# Simulation Test Bed for Drone-Supported Logistics Systems

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ABSTRACT

Same-day delivery is an increasingly relevant logistics service because of a continued boom in e-commerce. As customer orders are submitted dynamically during the day, companies need to dispatch vehicles from distribution centers to fulfill these orders as they come in. Given their advantages over conventional vehicles such as direct flight, no road traffic, and no driver/operator requirements, autonomous drones have recently been proposed for last mile package delivery. This study examines in what situations drones could be used to resupply trucks to reduce the time and/or cost of delivery. Drones can be used to dispatch packages from the distribution center to transshipment points where trucks can pick up packages instead of returning to the distribution center. The use of drones requires a new transportation network and routing. A simulation using SIMIO was developed to assess the impact of using drones to resupply trucks through transshipment points. Both a subset of the city of Boston and a portion of the rural area around Pittsfield, MA were used with package delivery orders arriving throughout the simulated time. Through dynamic dispatching for same-day delivery, orders were delivered significantly faster when transshipment points were resupplied by drones than in conventional last mile delivery. In the Pittsfield region analysis, the baseline with one transshipment point was 36% faster than conventional package delivery. The total truck distance traveled while delivering packages was also reduced by 24% or on average 80km per 8-hour work day. In the Boston case study, the baseline scenario of 4 transshipment points was 66% faster (2 hours) at delivering packages than conventional package delivery. Four transshipment points also resulted in a 10% or 60km a day less distance traveled for the trucks. Our research indicates that last mile package delivery companies can use drones and transshipment points to reduce package delivery time as well as truck travel distance.

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# 1 INTRODUCTION

## 1.1 Urbanization

According to the United Nations Department of Economic and Social Affairs, 68% of the world population will be living in urban areas by 2050. It is projected that by 2030 the world will have 43 megacities with more than 10 million inhabitants. Currently there are 33 of these megacities and they already account for 12.5% of the world population (United Nations, 2018).

With this high density in population comes a high density in consumers and an extremely high concentration of demand for products. In the megacities, shopping malls and small retail stores are abundant, although getting there within open hours and wading through the traffic and other customers is a deterrent to consumers.

### 1.1.1 E-commerce and Courier Service Companies

The response to this challenge comes from e-commerce and couriers. Companies like Amazon, Alibaba, and JD.com are booming because of their early access to this market. Courier service companies like UPS, FedEx, DHL, and SF have experienced rapid business growth in their package delivery service segments. These companies are thriving due to the need for customer convenience such as extremely fast delivery directly to the customers. In this sense both convenience and cost factor into market share growth. According to Wallace (2017) the biggest reasons a customer chooses one delivery method over another are user experience, price, and delivery times. Challenges e-commerce and courier service companies are facing also include the high risks associated with the costs and safety concerns of traffic and road travel.

### 1.1.2 Traffic Congestion and Safety

In 2018 USA drivers spent an average of 97 hours a year in traffic, which led to time and inefficiency costs equal to almost $87 billion (INRIX, 2019). The traffic within cities not only increases air and noise pollution, but also influences local businesses.

In 2016, traffic deaths in the U.S. increased 6 percent, to 40,200, according to estimates released by the National Safety Council (Boudette, 2017). In China the boom in online takeout services has led to a sharp rise in road accidents involving food delivery drivers, largely because the couriers break traffic rules to avoid fines for being late (ChinaDaily.com, 2017). Traffic and vehicle deaths may be reduced by implementing some alternative delivery methods such as drones, thereby reducing the risk to e-commerce and courier service companies.

## 1.2 Unmanned Aerial Vehicles

A large proportion of customers want the cheapest price, the highest quality and the fastest delivery. For instance, it is expected that same-day delivery and instant delivery will reach 20-25% of market share by 2025 (Joerss, Neuhaus, & Schröder, 2016). For distributors and retailers, it is a challenge to keep the costs low while providing the best service possible. Traffic congestion and safety become extremely important to distributors and retailers, due to the costs of inefficiencies and injuries. To meet customer expectations and increase market share, new delivery methods that are faster and more reliable than a traditional delivery method, with a truck and human, are required.

New technologies for urban delivery are being developed to reduce the operating expenses for the company, and improve the service provided to the customer. One of these technologies is unmanned aerial vehicles (UAV), more commonly known as drones. These vehicles have become more and more capable. They carry heavier weights, fly longer distances, and are better able to avoid obstacles than previous drone designs and they do all this without the intervention of an operator.

### 1.2.1 The Drone Advantages

Drones can get to the destination faster than conventional delivery trucks since they are not limited to road network and traffic, they can fly on a direct route, and they do not need to look for a traditional parking spot. They are also cheaper since they do not need an operator, pending Federal Aviation Administration (FAA) regulation changes, and can theoretically operate 24 hours a day. Companies have advertised electricity costs of $0.02 per kilometer for ten-pound packages delivered by drones compared to $0.50 per kilometer for trucks (Workhourse Group, 2019). If something goes wrong with the delivery truck, many packages may be delayed, whereas with a drone a minimal number are delayed. All the above reasons and more make drones an ideal candidate for delivering packages to customers.

### 1.2.2 The Challenges

Despite these advantages there are some things that drones cannot do as well as conventional delivery trucks. Delivery trucks can carry more, bigger, and heavier packages. A drone is not good at waiting. If the customer is not on site to receive the package or the drone is running out of power, the drone is limited to returning without delivering the package. Current drones cannot combine multiple packages for multiple destinations since they cannot sort out the correct one. For every Direct to Customer delivery, drones need to fly back and forth because they can only carry a package for one customer, wasting time and energy. If a delivery address does not have a drone-ready drop-off point or a signature is required, a drone is not an option.

## 1.3 The Drone Delivery Models

As with most technologies, there are advantages and disadvantages with using drones, but what is generally accepted is that these vehicles can bring added value to the package delivery services currently offered. What is not as clear is how to use drones to best complement current package delivery techniques. The four models outlined below are all being researched or tested and have the potential to change conventional package delivery.

### 1.3.1 Direct to Customer

In this scenario the drone leaves from the DC and delivers the package directly to the customers as shown in Figure 1. Amazon is experimenting with this and companies like Zipline are already operational (Ackerman & Strickland, 2018). However, in an urban environment this mode of operation might not be the best. Due to the high population density it is likely that multiple packages would need to be delivered to the same building. A high density in delivery addresses might lead to an over-crowded airspace around the apartment buildings. Another drawback of this solution is that the receiver must be on site.

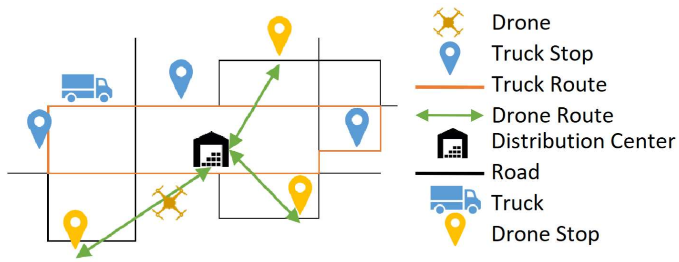



*Figure 1. Direct to Customer. In Direct to Customer the drones deliver directly to a customer from the DC while a truck is also performing conventional delivery from the DC.*

### 1.3.2 DC to Truck to Drone

This is a system where the truck batches the orders and acts as a mobile distribution center. Either the truck or the drone is taking care of the last mile as represented in Figure 2. This way of working allows the trucks to travel shorter routes and the drones can be used for supplying remote customers. UPS is already experimenting with DC to Truck to Drone (Petrova, 2017).

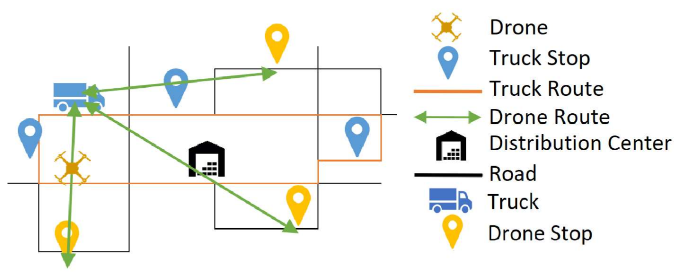



*Figure 2. DC to Truck to Drone. In DC to Truck to Drone the truck picks up the packages from the DC and the drone is dispatched to customer locations from the truck while the truck is making deliveries.*

Packages can be batched to bring them closer to the customer. The final delivery can be done by either the delivery person or the drone. The best mode can be selected based on the distance to the customer, the size of the package, and the number of packages to be delivered. A disadvantage of this system is that the truck can only deliver the packages that it picked up at the DC at the beginning of its route. To achieve same-day delivery, additional trucks need to be dispatched or trucks need to return to the DC for additional runs. Having more trucks or multiple runs results in a less efficient use of time and capacity.

### 1.3.3 Drone Resupply of Transshipment Points

In this model the drones continuously deliver packages from the DC to remote transshipment points (TPs) dispersed throughout the delivery area. A representation of the Drone Resupply of Transshipment Points model with one transshipment point is in Figure 3. The truck picks up the packages, that were dropped off by the drone, at the transshipment points and delivers the packages to the final customers. The truck returns to the transshipment points to pick up packages delivered by the drones throughout the day enabling same-day delivery without the need to return to the DC.

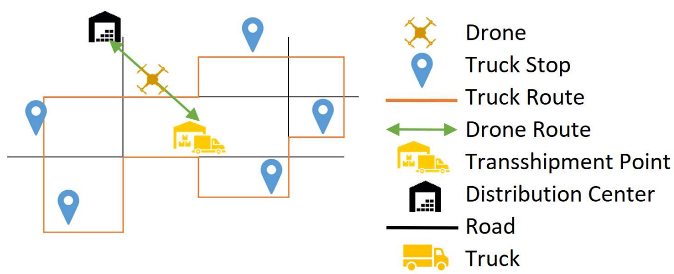



*Figure 3. Drone Resupply of Transshipment Points. Drones transport packages from the DC to the transshipment point for the truck to make deliveries.*

### 1.3.4 Drone Resupply of Trucks

This model is different from the Drone Resupply of Transshipment Points in that the drone is not making deliveries to a transshipment point, but to the truck instead, as depicted in Figure 4. The trucks set out on their route to deliver packages already at the DC to the customers. During the route drones constantly resupply trucks with packages that were ordered for same-day delivery. After resupplying the truck, the drone flies back to the DC. The truck handles the last mile by conventionally delivering the packages directly to the customers. This allows for batch delivery at the destination and packages do not need to wait at the DC for a truck to come back.

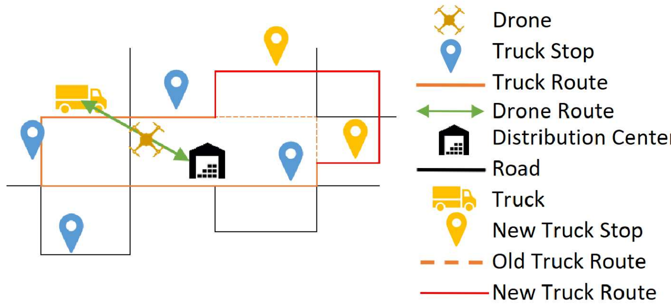



*Figure 4. Drone Resupply of Trucks Model. In the Drone Resupply of Trucks model, the drone delivers packages to the truck while it is delivering other packages, the route gets modified and the truck delivers the old and the new packages.*

## 1.4 Objective and Scope

To provide insights related to the challenges that come with the Drone to Resupply Transshipment Points model, a simulation model was built. Our hypothesis is that by using the Drones to Resupply Transshipment Points model both delivery time and travel distance can significantly be reduced when compared with the traditional Truck-only model. The simulation was used to quantify the potential improvements to delivery time and truck travel distance reductions. The distance traveled by the trucks can be used as a proxy for the costs and cost reduction. Some of the parameters influencing delivery times and cost savings were explored through running experiments and sensitivity analysis with the models.

