Crowdsourced Delivery with Drones in Last Mile Logistics

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Abstract

We consider a combined system of regular delivery trucks and crowdsourced drones to provide a technology-assisted crowd-based last-mile delivery experience. We develop analytical models and methods for a system in which package delivery is performed by a big truck carrying a large number of packages to a neighborhood or a town in a metropolitan area and then assign the packages to crowdsourced drone operators to deliver them to their final destinations. A combination of heuristic algorithms is used to solve this NP-hard problem, computational results are presented, and an exhaustive sensitivity analysis is done to check the influence of different parameters and assumptions.

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1 Introduction

The number of deliveries and the revenue obtained from delivery operations have been growing continuously and rapidly during the last two decades, thanks to the exponential growth of e-commerce. However, the efficiency of delivery operations still remains a big challenge. The last mile of delivery process has consistently been one of the most expensive (nearly or even more than 50% of the total cost), least efficient, and most polluting part of the entire parcel delivery supply chain [7, 6]; the fact that Amazon Flex has been paying \$18-\$25 for Uber-like package delivery services [1], while they have not increased their hourly wages to \$15 up until just recently [2], speaks to the expensiveness of the last-mile delivery operations.

The expensiveness of last-mile delivery is due to a number of factors including the facts that it is a labor-intense operation, it is a scattered operation serving different individual customers at dispersed places, which often results in underutilized carrier capacity, and that such deliveries are usually very time-consuming because of road congestion, accessibility of the destinations, and most importantly unattended deliveries. The rapidly increasing importance of same day and same hour delivery in our lives will make this operation even

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more inefficient. Such deliveries are mostly used for low-value high-frequency products such as grocery items for which the shipping cost could quickly become disproportionate in the eyes of consumers.

The advancement of technology can revolutionize the conventional delivery practices and boost the efficiency. Among these advancements are the recent efforts to adopt *autonomous vehicles*, *unmanned aerial vehicles* (UAVs), *automated guided vehicles* (AGVs), and other *droids* in package delivery operations. The integration of autonomous and semi-autonomous technologies into the last-mile delivery operations in a centralized or decentralized manner have the potential to remove or mitigate the long-lasting factors such as pooling and routing inefficiencies that have been contributing to the expensiveness of last-mile delivery.

In an earlier work, we have shown that for a centralized delivery system to be competitive with the decentralized household shopping model, a very large portion of the population have to adopt the centralized system and shows inefficient pooling as the primary cause of inefficient last-mile delivery [3]. This paper analyzes the impact of decentralization, in particular crowdsourcing of the last part of the last-mile delivery operations when integrated with new technologies, on the efficiency of pooling and clustering customers.

In this paper, we combine the autonomous delivery vessels with regular delivery trucks, vans, cars, and bikes to provide a technology-assisted crowd-based last-mile delivery experience and a better and smoother transition to a fully autonomous parcel delivery ecosystem. We develop analytical models and methods for one of these intermediary systems, in which package delivery is performed by a big truck carrying a large number of packages to a neighborhood or a town in a metropolitan area and then assign the packages to crowdsourced delivery agents who operate *drones* to deliver them to their final destinations. To the best of our knowledge this is the first work studying this problem. A combination of heuristic algorithms is used to solve this NP-hard problem and an exhaustive sensitivity analysis is done to check the influence of different parameters and assumptions such as speed ratio of drones and trucks, the number of drones in the service region, and the distribution of the customers. The simulation results show significant savings in the total delivery cost under reasonable assumptions.

1.1 Related Work

Sharing economy indicates a system in which people share access to goods and services as opposed to ownership [13] and it has been extensively studied. However, the application of sharing economy system in delivery services has received less attention and only a few number of research articles exist about this topic. The paper [12] proposed the idea of crowd-based operations in city-level logistics which is also a kind of sharing economy logistics. They indicated that there are four kinds of crowd-based logistics which are crowdsourced delivery, cargo-hitching, receiving packages and returning packages. There have been a number of experimental and theoretical research related to this topic.

On the experimental side, the paper [9] used a survey to analyze potential driver behavior in choosing to work as a part-time crowdsourced shipper. Meanwhile, the paper [11] also created a survey to study the determinants of crowd-shipping acceptance among drivers. The paper [4] developed an agent-based simulation model for the crowdsourced last-mile delivery service with the existence of central pickup location/warehouse and identified the important factors influencing its performance. They ran the simulation in Washington DC area and UPS stores as package stations.

