Facility and Routing Decisions in Truck-Drone Distribution

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ABSTRACT

Drones have the potential to be major players in the field of last-mile delivery, especially with the rise of e-commerce. However, they face several technological and regulatory restrictions for large-scale implementation. Combining drones with traditional ground delivery vehicles can bridge this gap while achieving significant improvements in distribution cost and speed over vehicle delivery alone.

This research project focuses on modeling and solving the Location-Routing Problem with drones as an ancillary mode of delivery. The goal is to develop a model that identifies the optimal locations for the distribution facilities, as well as the set of combined routes that the trucks and drones will follow to deliver parcels to customers.

To solve this problem, a two-steps metaheuristic approach is developed and implemented. The customer locations are first grouped into clusters with centroid positions where trucks would park, dispatch, and retrieve the onboard drones that perform the last step of the delivery. Once the optimal truck parking locations are identified, the selection of the optimal distribution facilities and the truck routes are determined simultaneously, by implementing the Multiple Ant Colony Optimization algorithm. The validation of the model revealed high reliability with a 1% average optimality gap from the exact solution.

When applying the model to a real road network, with 200 customers and 5 candidate depot locations, the model confirmed a 24% saving in daily distribution costs from adding 3 drones to every delivery truck. The savings opportunity is less sensitive to the number of drones per truck and the drones' speed, and more sensitive to the trucks' speed and the drones' traveling cost per mile. The analysis reveals that adding drones will generate savings as long as the traveling cost of drones is lower than that of trucks at around $4.00 on average for last-mile delivery.

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1. Introduction

1.1. Background and Motivation

The widespread adoption of e-commerce business models has been placing increased emphasis on last-mile delivery logistics. Businesses have increased their involvement in delivering lighter and more frequent parcels to end customers, and in the race to capture the largest market share, the competition on fulfillment speed has become fierce. Companies are considering new and innovative ways to deliver their products, and a few have been putting significant research and development efforts into incorporating unmanned autonomous vehicles, such as drones and delivery robots, into their distribution networks (Aurambout, Gkoumas & Ciuffo, 2019). In 2013, Amazon was the first company to publicly propose using drones in its delivery services (CBS Interactive Inc., 2013). In October 2019, UPS was the first company to receive a full drone operating license issued by the Federal Aviation Administration (FAA), allowing it to expand its current small drone-delivery service pilots into a country-wide network (UPS, 2019).

In comparison with trucks and vans, drones are more agile, less dependent on traffic conditions, and almost unbound by obstacles (natural or human-made). Delivery robots are typically small in size; hence they can travel on sidewalks and do not have to park. With such features, these new technologies may seem like the perfect replacements for the traditional parcel transportation methods (DHL, 2014). However, trucks and vans still have their place in the parcel delivery logistics. Because of their larger sizes and the fact that urban designers have long considered their implications when planning cities, manned vehicles can travel continuously for longer durations and further distances, while carrying considerably more items. The ground vehicles are also largely not hindered by the weather conditions.

This capstone project discusses the interrelation between these two modes of transportation, both strategically and operationally. Specifically, it considers an intermodal truck-drone configuration at a small scale of primary and secondary movers. The primary movers are the traditional vehicles, which carry the parcels out of the distribution facilities for most of the haul, and then park temporarily after covering a certain distance. Moreover, while the trucks are stationary, the drones separate from the vehicles and act as a secondary delivery system on shorter hauls, where they are referred to as the "ancillary mode." The trucks remain in place and wait for the drones to return. The particular focus of this study is on the optimal routing of the vehicles and the optimal selection of the delivery facilities. In the Operations Research (OR) literature, the connection between the routing and the location decision is commonly referred to as the Location Routing Problem (LRP).

While the primary aim of this project is to create the foundation for a decision-support tool that optimizes commercial delivery, the findings in this research can be of value to other operations where ancillary vehicles can be integrated. Examples of candidate operations include humanitarian and disaster relief, military, firefighting, intermodal passenger transportation, agriculture and irrigation, and aerial surveillance, among others.

1.2. Research Problem

This research project investigates the implications of introducing autonomous vehicles as ancillary modes to the LRP, in order to accurately and efficiently account for their features. Such a problem is referred to as the Location Routing Problem with Ancillary Modes (LRPAM).

This model is concerned with both the strategic decision of locating the optimal distribution facilities, in addition to the operational decision of routing and coordinating the truck-drone delivery. The system comprises multiple facilities and a fleet of trucks that can carry one or more drones.

To gain further insights, the LRPAM model is applied to explore how the implementation of the integrated truck-drone distribution systems could influence the delivery service levels and efficiency. The said model is also applied to better understand what differentiates this combined system from the traditional truck-only distribution ones. The robustness of the operational strategies that can be developed from the model's outputs is also assessed, along with the sensitivity of such plans to any foreseen advancements in autonomous vehicle technologies (in speed, reach, reliability, and other aspects).

1.3. Research Objectives and Main Goals

The main objectives of this research project are:

- To develop a model and a decision-support tool that recommends a financially effective distribution plan. This plan is based on decisions that are generated to minimize the objective variable of the total cost of distribution, while adhering to the constraints of the operation.
- The decisions in the plan fall under two categories:
    - Strategic: The location of the distribution facilities.
    - Operational: The set of routes that the trucks and the drones would follow.
- The model is created based on a heuristic approach that balances both the optimality of the solution and its computational efficiency.
- Exact optimization is used to benchmark the model's proximity to the real optimal solution.

2. Literature Review

To the best of the authors' knowledge, research on the intermodal truck-drone delivery in the Location Routing Problem (LRP) has never been attempted before.

To develop a good about drones, this chapter starts by establishing the current state of the industry and the governments on delivery drones as of early 2020. Following that, it provides a brief review of the research and modeling done on the Operations Research (OR) problems that form the LRPAM under the scope of drone delivery. This second part of the literature review, starting with Section 2.3 is necessary to formulate the math behind the model that this research capstone project develops.

2.1. Technological Capabilities and Considerations of Drones for Delivery Operations

The possibility of using drones for parcel delivery has been sparking the interest of many companies. Several businesses have been developing drones with the intent of using them in their commercial parcel distribution operations. As such, most of these efforts have been conducted as private research and development, with the exact metrics of the machines considered to be “trade secrets” that may lead to competitive advantage in the near future (Bloomberg, 2019). Because of this scarcity of scientific publications, most of the publicly available information on current drone specifications comes from corporate publications and news releases. Table 1 shows a summary of the current published specifications of delivery drones. The most relevant specifications include:

- Speed: Horizontal travel speed between two locations.
- Round-trip distance range: Furthest reported distance that can be traveled to and back on a single battery charge.
- Endurance: Longest reported duration of continuous flight on a single battery charge.
- Payload: Heaviest (or largest) parcel that the drone can carry. The payload does not include the weight of the drone itself.
- Size: Horizontal span of the drone while parked on the ground, as measured along its widest direction. The horizontal span is considered an indicator of the device's footprint and a rough estimator of how many drones could fit and be launched from a delivery truck.

The progression of improvements in drone capabilities over the past two decades suggests that drones have become very competitive with vehicles in terms of direct travel speed. The effective travel speed of drones is even better, considering that drones travel directly without the need to slow down for turns and traffic. It is noted that drones are slowly catching up in terms of reach as well. Nevertheless, drones are far behind in terms of payload capacity and total endurance (DHL, n.d.). While the maximum payload of today’s delivery drones appears to be relatively low and restrictive, a carrying capacity of as low as 5 lbs (2.3 kg) would cover 80% of the expected orders to the consumers of e-retailers, such as Amazon (Bloomberg, 2019).

