	24810.5	20199.2	18.6	10800.0
f3-70	21872.0	21869.8	0.0	393.0	3384.0	363.8	89.2	10800.0	27.4	2.2	91.9	10800.0	30227.5	23448.8	22.4	10800.0
f3-80	25216.0	25072.1	0.6	10800.0	3482.0	621.7	82.1	10800.0	24.2	4.8	80.3	10800.0	34236.8	26729.2	21.9	10800.0
f3-90	29048.0	29045.1	0.0	2395.0	4108.0	406.5	90.1	10800.0	30.3	2.9	90.6	10800.0	38127.2	30649.2	19.6	10800.0
f3-100	31466.0	31348.3	0.4	10800.0	4544.0	229.0	95.0	10800.0	32.5	2.2	93.2	10800.0	42024.5	33291.8	20.8	10800.0
Average	**17885.6**	**17858.3**	**0.1**	**2567.4**	**2485.2**	**516.0**	**65.0**	**9720.1**	**18.2**	**3.8**	**62.9**	**9720.1**	**22880.4**	**19217.8**	**11.2**	**8116.7**
Total average	**12135.4**	**12124.7**	**0.0**	**1256.9**	**1894.1**	**464.7**	**58.3**	**8704.5**	**14.8**	**3.3**	**60.2**	**9001.2**	**15517.0**	**13259.1**	**8.8**	**6889.7**