Using drones for parcel deliveries poses various legal, technical, and social challenges. This research focuses on the practical and operational challenges introduced by using drones and does not address the legal, technical, and social challenges. Although our simulation model can be used for any city, our results are only based on location and delivery data from Boston, MA and Pittsfield, MA.

# 2 LITERATURE REVIEW

In this chapter, we give an overview of previous and ongoing research related to using drones for deliveries. Practical examples of operational drones or drones in testing will be reviewed first. Most practical applications are conducted by companies intending to use drones for delivery. Then we review drone models in academics. Finally, the relationships between the model built for this research and how it complements existing and ongoing research will be discussed.

## 2.1 Practical Applications

Most applications use and test three types of drone delivery models. The first type is one in which the drone goes directly from the distribution center (DC) to the customer. Zipline is a company that has been operating drones from DCs to customers since 2016 and is probably the most successful so far (Ackerman & Strickland, 2018; Zipline, 2018). DHL with its “parcelcopter” is also doing successful trials in East Africa (Kesteloo, 2018). These companies are using drones to reach customers that are otherwise very isolated due to a lack of infrastructure or difficult terrain. To apply this concept in a more urban environment has proven to be more challenging. The Amazon Prime Air project and Google Wings project are trying to use drones in an urban setting. Both companies face challenges related to legal limitations such as FAA regulations requiring an operator for commercially operated drones and line of sight, in addition to technical challenges related to safety and collision avoidance (Dorr, 2018). For instance, the Google Wings project has included redundant systems for all flight hardware and software, as well as implementation of an Unmanned Air System Traffic Management platform to manage flight paths and routing to avoid collisions (Heath, 2018).

The second type is more suited for the urban environment. In this model, a drone travels with the delivery truck and assists with the last mile deliveries. According to pilots run by UPS and AMP Electric the model can help reduce delivery cost, but delivery times are barely affected and the customers still need a safe place for the drone to drop the package (Weise, 2017; Robinette, 2014).

The third type is less popular and as far as we know has only been tested by Mercedes-Benz Vans and Matternet Drones in Zurich Switzerland (Rees, 2017). In this model the drone is not used for the last mile delivery, but for resupplying the delivery trucks. The trucks are equipped with a landing platform and there are plans for automated package collection and battery swaps. Drones resupplying trucks takes away the need for a landing zone and does not require any change of operation from the customers side. In addition, delivery times and costs can be reduced.

## 2.2 Academic Research

The three models that are being studied in practice are also being studied in academia. A vehicle routing problem (VRP) is at the center of most of these studies.

The first model or the DC to Customer model was studied by Dorling et al. (2017). They propose two VRP variants, one focusing on minimizing costs given a delivery window and one minimizing delivery times given a budget. Also, Cheng, Adulyasak, & Rousseau (2018) use a variant of this VRP but use a Branch-and-Cut algorithm. Others look at this problem more in line with current practical applications, e.g. the drones deliver one package each from the DC to the customer and then fly back to the DC.

Haidari et al. (2016), uses the DC to Customer system as a simulation for vaccine delivery in the Gaza province of the Republic of Mozambique. They conclude that the cost of delivering vaccines in the region could be reduced and availability improved. The amount of improvement greatly depends on the demand, speed of road vehicles, and the distances to be travelled.

The second model for drone delivery, and the way UPS and AMP Electric are trying to use drones, is studied by Murray and Chu (2015). They call this model the “Flying Sidekick Traveling Salesman Problem” (FSTSP). They use conventional trucks and a truck route but add a drone to assist the truck in delivering certain packages to minimize delivery times. Ha, Deville, Pham, and Hà (2018) further builds on that and adjusts the Mixed Integer Linear Program (MILP) and heuristics described by Murray and Chu (2015) to minimize the costs of the FSTSP. The models are simplified. All packages are the same size and weight, one package per drone, one drone per truck, with fixed battery time regardless of load, fixed speed, fixed start, and fixed end points. Multiple models that each relax these constraints are described by Wang, Poikonen, and Golden (2017). Another addition to the FSTSP is providing for reverse logistics in the delivery system. Ham (2018) would use the drones to deliver the package from the truck but then use that same drone to go pick up another package and bring it back to the truck. The main difference between these papers is the solution approach they use to solve the related routing problems.

The third type of drone delivery provides same-day deliveries and the extended range of trucks. The only research that we are aware of at this time was performed by Dayarian, Savelsbergh and Clarke (2017). They propose to use drones for resupplying delivery trucks. Drones resupplying trucks can be done either at the end of the truck's route or during the truck's route. The aim is to deliver as many packages within a given time window. The model is naturally highly dynamic, and to simplify the model for research they have reduced the problem to having only one DC, one truck, and one drone.

## 2.3 Our Study

In our research, we achieve same-day delivery by having drones resupply transshipment points (TPs) and trucks doing small local routes and loading at the TPs. Avoiding the loading at the DC saves a lot of travel time and distance for the truck. As far as we know, there has been no research done on this type of drone use. The simulation model we built was based on the cities of Boston and Pittsfield, MA. Better insights on Drone Resupply of Transshipment Points for real urban environments can be obtained with our simulation model. Our simulation model is discussed in detail in Section 3, Methodology.

# 3 METHODOLOGY

As our literature review pointed out, there has been very limited study on using drones to resupply transshipment points. We explore in what circumstances a Drone Resupply of Transshipment Point system would be preferred over the conventional delivery system, for instance if delivery time or cost was reduced. In this section, we describe the methods used to develop and manipulate the simulation as well as how we plan to gain a better understanding of the different delivery systems. First, we describe the simulation model with all its objects and baseline parameters. Then, we present an overview of our performance measures, followed by a brief description of the different delivery systems we simulated and compared. Finally, we define the parameters that were used in the sensitivity analysis.

## 3.1 The Simulation Models

Simio 10.181 is used for modeling and simulating the proposed delivery systems. Below we describe the objects with their main properties and parameters. All simulations were run with a 70-hour warm-up period to achieve steady-state and an 80-hour simulation time representing 10 delivery days without breaks. To determine the baseline scenario parameters in the Drone Resupply of Transshipment Points model and the comparable Truck-only case, 100 simulations are performed for the different numbers of transshipment points and the DC (Truck-only). The results from the 100 simulations for each parameter were averaged. All subsequent tests were performed with 25 simulations for each parameter, and results were averaged.

### 3.1.1 The Environment

We used subsets of the city of Boston, MA and the city of Pittsfield, MA to model a realistic coverage area containing delivery points in each city. All the packages are distributed from one distribution center in each city to all the delivery points.

### 3.1.2 The Delivery Points

Customer locations are scattered throughout the city subset and they represent the destinations for packages. The customer acts as the sink of the model, where on arrival at the customer each model entity (package) is no longer simulated. Each delivery address has a population. The population is used to model the probability that an address is chosen as the destination of a package. The population at each delivery address is defined as the number of times an address appeared in the raw delivery data. For instance, if multiple packages were delivered to the same destination, it may have had a weight of 2 (population of 2) or a weight of 3.

### 3.1.3 The Distribution Center

One distribution center is located within the city. All packages originate at the distribution center. The distribution center generates packages for different destinations. In Boston, the DC has a truck picking up packages for local deliveries according to the transshipment point optimization introduced in Section 3.1.4 for all the Drone Resupply of Transshipment Point models as well as the DC only model. In Pittsfield, the trucks only pick packages up from the DC in the Truck-only model because the DC is outside the delivery area and no customers are allocated to the DC with the customer transshipment point optimization model introduced in Section 3.1.4. Any package that is being routed to a customer served by a transshipment point instead of directly by the DC has two destinations. The first destination is a transshipment point and the final destination is the customer delivery address.

### 3.1.4 The Transshipment Points

The transshipment points are in the delivery areas and are where the trucks pick up packages that were dropped-off by drones. Each city is simulated with a varying number of transshipment points in the Drone Resupply of Transshipment Points models. An optimization model is solved to obtain the optimal locations of transshipment points considering customers locations. In the Drone Resupply of Transshipment Point models Boston customers can be assigned to the DC, because the DC is in the delivery area. In contrast Pittsfield customers cannot be assigned to the Pittsfield DC, because the DC is outside the delivery area, therefore all Pittsfield customers are serviced out of a transshipment point. The optimization determined the optimal coordinates for the transshipment points not at the DC, then we assigned the transshipment point location to the same coordinates as the closest customer delivery address. This simulated a package delivery company selecting locations based on proximity to customers and minimizing delivery times and distances. An example of the transshipment points and the customer locations assigned to them for four transshipment points and the DC is shown in Figure 5 for Boston. The maps of transshipment points for all additional scenarios are in Appendix A.

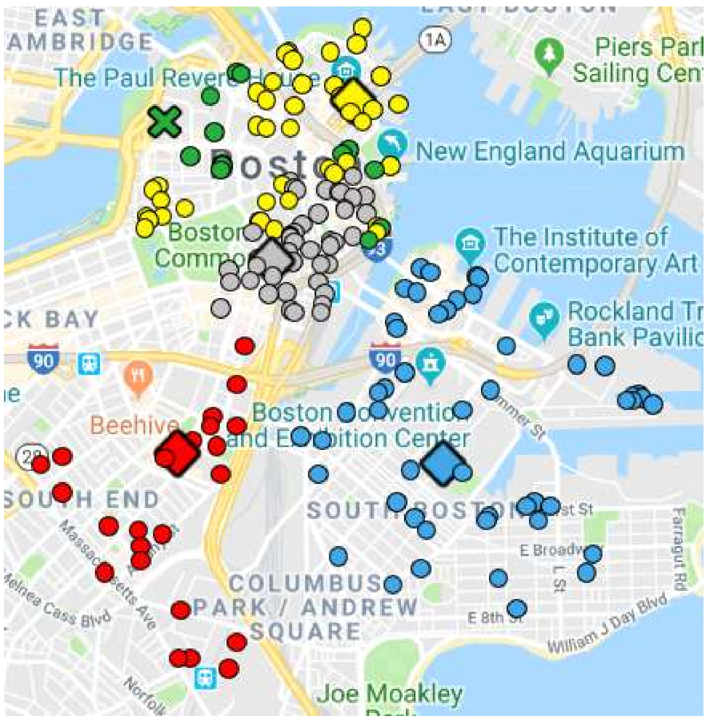



*Figure 5. Transshipment Points and Customer Assignments for 4TPs in Boston. For the 4TP scenario in Boston the transshipment points are shown by colored diamonds and the DC is the green X, customers assigned to the transshipment points or DC are coordinated by color.*

The objective function, Equation (1), minimizes the total time it takes the drone to fly from the DC to a TP ($t'$) and the time (t) it takes the truck to drive from a transshipment point (j) to a customer delivery address ($i$). The drone travel time is weighted by factor α because the cost per kilometer of a drone is lower than the cost per kilometer of a truck. The objective function uses the binary decision variable $x$ to indicate which TP (j) serves which customer (i). Each customer must be served by one TP (Equation 2). The number of TPs in the network should be equal to $\beta$, Equation (3). The decision variable y indicates whether a TP (j) is used in the network. Equation (4) makes sure that nothing is sent from a TP that's not in use. $N$ is the total number of customers. Both decisions variables $x$ and $y$ are binary variables, Equation (5). In the optimization, the Boston DC is included in the customer location list because the DC is within the package delivery area. In Pittsfield, the DC is not included in the list of customers because it is outside the package delivery area. Table 1 gives an overview of all the optimization variables, constants, and indexes used in the transshipment point optimization model.