Many operational aspects could make drones a valuable alternative to vans in last-mile delivery. These include the unnecessity for navigation around land obstacles, the ability to travel on a direct path to the customer, the higher potential for safe automated navigation, and the operability in areas with no connecting roads. Additionally, drone delivery can be the solution to many logistical challenges that arise from the increased urbanization, especially in megacities (The UN defines megacities as cities with a population exceeding 10 million). Drones have an enormous potential to reduce traffic congestion and pollution in heavily populated areas, by partially replacing delivery vans and trucks (DHL, 2014). In addition, drones can be designed to be highly resistant to weather fluctuations. An example is an account by Flirtey, the Nevada-based drone delivery company, of their drones' capability to withstand 95% of weather conditions (FreightWaves, 2019). Perhaps the most appealing aspect of drones in delivery is their overwhelmingly low cost-per-mile of $0.05, versus $4.00 in same-day deliveries using ground couriers (Kim, 2016). As it turns out, the expected drop in delivery prices is the primary reason why consumers would choose drone delivery, and is even prioritized over the premise of faster service (McKinsey, 2016).

Almost the entirety of corporate-published information on delivery drones is based on direct delivery from the distribution facility to the parcel's final destination, using a drone alone, and with no intermediary mode such as an automobile. The focus on direct drone delivery may have influenced the direction that the delivery drone research and development took under corporations, focusing primarily on extending the speed and the reach of drones, rather than their carrying capacity. An uncommon exception to this direction is the patented system by Workhorse, where its drone carries the parcel out of an electric truck to the final delivery destination (Workhorse, n.d.). This intermodal system has been tested in partnership with UPS (UPS, 2017).

Table 1: Summary of published specifications and capabilities of delivery drones (direct facility to destination).

Company	Speed *(km/h)*	Roundtrip range *(km)*	Endurance *(minutes)*	Payload	Size *(m)*	References
Amazon	161	12	30	2.3 kg	1.8m	(Bloomberg, 2019) (Raconteur, 2018)
DHL	130	32.5	40	4kg	1.8m	(DHL, n.d.)
UPS	-	-	30	4.5kg	-	(UPS, 2017)
Workhorse	72	-	-	0.6 ft^3	-	(Workhorse, n.d.)
EHang + DHL	-	-	-	5 kg	-	(DHL, 2019)
Rakuten	-	-	15	2 kg	-	(Nikkei Asian Review, 2019)
Uber Eats	48	9.7	-	"2 meals"	-	(Hawkins, 2019)
Wing	112	20	-	1.5 kg	1.3m	(Wing, n.d.)

2.2 Drone Regulations

Drones are approaching the stage where they can be ready for use in commercial logistics from technological and operational perspectives. However, they remain more hindered by governmental regulations. These regulations have been evolving at a much slower pace compared to the rapid advancements in drone science and technology. It is estimated that the US economy is losing 10 billion USD annually because of the strictness of the delivery drone regulations (DHL, 2014). This reluctance by governments to embrace drone delivery is not entirely unreasonable, as governments hold the ultimate responsibility for maintaining public safety and ensuring that no harm befalls humans and environments. From the regulators' perspective, all relevant risks must be identified and mitigated before giving corporations the approval to launch their commercial operations.

In the United States, most federal regulations on drones restrict their commercial use. The Federal Aviation Administration (FAA) regulation for small Unmanned Aircraft Systems (UAS), "Operations Other Than Model Aircraft," covers a broad spectrum of commercial uses for drones. The regulation states that drones must fly below 400 feet (120 meters) and at less than 100 miles per hour, and they can only fly during daylight (30 minutes before official sunrise to 30 minutes after official sunset). Furthermore, drones cannot fly over people, and with some exceptions, they must weigh under 55 pounds (25 kilograms). Most importantly, during operation, the drones must always be kept in the operators' line of sight, or a visual observer is required to keep the aircraft within unaided sight. Given such rules, companies such as UPS, which recently received an FAA license to operate drone delivery commercially, are allowed to fly drones fully autonomously only on pre-programmed routes monitored by remote human pilots. This requirement makes the business model of drone delivery less viable, making future changes a necessity for achieving profits and enabling scalability (Wyman, 2018).

Fortunately for businesses, the FAA has begun to show signs of reconsideration of its laws. Under FAA's recently introduced UAS Integration Pilot Program (UAS IPP), the administration is providing licenses to 10 participant organizations in select locations to run a pilot of their services under relaxed rules for the full program's duration (2.5 years). This temporary approval is provided in exchange for data and insights that will support the FAA in crafting the future set of rules and regulations. Flirtey's license has allowed the company to operate up to 10 drones at once by the same human pilot, even at night and beyond the visual line of sight (FreightWaves, 2019). Unifly, another UAS IPP participant that has been granted a license to operate in Alaska, has reported that "flight over people" is also allowed (Unifly, n.d.).

The US is not alone in restricting commercial drone operations, as similar regulations are enforced around the world. In China, the Civil Aviation Administration of China (CAAC) does not allow drones to fly in densely populated areas and higher than 120 meters. Drones must also remain within the operator’s sight all the time (UAV Coach, 2020). In Australia, the Civil Aviation Safety Authority (CASA) restricts that drone must not fly higher than 120 meters (400 ft) above the ground, and must be kept at least 30 meters away from other people. Drones can only fly during the day and must be within visual line-of-sight. On top of that, drones are not allowed to fly over people (RPAS, 2019). In Europe, drones are regulated by the European Aviation Safety Agency (EASA) and various national regulators, depending on drone size. However, the rules are also very similar (Lomas, 2019). As the drone landscape has changed rapidly over the last several years, the regulations are expected to be updated to find the balance between ensuring public safety and creating space for business innovation.

2.3. Vehicle Routing Problem with Drone (Intermodal)

Over the past decade, academics have extensively researched the truck-drone system optimization problem with various configurations of the relationship between the two modes of transportation. Otto, Agatz, Campbell, Golden, and Pesch (2018) provide a comprehensive overview of the literature in this field. Table 2 summarizes the most relevant literature to this research project, particularly papers on different truck-drone configurations.

Murray and Chu (2015) first studied the truck and drone problem by introducing the **Flying Sidekick Traveling Salesman Problem (FSTSP)**. The problem is an extension of the TSP, where only one truck is equipped with a single drone that delivers the goods to customers. The drone is dispatched from the truck at a customer location. It delivers goods to a customer while the truck can continue to visit other customers. After delivering, the drone is picked up by the truck at a rendezvous customer location. The drone must be picked up before its battery runs out. The objective of the problem is to minimize the completion time of the route. Since the FSTSP is an NP-hard problem that is computationally expensive using exact methods, Murray and Chu (2015) develop three heuristics solutions: Clark Wright saving, Nearest Neighbor, and Sweep algorithm. The heuristics are tested on small numbers of customers and are shown to be time-efficient, with an average optimality gap ranging between 0.22% and 10.68%. Ponza (2016) presents an improved formulation for the FSTSP and uses Simulated Annealing metaheuristic to solve the same problem for instances of up to 200 customers. The results showed an improvement in the delivery time of the drone-assisted truck-delivery systems. The amount of improvement depends on the number of customers, ranging from 5% up to 20%.

One variation of FSTSP is the **Traveling Salesman Problem with Drone (TSP-D),** which is introduced by Agatz, Bouman, and Schmidt (2018). The TSP-D is very similar to the FSTSP, but it assumes that the drone is faster than the truck and that both vehicles travel on the same road network. This problem also assumes that the drone can be dispatched and picked up in different positions, and that the truck travels to another node while the drone is delivering. The objective is to minimize the operational cost by solving the problem using a combination of a greedy and an exact partitioning algorithm. The heuristic is capable of solving problems with up to 100 customer locations in 20 minutes. The results show operational cost savings reaching up to 30%.

Yoon (2018) and Kuang (2019) later introduce more complexity to the **FSTSP** by assigning a fixed number of drones available per truck. While Yoon (2018) focuses on the exact method with relatively small instances, Kuang (2019) uses a genetic algorithm to solve the problem heuristically on a larger problem size. The objective of both research papers is to minimize the total operational costs, which comprise the fixed costs associated with the introduction of each additional drone, the trucks' variable costs that account for fuel and labor expenses, and the drones' variable costs that account for the electricity expenses. The results of Kuang (2019) show up to a 55% saving opportunity when using the exact method on small instances, and 7%–9% savings when using a genetic algorithm on a bigger problem size of up to 158 customers.