Table 2: ALNS performance against the collaborative scheme models

	CS1			CS2			CS3			CS4		
	ALNS	**UB**	Δ(%)	**ALNS**	**UB**	Δ(%)	**ALNS**	**UB**	Δ(%)	**ALNS**	**UB**	Δ(%)
f1-10	2142.0	2142.0	0.0	398.0	398.0	0.0	3.2	3.2	0.0	2708.4	2708.4	0.0
f1-20	3341.0	3341.0	0.0	472.0	472.0	0.0	4.0	4.0	0.0	4098.6	4075.2	−0.6
f1-30	4563.0	4563.0	0.0	684.0	674.0	−1.5	5.6	5.6	−0.4	5912.6	5569.6	−5.8
f1-40	4969.0	4969.0	0.0	698.0	828.0	18.6	6.1	8.0	30.3	6231.8	6231.8	0.0
f1-50	5659.0	5659.0	0.0	788.0	998.0	26.6	6.3	9.4	48.3	6952.1	6952.1	0.0
f1-60	6682.0	6682.0	0.0	812.0	1238.0	52.5	6.0	10.8	80.3	8025.6	8025.6	0.0
f1-70	8357.0	8357.0	0.0	930.0	1582.0	70.1	6.6	12.7	92.8	9844.7	10091.3	2.5
f1-80	8139.0	8139.0	0.0	1104.0	1830.0	65.8	8.3	15.8	90.7	9742.9	10579.3	8.6
f1-90	10104.0	10104.0	0.0	1066.0	2108.0	97.7	6.9	16.2	134.5	11877.1	12111.7	2.0
f1-100	10808.0	10808.0	0.0	1192.0	2020.0	69.5	7.6	17.3	126.5	12524.0	13016.6	3.9
Average	**6476.4**	**6476.4**	**0.0**	**814.4**	**1214.8**	**39.9**	**6.1**	**10.3**	**60.3**	**7791.8**	**7936.2**	**1.1**
f2-10	2906.0	2906.0	0.0	338.0	338.0	0.0	2.6	2.6	0.0	3287.0	3287.0	0.0
f2-20	4562.0	4562.0	0.0	504.0	504.0	0.0	3.8	3.8	0.0	5152.7	5152.7	0.0
f2-30	7701.0	7606.0	−1.2	854.0	1060.0	24.1	6.0	7.1	19.1	8749.8	8749.8	0.0
f2-40	8988.0	8988.0	0.0	1086.0	1608.0	48.1	7.8	13.2	70.1	10421.5	10421.5	0.0
f2-50	11107.0	11083.0	−0.2	1216.0	1946.0	60.0	8.6	15.1	75.9	12785.8	13264.5	3.7
f2-60	13403.0	13403.0	0.0	1556.0	2494.0	60.3	11.3	19.7	74.0	15358.5	18460.8	20.2
f2-70	14704.0	14680.0	−0.2	1536.0	2432.0	58.3	10.6	19.1	80.9	16758.0	17668.2	5.4
f2-80	17978.0	17946.0	−0.2	1864.0	2898.0	55.5	13.2	24.3	84.3	20302.1	24717.8	21.7
f2-90	18791.0	18786.0	0.0	1858.0	3204.0	72.4	12.5	25.9	107.0	21248.5	26136.6	23.0
f2-100	20567.0	20481.0	−0.4	1724.0	3340.0	93.7	10.4	28.8	175.5	22668.3	29485.2	30.1
Average	**12070.7**	**12044.1**	**−0.2**	**1253.6**	**1982.4**	**47.2**	**8.7**	**16.0**	**68.7**	**13673.2**	**15734.4**	**10.4**
f3-10	4244.0	4244.0	0.0	486.0	486.0	0.0	3.6	3.6	0.0	4969.6	4969.6	0.0
f3-20	7350.0	7350.0	0.0	844.0	862.0	2.1	6.0	6.0	0.0	8474.8	8474.8	0.0
f3-30	10094.0	10094.0	0.0	994.0	1514.0	52.3	6.3	7.8	23.2	11441.5	11382.0	−0.5
f3-40	13567.0	13467.0	−0.7	1162.0	1776.0	52.8	7.0	13.2	89.2	14985.8	15024.2	0.3
f3-50	17140.0	17140.0	0.0	1502.0	2124.0	41.4	9.0	15.8	76.3	19150.1	19526.5	2.0
f3-60	19059.0	18959.0	−0.5	1728.0	2572.0	48.8	11.0	21.4	94.0	21078.1	24810.5	17.7
f3-70	21872.0	21872.0	0.0	2340.0	3384.0	44.6	16.5	27.4	65.9	24663.2	30227.5	22.6
f3-80	25216.0	25216.0	0.0	2252.0	3482.0	54.6	14.0	24.2	72.4	28076.3	34236.8	21.9
f3-90	29048.0	29048.0	0.0	2420.0	4108.0	69.8	14.1	30.3	113.8	32076.5	38127.2	18.9
f3-100	31652.0	31466.0	−0.6	2992.0	4544.0	51.9	19.2	32.5	69.3	35096.4	42024.5	19.7
Average	**17924.2**	**17885.6**	**−0.2**	**1672.0**	**2485.2**	**41.8**	**10.7**	**18.2**	**60.4**	**20001.2**	**22880.4**	**10.3**
Total average	**12157.1**	**12135.4**	**−0.1**	**1246.7**	**1894.1**	**43.0**	**8.5**	**14.8**	**63.1**	**13822.1**	**15517.0**	**7.2**

Table 3: Heuristic solutions cost breakdown

Methods	Costs	Instances F1	Instances F2	Instances F3	Average	Total
I1	**Fix**	2750.0	2750.0	2750.0	2750.0	35816.5
	Var.	3724.8	3601.6	3640.8	3655.7	
	Env.	40.0	38.7	39.1	39.3	
	Ship.	23873.0	29381.0	34860.4	29371.5	
I2	**Fix**	405.0	615.0	825.0	615.0	32111.1
	Var.	1997.2	2012.0	2297.0	2102.1	
	Env.	21.5	21.6	24.7	22.6	
	Ship.	23873.0	29381.0	34860.4	29371.5	
CS1	**Fix**	275.0	470.0	675.0	473.3	14219.7
	Var.	1134.4	1594.0	1957.4	1561.9	
	Env.	12.2	17.1	21.0	16.8	
	Timing	190.0	320.0	360.0	290.0	
	Ship.	6305.9	11762.8	17564.2	11877.6	
CS2	**Fix**	230.0	445.0	665.0	446.7	18309.7
	Var.	584.4	808.6	1007.0	800.0	
	Env.	6.3	8.7	10.8	8.6	
	Timing	5270.0	5380.0	5210.0	5286.7	
	Ship.	5908.1	11671.7	17723.4	11767.7	
CS3	**Fix**	270.0	470.0	720.0	486.7	18625.0
	Var.	563.8	806.2	993.6	787.9	
	Env.	6.1	8.7	10.7	8.5	
	Timing	4880.0	5200.0	5490.0	5190.0	
	Ship.	6245.7	11861.8	18348.4	12152.0	
CS4	**Fix**	260.0	450.0	670.0	460.0	13837.3
	Var.	965.4	1164.8	1417.0	1182.4	
	Env.	10.4	12.5	15.2	12.7	
	Timing	400.0	510.0	370.0	426.7	
	Ship.	6156.0	11581.5	17529.0	11755.5	