*Table 1. Optimization Model Parameters. All variables, constants, and indexes used in the Transshipment Point Optimization Model.*

| Notation | Description |
|---|---|
| $i$ | Index representing all customer locations. |
| $j$ | Index representing all potential transshipment point locations. |
| α | Weighting for drone travel time compared to truck travel time. |
| $\beta$ | Number of transshipment points in a scenario. |
| $x$ | Decision variable for a transshipment point to a customer. |
| $y$ | Decision variable for the number of transshipment point locations opened. |
| $N$ | Total number of customers. |
| $t$ | Time for a truck to drive from a transshipment point to a customer delivery address. |
| $t'$ | Time for the drone to travel from the DC to a transshipment point. |

The Transshipment Point Optimization Model for minimizing travel time between customer locations is formulated as follows:

$$Minimize \sum_{i}\sum_{j} x_{ij} \times (t_{ij} + \alpha \times t_j') \tag{1}$$

$$\sum_{j} x_{ij} = 1 \qquad \forall i \tag{2}$$

$$\sum_{j} y_j = \beta \tag{3}$$

$$\sum_{i} x_{ij} \leq N \times y_j \qquad \forall j \tag{4}$$

$$x_{ij},\ y_j \in \{0,1\} \tag{5}$$

### 3.1.5 The Packages

As Boston and Pittsfield have different package delivery demand, the simulated package (model entity) arrival rate is different for each city. Both cities were simulated assuming 10% of packages currently delivered by the simulated package carrier were expedited to use drones. It was also assumed that all the packages ordered for expedited (drone) delivery were ordered during an 8-hour working day to calculate the package interarrival time (IAT). The package IAT is the time between package arrivals calculated from a sample of packages delivered on a single day by a package delivery service. In Boston, the sample area had 5,020 packages delivered in 8 hours, with 10% expedited. Boston thereby has an average package arrival rate of 1.0 packages per minute (or an interarrival time of 1.0 minutes per package). In Pittsfield, the sample area had 260 packages delivered in 8 hours, with 10% expedited. Pittsfield therefore has an average package arrival rate of 0.055 packages per minute (or an interarrival time of 18 minutes per package). A sensitivity analysis for Boston and Pittsfield was conducted with twice as many packages arriving per day or an interarrival time of 0.5 and 9 minutes, respectively, half the calculated interarrival times. The faster package interarrival times were simulated to assess the potential impact of both growing demand and seasonal fluctuations such as the holidays. The orders were generated with an exponential distribution around the mean of the package arrival rate for each city. Each delivery address has a defined population based on the raw delivery data (e.g. apartments). Each package has two destinations, the final destination at a customer delivery address and an intermediate destination at a transfer point. The final destination of the packages is uniformly distributed across the total population at the simulated delivery addresses. Effectively, giving each delivery address a different weight. Before each package is delivered to its final destination, it is delivered to the transshipment point by the drone from the DC.

### 3.1.6 The Delivery Trucks

The delivery trucks load the goods at the distribution center. The truck is not simulated with a maximum capacity as a constraint for two reasons. First, drone deliverable packages are smaller and therefore do not take up as much room in the truck. Second it is unlikely for a truck to achieve same-day delivery to many different addresses if it is at small (drone deliverable) package capacity. Truck loading time is directly proportional to the number of packages being loaded using 20 seconds per package. The truck drops the packages off at the destinations by following the shortest path first. A truck uses distance and time data extracted from Google Maps Distance Matrix API. Loading the truck at a transfer point or unloading it at a delivery point takes 90 seconds per stop and 20 seconds per package. When all packages have been delivered the truck waits at its current location until a transshipment point requests a pickup. The truck then travels to the transshipment point that makes the request to load packages and repeat the delivery process.

### 3.1.7 The Drones

The drones are loaded at the distribution center and have a fixed package carrying capacity set in each simulation scenario. The loading or unloading of a drone takes 20 seconds per package and is assumed to be automated (Peterson, 2017). Drones do not need to follow the road and can fly in a straight line, ignoring altitude changes that are not being simulated. A drone flies at a set speed determined in each simulation. After transferring the load from the drone to the transshipment point the drone flies back to the DC where it can be loaded again.

## 3.2 Performance Measures

To evaluate the performance of the model and the performance of the different scenarios we used two key performance indicators: truck distance (as a proxy for cost) and average delivery time.

The cost of a drone is 0.02 USD per km traveled and the cost of a truck is 0.5 USD per kilometer traveled, converted from per mile to per km (Workhourse Group, 2019). The drone cost is based on electricity usage and the truck cost is based on operating cost excluding driver salary. Driver salary is excluded because our simulations require a driver to deliver the package to the customer whether drones are utilized or not. We multiplied the distance traveled by both drones and trucks and by the above costs to determine total final cost.

Customers simulated in these models chose same-day delivery because speed of delivery was important, thereby average time to deliver a package is a key performance indicator. Time to deliver a package is the time it takes from package creation (model entity creation or package order) to delivery at the customer address.

## 3.3 Scenario Parameters for Simulation

Using our simulation models, we ran several scenarios. Each used different parameters, and we monitored the impact of each of these parameters on the performance measures mentioned above. More specifically, we considered the following parameters for analysis:

*Drone capacity:* The package capacity of a drone is set for each scenario, ranging from 4-10 packages. We expect increasing the capacity will reduce the travel distance of the truck and delivery time.

*Drone speed:* We assume that the speed of the truck is determined by the city traffic and cannot be changed. The speed of the drone could vary, though, and therefore could impact the performance. Faster drones may improve the delivery time because they can pick up and deliver the packages from the DC to the transshipment points faster.

*Number of drones:* By increasing the number of drones, more packages can be supplied to the transshipment points, and therefore the trucks can pick up the packages earlier. Capital cost increases with the addition of drones, but the variable cost increases or decreases depending on the model parameters.

*Number of trucks:* The number of trucks available for delivering packages influences the package delivery time. The more trucks available, the faster the packages can be delivered because there are fewer packages per truck.

*Number of transshipment points:* The number of transshipment points affects how close the customer locations are to the transshipment points. A greater number of transshipment points causes customer locations to be closer to their assigned transshipment points. Closer proximity to a transshipment point enables a truck to have shorter routes after picking packages up from a transshipment point. Both distance and time from a transshipment point to a respective customer location is reduced. The trucks need to travel to each new transshipment point when packages are available for pick up. Traveling to each subsequent transshipment point could increase the travel distance of the truck.

### 3.4 Delivery Models for Simulation

Packages can be delivered in various ways. Our simulation model supports two different delivery systems. We compare these systems with each other using the performance measures and scenarios described in Section 3.2 and Section 3.3.

#### 3.4.1 Truck-only

"Truck-only" is the conventional delivery system, and no drones are used for the simulation. Figure 6 displays a representation of the conventional delivery system. We use the Truck-only model to set a benchmark for comparison to the model with drones added.


*Figure 6. Truck-only Model. The Truck-only model is the conventional delivery where a truck delivers packages to customers from the DC.*

#### 3.4.2 Drone Resupply of Transshipment Points

In the Drone Resupply of Transshipment Points model, the drones pick the packages up from the DC and deliver packages to a transshipment point. The number of transshipment points varies, and the locations were set based on the transshipment point optimization presented in Section 3.1.4. The drone has a package carrying capacity and only picks up packages meant for one transshipment point at a time. The trucks return to the transshipment points to pick up packages and deliver them to their final destinations.

# 4 Results and Discussion

The results were split into two main sections; the first section presents the results and discussion for the Boston case study; the second section contains the results and discussion for the Pittsfield case study. Both sections start with the Truck-only model which is used for comparison to the Drone Resupply of Transshipment Points models and then the baseline scenario is established. Finally, the results for all remaining defined scenarios (see Section 3.3) are presented.

## 4.1 Boston Case Study

The city of Boston is used to represent an urban package delivery environment. Two package interarrival times were used as model parameters. The Truck-only and the Drone Resupply of Transshipment Points models, described in detail in the Methodology, are simulated in this case study.

### 4.1.1 Boston Truck-only Case

A Truck-only model was created in Boston to compare the results of the Boston Drone Resupply of Transshipment Points model. The Truck-only simulation consisted of delivery directly from the DC to the customers; see Table 2. To achieve a delivery time of about 3 hours, 7 trucks were used for an IAT of 1 minute and 14 trucks were used for an IAT of 0.5 minutes. The average total truck distance traveled doubled for the faster interarrival time as expected but the average delivery time did not stay the same when doubling the number of trucks. This indicates that even though the number of trucks is doubled, the trucks were picking up more packages at the DC for each route when the IAT is shorter.

*Table 2. Boston Truck-only. Results for the Boston Truck-only model for each interarrival time studied.*

| Interarrival Time (minutes) | # of Trucks | Average Delivery Time (hours) | Average Total Truck Travel Distance (km) |
|---|---|---|---|
| 1 | 7 | 2.95 | 571 |
| 0.5 | 14 | 3.31 | 1134 |

### 4.1.2 Boston Baseline Scenario

The parameters for the Boston baseline scenario for the Drone Resupply of Transshipment Points model are listed in Table 3 for each interarrival time studied. The parameters were selected to achieve a steady-state 3-hour average delivery time from the time of order/package creation in the model for a given interarrival time.

*Table 3. Boston Baseline Parameters. Here are the selected parameters for both 1-minute and 0.5-minute interarrival times.*

| Interarrival Time (minutes) | # of Transshipment Points | # of Trucks | # of Drones | Drone Capacity (packages) | Drone Speed (km/hr) |
|---|---|---|---|---|---|
| 1 | 4 | 7 | 5 | 5 | 50 |
| 0.5 | 4 | 14 | 5 | 5 | 50 |

The interarrival time is the calculated package arrival rate from a sample of packages delivered on a single day by a package delivery service. As shown in Table 4 and in Figure 7, as transshipment points were added to the Boston models, both the package delivery time and total distance traveled by the truck decreased, except when the number of TPs increases from 1TP to 2TPs.

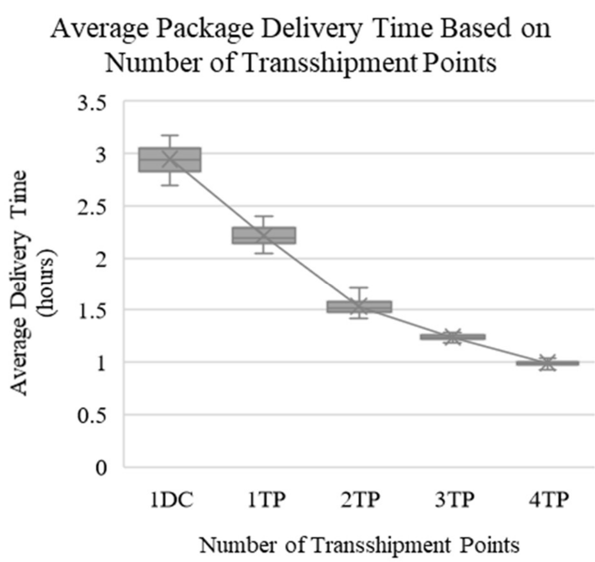
The reduction in distance traveled is driven by two factors. First, the DC to TP distance that the truck no longer needs to travel and second, the local truck routing. The location of TPs was optimized using delivery times (see Section 3.1.4) and this creates non-circular clusters (see Appendix A1). Where the cluster with 1TP can still be considered circular, by adding a second TP the clusters become less circular. This means that although the time between points is faster the distances might not be because some routes may use roads that are long but high speed. As more TPs are being added, the clusters become more circular and the routes become more efficient with respect to both time and distance.

