A Freight Share-a-Trip Problem

Dingtong Yang (dingtony@uci.edu), Michael Hyland (hylandm@uci.edu), R. Jayakrishnan (rjayakri@uci.edu)

University of California-Irvine
Civil and Environmental Engineering
Institute of Transportation Studies,
4000 Anteater Instruction and Research Bldg. (AIRB)
Irvine, CA 92697-3600

1. Introduction

The recent decade has seen increased demand for package delivery services due primarily to convenient online shopping. The online purchase volume in the year 2022 is estimated to double 2016 volumes (Ivanov & Eby, 2018). Designing new logistic systems in urban areas could both save costs for logistic companies and reduce carbon emissions (Huang, Savelbergh & Zhao, 2018). To deal with the intensive load of last-mile urban package delivery, logistics companies may choose to either increase their investments in facilities, vehicles, and dedicated drivers or employ crowdsourcing services wherein drivers use their own personal vehicles at their convenience to deliver packages for the logistic company. Compared with conventional package delivery, which involves dedicated delivery vehicles and personnel, crowdsourced trip-shared delivery has the potential to reduce logistics costs and emissions. The goal of this study is to formulate and solve a large-scale urban package delivery problem with crowdsourced vehicles.

This study attempts to construct a combined urban package delivery system (Figure 1). The system serves an area with both dedicated vehicles and crowdsourced vehicles (shared vehicles). In the proposed crowdsourced system, the shared vehicles detour slightly from their already planned trip/route in order to pick up packages at the distribution center and deliver them to houses/business along their original route. In the system, logistics service providers know the information about the packages and the itinerary of drivers who are willing to share their trips to deliver some packages.

![Figure 1. A Combined Freight Delivery System](image-url)
A few pilot programs have been launched by Walmart, DHL, and Amazon in recent years to utilize non-dedicated vehicles for delivery (Archetti, Savelsbergh & Speranza, 2016, Arslan et al, 2018). However, important research questions related to crowdsourced urban delivery remain. For example, what vehicles could be utilized for freight share-a-trip? What price should be paid to share-a-trip vehicle drivers? The main contributions of this study include (i) modeling the deterministic-static and stochastic-dynamic versions of the package share-a-trip delivery problem; (ii) analyzing the potential cost savings that may result from crowdsourcing compared to only using dedicated vehicles and drivers; and (iii) proposing and comparing three policies to solve the stochastic-dynamic share-a-trip delivery problem.

2. Modelling the Problem

This section describes the model for the freight share-a-trip problem and briefly describes the solution algorithms.

The problem contains two types of vehicles, shared-personal vehicles (sedans and SUVs, represented by $S$) and dedicated vehicles (vans and medium-duty trucks, represented by $D$) for delivery. Each individual shared-personal vehicle is represented as $s_k$ ($s_k \in S$) with a heterogeneous capacity $q_{sk}$. The earliest departure time from the distribution center hub and latest arrival for a shared-personal vehicle $s_k$ at its own destination are denoted by $T_d^{sk}$ and $T_a^{sk}$, respectively. Each dedicated vehicle is denoted by $d_k$ ($d_k \in D$) without capacity or time window constraints.

The set of packages to be delivered is defined as $P$. Each individual package is represented as $p$ ($p \in P$). Each package $p$ also has an earliest pickup (departure from distribution center) time and latest delivery (arrival at destination) time, denoted as $T_d^{pi}$ and $T_a^{pi}$ respectively.

The service network is defined as $G = (N, A)$. $N$ includes the distribution center (or hub), all drop-off points for packages, and the designated destinations for shared-personal vehicles. $A$ is the set of arcs/links connecting vertexes/nodes. For any node pair $i, j \in N$, the tuple $(i, j)$ is used to denote the link from Node $i$ to Node $j$. The location of the distribution center is denoted $h \in N$; it is also the departure hub for dedicated vehicles, $0 \in N$, and the arriving hub of dedicated vehicles, $h \in N$. The drop-off location of each package $p$ is represented as $N_p$. The designated destination of each shared-personal vehicle $s_k$ is represented as $N_{sk}$. The averaged monetized travel cost (fuel, time, human resource etc.) on a link $(i, j)$ is represented as $c_{ij}^s$ and $c_{ij}^d$ for shared-personal vehicles and dedicated vehicles, respectively. The travel time on a link $(i, j)$ is represented as $\tau_{ij}$. The monetized cost for each shared-personal vehicle to travel from its origin to the distribution center $0$ is represented as $c_{0sk}$. The monetized cost for each shared-personal vehicle to travel directly from its origin to its destination is represented as $c_{sk}$. For each shared-personal vehicle, when dropping off a package, a delay happens. To compensate the delay cost for shared-vehicle driver, a fixed cost term $e$ is introduced for every stoppage.