Among the relevant theoretical research, the paper [5] discussed the idea of encouraging individuals/shoppers in a store who are willing to deliver packages for online customers on their way back home. They used vehicle routing problem with occasional drivers (VRPOD) as the main idea of their model. They presented a bi-level methodology for matching and routing problem, where the first level is a deterministic IP model for VRPOD and the second level is a stochastic model to minimize the expected delivery costs subject to uncertain occasional drivers who could accept the delivery tasks. Many researchers explored the crowdsourced delivery service with crowdsourced drivers to come to the package center to pickup the packages and deliver them to the destination. The paper [8] introduced a route-planning problem that involves the use of crowdsourced drivers and dedicated vehicles in case that crowdsourced drivers are not available to perform some real-time delivery tasks. They present a rolling horizon framework and an exact solution approach based on a matching formulation to solve the problem. They also compared their results with the traditional delivery system and concluded that the use of crowdsourced drivers can significantly reduce the costs. The paper [10] used Ant Colony Optimization to solve the crowdsourced delivery problem with multiple pickup and delivery with crowdsourced vehicles only. They used Analytical Hierarchical Process to evaluate several scenarios in this problem and provide the best scenario to consider. Their results show that by implementing multiple pickup and delivery, there was 47% reduction on number of trips, 20% reduction on total distance and 14% on duration.

Very few papers in the literature consider the cooperative delivery system with a truck and crowdsourced carriers. The paper [13] was the first to evaluate the use of shared mobility for last mile delivery services in coordination with delivery trucks. They tried to minimize the combined transportation and outsourcing cost of the trucks and shared mobility. They also considered minimizing greenhouse gas emissions as one of their objectives. They used an analytical model and found that crowdsourced shared mobility is not as economically scalable as the conventional truck-only system with respect to the operating costs, that is because of the payment to shared delivery drivers accounts for the shared rides market. However, they state that a transition towards this model can create economic benefits by reducing the truck fleet size and adding operational flexibilities.

There is a lack of a study on the design of a cooperative delivery system with a truck and autonomous or semi-autonomous crowdsourced carriers. In this paper we fill this gap.

2 Problem Statement

Consider a residential area in which one truck has to go through all the neighborhoods in this area to deliver some packages. There are also private drone operators in the area that could deliver packages from the truck to their final destination (households). When the truck stops at a neighborhood corner, the crowd-based drones, after receiving an order from the courier, will fly from their base to that corner to pick up the packages, deliver them to the customers and go back to their base, i.e. operator's house, for recharging the battery. The objective is to design a coordinated system between the truck and these drones in a way that minimizes the total time spent on fulfilling the demand of all customers in that area. Figure 1 shows an illustration of this cooperative delivery between a truck and crowd-sourced drones. In this problem we assume that:

1. Each drone can only carry one item at a time.
2. The charging time for drones at home is 0 (can change to a new battery).
3. There is no weight limit for a drone to carry the package.
4. The speed of drones are three times the speed of of the truck.
5. If there is no drone nearby, the truck will serve all the customers.
6. Drone returns to its base for recharging after each delivery.
7. Each drone base launches only one drone.

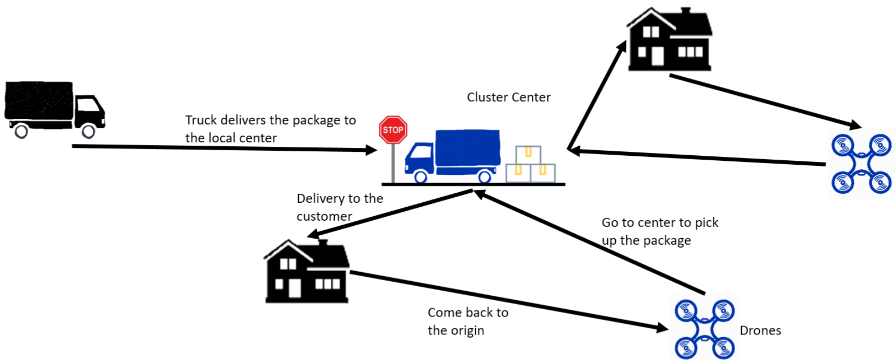


Figure 1 Crowd-sourced Drone Delivery.