Using drones and TPs for delivering packages has a big impact on delivery times. Adding one TP and using 5 drones for resupplying those TPs reduces the delivery time 25% to 28% compared with only shipping from the DC. Adding 4 TPs and 5 drones results in a delivery time decrease of 66% to 73% for IATs of 1 minute and 0.5 minutes, respectively. The impact on truck distance traveled is much less, however, still significant. Using 4TPs and 5 drones the total distance traveled by the trucks decreases 4% to 11% depending on the interarrival time.

Given the benefits of more transshipment points, the Drone Resupply of Transshipment Points model with four TPs was selected for the baseline scenario. Other scenarios vary the number of trucks, the number of drones, the drone capacity, or drone speed for comparison.

*Table 4. Boston Key Performance Indicator Comparison. Truck distance is multiplied by $0.5/km, drone distance is multiplied by $0.02/km to get the average total cost for each scenario. Total cost and average delivery time for the numbers of transshipment points indicate there are competing optimal solutions.*

| 1 Minute Interarrival Time | | | | | 0.5 Minute Interarrival Time | | | | |
|---|---|---|---|---|---|---|---|---|---|
| # TPs | Drone Distance (km/day) | Truck Distance (km/day) | Total Cost ($/day) | Avg. Delivery Time (hours) | # TPs | Drone Distance (km/day) | Truck Distance (km/day) | Total Cost ($/day) | Avg. Delivery Time (hours) |
| 0TP (Truck-only) | 0.0 | 571.0 | 286 | 2.95 | 0TP (Truck-only) | 0.0 | 1134.0 | 567 | 3.30 |
| 1TP | 1218.8 | 538.5 | 294 | 2.22 | 1TP | 1658.6 | 1022.3 | 544 | 2.38 |
| 2TP | 1717.2 | 553.8 | 311 | 1.53 | 2TP | 2201.6 | 1142.9 | 615 | 1.49 |
| 3TP | 1809.7 | 542.3 | 307 | 1.24 | 3TP | 2260.6 | 1115.1 | 603 | 1.17 |
| 4TP | 1943.7 | 507.3 | 293 | 1.00 | 4TP | 2346.8 | 1082.1 | 588 | 0.89 |



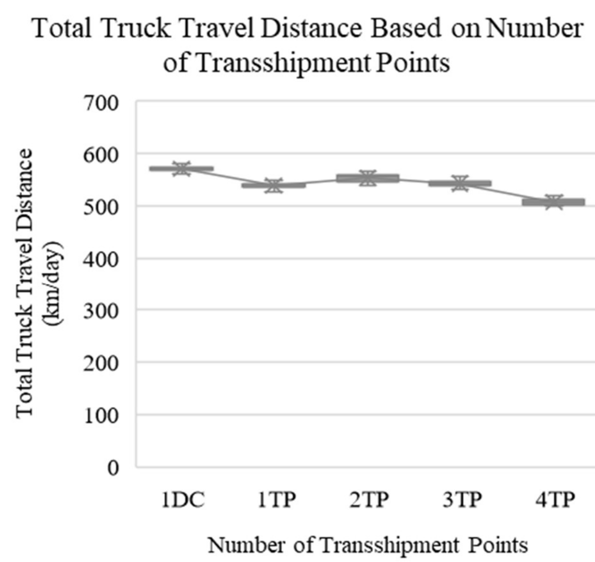




*Figure 7. Boston Baseline Selection. In Boston the total distance traveled by the trucks and the package delivery time decreased as transshipment points were added. Given the benefits of faster delivery and less distance four transshipment points was selected for the baseline scenario. Plots are for an IAT of 18 minutes.*

### 4.1.3 Analysis of Boston Case Study

The simulations for Boston were most sensitive to the interarrival time of packages. The interarrival time is the most closely related parameter to the capacity and utilization of the network. The models were also very sensitive to the number of trucks and transshipment points. Drone speed and drone capacity were not as influential because the models were more likely to be capacity constrained by the delivery of packages by the trucks.

Changing the number of drones, drone capacity, or drone speed individually did not have statistically significant impacts on the total distance traveled by the delivery trucks. For instance, reducing the number of drones would have negligible impact until the drones could no longer keep up with transferring the packages from the DC to the TPs. In the case that there are not enough drones, the simulation cannot reach steady-state and the packages would then build up at the DC. Varying the number of drones for an IAT of 0.5 minutes displays this effect on the total truck travel distance, as seen in Appendix B1, Truck Distance for Varying Number of Drones. In the simulation with three drones, the drones were not able to keep up with delivering packages to the transshipment points causing the delivery time to increase. The total truck travel distance may be influenced by the drone speed, drone capacity, and number of drones but more simulations would need to be run to have statistical significance for evaluation.

The delivery times of the packages were impacted by the drone delivery speed, however in most cases the delivery time is not impacted by the number of drones or drone capacity. The number of drones and drone capacity did not have a statistically significant impact unless the drones could no longer keep up with transferring packages from the DC to the TPs. The boxplot for varying the number of drones for an IAT of 0.5 minutes, in Appendix B1, shows how the package delivery time with three drones raises to 6-7 times the other values. The increase in package interarrival time is because the packages are building up at the DC instead of being delivered to the TPs. Drone speed does have a statistically significant impact on the package delivery time for an IAT of 0.5, the boxplot is in Appendix B1, with a 10% decrease in delivery time when drone speed is increased from 40 km/hr to 60 km/hr. The drone speed has a statistically significant impact for an IAT of 0.5 and does not for an IAT of 1.0 because the variation observed at the shorter IAT is lower and the drones are closer to being the limiting factor for delivery.

## 4.2 Pittsfield Case Study

The Pittsfield, MA Region was selected to represent package delivery in a rural environment instead of an urban environment. Package delivery was tested in Pittsfield with the same model scenarios as Boston with different parameter values.

### 4.2.1 Pittsfield Truck-only Case

A Truck-only model was created for the Pittsfield region to compare the results from the Pittsfield Drone Resupply of Transshipment Points model. The Truck-only model represents conventional delivery and the results are displayed in Table 5. Both interarrival time simulations used 1 truck because steady-state was achieved with average delivery times of less than 3 hours.

*Table 5. Pittsfield Truck-only. Results for the Boston Truck-only model for each interarrival time studied.*

| Interarrival Time (minutes) | # of Trucks | Average Delivery Time (hours) | Average Total Truck Travel Distance (km) |
|---|---|---|---|
| 18 | 1 | 1.06 | 338.2 |
| 9 | 1 | 2.66 | 253.9 |

### 4.2.2 Pittsfield Baseline Scenario

The baseline parameters used in Pittsfield are different from Boston's baseline parameters because the IAT of packages is high, causing a package delivery time well below 3 hours with one truck and one drone for all simulations. The parameters used for the Pittsfield baseline are in Table 6.

*Table 6. Pittsfield Baseline Parameters. Here are the baseline parameters for each interarrival time studied in Pittsfield.*

| Interarrival Time (minutes) | # of Transshipment Points | # of Trucks | # of Drones | Drone Capacity (packages) | Drone Speed (km/hr) |
|---|---|---|---|---|---|
| 18 | 1 | 1 | 1 | 5 | 50 |
| 9 | 1 | 1 | 1 | 5 | 50 |

The number of trucks and drones were selected to represent a simple system that achieves 3-hour delivery or better, under steady-state operation, for each interarrival time. One transshipment point was selected as the baseline for the Pittsfield analysis as it represented the optimal delivery time for the minimum number of trucks and drones as represented in Figure 8. Other scenarios used higher numbers of transshipment points, trucks, and drones or varied drone capacity and speed for comparison. In Pittsfield, adding a drone and 1 TP had a 35% reduction in package delivery time and a 23% reduction in the number of miles driven by a truck compared to the Truck-only simulation for an IAT of 18-minutes. The reduction in truck miles, when combined with the added drone travel distance, resulted in a variable cost decrease of 17%.

The transshipment point results indicate that a company implementing Drone Resupply of Transshipment Points may need to choose between lowest cost and fastest delivery time depending on the model scenario. For instance, the 9-minute interarrival time resulted in the variable cost being optimal at 0 TPs while the delivery time was optimal at 2 TPs. The 18-minute IAT simulation also had different optimal solutions, 1 TP for delivery time and 2 TPs for average cost, see Table 7.

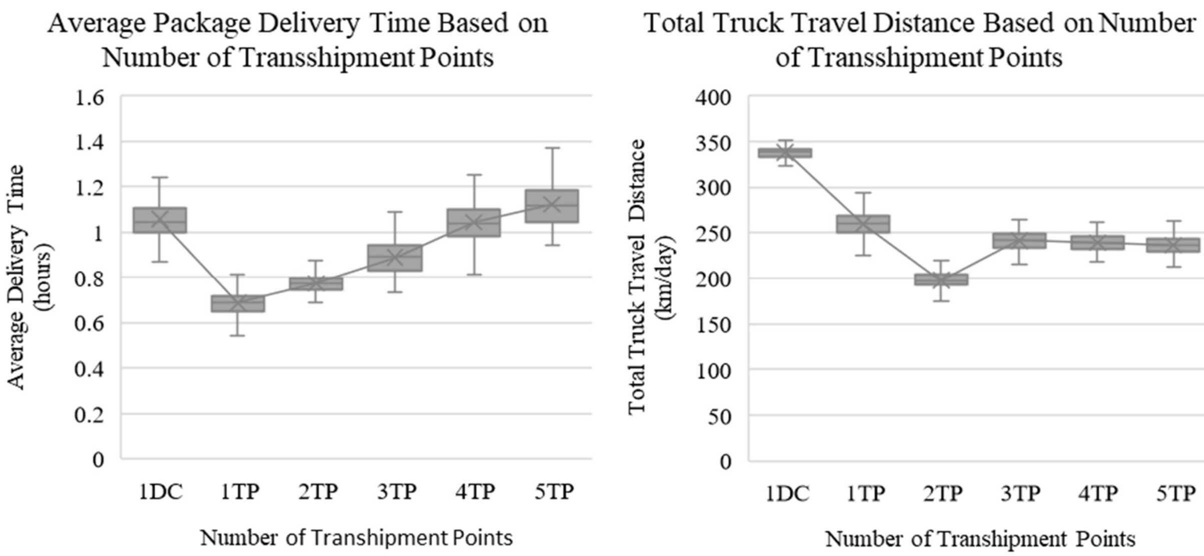



*Figure 8. Pittsfield Baseline Selection. Pittsfield transshipment points had a distinctive effect on both total truck travel distance and package delivery times. Delivery time is optimal for one transshipment point and total truck travel distance is optimal for two transshipment points. Plots are for an IAT of 18 minutes.*

Contrary to what we see in Boston, the delivery times go up when adding more than 1 TP. The reason for this is that there is only one truck servicing all the customers. The time savings of not having to travel back and forth between the DC and the customers is partly undone because now the truck travels between multiple transshipment points. The more transshipment points are added the more time is lost traveling between the transshipment points. We do see that the distance traveled by the truck is still improving when more TPs are added, because of the topology of the area (see Appendix A2). More TP's generally provide a more distance efficient route, but there is still a penalty for the inter TP traveling which causes the distance traveled to go up when increasing the number of TPs from 2 to 3.