877.6$ in total average. The timing penalty cost is relatively small at 290$. The greatest difference comes from instances from group *f1*, where we see an improvement of 72.8% in the total cost. Even if CS1 does not focus on variable cost minimization, it reduces from 2 102.1$ for I2 to 1 561.9 $ in CS1, an improvement of 25.7%.

Model CS2, which focuses on fix and variable costs minimization, gives a variable total average cost of 800.0$, a significant improvement of 61.9% from I2 (78.1% from I1). We note that the average variable cost between each group increases. Since the number of requests per instance is the same from a group to another, but the average number of pallets per request increases, it makes senses that the distances increase because more trips are required. This is demonstrated by the fix costs, which are 275$ for *f1* instances, 470$ for *f2* and 665$ for *f3*. We see a drastic increase in the timing penalties for each instance groups. However, in total average, the combination of timing and shipping costs still gives an average saving of 41.9% (timing penalty of 5 286.7$ and shipping cost of 11 767.7$). Collaborative scheme CS3 leads to very similar results in general.

As expected, CS4 gives very similar results in terms of costs to CS1 as the shipping cost are predominant. In total average, the total shipper cost is 12 182$ (timing penalty 426.7$ + shipping 11 755.5$). In comparison with I1 or I2, it represents an improvement of 58.5%. The total average variable cost of CS4 is 1 182.4$. An improvement of 43.8% from I2, and of 24.3% from CS1. The benefit of adding variable and/or environmental costs 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.

Table 4 presents a cross comparison of each objective function value. Each row represents collaborative scheme solutions used and each column represents the objective function evaluated. We take the total average of solutions cost of each scheme. For example, if one uses the solution found by CS1 (first row) and compute its costs using the objective function of CS2, we found this solution is 38.7% worse than the solution from CS2. In the same way, the solution from CS1 increases the cost of CS3 by 49.6% in comparison with the solution obtained with CS3.

We can see that the average solution of CS1 generates a large increase of distance based costs (CS2 and CS3). CS1 solution leads to an increase of 49.6% of the objective function of CS3. Solutions from CS2 and CS3, in comparison with CS1 solution, increase the cost by 28.7% and 29.8% (shipping and timing). Collaborative scheme CS4 is only 0.1% worse than the CS1 solution and leads to an increase of 24.1% and 33.4% for CS2 and CS3 objective functions, respectively. It shows that a collaborative scheme including shippers, carrier and external component costs leads to a well-balanced solution in terms of all collaborative scheme functions.

Table 4: Cross-comparison of collaborative schemes objective functions

		Impact on objective function			
		CS1	CS2	CS3	CS4
Average solutions	CS1	–	38.7%	49.6%	2.7%
	CS2	28.7%	–	1.5%	24.4%
	CS3	29.8%	2.2%	–	25.7%
	CS4	0.1%	24.1%	33.4%	–

5.4. Potential reductions in greenhouse gas emissions

In this section we study potential reductions in GHG emissions, CO_2e), that can be obtained by employing our solutions. Using data obtained from Transport Canada (2014), we assume that each heavy-duty truck used for the activities described in this paper consumes 46.9 L/100 km, and that each liter of diesel produces 2.79 kg of CO_2e.