A generalized problem of **FSTSP** is **Vehicle Routing Problem with Drones (VRPD),** where multiple trucks are available, and the relationship between the trucks and the drones is many to many. Wang and Sheu (2019) study this problem in a real-world setting, where a drone is not necessarily dispatched and picked up by the same truck. The objective is to maximize the cost savings and determine the possible route for both trucks and drones. To solve the problem, Wang and Sheu (2019) develop an arc-based model and branch-and-price heuristic. The computation results show that the cost-saving opportunity is up to 20%.

A variation of VRPD is the **Vehicle Routing Problem with Drones and En Route Operations (VRPDERO)**. This extension was introduced by Schermer and Oliver (2019). Compared to the VRPD, the VRPDERO assumes that drones may also be launched and retrieved at some separate locations on every arc. Schermer and Oliver (2019) develop an exact-solution method (Mixed Integer Linear Programming) for smaller instances. To address larger instances, a heuristic that combines components from Variable Neighborhood Search (VNS) and Tabu Search (TS) was also proposed. The research shows the potential in reduced solving time and higher utilization of drones with the possibility of launching and retrieving drones en route. Schermer and Oliver (2019) conclude that the en-route operations seem most viable if the drone endurance is small, or its velocity is sufficiently large.

Carlsson and Song (2017) introduce the "**Horsefly Routing Problem**," a hybrid approach in which there is no restriction on the location of where drones are dispatched and retrieved. Drones can deliver a package to customers while making return trips to a truck that is moving. The only restriction is only 1 drone is available per truck. To understand how much improvement in delivery time can be realized, and because of the complexity of the problem, the continuous approximation method was used. The result showed that the efficiency of the delivery system is proportional to the square root of the ratio of the speed of trucks and drones. Campbell, Sweeney, and Zhang (2017) also use the continuous approximation approach with the highlight of the economic advantages of such a system in many settings. The first key finding is that the savings from the truck-drone system arise from the reduced route costs and from allowing demand to be covered with fewer routes. The second is that the benefits from the truck-drone delivery depend strongly on (1) the relative operating costs-per-mile for the trucks and the drones, (2) the relative stop costs for trucks and drones, and (3) the spatial density of customer. The last key finding from the paper is that the measure of savings intensity per square mile provide perspectives that highlight the conditions and regions likely to generate the greatest savings.

Table 2: Summary of reviewed literature on Vehicle Routing Problem with Drone (Intermodal).

Paper	Problem Type	Number of Truck : Drone	Objective	Solution Method	Number of Customers	Result
(Murray & Chu, 2015)	FSTSP	1 : 1	Delivery Time	Integer Programming	10	Potential saving opportunity
				Saving	10	
				Nearest Neighbor	10	
				Sweep	10	
(Ponza, 2016)	FSTSP	1 : 1	Delivery Time	Simulated Annealing metaheuristic	Up to 200 nodes	10-15% delivery time reduction for 100 customers. <5% for more than 200
(Agatz et al., 2018)	TSPD	1 : 1	Operational Cost	Route first—cluster second procedure	Up to 100	Up to 30% saving opportunity
(Kuang, 2019)	TSP with multiple drones	1 : Up to 4	Operational Cost	Genetic algorithm	158	7% - 9% saving opportunity
(Yoon, 2018)	TSP with multiple drones	1: Many	Operational Cost	Exact	10	Up to 55% saving opportunity
(Wang & Sheu, 2019)	VRPD	Many: Many	Operational Cost	Exact (MILP)	15	Average saving of 20%
				Branch-and-price Heuristic	20	
(Schermer & Oliver, 2019)	VRPDERO	Many: Many	Delivery Time	Exact Solution (MILP)	10	5 - 15% reduction in delivery time
				Variable Neighborhood Search (VNS) and Tabu Search (TS)	Up to 50 nodes	
(Sweeney et al., 2017)	VRPD	1 : 1	Operating Cost	Continuous approximation (CA)	Max density 500/mile2	-
(Carlsson & Song, 2017)	Horsefly Routing Problem	1 : 1	Delivery Time	Continuous approximation (CA)	-	-

2.4. Facility Location Problem (FLP) with Drone Delivery

In studying direct drone delivery (facility to customers), many researchers have focused on this mode's effect on the location of distribution facilities, under the assumption that a drone is not capable of servicing more than a single demand node before returning to the facility. Shavarani, Nejad, Rismanchian, and Izbirak (2018) argue that in addition to warehouses, it is necessary to introduce refueling (or recharging) facilities in a realistic drone distribution network, to make up for the drones' low endurance. In this paper, San Francisco was chosen for an FLP case study with drone delivery. The model's objective was to minimize the total cost of distribution, establishment of facilities, and procurement of drones, by selecting the best mix of distribution and refueling facilities from a set of discrete locations. The model relied on a Genetic Algorithm (GA) to solve this problem, citing the GA's suitability for FLPs. The GA is further refined by integrating greedy-algorithm elements and having its parameters tuned using the Taguchi statistical methods to improve robustness. This tuned hybrid GA runs at a much-improved computational efficiency and gives a better solution, under which the research claims that implementing a drone distribution system to the city would pay for itself in just one year.

While papers such as Shavarani et al. (2019) consider the variable component of the drones' operational cost to be linear in proportion to the number of miles traveled and under the assumption of constant flight speed, Chowdhury, Emelogua, Marufuzzamana, Nurre and Bian (2017) chose to model the drones' operational cost non-linearly in their paper on FLP for disaster relief operations. Realistically, the drone flight had been divided into multiple stages that approximate the actual stages of flight, with the drone operating cost being equal to the product of the time spent, the power consumed during this time, and the energy cost for each stage of the flight.

Chowdhury et al. (2017) allow both drones and trucks to be dispatched from the same facility in their FLP model. However, each would tour independently, and not in succession. To the best of the authors' knowledge, there are no papers that integrate intermodal truck-drone delivery into the FLP.

2.5. Concluding Remarks on Literature Review

Since drones were first considered in logistics, many efforts have been made to integrate drones into classical Operations Research (OR) problems. The results from various papers have shown that integrating drones into distribution models consistently generated cost and time savings. The papers agree that it is seldom feasible to find an exact solution for a realistic problem. Therefore, they often opt for heuristic or metaheuristic methods for problems of realistic size.

While researchers have worked extensively on the joint truck and drone delivery in the VRP, it does not appear that this combined mode of transportation has been introduced to problems that concern facility location and selection, whether it is a VRP or an LRP. This combination is a gap in knowledge that this research project fills.

3. Methodology

This chapter provides the operational, logical, and mathematical details of the Location Routing Problem with Ancillary Modes (LRPAM) that this research project models, as well as the methodology used.

3.1. Problem Description

In this problem of parcel distribution, a region of demand nodes has to be served from one or more distribution facilities selected from a set of candidate locations. Delivery starts with trucks that depart from distribution centers (DCs). These trucks are loaded with the parcels to be delivered, along with one or more drone onboard each truck. The trucks travel from the DCs and stop at specific parking locations, and while the trucks are parked, the final delivery is completed by drones that fly out of the trucks and towards the customer locations. The locations at which the trucks will stop are determined within the model in the form of x and y coordinates of points in a Euclidean plane that emulates the service region. For each customer location (demand node), a drone that carries a parcel is dispatched from a parked truck, which is then dropped at the demand node. The drone returns to its truck, the drone’s battery is replaced with a fully charged one, the next parcel is loaded, and the drone dispatches to the next demand node. The process of reloading and resending the drone to a different customer continues until the last demand node in the current cluster is served. Next, the truck may either move to the next parking location or return to its DC, depending on the model’s decision.

Figure 1 illustrates the operational steps for serving a single demand node. A similar operational mechanism had been studied by Chang and Lee (2018) for a single-facility distribution operation.