*Table 7. Pittsfield Key Performance Indicator Comparison. Truck distance is multiplied by $0.5/km, drone distance is multiplied by $0.02/km to get the average total cost for each scenario. Total cost and average delivery time for the numbers of transshipment points indicate there are competing optimal solutions.*

| 18 Minute Interarrival Time | | | | | 9 Minute Interarrival Time | | | | |
|---|---|---|---|---|---|---|---|---|---|
| # TPs | Drone Distance (km/day) | Truck Distance (km/day) | Total Cost ($/day) | Avg. Delivery Time (hours) | # TPs | Drone Distance (km/day) | Truck Distance (km/day) | Total Cost ($/day) | Avg. Delivery Time (hours) |
| 0TP (Truck-only) | 0 | 338.2 | 169 | 1.06 | 0 TP (Truck-only) | 0 | 253.9 | 127 | 2.66 |
| 1TP | 519.9 | 259.6 | 140 | 0.69 | 1 TP | 639.7 | 258.5 | 142 | 2.13 |
| 2TP | 615.0 | 197.7 | 111 | 0.77 | 2 TP | 678.5 | 249.8 | 138 | 1.84 |
| 3TP | 628.7 | 241.4 | 133 | 0.89 | 3 TP | 682.0 | 251.0 | 139 | 2.08 |
| 4TP | 650.8 | 239.5 | 133 | 1.04 | 4 TP | 683.8 | 242.7 | 135 | 2.31 |
| 5TP | 661.8 | 236.4 | 131 | 1.12 | 5 TP | 683.8 | 238.7 | 133 | 2.46 |

### 4.2.3 Analysis of Pittsfield Region Case Study

The Pittsfield simulations delivery times were most sensitive to the IAT, resulting in approximately double the delivery time when IAT is lowered from 18 to 9 minutes. The utilization of the network is higher when the IAT is lowered, causing more packages to be delivered on each truck route. More packages on each truck route results in a significantly longer package delivery time. The delivery time for an IAT of 9 minutes is more than double the delivery time for all scenarios except when the number of trucks is increased.

When the utilization is high, caused by the low IAT, adding a truck substantially reduces the delivery time from 2.1 hours to 0.7 hours, see Appendix B2 Delivery Times for Varying Number of Trucks plots. However, adding additional trucks, 3 or more trucks in the system, does not reduce the delivery time further because the utilization is very low. For instance, the delivery time only increased 0.1 hours from 0.5 hours to 0.6 hours for an IAT of 9 minutes compared to an IAT of 18 minutes.

In contrast to delivery time, the IAT has little effect on the distance traveled in Pittsfield in all scenarios except when varying the number of trucks, because of the layout of Pittsfield. When the IAT is low the truck will carry more packages per route and most addresses are located near 3 main streets. Even with the additional packages on the truck the layout of the roads results in the truck traveling approximately the same routes, resulting in little extra distance traveled, see Appendix A2. Adding one more truck, however, does double the distance traveled, because now two trucks are used on the same route, reducing the number of packages on a truck and the efficiency of the routes. Using more than two trucks does not influence the distance traveled because they are not utilized.

The drone speed does not affect the travel distance of the trucks; however, it does have some effect on the delivery times. Since the travel time of the drone is a considerable portion of the total delivery time, faster drones get to the TP faster resulting in faster average package delivery times.

The number of drones and the capacity of the drones does not affect delivery time or travel distance. That is because the drone is not fully loaded for any of the tested drone capacities for IATs of 18 or 9 minutes, see Appendix B2.

# 5 CONCLUSIONS

## 5.1 Summary and Conclusions

Companies intending to implement Drone Resupply of Transshipment Points should first evaluate the region, the location of their customers, and the IAT of the orders for the region. Depending on the number of transshipment points delivery time and cost may vary and the optimum will depend on the region and the IAT. Using our optimization model, see Section 3.1.4, the TP locations for varying numbers of transshipment points can be determined. Using the attained TP locations in our simulation model an indication of delivery times and truck travel distance can be calculated.

Based on our findings, when simulating the Boston and Pittsfield regions, we found that the number of transshipment points is highly dependent on the region. The optimum number of TPs for minimizing delivery times will vary from region to region.

Generally, when compared with the traditional Truck-only model, adding one drone and one transshipment point to a network will reduce both the delivery time and total truck travel distance. Adding additional TPs does not guarantee a further reduction of delivery times or travel distance. The outcome of adding more TPs mostly depends on the region being served.

Another factor in determining the delivery times is the number of trucks. In general, the more trucks the faster the delivery time and the higher the distance traveled. Therefore, there is a trade-off between truck travel distance (cost) and delivery time.

Companies will also need to ensure that the number of drones, drone capacity, and drone speed match the demand requirements. If the number of drones, drone capacity, and drone speed are high enough to prevent a buildup of packages at the DC (maintain steady-state operation), they will not have major impacts on delivery speed or travel distance (cost).

## 5.2 Future Research Opportunities

Our research on the Drone Resupply of Transshipment Point model represents a feasible solution to last mile delivery, however it does not represent an optimal solution. Many opportunities for further refinement and optimization exist. Some potential improvements and variations are summarized below.

The Drone Resupply of Transshipment Point model could be further refined by selecting packages for the next drone delivery to a transshipment point based on possible package delivery routes. In our simulations, the packages are selected for delivery to transshipment points on a first-in first-out (FIFO) basis. All packages meant for one transshipment point are added to a drone's delivery if the drone's capacity has not been exceeded yet. An improvement would determine which packages to deliver to a transshipment point for truck delivery based on an optimal vehicle route instead of FIFO.

The Drone Resupply of Trucks model also needs to be compared to all other drone delivery models, see Section 3.1.4, and conventional package delivery for determination of the optimal drone delivery method. Instead of the truck returning to a previously determined transshipment point, to pick up packages dropped off by a drone, the truck could meet the drone at customer locations along its route. The drone and truck would need to be coordinated to prevent significant waiting time of either vehicle. Drone Resupply of Trucks prevents the return trip to the centralized location and in addition, packages could be selected based on the current location of the truck for more efficient routing. Drawbacks of the dynamic vehicle routing required in this implementation could consist of intensive computation time and difficulty matching the drone to truck meeting times considering traffic or other unknown variables.

Another opportunity incorporates a package delivery deadline into the vehicle routing. Our simulations computed the average package delivery time for comparison between models but did not use a package delivery deadline in determining vehicle routing. The average package delivery time was reasonable with less than 3-hour delivery, however the maximum package delivery times may need to be restricted to ensure same-day delivery. Incorporating a package delivery deadline into the vehicle routing could be used to achieve a target service level.

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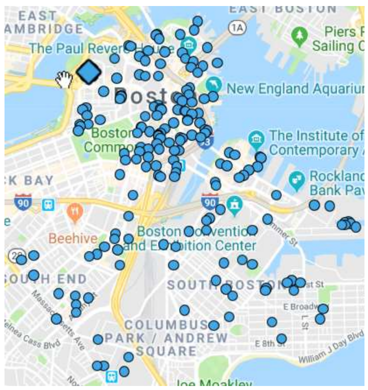
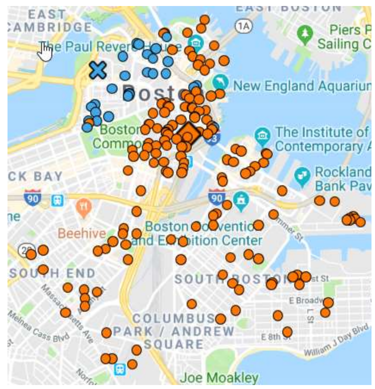
# APPENDIX A

Appendix A contains all customer to TP or DC maps developed using the Transshipment Point Optimization Model presented in Section 3.1.4.

1. Boston



(a)



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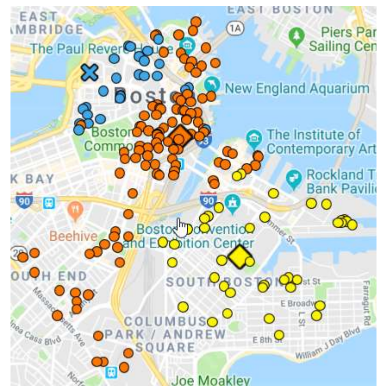

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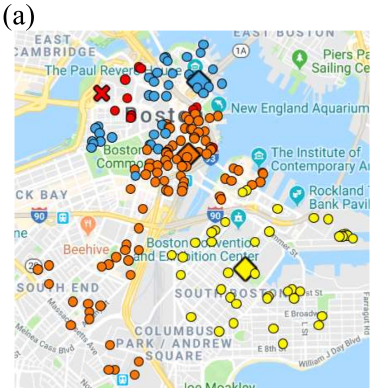

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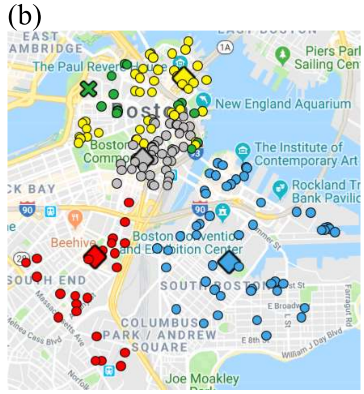
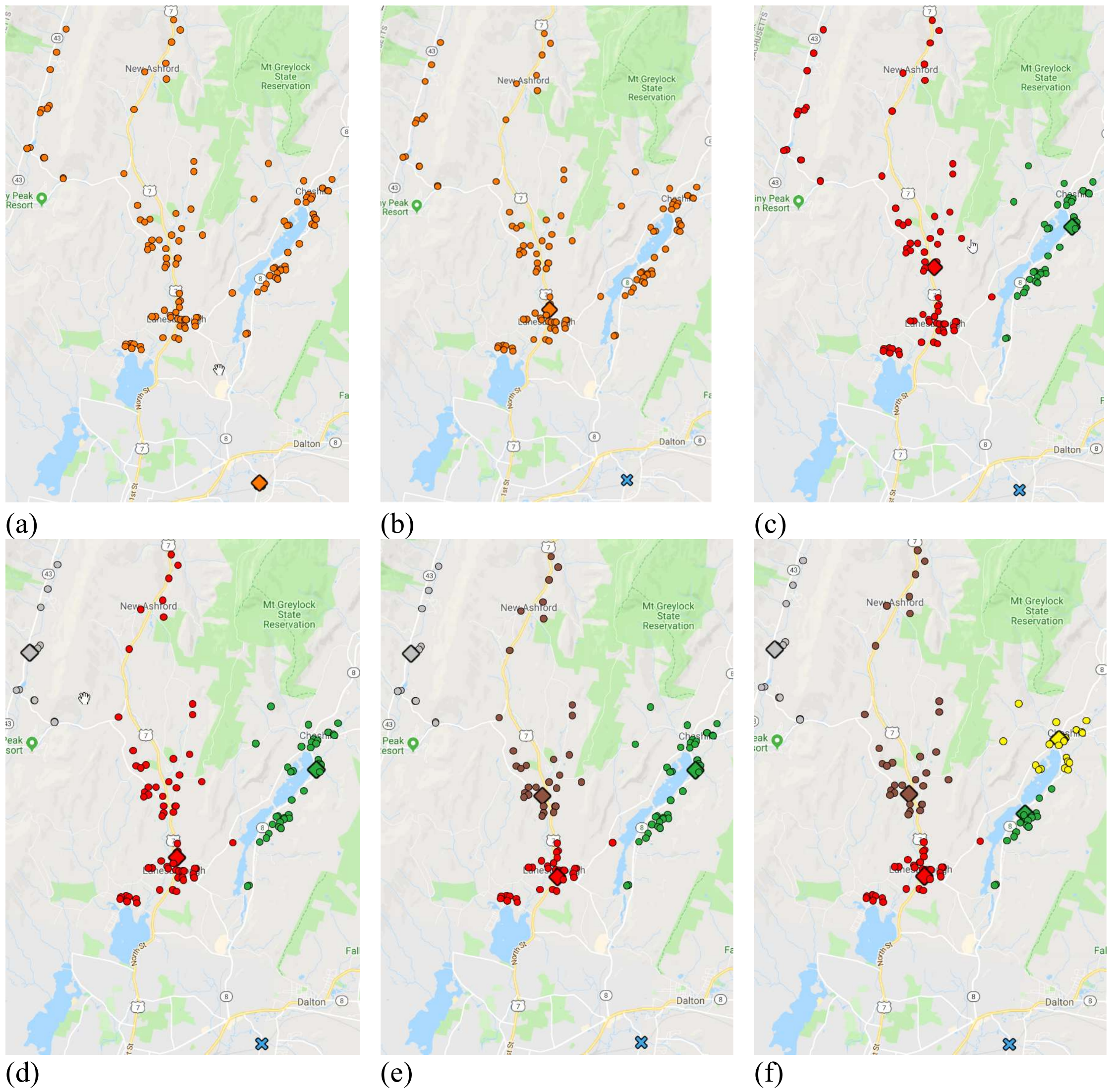