3 Problem Formulation

3.1 Problem with One Center

In the problem with one center, there is no truck route and truck operates as a depot for a fleet of drones to pick up the package and deliver them to the customers. The problem with one center is important to study because it sets a a basis for the general problem and also it helps to understand the dynamics inside a cluster in a better way. The insight behind our algorithm is partly driven by this sub-problem. Before we present our model for this problem we define the parameters and variables as follows.

Sets:

sets	meaning
C	Customer Nodes
D	Drone Nodes
T	Truck nodes, only one node, call it node 0

Parameters:

parameters	meaning
n_C	Number of customer nodes
n_D	Number of drone nodes
d_{ij}	Route length going from node $i \in D$ to the center node and then to node $j \in C$ and back to node i
v_D	Speed of drones
c_{ij}	$= \frac{d_{ij}}{v_D}$, time spent by a drone for traversing the route $i - 0 - j - i$
L	Longest distance a drone can travel without charging battery

Decision Variables:

variables	meaning
x_{ij}	Binary decision variable. It is 1 when a drone travels from node $i \in D$ to the center node 0 and then to node $j \in C$ and back to node i. It is 0 otherwise.
q_i	Total travel time of the drone with base at node i
Q	Maximum time spent by all drones

The model can be written as following

$$\text{minimize} \quad Q$$

Subject To:

$$\begin{aligned}
\sum_{i \in D} x_{ij} &= 1\,, & \forall j \in C & \qquad (1)\\
d_{ij} x_{ij} &\leq L\,, & \forall i \in D, j \in C & \qquad (2)\\
\sum_{j \in C} c_{ij} x_{ij} &\leq q_i\,, & \forall i \in D & \qquad (3)\\
q_i &\leq Q\,, & \forall i \in D & \qquad (4)\\
q_i &\geq 0 & &\\
Q &\geq 0 & &\\
x_{ij} &\in \{0, 1\} & &
\end{aligned}$$

The objective is to minimize the maximum time of each drone route. Constraint (1) makes sure all customers have been visited once. Constraint (2) ensures the distance traveled by each drone does not exceed the maximum distance allowed by drones. Constraints (3) finds the time spent by each drone and Constraint (4) calculates the maximum time among all drones.

3.2 General Problem

In the general problem we assume that the truck only stops at a customer location and while stopping there that location will serve as a center to drones as well to pickup the packages. The mathematical formulation of the problem is as follows:

Sets:

sets	meaning
C	Customer Nodes
D	Drone Nodes

Parameters:

parameters	meaning
n_D	Number of drone nodes
n_C	Number of customer nodes
v_D	Speed of drones
v_T	Speed of trucks
$d_{pp'}$	Distance between node $p \in C$ and $p' \in C$
$c_{pp'}$	$= \frac{d_{pp'}}{v_T}$, time spent by the truck travelling from node $p \in C$ to node $p' \in C$
d_{ij}^p	Route length going from node $i \in D$ to the center node $p \in C$ and then to customer node $j \in C$ and back to node i
c_{ij}^p	$= \frac{d_{ij}^p}{v_D}$, time spent by a drone for traversing the route $i - p - j - i$
L	Longest distance a drone can travel without charging battery
M	A big number

Decision Variables:

variables	meaning
y_p	Binary decision variable equal to 1 if node $p \in C$ is served by the truck and 0 otherwise
x_{ij}^p	It is 1 when a drone travels from node $i \in D$ to the center node $p \in C$ and then to customer node $j \in C$ and back to node i. It is 0 otherwise.
q_{ip}	Total travel time of the drone with base at node $i \in D$ that is assigned to center $p \in C$
Q_p	Maximum time spent by all drones assigned to center $p \in C$
$\gamma_{pp'}$	Binary decision variable equal to 1 if the path from p to p' has been used
u_p	dummy variable
$\delta_{pp'}$	Binary decision variable equal to 1 if $y_{p'} = \gamma_{pp'} = 1$
$\varepsilon_{pp'}$	Binary decision variable equal to 1 if $y_p = \gamma_{pp'} = 1$

The model for the general problem can be written as following:

$$\text{minimize} \quad \sum_{p \in C} \sum_{p' \in C} c_{pp'} \gamma_{pp'} + \sum_{p} Q_p$$