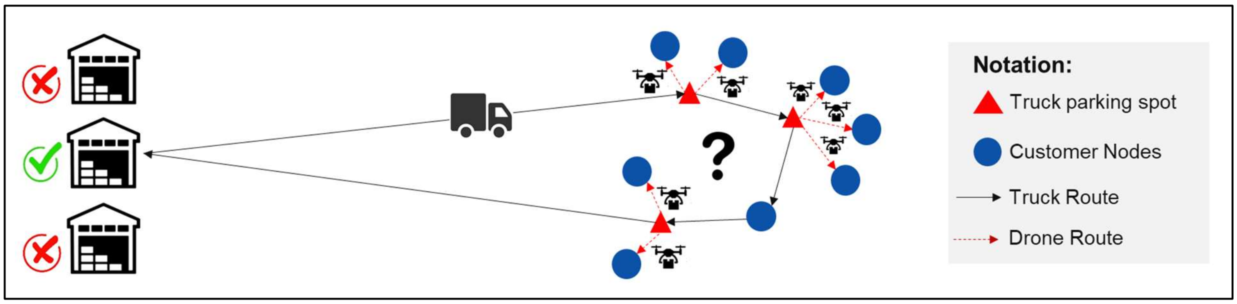

Figure 1: Illustration of the truck-drone delivery operation

The approach of this research as described above allows modeling the problem as an extension of the transshipment problem. With this model, the following decisions are to be made:

- The choice of DCs to be activated out of a discrete set of candidates (*D*: Supply nodes).
- The number and the locations of the truck parking spots, as positioned on a continuous service region (*K*: Transshipment nodes).
- The specific routing and assignment of vehicles to deliver all parcels to their expected delivery locations (*J*: Demand nodes).

Figure 2 is a simplified illustration of the relationships and the flows between the 3 sets of nodes.

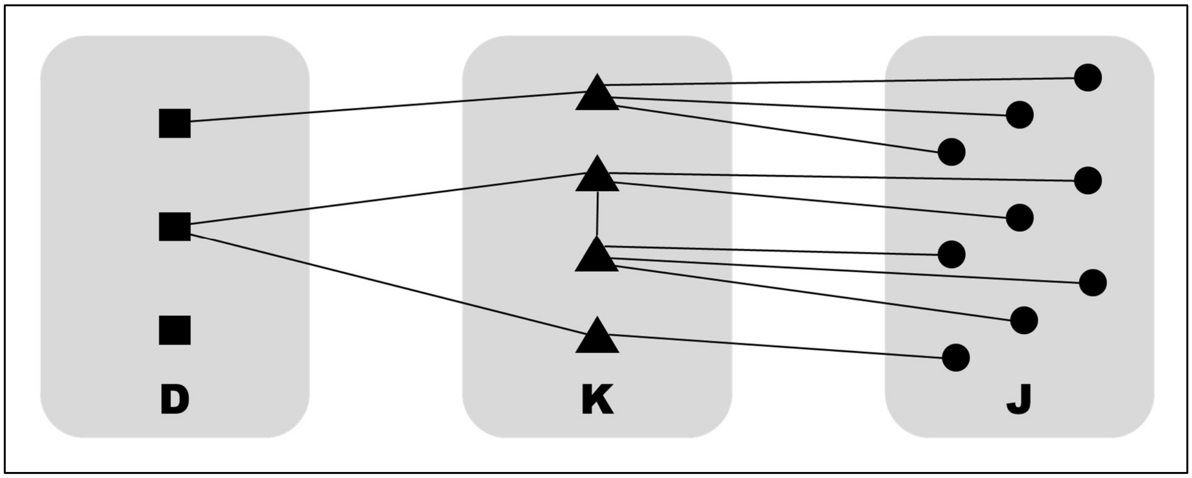

Figure 2: Transshipment representation of the model

What differentiates this model from a typical transshipment model is the fact that the transshipment nodes are not predetermined and are to be created by the model itself on the Euclidian plane. In addition, the return route of the vehicles needs to be considered, both in terms of cost and routing.

To position the parking spots for the trucks (*K* nodes) on the Euclidean plane, the demand region is divided into circle-shaped clusters, where a truck stops at the center of a circular cluster and starts dispatching the drones with parcels to the customer locations (*J* nodes). The size and the number of nodes in each of these clusters must adhere to the constraints in drones' reach and in trucks' carrying capacity. The detailed mathematical formulation can be found in Section 3.3.

3.2. Modeling Assumptions

To clearly articulate the problem, the assumptions in this section have been made. They provide a reasonable mathematical approximation of the whole physical operation.

3.2.1 Geometric Considerations

The following assumptions relate to the geometric space where the problem is modeled:

- All nodes exist on a Euclidian plane, with x and y coordinates assigned to each node.
- Depending on the mode of travel, a circuity factor is applied to the Euclidean distance (straight-line distance) to approximate the travel distance more realistically. The circuity factor applied to drones is always lower than that applied to trucks, to capture their ability to travel straight between nodes instead of adhering to ground-travel infrastructure (roads). The values for the circuity factors are outlined in Section 4.2.

3.2.2 Fleet Information

The following assumptions relate to the vehicles in the distribution network:

- The entire fleet of trucks is assumed to share the same specifications in terms of travel speed, parcel-carrying capacity, drone loading slots, and operating cost.

- The entire fleet of drones is assumed to be uniform in terms of speed, reach, and operating cost.
- Each drone is capable of carrying exactly one parcel. As such, a drone would only visit one J node per dispatch.
- The difference in the traveling cost between loaded and unloaded vehicles is not considered in this study.

3.2.3 Truck-Drone Relationship and Other General Assumptions

The following assumptions describe the relationship between the truck and the drone modes in the model, as well as other assumptions:

- All parcels are assumed to be uniform in weight and volume. None of the parcels has distinctive features that affect the drones' capabilities or operational costs.
- The facility locations (*D* nodes) are selected from a set of candidate locations.
- All active customer locations (*J* nodes) are known and are deterministic per problem set. Each *J* node requires the delivery of exactly one parcel. If a customer requires multiple parcels, their location is modeled as multiple overlapping nodes of the same coordinates.
- A truck may not serve a customer node directly. All deliveries to *J* nodes must be carried out via drone delivery.
- Drones may not dispatch from the distribution centers (*D* nodes) to the *J* nodes directly. All drones must be launched from trucks at *K* nodes.

- The same drone may be repeatedly dispatched from the same truck at the same parking location (*K* node) to serve different *J* nodes.
- A drone may only be dispatched while its carrier truck is parked and remains stationary. Drones may only return to their original carrier trucks at the same *K* node.
- A truck may not move until all of its drones are back on board.
- The same truck may visit multiple *K* nodes on the same tour.
- Each truck must return to the same *D* node (distribution facility) it left from.
- The traveling speed of the drones is assumed to be constant. As such, drone travel is taken to be constrained by distance range only (maximum roundtrip traveling distance).
- With each dispatch, the drone is assumed to have swapped batteries and to be traveling with a full energy charge that allows it to travel its full reach repeatedly.

3.3. Mathematical Formulation

To develop a valid mathematical model for the multimodal LRPAM, and in preparation for a comparison to the truck-only LRP, this section develops the mathematical formulation for both problems.

3.3.1. Notation

Sets:

D	= Set of potential depots, let ***m*** **be the number of depots.**
J	= Set of all customers, let ***n*** **be the number of customers.**
K	= Set of all parking spots, **let *k* be the number of parking spots.**
N	= $\{D \cup J\}$, where:
	$J = (1,2 \dots n)$, $D = (n+1, \dots n+m)$.
N'	= $\{D \cup P\}$, where:
	$P = (1,2 \dots k)$, D = $(k+1, \dots p+m)$.

Indices:

d	Represent depots.
i, j	Represent customer, depots, and parking spots.
p	Represent parking spots.

<u>Parameters:</u>

f_i	Cost of opening depot *i.*
W_i	Capacity of depot *i.*
Q_{max}	Truck capacity.
F_{drone}	Fixed cost per drone used ($/drone/truck).
F_{truck}	Fixed cost per truck used per route ($/route).
c_d	Drone travel cost per km of distance ($/meter).
c_t	Truck travel cost per km of distance ($/meter).
c_{t-w}	Truck idle waiting cost ($/second).
h	Number of drones per truck.

v_{dr} Average drone speed.

v_t Average truck speed.

q_i Demand of customer node $i = (1,2 \dots n)$.

s_i Truck waiting time at customer nodes $i, i \in J$.