(e)

*Boston TP positioning: (a) DC Only (Truck-only) model, (b) One-TP model, (c) Two-TP model, (d) Three-TP model, (e) Four-TP model.*

2. Pittsfield, MA

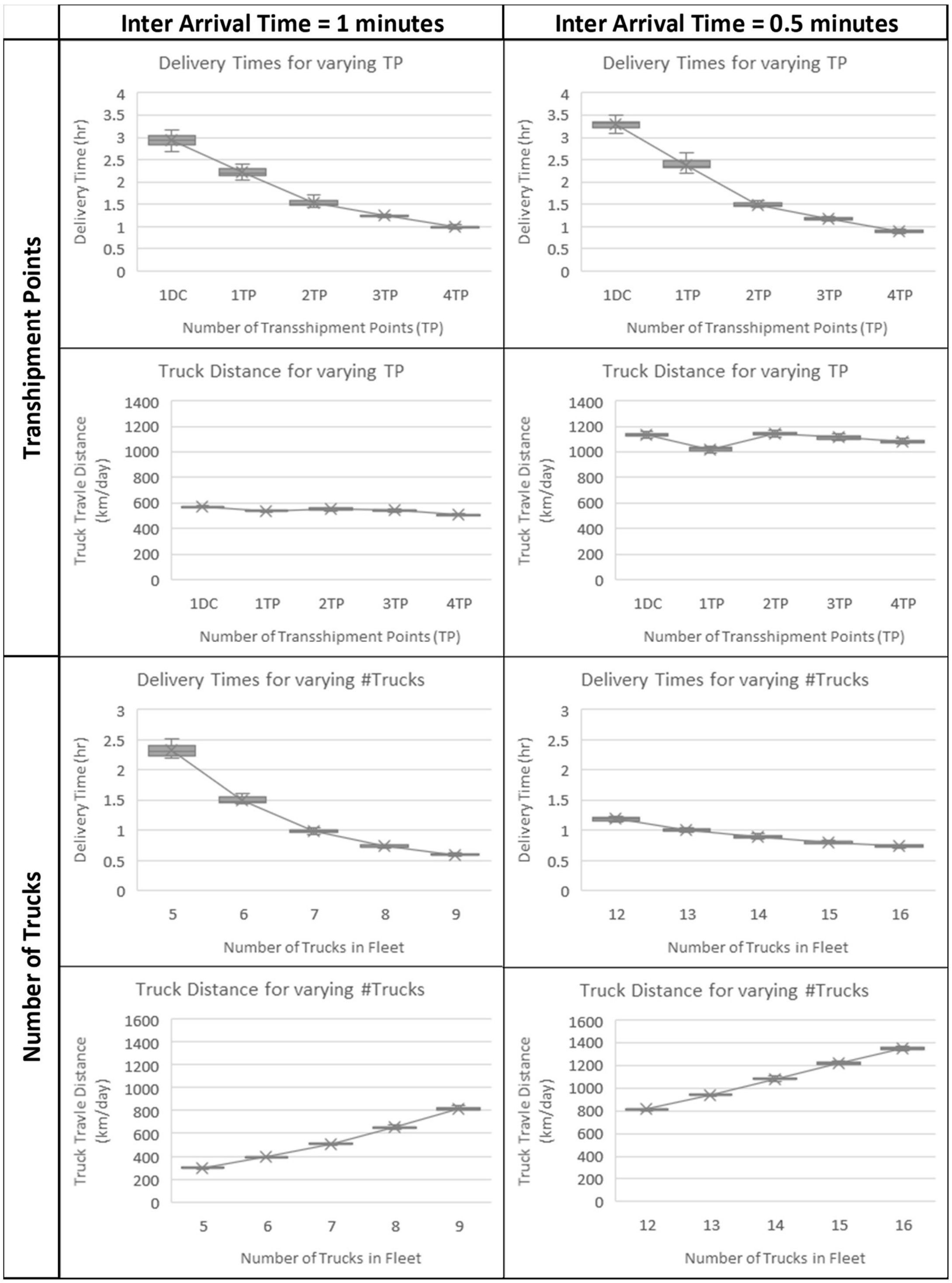


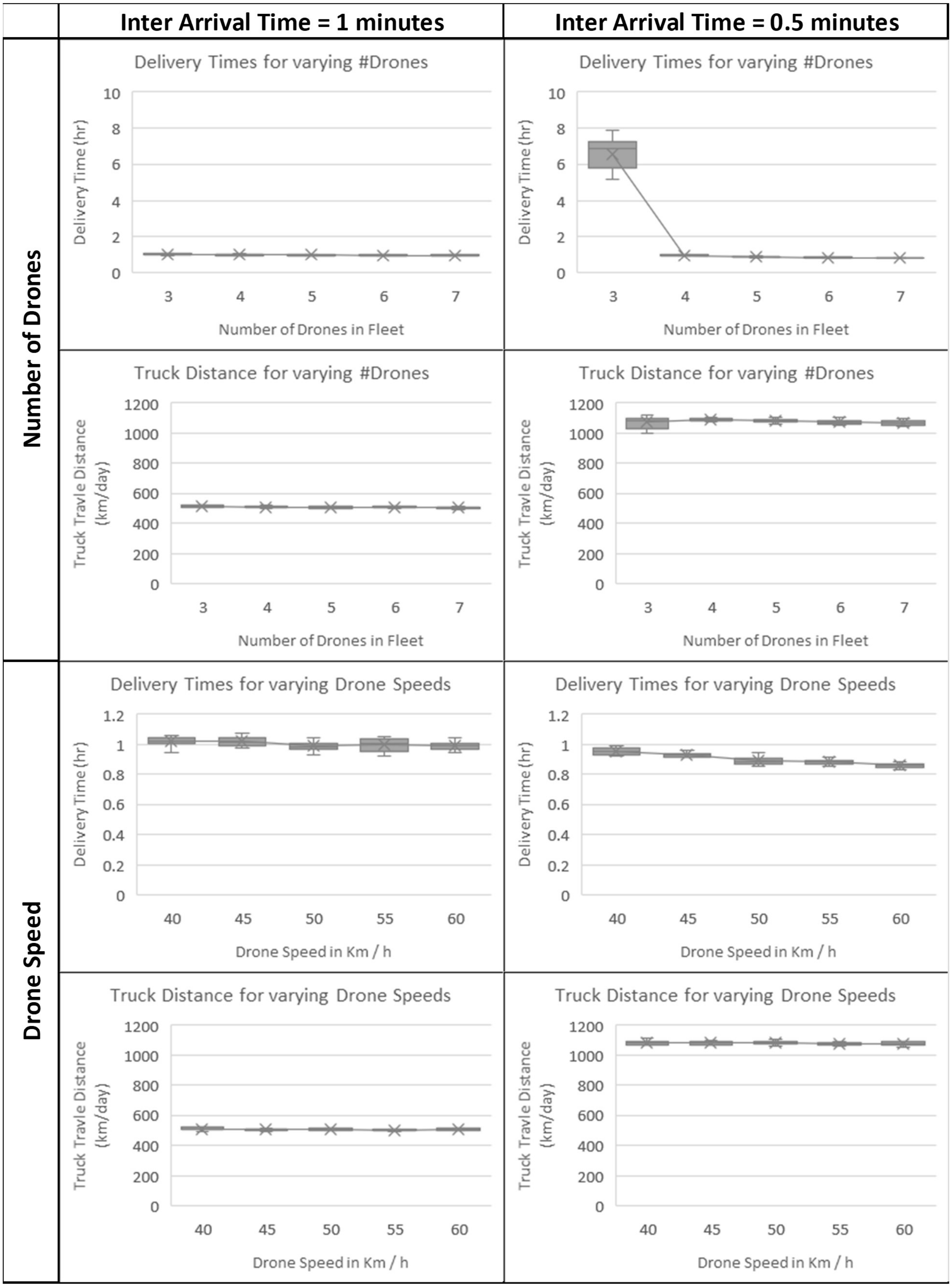

*Pittsfield TP positioning: (a) DC Only (Truck-only) model, (b) One-TP model, (c) Two-TP model, (d) Three-TP model, (e) Four-TP model, (f) Five-TP model.*

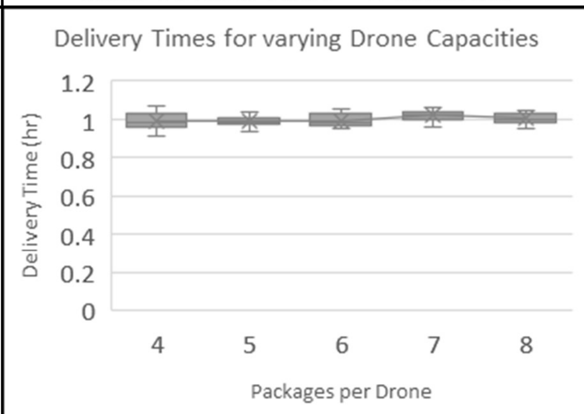
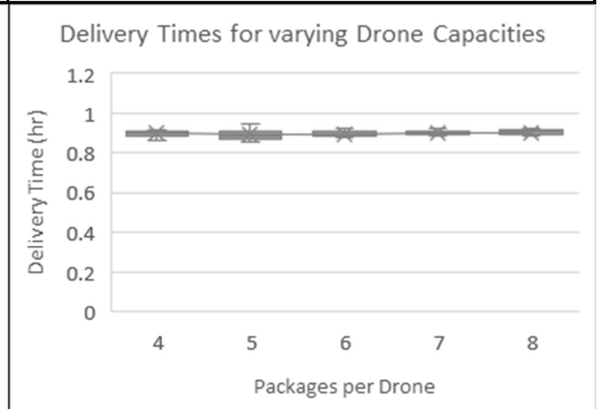
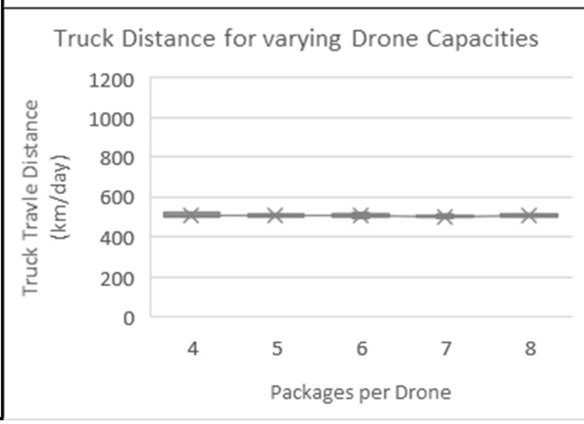
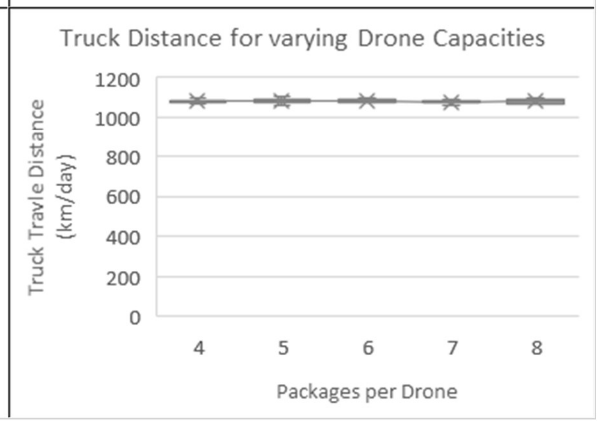
# APPENDIX B

All delivery time and total truck travel distance boxplots for all scenarios tested as discussed in Section 4.