We first formulate the problem as a static multi-capacitated-vehicle pickup and delivery problem with time window constrainst ($m$-CVPDPTW) with a minimum total delivery cost objective function. The complete formulation is a quadratic-integer program.

$$\min_{x, z, t} \sum_{k \in S} \left( Z_{sk} \left( c_{0sk} + \sum_{(i,j) \in A} c_{ij}^s x_{ij}^k - c_{sk} \right) + \sum_{(i,j) \in A} e \left( x_{ij}^k - 1 \right) \right) + \sum_{k \in D} \sum_{(i,j) \in A} c_{ij}^d x_{ij}^k$$

(Constraints include standard vehicle routing constraints, capacity, and time window constraints).
In the dynamic setting, we discretize the daily operation into time periods (or stages). We assume that exact information about packages and shared vehicles (e.g., location of delivery, time window) is unknown before the beginning of the first stage and may appear over time.

The service region is separated into $m$ zones/blocks. At each stage, all the packages are separated by delivery zones and recorded in a list/vector of size $m$ (e.g., $State_p = [N_{p,1}, N_{p,2} ... N_{p,m}]$).

The state variable has three components. The size $m$ package delivery zone vector is the first component of the state vector. All shared vehicles are also coded as a list/vector by their destination zones. To deal with the routing/path finding problem, we solve an offline problem that involves enumerating the possible paths/routes of shared vehicles. To enumerate the possible routes of shared vehicles, we perform a backtracking for each shared vehicle from its destination zone and checking the time window of travelling during the process. One available route for a shared vehicle is represented as a collection of tuples of location time combination, e.g., $[[\text{Origin}, \text{time}_0], (\text{Node}_1, \text{time}_1), (\text{Node}_2, \text{time}_2) ..., (\text{Destination}, \text{time}_\text{end})]$. The second component of the state vector is the set of all possible paths/routes for each vehicle at the beginning of the stage. The third component of the state vector is the dedicated vehicle/truck route or availability. Therefore, for each stage, the state variables will be a combination of deliverable package set, available shared vehicle route set, and dedicated vehicle set. The overall objective is to minimize the total delivery cost, which is:

$$U_t(E_t) = \min_{a_t}\{C_t(E_t, a_t) + \gamma \sum_{E' \in E} C(E'|E_t, a_t)U_{t+1}(E')\}$$

where $U_t$ is the total cost from stage $t$ onward, and $E_t$ is the state of stage $t$. $a_t$ is the action taken at stage $t$, and $C_t$ is the delivery cost incurred during stage $t$. $\gamma$ is the discount factor for future stages.

We have two control options for a package at each stage, namely, assigning it to a vehicle (either a shared one or a truck) or holding it until a later stage (without offending the time window constraints). We are trying to match as many packages as possible to shared vehicles in order to reduce the dedicated truck usage. In each stage, we are solving a matching problem between packages and possible vehicle routes as follows:

$$\text{Min } Z = \sum_{i \in P} \sum_{k \in S} e \times x_{i,p} + \sum_{v \in S} \sum_{r \in R_k} c_{v,p} x_{k,r}$$

$$\sum_{k \in S} x_{i,k} \leq 1, \forall i \in P \ (1)$$

$$\sum_{i \in P} x_{i,k} \leq q_{sv}, \forall k \in S \ (2)$$

$$\sum_{r \in R_k} x_{k,r} = 1, \forall k \in S \ (3)$$

$$x_{i,k} = \sum_{d_{i} \in r} x_{k,r}, \forall (i,k) \in (P,S) \ (4)$$

$$x_{i,k}, x_{k,r} \in \{0,1\}$$
In this formulation, we have two decision variables $x_{i,k}$ and $x_{k,r}$. The first one is the binary variable of matching a package $i$ to a vehicle $k$, and the second one is the binary variable of choosing a route $r$ for vehicle $k$. $e$ is the per package payment to a vehicle (cost of delivery) for delivering. $c_{v,r}$ is the detour cost for vehicle $k$ when route $r$ is chosen. Constraint (1) is the matching constraint for packages. Constraint (2) is the capacity constraint for vehicles. Constraint (3) ensures only one route for a vehicle $k$ is active. Constraint (4) is the linkage constraint for the two decision variables.