Subject To:

$$\begin{aligned}
\sum_{p \in C} y_p &\geq 1\,, && (5)\\
\sum_{p \in C} \sum_{i \in D} x_{ij}^p &= 1 - y_j\,, \qquad \forall j \in C && (6)\\
x_{ij}^p &\leq y_p\,, \qquad \forall i \in D, j, p \in C && (7)\\
d_{ij}^p x_{ij}^p &\leq L\,, \qquad \forall i \in D, j, p \in C && (8)\\
\sum_{j \in C} c_{ij}^p x_{ij}^p &\leq q_{ip} + M y_p\,, \qquad \forall i \in D, p \in C && (9)\\
q_{ip} &\leq Q_p\,, \qquad \forall i \in D, p \in C && (10)\\
\sum_{p \in C} y_p \gamma_{pp'} &= y_{p'}\,, \qquad \forall p' \in C && (11)\\
\sum_{p' \in C} y_{p'} \gamma_{pp'} &= y_p\,, \qquad \forall p \in C && (12)\\
u_p - u_{p'} + \sum_{p \in C} \gamma_{pp'} &\leq \sum_{p \in C} y_p - 1\,, \qquad 2 \leq p \neq p' \leq \sum_{p \in C} y_p && (13)\\
x_{ij}^p, \gamma_{pp'}, \delta_{pp'}, y_p &\in \{0,1\}\\
q_{ip}, Q_p &\in \mathbb{R}\\
u_p &\in \mathbb{N}
\end{aligned}$$

The objective function minimizes the sum of the time that truck takes to travel between the stopping centers on its route and the total time that it takes to serve clusters of customers with drones at these stopping points. Constraint (5) ensures that at least one customer node is set to be truck node. Constraint (6) ensures all customers are visited once either by the truck or by one of the drones. Constraint (7) ensures that drones can only fly to a center node that is visited by the truck. Constraint (8) ensures that a drone cannot fly more than its battery limit. Constraints (9) and (10) are used to find the time spent at each stop of the truck to serve a cluster of customers. Finally, constraints (11)-(13) are TSP constraints for the truck.

To linearize the $y_{p'}\gamma_{pp'}, y_p\gamma_{pp'}$ term, we add two dummy variables $\delta_{pp'}, \varepsilon_{pp'}$ and six more constraints as

$$\delta_{pp'} \geq y_{p'} + \gamma_{pp'} - 1 , \qquad \forall p, p' \in C \tag{14}$$
$$\delta_{pp'} \leq \gamma_{pp'} , \qquad \forall p, p' \in C \tag{15}$$
$$\delta_{pp'} \leq y_{p'} , \qquad \forall p, p' \in C \tag{16}$$
$$\varepsilon_{pp'} \geq y_p + \gamma_{pp'} - 1 , \qquad \forall p, p' \in C \tag{17}$$
$$\varepsilon_{pp'} \leq y_p , \qquad \forall p, p' \in C \tag{18}$$
$$\varepsilon_{pp'} \leq \gamma_{pp'} , \qquad \forall p, p' \in C \tag{19}$$

Meanwhile, constraints (11) and (12) need to be modified to (20) and (21) respectively as following:

$$\sum_{p \in C} \varepsilon_{pp'} = y_{p'} , \qquad \forall p' \in C \tag{20}$$
$$\sum_{p' \in C} \delta_{pp'} = y_p , \qquad \forall p \in C \tag{21}$$

We solved this model for small instances but for larger problems we rely on a heuristic algorithm.