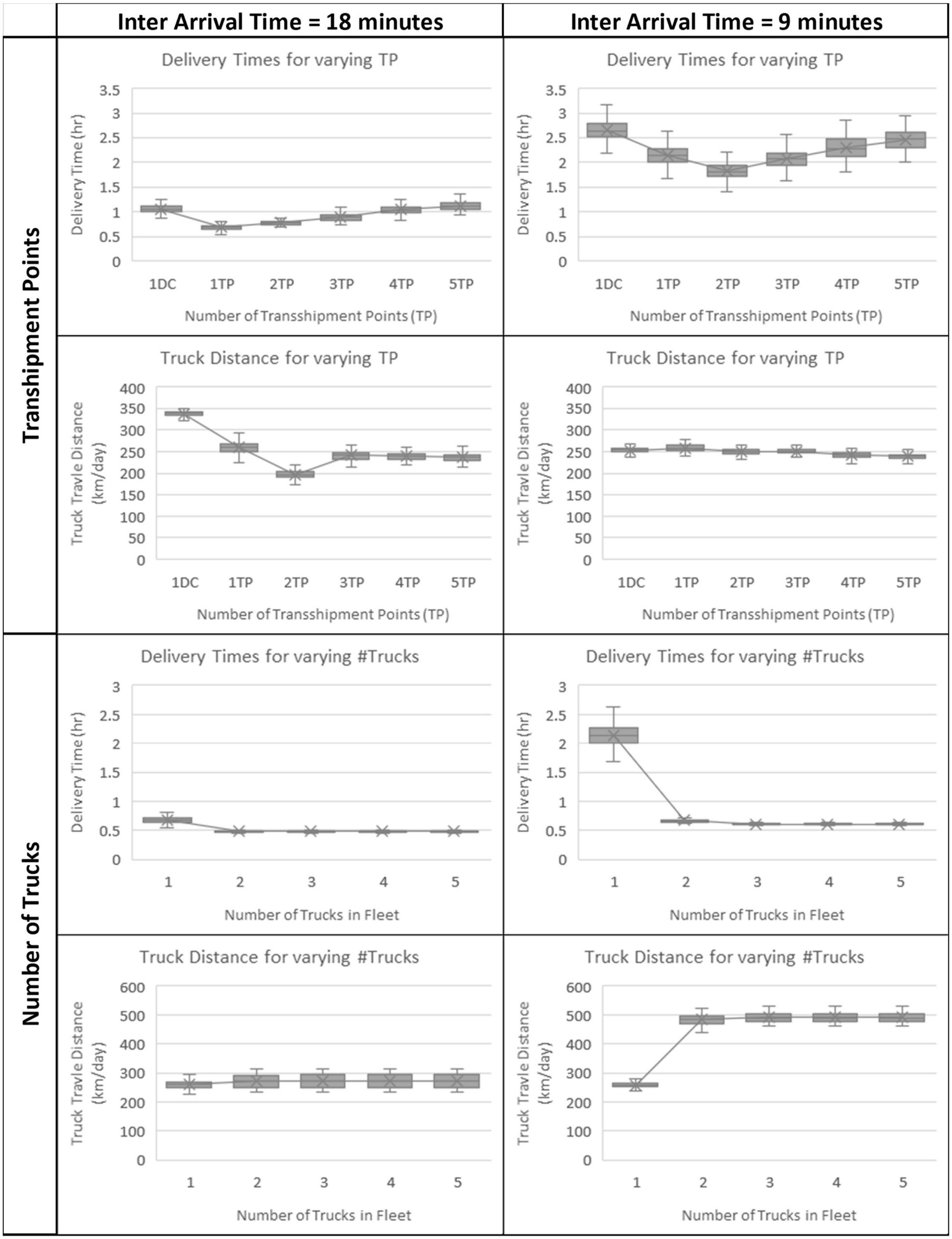
1. Boston

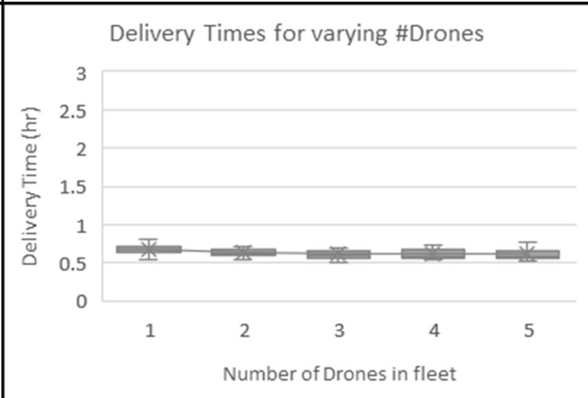
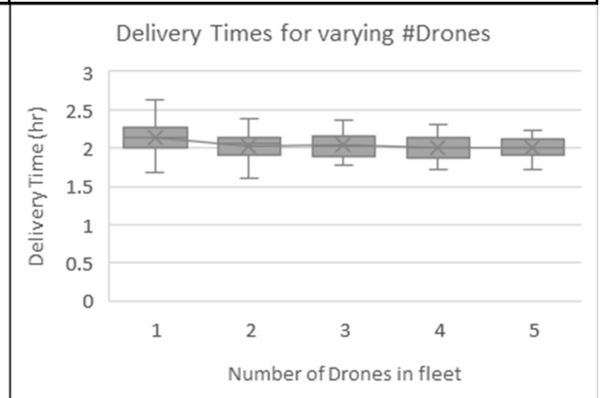
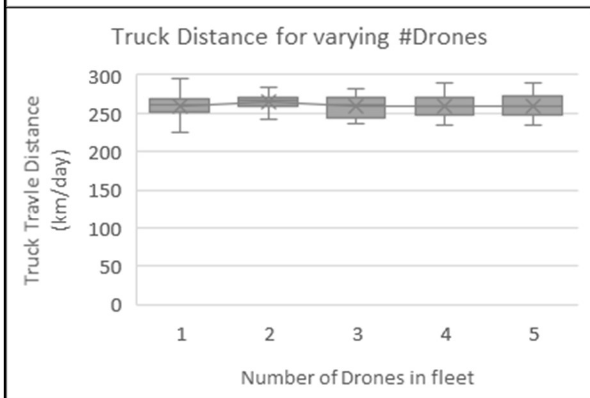
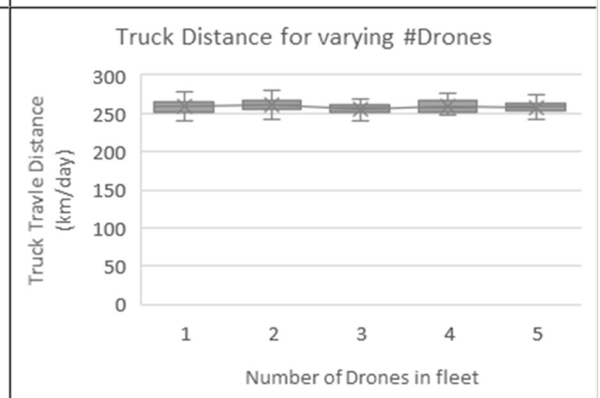
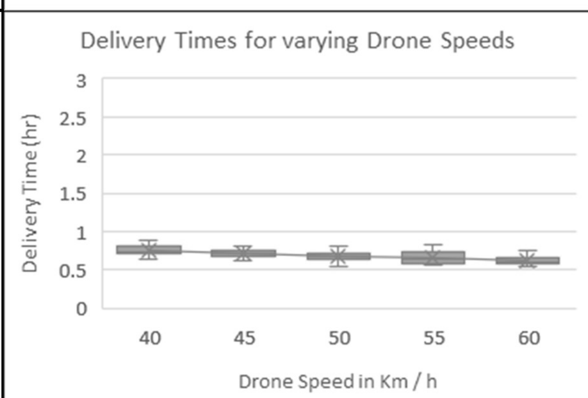
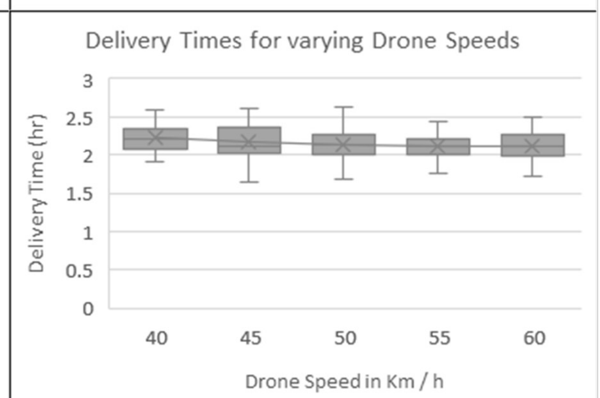
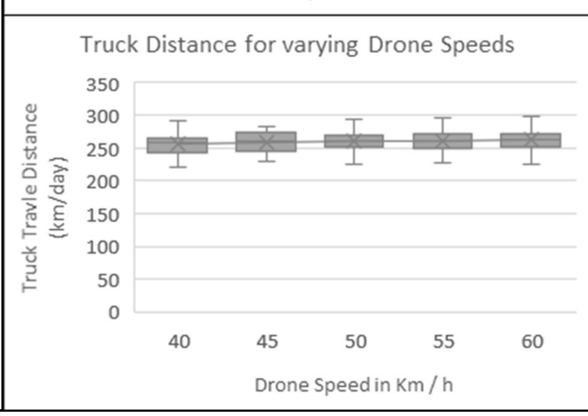
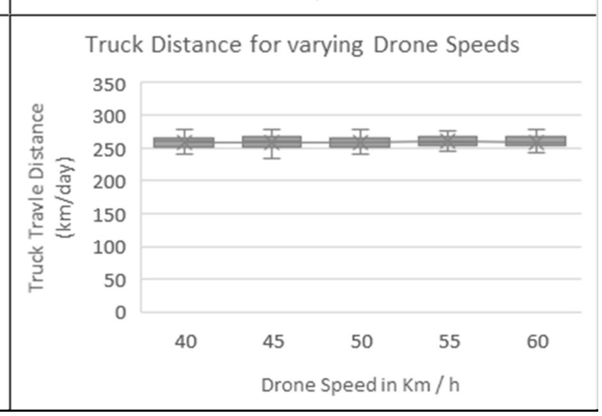