This study considers three policies for dynamically assigning packages to vehicles. First, assign packages as early as possible to feasible vehicles (holding as few packages as possible). Second, assign a package $r$ to a vehicle route only if the vehicle’s shortest path route includes package $r$’s drop-off zone; otherwise, hold the package for an additional $\Delta t$ stages. Third assign a package $r$ to a vehicle route only if the vehicle’s shortest path route includes package $r$’s drop-off zone; otherwise, continue to hold the package until not assigning it would violate the time-window constraint.

We can also introduce a variable $y_i$ to indicate whether a package is assigned or not. We can have additional constraints:

$$y_i = \sum_{v \in S} x_{i,k}, \forall i \in P$$

Constraint (5) could be adjusted based on the different policies. When we use the first type of policy, we will not need Constraint (5), but Constraint (1) will needs to change to an equality constraint. For the second and third policies (holding for $\Delta t$ stages), we will keep (5) and introduce:

$$y_i \geq [e - \sum_k (e \times x_{i,k} + \sum_r c_{k,r} x_{k,r}) + 1], \forall i \in P$$

$$y_i = 1, \forall i \in P_w$$

Constraint (6) ensures that the packages with the lowest possible delivery cost will be assigned at each stage. Constraint (7) ensures the waiting set of packages will be delivered if they have been waited for enough stages.

3. Preliminary Results

For the dynamic case, we apply the proposed solution approach to the Nguyen-Dupuis Network (bi-directional). Node 1 is selected as the depot. In total, 20 packages are generated following a uniform distribution across 12 zones and 3 stages. In addition, 30 shared vehicles are generated following a uniform distribution for their origins and destinations. We test the following three policies for assigning packages to shared/dedicated vehicles:
1. Assigning packages to vehicles at the earliest possible stage
2. Assigning packages to vehicles with the shortest possible detour, holding unassigned packages for one additional stage
3. Assigning packages to vehicles with shortest possible detour, holding unassigned packages until the latest possible stage

We compare the total cost of delivery for the set of 20 package across these three strategies with the conventional VRP delivery (Table 1). In Table 1, we mainly compare total vehicle miles travelled (VMT) and monetized cost for delivery.

**Table 1. Summary of Results**

<table>
<thead>
<tr>
<th></th>
<th>Vehicle Miles Travelled (VMT)</th>
<th>VMT Savings (w.r.t VRP)</th>
<th>Monetary Cost (in dollars)</th>
<th>Cost Savings (w.r.t VRP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dedicated Delivery</td>
<td>118.37</td>
<td>N/A</td>
<td>$85.64</td>
<td>N/A</td>
</tr>
<tr>
<td>Policy 1</td>
<td>81.25</td>
<td>31.4%</td>
<td>$66.68</td>
<td>22.13%</td>
</tr>
<tr>
<td>Policy 2</td>
<td>78.13</td>
<td>34.0%</td>
<td>$62.97</td>
<td>26.47%</td>
</tr>
<tr>
<td>Policy 3</td>
<td>96.88</td>
<td>18.15%</td>
<td>$72.4</td>
<td>15.46%</td>
</tr>
</tbody>
</table>

Table 1 shows that using shared vehicles for delivery could reduce VMT and operational costs significantly. Out of the three policies, Policy 2 saves the most in terms of both VMT and monetary cost. VMT savings is about 34% and cost savings is around 26% compared to dedicated vehicles only. Policy 1 has similar level of performance as Policy 2. It is also interesting to observe that Policy 3 underperforms the other policies. One potential explanation for it may be the long holding time for packages. When a package has been held until the last possible stage before the end of its time window, it may still have no “least cost” vehicle matching, then a dedicated vehicle must be used to deliver it, which will incur unnecessary cost.

**4. Conclusion**

In this study, we model the dynamic case of urban package share-a-trip delivery. We also propose three policies to assign packages to shared and dedicated vehicles. The results show that compared to conventional VRP with dedicated vehicles, share-a-trip delivery can reduce VMT by around 30% and cost by around 20%. The results also show that holding a package for additional periods could bring additional cost saving. However, holding a package for too long can also incur unnecessary cost for delivery.

**Reference:**