D_{max} Maximum number of depots can be opened.

d_{ij} Distance from node *i* to node *j.*

$t_{dr-unload}$ Time required for a drone to unload a parcel.

$t_{dr-load}$ Time required to load a parcel onto a drone and dispatch it.

M A very large number.

Decision variables:

X_{ijd} Binary, $X_{ijd} = 1$ if edge (i, j) is traversed from node *i* to *j* originated from depot *d*.

Y_{ij} Non-negative continuous variable denoting the total load remaining in the vehicle before reaching node j while traveling along (i, j).

Z_d Binary, $Z_d = 1$ if depot d is opened.

3.3.2. Truck-only Mathematical Formulation (LRP)

The proposed Mixed Integer Linear Programming (MILP) formulation is referenced from Salhi, Imran, and Wassan (2014). It is a flow-based formulation which utilizes four index binary variables that identify a vehicle that travels along an edge, and the depot it originated from.

Figure 3 shows a simplified illustration of the relationships and the flows between depots and customer nodes in LRP with the truck-only configuration.

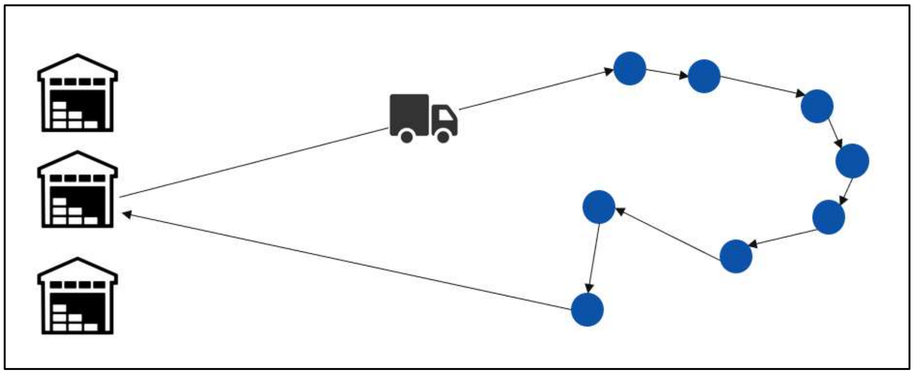

Figure 3: Truck-only configuration - LRP

Objective function:

Minimize:

$$Z = \sum_{i=0}^{n} f_i \cdot Z_i + F_{truck} \sum_{i=n+1}^{n+m} \sum_{j=1}^{n} \sum_{d=n+1}^{n+m} X_{ijd} \tag{1}$$

$$+ \sum_{i=1}^{n+m} \sum_{j=1}^{n+m} \sum_{d=n+1}^{n+m} c_t \cdot d_{ij} \cdot X_{ijd} + \sum_{i=1}^{n} s_i \cdot c_{t-w}$$

Subject to:

$$\sum_{i=1}^{n+m} \sum_{d=n+1}^{n+m} X_{ijd} = 1, \qquad j = 1, \ldots, n \tag{2}$$

$$\sum_{j=1}^{n+m} \sum_{d=n+1}^{n+m} X_{ijd} = 1, \qquad i = 1, \dots, n \tag{3}$$

$$\sum_{i=1}^{n+m} X_{ijd} = \sum_{i=1}^{n+m} X_{jid}\,, \quad j = 1, \dots, n+m; \;\; d = n+1, \dots, n+m \tag{4}$$

$$\sum_{i=n+1}^{n+m} \sum_{j=1}^{n} Y_{ij} = \sum_{i=1}^{n} q_i \tag{5}$$

$$\sum_{i=1}^{n+m} Y_{ij} - \sum_{i=1}^{n+m} Y_{ji} = q_j, \qquad j = 1, \dots, n \tag{6}$$

$$Y_{ij} \le \sum_{d=n+1}^{n+m} X_{ijd} \cdot Q_{max}\,, \qquad i = 1, \dots, n+m; j = 1, \dots, n+1 \tag{7}$$

$$X_{d_1 i d_2} = 0, \qquad d_1 \ne d_2 = n+1, \dots, n+m; i = 1, \dots, n \tag{8}$$

$$X_{i d_1 d_2} = 0, \qquad d_1 \ne d_2 = n+1, \dots, n+m; i = 1, \dots, n \tag{9}$$

$$\sum_{i=1}^{n+m} \sum_{j=1}^{n} X_{ijd} \cdot q_j \le W_d, \qquad d = n+1, \dots, n+m \tag{10}$$

$$M \cdot Z_d - \sum_{i=1}^{n+m} \sum_{j=1}^{n+m} X_{ijd} \geq 0, \qquad d = n+1, \dots, n+m \tag{11}$$

$$\sum_{d=n+1}^{n+m} Z_d \leq D_{max}, \qquad d = n+1, \dots, n+m \tag{12}$$

The objective function (1) represents the total cost, which includes the fixed cost of opening depots, the vehicle fixed cost, the traveling cost, and the idle waiting cost. Constraints (2) and (3) ensure that exactly one vehicle route enters and leaves each customer. Constraint (4) guarantees that at most, one vehicle originating from a given depot will cover an edge (i, j) . Constraint (5) shows that the total quantity leaving all depots is exactly equal to the total customers' demand. Constraint (6) is the sub-tour elimination constraint, which guarantees that the quantity of parcels remaining after visiting customer *j* is exactly the quantity before visiting this customer minus the demand of the said customer. Constraint (7) ensures that the vehicle capacity is not exceeded. Constraints (8) and (9) guarantee that a truck leaving a depot (or returning to a depot) cannot be linked to a different depot, respectively. Constraint (10) refers to the depot capacity. Constraint (11) ensures that an established depot is considered open if at least one vehicle originates from it. Constraint (12) refers to the maximum number of depots that can be opened.

3.3.3. Truck-Drone Mathematical Formulation (LRPAM)

For the LRPAM with Truck and Drone configuration, as illustrated in Figure 4, the main idea is that the customer nodes are grouped into clusters based on a set of drone constraints. A truck travels from a depot to the centroids of the clusters, where it parks and dispatches drones to deliver parcels to customers.

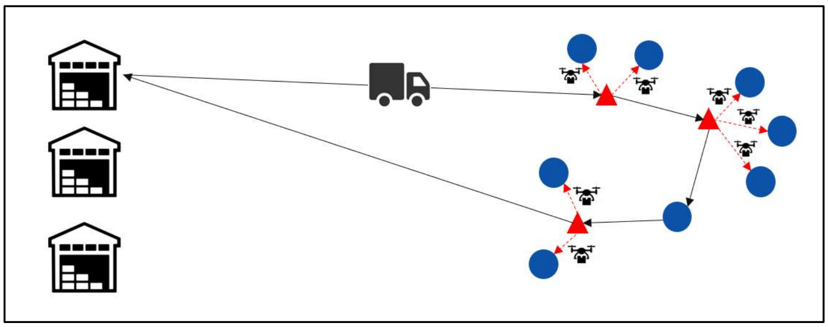

Figure 4: Truck-drone configuration - LRPAM

To formulate the MILP for this configuration, a flow-based formulation with four index binary variables is also used, but with some modifications to include additional costs, such as the truck waiting cost, the drones' fixed cost, and the drones' travel cost. For each cluster p, let the truck waiting time be s'_p and the drone traveling cost be c'_p. The total cost for the truck-drone configuration is shown below as Equation (13).

Objective Function:

Minimize**:**

$$Z = \sum_{i=0}^{n} f_i y_i + F_{truck} \sum_{i=k+1}^{k+m} \sum_{j=1}^{k} \sum_{d=k+1}^{k+m} X_{ijd} + \sum_{i=1}^{k+m} \sum_{j=1}^{k+m} \sum_{d=k+1}^{k+m} c_t \times d_{ij} \times X_{ijd} + \sum_{i=1}^{k} s'_i \times c_{t-w} + \sum_{i=k+1}^{k+m} \sum_{j=1}^{k} X_{iji} \times F_{drone} \times h + \sum_{i=1}^{p} c'_i \tag{13}$$

The constraints set from the truck-only configuration (Equations 2~12) also apply to the truck-drone configuration, with customer nodes being replaced by parking spots.