Inter Arrival Time = 1 minutes
Inter Arrival Time = 0.5 minutes
Number of Drones
Drone Speed
Delivery Times for varying #Drones
Delivery Time (hr)
Number of Drones in Fleet
Truck Distance for varying #Drones
Truck Travle Distance (km/day)
Number of Drones in Fleet
Delivery Times for varying Drone Speeds
Delivery Time (hr)
Drone Speed in Km / h
Truck Distance for varying Drone Speeds
Truck Travle Distance (km/day)
Drone Speed in Km / h

| | Inter Arrival Time = 1 minutes | Inter Arrival Time = 0.5 minutes |
|---|---|---|
| **Drone Capacity** |   |   |
| |   |   |

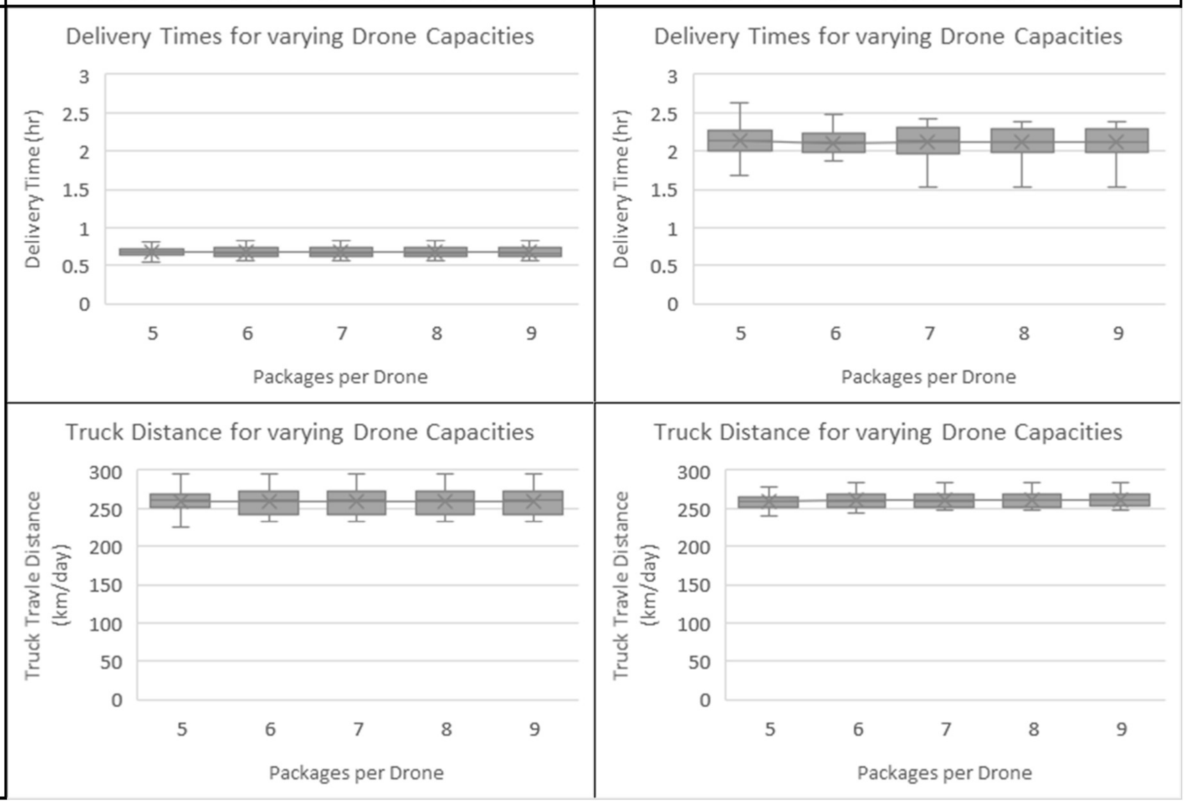
2. Pittsfield



| | Inter Arrival Time = 18 minutes | Inter Arrival Time = 9 minutes |
|---|---|---|
| **Number of Drones** |  |  |
| |  |  |
| **Drone Speed** |  |  |
| |  |  |

| | Inter Arrival Time = 18 minutes | Inter Arrival Time = 9 minutes |
|---|---|---|

**Drone Capacity**



# APPENDIX C

All Boston delivery time and daily truck travel distance for all scenarios.

| | | | | | Inter Arrival Time | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 0.5 | | | | | 1 | | | | |
| # Transhipment Points | #Drones | Drone Speed | Drone Capacity | #Trucks -> | 12 | 13 | 14 | 15 | 16 | 5 | 6 | 7 | 8 | 9 |
| 1DC | 5 | 50 | 5 | Delivery Time | | | 3.30 | | | | | 2.95 | | |
| | | | | Daily Truck Travel Distance | | | 1,134.27 | | | | | 571.03 | | |
| 1TP | | | | Delivery Time | | | 2.38 | | | | | 2.22 | | |
| | | | | Daily Truck Travel Distance | | | 1,022.26 | | | | | 538.49 | | |
| 2TP | | | | Delivery Time | | | 1.49 | | | | | 1.53 | | |
| | | | | Daily Truck Travel Distance | | | 1,142.95 | | | | | 553.85 | | |
| 3TP | | | | Delivery Time | | | 1.17 | | | | | 1.24 | | |
| | | | | Daily Truck Travel Distance | | | 1,115.12 | | | | | 542.35 | | |
| 4TP | 3 | | | Delivery Time | | | 6.59 | | | | | 1.04 | | |
| | | | | Daily Truck Travel Distance | | | 1,070.53 | | | | | 515.77 | | |
| | 4 | | | Delivery Time | | | 0.98 | | | | | 1.01 | | |
| | | | | Daily Truck Travel Distance | | | 1,087.33 | | | | | 510.77 | | |
| | 5 | 40 | | Delivery Time | | | 0.96 | | | | | 1.02 | | |
| | | | | Daily Truck Travel Distance | | | 1,083.44 | | | | | 510.51 | | |
| | | 45 | | Delivery Time | | | 0.93 | | | | | 1.02 | | |
| | | | | Daily Truck Travel Distance | | | 1,080.75 | | | | | 505.92 | | |
| | | 50 | 4 | Delivery Time | | | 0.90 | | | | | 0.99 | | |
| | | | | Daily Truck Travel Distance | | | 1,079.90 | | | | | 509.18 | | |
| | | | 5 | Delivery Time | 1.19 | 1.01 | 0.89 | 0.80 | 0.74 | 2.33 | 1.50 | 0.99 | 0.73 | 0.60 |
| | | | | Daily Truck Travel Distance | 814.58 | 941.35 | 1,082.09 | 1,223.41 | 1,353.95 | 296.55 | 391.15 | 507.30 | 651.80 | 817.62 |
| | | | 6 | Delivery Time | | | 0.89 | | | | | 0.99 | | |
| | | | | Daily Truck Travel Distance | | | 1,081.03 | | | | | 510.11 | | |
| | | | 7 | Delivery Time | | | 0.90 | | | | | 1.02 | | |
| | | | | Daily Truck Travel Distance | | | 1,075.88 | | | | | 503.92 | | |
| | | | 8 | Delivery Time | | | 0.90 | | | | | 1.00 | | |
| | | | | Daily Truck Travel Distance | | | 1,079.42 | | | | | 508.34 | | |
| | | 55 | 5 | Delivery Time | | | 0.88 | | | | | 1.00 | | |
| | | | | Daily Truck Travel Distance | | | 1,074.96 | | | | | 503.14 | | |
| | | 60 | | Delivery Time | | | 0.86 | | | | | 0.99 | | |
| | | | | Daily Truck Travel Distance | | | 1,075.17 | | | | | 508.77 | | |
| | 6 | 50 | | Delivery Time | | | 0.86 | | | | | 0.99 | | |
| | | | | Daily Truck Travel Distance | | | 1,072.31 | | | | | 509.52 | | |
| | 7 | | | Delivery Time | | | 0.85 | | | | | 0.98 | | |
| | | | | Daily Truck Travel Distance | | | 1,068.97 | | | | | 505.67 | | |

All Pittsfield delivery time and daily truck travel distance for all scenarios.

| | | | | | Inter Arrival Time | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 9 | | | | | 18 | | | | |
| # Transshipment Points | #Drones | Drone Speed | Drone Capacity | #Trucks -> | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 |
| 1DC | 1 | 50 | 5 | Devlivery Time | 2.66 | | | | | 1.06 | | | | |
| | | | | Daily Truck Travel Distance | 253.91 | | | | | 338.20 | | | | |
| 1TP | | 40 | | Devlivery Time | 2.23 | | | | | 0.76 | | | | |
| | | | | Daily Truck Travel Distance | 258.99 | | | | | 256.08 | | | | |
| | | 45 | | Devlivery Time | 2.16 | | | | | 0.72 | | | | |
| | | | | Daily Truck Travel Distance | 259.13 | | | | | 258.70 | | | | |
| | | 50 | | Devlivery Time | 2.13 | 0.67 | 0.61 | 0.61 | 0.61 | 0.69 | 0.49 | 0.48 | 0.48 | 0.48 |
| | | | | Daily Truck Travel Distance | 258.50 | 482.87 | 490.02 | 490.09 | 490.09 | 259.59 | 272.71 | 272.93 | 272.93 | 272.93 |
| | | | 6 | Devlivery Time | 2.11 | | | | | 0.69 | | | | |
| | | | | Daily Truck Travel Distance | 260.46 | | | | | 259.31 | | | | |
| | | | 7 | Devlivery Time | 2.12 | | | | | 0.69 | | | | |
| | | | | Daily Truck Travel Distance | 260.74 | | | | | 259.35 | | | | |
| | | | 8 | Devlivery Time | 2.11 | | | | | 0.69 | | | | |
| | | | | Daily Truck Travel Distance | 260.81 | | | | | 259.35 | | | | |
| | | | 9 | Devlivery Time | 2.11 | | | | | 0.69 | | | | |
| | | | | Daily Truck Travel Distance | 260.97 | | | | | 259.35 | | | | |
| | | 55 | 5 | Devlivery Time | 2.12 | | | | | 0.67 | | | | |
| | | | | Daily Truck Travel Distance | 259.67 | | | | | 259.81 | | | | |
| | | 60 | | Devlivery Time | 2.12 | | | | | 0.62 | | | | |
| | | | | Daily Truck Travel Distance | 258.81 | | | | | 262.12 | | | | |
| | 2 | 50 | | Devlivery Time | 2.03 | | | | | 0.64 | | | | |
| | | | | Daily Truck Travel Distance | 260.34 | | | | | 264.75 | | | | |
| | 3 | | | Devlivery Time | 2.04 | | | | | 0.62 | | | | |
| | | | | Daily Truck Travel Distance | 256.15 | | | | | 258.20 | | | | |
| | 4 | | | Devlivery Time | 2.00 | | | | | 0.62 | | | | |
| | | | | Daily Truck Travel Distance | 259.02 | | | | | 258.59 | | | | |
| | 5 | | | Devlivery Time | 2.00 | | | | | 0.62 | | | | |
| | | | | Daily Truck Travel Distance | 257.73 | | | | | 258.78 | | | | |
| 2TP | 1 | | | Devlivery Time | 1.84 | | | | | 0.77 | | | | |
| | | | | Daily Truck Travel Distance | 249.76 | | | | | 197.67 | | | | |
| 3TP | | | | Devlivery Time | 2.08 | | | | | 0.89 | | | | |
| | | | | Daily Truck Travel Distance | 250.98 | | | | | 241.44 | | | | |
| 4TP | | | | Devlivery Time | 2.31 | | | | | 1.04 | | | | |
| | | | | Daily Truck Travel Distance | 242.66 | | | | | 239.45 | | | | |
| 5TP | | | | Devlivery Time | 2.46 | | | | | 1.12 | | | | |
| | | | | Daily Truck Travel Distance | 238.72 | | | | | 236.41 | | | | |