First, we show that the worst case scenario I1 and the best case I2 produce significantly different emission levels. We depict in Figure 3 savings in emissions and the number of tons of CO_2e 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 577.4 tons of CO_2e could be saved simply by grouping pickups, even without the consolidation proposed in this paper. This shows that the carrier behavior can have a major impact on their fuel consumption and thus GHG emissions.

We compare the potential savings of scheme CS3, minimizing the GHG cost, and scheme CS4 with the initial scenario I2 which seems more reliable than I1. Our analysis is depicted in Figures 4 and 5.

When our proposed collaborative scheme CS3 is considered, it becomes evident that these savings can be significantly higher, going from 65.3% for group *f3* up to 80.8% for group *f1*, reducing emissions of CO_2e by 231.0 tons per year on average for this group. These are shown in Figure 4. Finally, the all-encompassing collaborative scheme CS4 costs also shows important savings achieving 46.9% and 168.8 tons of CO_2e on average per year for instances of group *f1* (Figure 5).

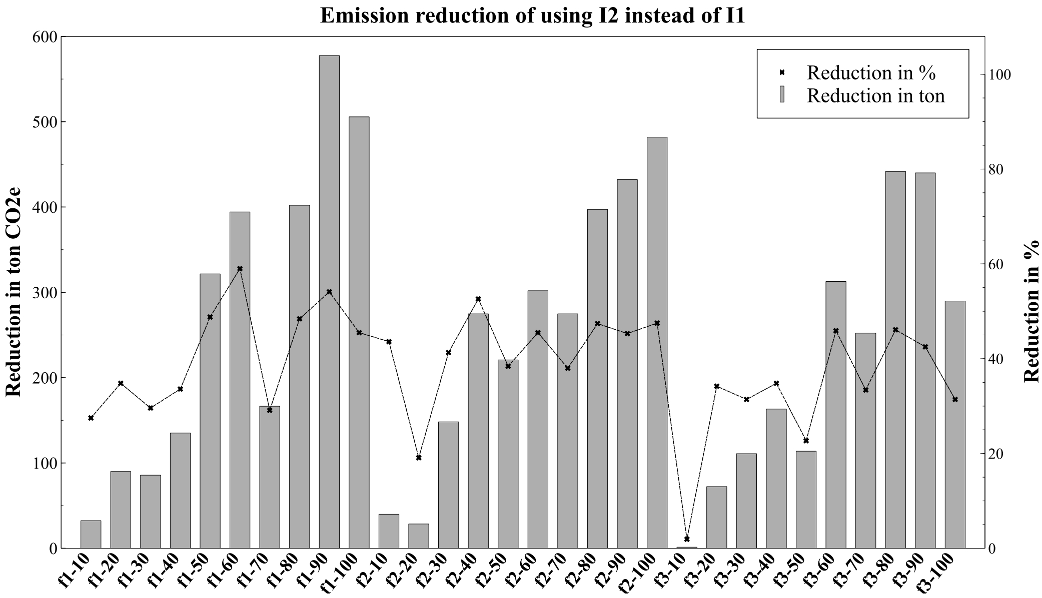