3.4. Proposed Methodology

The proposed methodology for solving the Location Routing Problem with Ancillary Modes (LRPAM) is composed of two steps that are illustrated in Figure 5. In summary, the customer demand is aggregated into fewer nodes to simplify the problem into a unimodal LRP, then the LRP is solved using the Multiple Ant Colony Optimization (MACO) metaheuristic. The MACO metaheuristic is explained in detail in Section 3.4.

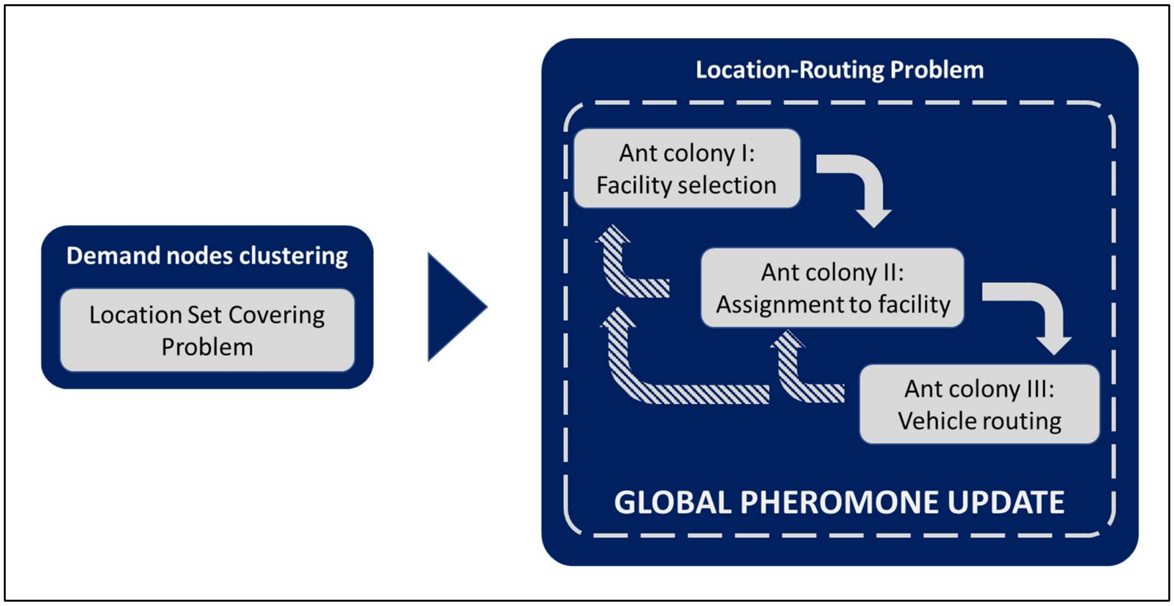

Figure 5: High-level representation of the methodology

To aggregate the customer demand into parking spots (nodes), clustering is performed based on the maximum range of the drones and the maximum capacity of trucks. The outcome of this step is a set of locations where the trucks can park and launch drones to deliver parcels to customers within the drones' flight range.

Following clustering, the next step is to select the facilities to be opened from a set of candidate locations, and then to construct the truck routes. A truck route will start and end at the same facility. While the truck is on its tour, it moves from one parking spot to another to deploy drones and wait for them to come back before moving to the next spot. Because this is an NP-hard problem, this project proposes to solve the problem heuristically by adopting the MACO algorithm introduced by Ting and Chen (2013).

3.4.1. Clustering of Demand Nodes

The proposed methodology hinges on the idea of aggregating the drone-fulfilled demand into fewer *K* nodes that the trucks will visit, hence transforming the complex problem of truck-drone delivery into a simpler Location Routing Problem (LRP) with only truck delivery. As shown in Figure 6, every parking spot is the centroid of a cluster that contains several customer nodes that will be served by drones.

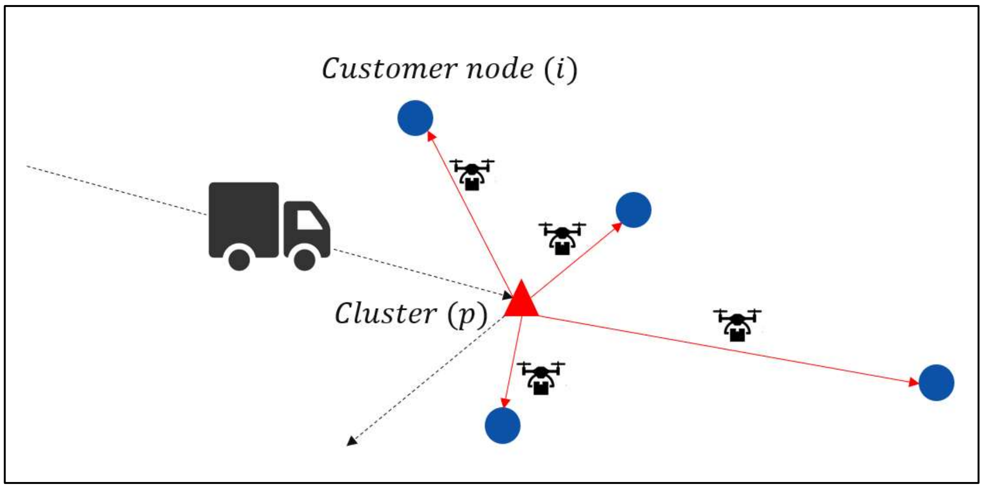

Figure 6: Illustration of a parking spot and the combination of both modes

The objective in clustering is to minimize the number of individual clusters while adhering to two constraints:

- The distance from the cluster's centroid to every customer node in the cluster must not exceed the maximum reach of the drones.

- The total number of nodes inside a cluster must not exceed the maximum allowable number of customers per cluster.

The approach to solving this problem is to use a "savings" algorithm, where customer nodes that are closest to each other are prioritized for grouping into the same cluster. The algorithm can be described as follows:

Step 1: Calculate the distances between every possible pair of customer nodes as $e(i,j),\ \ i,j = 1,\dots,n$.

Step 2: Rank the distances in descending order.

Step 3: Process the list, starting with the topmost entry. For each $e(i,j)$ under consideration, if:

- Neither nodes i nor j are assigned to a cluster, then calculate the centroid of cluster (p), which comprises nodes i and j. If the distance from the centroid to each node within the cluster (range constraint), and the maximum number of customers constraints are not violated, then cluster (p) is initiated to include nodes i and j.
- Node i has already been assigned to a cluster (p) while node j has yet to be assigned to any cluster, then re-calculate the centroid of cluster (p) with node j included. If the range and the maximum number of customers constraints are not violated, then cluster (p) is updated to include node j.

- Both nodes i and j have already been assigned to two different clusters (p), (p'), then calculate the centroid of the combined cluster, the union of (p) and (p'). If the range and maximum number of customers constraints are not violated, then cluster (p) is updated to include all of the nodes in cluster (p'), and cluster (p') is deleted.

Step 4: If the list $e(i,j)$ is not exhausted, return to Step 3, processing the next entry in the list; otherwise, stop. The solution consists of clusters created during Step 3. Any node that has not been assigned to a cluster during Step 3 is considered a cluster by itself.

Step 5: Calculate the drone variable cost c'_p for each cluster using Formula (14):

$$c'_p = \sum_{i \in U_p} 2 \cdot d_{pi} \cdot c_d \tag{14}$$

Where U_p is a set of customer nodes assigned to cluster (p).

Step 6: Calculate the truck waiting time s'_p at each parking spot using a “queuing” method. The idea is that drones start by serving the furthest customer nodes. The working time of each drone comprises the following elements: drone travel time, loading time, unloading time, and waiting time for the drone operator to become available. The Truck waiting time s'_p is the maximum value of the drones’ working time.