4 Solving Approach

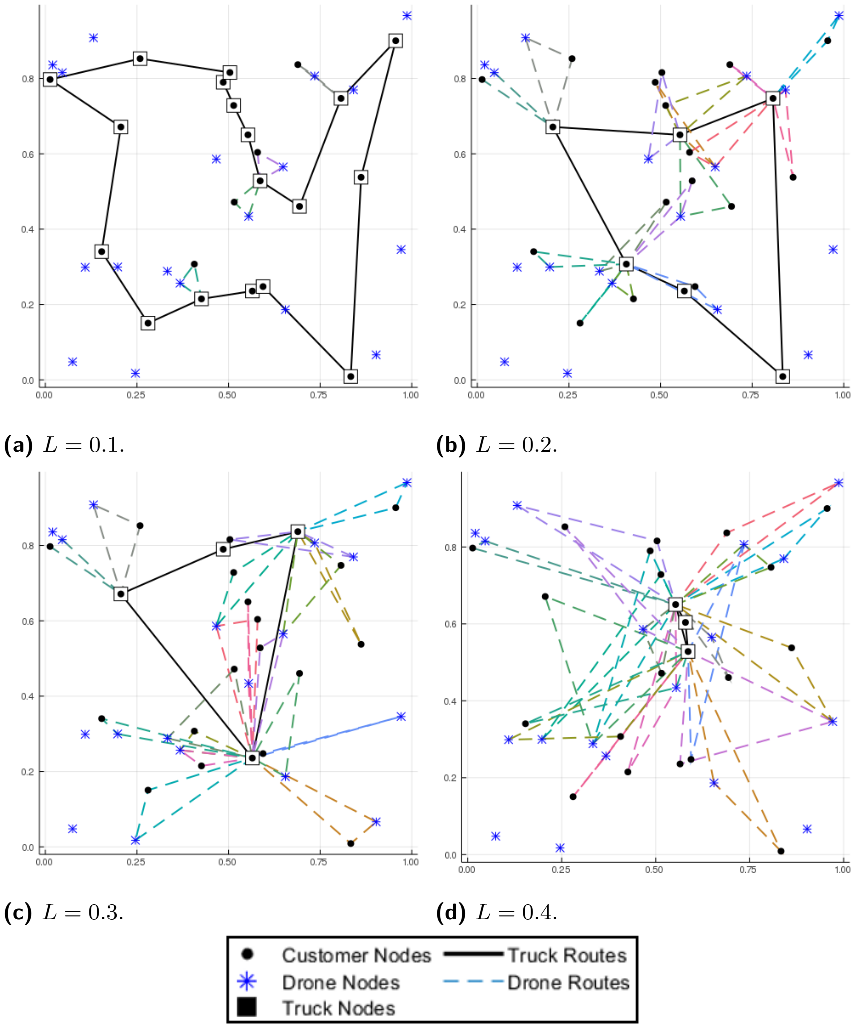
As the problem is NP-hard we take a heuristic approach to solve the problem. Our algorithm consists of several sub-routines as explained in the following. Let L be the the maximum distance a drone can fly with a full battery. We first cluster all customers to k centers (truck stops) using *k-means clustering algorithm* to ensure all customers are within radius $L/4$ of the centers. The choice of radius $L/4$ is to make sure that with one full battery the drones in each cluster can finish the delivery and return to their base. The number k is the minimum number that makes this feasible and will be found using a binary search. The feasible k means all customers are located in a circle that is centered at the cluster center with radius $L/4$. The final geographic partitioning is done using a *Voronoi partitioning scheme*. Then in each cluster, a *Tabu Search algorithm* will be used to solve the problem. In each cluster, several drones will fly from their origin (base), go to the truck center, deliver the packages to the customer and go back to their base. At the same time, *Lin-Kernighan-Helsgaun algorithm* will be used to solve the travelling salesman problem (TSP) to find the truck tour among the cluster centers and the customers that there is no drone available to serve them. If there is one cluster that has no drones in it, then all the customers in that cluster will be served by the truck.

The high-level steps of the algorithms are as follows:

Step 1: Running the binary search and the k-means clustering algorithm to find the minimum feasible k to cluster all customers into k clusters within radius $L/4$.

Step 2: Partitioning the region with the Voronoi tessellation generated by the k center points from Step 1 and assigning customers and drone bases to their nearest center.

Step 3: Running a Tabu Search algorithm to solve the sub-problem in each cluster where parcels are assigned to drones to be delivered to customers in a way that minimizes total delivery time.



(a) $L = 0.1$. **(b)** $L = 0.2$. **(c)** $L = 0.3$. **(d)** $L = 0.4$.

Figure 2 Examples of solutions obtained by the optimization model for different values of L (the maximum distance a drone can travel).

Step 4: Solving the truck tour by the Lin-Kernighan-Helsgaun algorithm to go through all cluster centers as well as all customer nodes that do not have any drone node in that cluster.