Figure 3: Emissions saving in tons and percentage – comparison between I2 and I1

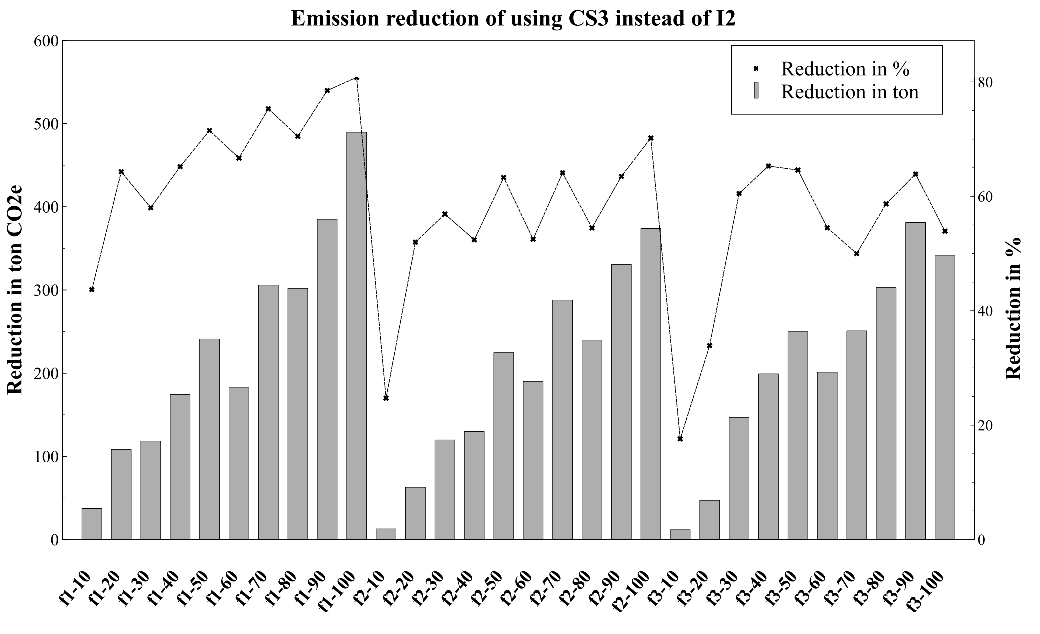

Figure 4: Emissions saving in tons and percentage – comparison between CS3 and I2

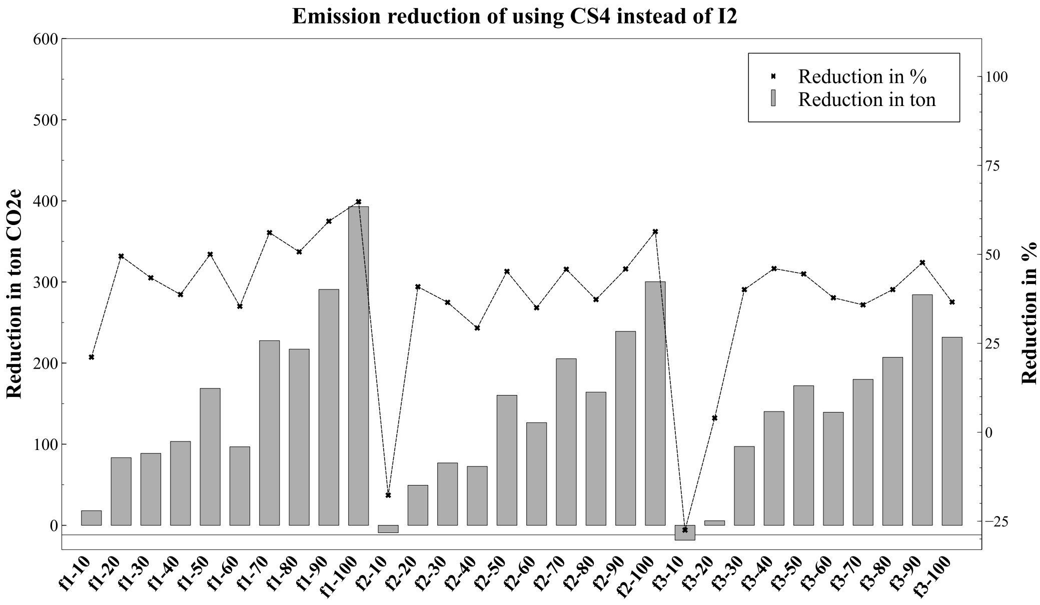

Figure 5: Emissions saving in tons and percentage – comparison between CS4 and I2

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 have shown 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 mileage 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 a very small impact on the service level. From a worst-case benchmark scenario, we show that mileage reductions of up to 3 043 km are possible when picking up 100 requests in a week.

From a city logistics perspective, we have estimated a reduction in GHG emissions stemming from the aggregation of orders to a single carrier. Our analysis shows a potential reduction of 80.8% in GHG emissions for small orders (up to 3 pallets per request), and of 65.3% 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 4899.7 tons of CO_2e per year are possible, while at the same time decreasing shipping costs by up to 93.0%.

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