The algorithm for calculating the waiting time at a specific parking spot is described below:

a. Calculate the drone traveling time between the cluster’s centroid and each customer node assigned to that cluster using Equation (15):

$$t_{pi} = \frac{d_{pi}}{v_{dr}} + t_{dr-unload} \qquad (15)$$

b. Sort the travel times in descending order.

c. Process the list starting from the topmost entry on the list. For each t_{pi} under consideration, if:

- The drone operator is available, then assign the earliest available drone to deliver to customer node i. The working time for that drone is updated to include t_{pi} and t_{dr-lo} . The drone operator time is updated to include $t_{dr-load}$.
- The drone operator is not available, then additional waiting time for the drone operator to become available will be added to the drone working time in addition to t_{pi} and $t_{dr-load}$.

d. If the list t_{pi} is not exhausted, return to Step c, processing the next entry in the list; otherwise, stop. The solution for the truck waiting time s'_p is the maximum value of the drones' working time, as the truck waits for the last drone to return.

3.4.2. Location-Routing Problem with MACO Metaheuristic

Since the LRP is an NP-hard problem that is computationally intractable to solve using the exact method, especially as the problem size increases, the proposed solving approach to this problem is the Multiple Ant Colony Optimization (MACO) algorithm introduced by Ting and Chen (2013).

The ant colony algorithm is a probabilistic technique that draws inspiration from the behavior of real ants. The ants find the shortest path between their nest and a food source by utilizing a local message exchange via the disposition of a pheromone trail.

Initially, ants wander randomly to find food. If they find food, they lay down pheromone trails as they return to their colony. The next wave of ants is more likely to choose the path that has a heavier amount of pheromone deposited rather than randomly travel. If they find food, they will return to the colony and deposit more pheromone on their trail. The pheromone level on all trails evaporates over time, and if the path is long, the pheromones will begin evaporating before more is deposited by subsequent waves of ants. In contrast, for shorter paths, it takes less time for an ant to travel down the path and back again, and therefore more pheromones are deposited, which makes the path more attractive to other ants. Because of this local message exchange mechanism, given a certain passage of time, only the shortest path will be followed (Karthik, 2018).

Ting and Chen (2013) solved both of the location and routing problems by decomposing the combined problem into three decision levels: location selection, customer-to-locations assignment (the customer being the parking spot in this capstone project’s case), and vehicle routing for each set of selected facilities and their assigned parking spots. Each level has its own "colony" with different pheromone matrices and pheromone updating rules. The three colonies are solved sequentially and have their own pheromone matrices and pheromone updating rules, which are used to record pheromone information for each colony. However, an essential feature of this solution method is the existence of a global pheromone matrix that will be updated based on the best constructed solution to ensure cooperation between the three said colonies. Ting and Chen's (2013) Multiple Ant Colony Optimization (MACO) methodology is summarized as follows:

Step 1: Depot Selection

To determine the location set, the first colony is implemented. At the s^{th} iteration, ant h will select a p_s^h number of depots to be opened from m candidate sites according to the selection rules, Equations (17) and (18). p_s^h is given by Equation (16) below.

$$p_s^h = \left\lfloor \frac{\sum_{i=1}^{n} q_i}{\sum_{i=n+1}^{n+m} \frac{W_i}{m}} \right\rfloor + U(1, r) \tag{16}$$

$$j = \begin{cases} arg\ max_{d \epsilon O_s^h} [\tau_d^s {\eta_d}^\alpha], & \text{if } q \le q_o \\ J, & Otherwise \end{cases} \tag{17}$$

$$J\colon\ P_d^h = \frac{\tau_d^s {\eta_d}^\alpha}{\sum_{d \epsilon 0_s^h} \tau_d^s {\eta_d}^\alpha} \tag{18}$$

Where:

- $U(1, r)$ is a random number following the uniform distribution in $(1, r)$, and r is a pre-specified number.
- O_s^h is the set of depots that are not yet selected by ant *h* at the *s*th iteration.
- τ_d^s is the pheromone level of depot d at the *s*th iteration.
- α is the parameter determining the influence of the pheromone level.
- η_d is given by:

$$\eta_d = \frac{W_d}{f_d} \tag{19}$$

- q is a random variable that is uniformly distributed between [0,1].
- q_o is the exploration factor of the first ant colony.

Step 2: Assigning parking spots to selected depots:

The goal of this step is to assign parking spot i to a selected depot *d* from the available deports without violating the depot's capacity constraints. The parking spot's assignment solution is constructed based on the construction rules in Equations (20) and (21).

$$k = \begin{cases} \arg\ max_{d \epsilon W_s^h} \left[{\tau'}_{id}^{s} {{\eta'}_{id}^{s}}^{\beta} \right], & q' \leq {q'}_o \\ D, & Otherwise \end{cases} \tag{20}$$

$$D:\ P_{id}^h = \frac{{\tau'}_{id}^{s} {{\eta'}_{id}^{s}}^{\beta}}{\sum_{d \epsilon W_s^h} {\tau'}_{id}^{s} {{\eta'}_{id}^{s}}^{\beta}}, \tag{21}$$

Where:

- W_s^h is the set of selected depots of ant *h* at the *s*th iteration.
- τ'^{s}_{id} is the pheromone level between parking spot i and depot d at the *s*th iteration
- β is the parameter determining the effects of the pheromone level.
- η'^{s}_{id} is given by:

$$\eta'^{s}_{id} = \frac{1}{min_{l \in A_d^{sh}} c_{il}} \tag{22}$$

- A_d^{sh} is a set of customer nodes that have been assigned to depot *d*, including the depot *d* itself.
- c_{il} is the distance between parking node i and node l
- q' is a random variable uniformly distributed between [0,1], and q'_o is the exploration factor.

Step 3: Constructing the vehicle routes for each set of depots and parking spots.

Once all the parking spots are assigned to a facility, the construction of vehicle routes for each depot can be regarded as an independent vehicle routing problem (VRP).

The main idea of this proposed solution is that each ant starts from a facility with the set of parking spots included in its route being empty. The ant selects the next parking spot to visit from the list of assigned parking spots, based on the probabilistic formula. After serving the parking spot, the truck capacity and the time used thus far by the ant are updated, and the process continues. The ant returns to the facility when either of the truck capacity or time window of the depot constraints is satisfied. Unless all of the assigned parking spots have been visited, a new ant will be sent to visit the remaining destinations.

Until all of the parking spots assigned to the facility are visited, the total distances traveled for that facility are computed. The process repeats for all of the opened facilities. When all ants have constructed their solutions, a local search 2-opt algorithm is executed on the best solution, which swaps any pair of crossed-over, non-consecutive edges with another pair of non-crossed ones to further improve the solution.

The route construction of the VRP follow Equations (23) and (24), which are the transition rules for ant h' at iteration s^{th}, moving from node i to node v.

$$\mathrm{v} = \begin{cases} \arg\, max_{v \epsilon Z_{is'}^{h'}} \left[\tau''^{s'}_{iv} \left(\eta''^{s'}_{iv} \right)^{\gamma} \right], & q'' \leq q''_{o} \\ V, & Otherwise \end{cases} \tag{23}$$

$$V:\ P_{iv}^{h'} = \frac{\tau''^{s'}_{iv} \left(\eta''^{s'}_{iv} \right)^{\gamma}}{\sum_{v \epsilon Z_{is'}^{h'}} \tau''^{s'}_{iv} \left(\eta''^{s'}_{iv} \right)^{\gamma}} \tag{24}$$

Where

- $Z_{is'}^{h'}$ is the set of nodes that are not visited by ant h' at the s^{th} iteration.
- $\tau''^{s'}_{iv}$ is the pheromone level between node i and node v at the s^{th} iteration.
- γ is the parameter determining the effect of the pheromone level.

- ${\eta''}_{iv}^{s'}$ is the savings of combining two nodes, i and v, in a single tour instead of visiting them on two different tours. Let o denote the selected depot, with the savings is given by:

$$ {\eta'}_{id}^{s} = d_{io} + d_{ov} - d_{iv} \tag{25}$$

- q'' is a random variable that is uniformly distributed between [0,1].
- ${q''}_{o}$ is the exploration factor that determines the relative importance of exploration Equation (23) versus exploration Equation (24).