5 Computational Results

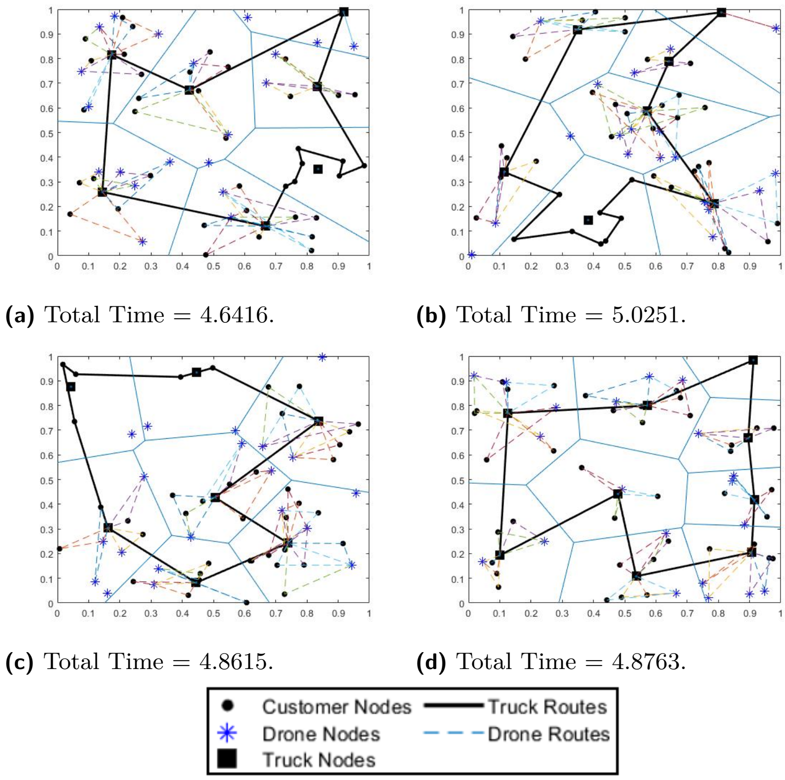
We tested both the model and the algorithm on a synthetic example with 40 customer nodes and 20 crowdsourced drone nodes distributed uniformly at random in a unit square, and the drone speed is three times the speed of the truck. Figure 2 illustrates solutions of instances of the problem solved by our optimization model for different values of L and Figure 3 shows an illustration of solutions of instance of the problem with different distribution of points solved by our algorithm. Figure 4 shows the TSP solutions, which represents the conventional centralized truck-only delivery system, for the same instances shown in its decentralized alternative in Figure 3. Table 1 compares the computational results of the our optimization

Table 1 Comparison between the results of the optimization model and the algorithm on a synthetic example with 40 customers nodes and 20 drone nodes distributed randomly in a unit box and for different values of L. The column "Time" shows the computational time in seconds.

L	**Model**		**Algorithm**		
	Time	Objective Value	Time	Objective Value	Gap (%)
0.05	15.18	4.19	0.78	4.19	0.00
0.1	47.60	4.06	0.56	4.07	0.00
0.15	338.91	3.82	0.47	3.88	0.02
0.2	210.12	3.40	0.88	3.57	0.05
0.25	997.18	3.14	0.83	3.68	0.17
0.3	276.66	2.65	0.95	3.08	0.16
0.35	126.63	2.22	1.55	2.77	0.25
0.4	76.29	1.86	1.65	2.94	0.58
0.45	3.97	0.91	2.13	2.58	1.83
0.5	34.18	0.53	3.35	1.39	1.61
0.55	41.05	0.50	4.99	1.21	1.43
0.6	46.62	0.50	5.19	1.21	1.43
0.65	49.85	0.50	12.42	0.84	0.67
0.7	54.61	0.50	11.98	0.80	0.59
0.75	55.81	0.50	11.48	0.84	0.67
0.8	78.87	0.50	11.61	0.80	0.59
0.85	77.26	0.50	11.80	0.85	0.71
0.9	80.48	0.50	11.44	0.80	0.59
0.95	80.64	0.50	12.00	0.81	0.62
1	81.25	0.50	11.40	0.82	0.64
Average	**138.66**	-	**5.87**	-	**0.63**

model and our heuristic algorithm for a number of these instances. As it is evident from the table, the algorithm is much faster than the optimization model (average time of 5.87 seconds versus 138.66 seconds) and the optimality of gap of the solutions provided by the algorithm is less than 2% in all instances with an average gap of 0.63%.

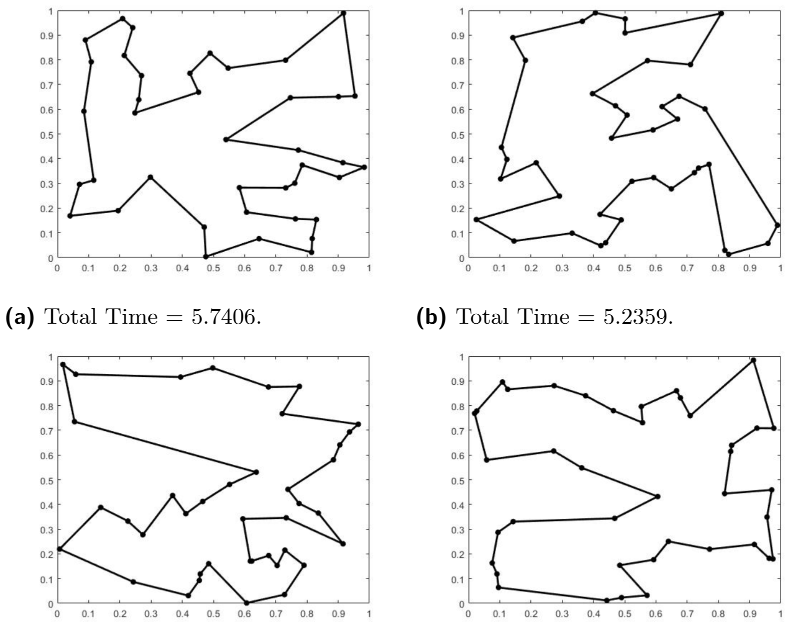
We also compared our model with the traditional centralized delivery system in which a single truck would deliver all packages. We found that, for our synthetic examples, the average delivery time if we combine a truck with crowdsourced drones will be 4.5698, while the average delivery time for the same problem if the truck serves all the customers will be 5.3866. This shows an almost 15% improvement in the efficiency of the last-mile delivery, in our randomly generated examples, if we combine truck delivery and drone delivery in the context of sharing economy platforms. This also helps us in finding the delivery schedule in a faster way; solving the pure TSP problem of the same size takes much longer than our optimization model since in our model many of the nodes are being served by the drones and the more complex part of the problem, which is the truck routing, is being solved for fewer stopping points. Furthermore, we have improved the original model by a) considering the closest customer to the center and sending the truck there instead of the cluster center, and b) considering battery utilization to allow multiple deliveries by one drone before the drone goes back to its base for recharging.



(a) Total Time = 4.6416. **(b)** Total Time = 5.0251.

(c) Total Time = 4.8615. **(d)** Total Time = 4.8763.

Figure 3 Solutions obtained by our algorithm for different random examples in a unit box with their objective function value.



(a) Total Time = 5.7406. **(b)** Total Time = 5.2359.

(c) Total Time = 5.3380. **(d)** Total Time = 5.2466.

Figure 4 TSP solutions (centralized truck-only delivery system) for the same instances of Figure 3.

Moreover, an extensive sensitivity analysis has been done with respect to several factors to study their impact on the quality of the solution and savings of the shared delivery system compared to the traditional truck-only delivery. These factors include speed of drones, number of available drones, a measure combining speed and number of drones, and customer distribution. Finally, a comparison is made between three models to measure the impact of shared delivery model on carbon foot print. These three models are the traditional truck-only delivery, delivery with a truck and a drone where the truck carries a drone and both deliver packages in a coordinated way, and shared delivery model.

6 Conclusion

In this paper we have developed a shared last-mile delivery model in which a truck carries packages to a neighborhood and then outsources the last piece of trip to private drone operators that can be ordered on a sharing economy platform. We have developed efficient algorithms to solve the problem under different assumptions. The results show that the shared delivery model (decentralized model) is much more efficient than the traditional truck-only delivery model (centralized model) in almost all possible scenarios. This is aligned with the results from [3]. The comparison between the shared delivery model and the coordinated delivery system, in which a truck carries and controls a drone during the delivery operation, depends on other factors such as number of available drones in the platform, their capacity and speed. For future work, one may look into considering different factors such as time windows for delivery to customers, time windows for drone availability, ability of drones to carry multiple packages at the same time, drones' weight capacity, and combination of the system with crowdsourced drivers.

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