Step 4: Updating Pheromone Matrices

The pheromone levels of the three ant colonies are updated based on the local and global updating rules. Like a real ant that deposits pheromone on a path it traverses, the local updating rule requires pheromone to be updated every time an ant constructs a solution. The local updating rules of the three ant colonies (depot selection, parking assignment at iteration sth and VRP route construction at iteration s'th) follow Equations (26), (27), and (28), respectively.

$$ \tau_{d}^{s+1} = (1-\rho) \times \tau_{d}^{s} + \rho \times \tau_{d}^{0} \quad if\ depot\ d \in T_h \tag{26}$$

$$ {\tau'}_{ij}^{s+1} = (1-\rho') \times {\tau'}_{ij}^{s} + \rho' \times {\tau'}_{ij}^{0} \quad if\ edge(i,j) \in T_h \tag{27}$$

$$ {\tau''}_{iv}^{s'+1} = (1-\rho'') \times {\tau''}_{i'}^{s'} + \rho'' \times {\tau''}_{iv}^{0} \quad if\ edge(i,v) \in T_{h'} \tag{28}$$

Where:

- T_h is the solution constructed by ant h.
- $T_{h'}$ is the VRP solution constructed by ant h'.
- ρ, p' and $\rho''$are the pheromone evaporation factor. $0 \leq \rho, \rho', \rho'' \leq 1$.
- τ_d^0 , ${\tau'}_{ij}^0$ and ${\tau''}_{iv}^0$ are the initial level of pheromone matrices.

Because the three ant colonies are independent, yet share both the global best solution and the iteration of the best solution, pheromone matrices of each colony are updated globally at the end of each iteration, further ensuring the cooperation between each colony. The global updating rules of the three colonies are described as follows by Equations (29) ~ (31):

$$\tau_d^{s+1} = (1-\rho) \times \tau_d^s + \rho \times \Delta\tau_d^s \tag{29}$$

$${\tau'}_{ij}^{s+1} = (1-\rho') \times {\tau'}_{ij}^s + \rho' \times \Delta{\tau'}_{ij}^s \tag{30}$$

$${\tau''}_{iv}^{s'+1} = (1-\rho'') \times {\tau''}_{iv}^{s'} + \rho'' \times \Delta{\tau'}_{iv}^{s'} \tag{31}$$

Where $\Delta\tau_d^s$, $\Delta{\tau'}_{ij}^s$ and $\Delta{\tau''}_{iv}^{s'}$ are the pheromone levels based on the iteration's best and worst solutions.

Ting and Chen (2013) tested multiple combinations of $r, \alpha, \beta, \gamma, \rho, \rho', \rho'', q_o, q'_o$, and q''_o. For each test instance, the algorithm was implemented for 10 runs and the reported result was the best solution found over theses 10 runs. Among all of the parameter combinations, they found that the parameter settings of $r = 3,\ \alpha = 1,\ \beta = 1,\ \gamma = 4,\ \rho = 0.1,\ \rho' = 0.1,\ \rho'' = 0.1,\ q_o = 0.5,\ q'_o = 0.1\ and\ q''_o = 0.5$ provide the best results. This capstone research project follows these same recommended parameter values for solving an LRP.

3.5. Model Implementation

Following the theoretical explanation of the model in the previous sections of this chapter, this section describes the implementation of the model.

3.5.1. Computational Capabilities

The model was built using Python programing language (version 3.7), and all computation was performed on a computer with the following specifications:

- Computer type: Laptop.
- Memory (RAM): 16.0 GB.
- Processor: Intel Core i7-8565U CPU, 1.80 GHz, 1992 MHz, 4 Cores, 8 Logical Processors.

3.5.2. Parameters Selection

Physical, Operational, and Financial Parameters:

For the model to become realistic, it is necessary to define the physical specifications and attributes that are fed into the computational model. Table 3 lists these physical parameters, which have also been described at the beginning of this chapter. The values for most of these parameters are based on the literature review in Chapter 2 of this report.

The fixed cost for each of the transportation modes is estimated as follows:

$$Fixed\ cost\ \left(\$/_{day}\right) = \frac{\frac{Purchase\ cost\ (\$)}{Lifespan\ (years)} + Maintenance\ cost\ \left(\$/_{year}\right)}{Annual\ days\ of\ operation\ \left({}^{days}/_{year}\right)} \tag{32}$$

The parameters for the above equation were based on the average rates and values at the time of writing this report (Mercedes-Benz, 2020; repairpal.com, n.d.; sidehusl.com, 2017; Sudbury & Hutchinson, 2016; University of South Florida's Vehicle Repair Shop, 2017).

A number of parameters in

Table 3 were estimated based on the judgment of the authors of this project. All numeric values have been converted to their International System of Units (SI) counterparts to maintain dimensional consistency in the calculations.

Table 3: List of the physical parameters used in the model, converted to their SI equivalent values when applicable.

Input Parameters		Value	Unit of measurement
F_{drone}	Fixed cost per drone used	3.0769230	$/drone/truck/day
F_{truck}	Fixed cost per truck used	20.855944	$/truck/route/day
c_d	Drone travel cost	0.0000311	$/meter
c_t	Truck travel cost	0.0027968	$/meter
c_{t-w}	Truck idle waiting cost	0.0059722	$/second
h	Number of drones per truck	3	-
v_{dr}	Average drone's speed	16	meter/second
v_t	Average truck's speed	7	meter/second
s_i	Truck parking time at each customer node	90	second
$t_{dr-unload}$	Time required for a drone to unload a parcel	15	second
$t_{dr-load}$	Time required to load a parcel onto a drone and dispatch it	20	second
Q_{max}	Truck capacity	10, 30	parcel/truck
k_{drone}	Circuity factor of drone travel	1	-
k_{truck}	Circuity factor of truck travel	2.46	-

Parameters for the Multiple Ant Colony Optimization Parameters:

The set of parameters used in the MACO were adapted from Ting and Chen (2013). They tested multiple combinations of the parameters and found that the parameters setting described in Table 4 below provided the best results. Section 3.4.2 gives a detailed explanation of the significance of each of these parameters.

Table 4: Parameter values used in the MACO implementation

Variable	Value
Pre-selected numbers influencing the maximum number of locations opened.	$r = 3$
Pheromone influence of the first Ant Colony (Location Selection)	$\alpha = 1$
Pheromone influence of the second Ant Colony (Parking Assignment)	$\beta = 1$
Pheromone influence of the third Ant Colony (VRP)	$\gamma = 4$
Evaporation factor of the first Ant Colony (Location Selection)	$\rho = 0.1$
Evaporation factor of the second Ant Colony (Parking Assignment)	$\rho' = 0.1$
Evaporation factor of the third Ant Colony (VRP)	$\rho'' = 0.1$
Exploration factor of the first Ant Colony (Location Selection)	$q_o = 0.5$
Exploration factor of the second Ant Colony (Parking Assignment)	$q'_o = 0.1$
Exploration factor of the third Ant Colony (VRP)	$q''_o = 0.5$
Number of Iterations (VRP)	$\frac{n}{5}$
Number of Iterations (LRP)	25

3.5.3. Model Validation

As the LRPAM model developed in this capstone project relies on the use of a metaheuristic method, which is the Multiple Ant Colony Optimization (MACO) algorithm, it is necessary to evaluate the reliability of the proposed model. Comparing the optimality of the model's solution with the solution obtained by a Mixed Integer Linear Programming (MILP) solver is necessary.

For validation purposes, a commercial MILP solver, the Gurobi Optimizer was used to solve the same sets of instances as the model developed in this project. The MILP solver was set to find the optimal solution with an optimality gap of 1% and within a time limit of 1 hour.

Validation Data

Many standard instances for benchmarking LRP, such as the “Barreto Set” or the “Prodhon Set,” have been used in literature (Prodhon & Prins, 2014). However, such sets are not suited for implementation in this capstone project because of multi-unit demand per customer. Instead, to evaluate the model’s reliability, 15 problem instances are developed as outlined in Table 3.3.

The sizes of the service regions were selected to approximate the areas of actual cities in the United States, namely, Cambridge (Massachusetts), Manhattan (New York), and downtown San Francisco (California). The *x* and *y* coordinates for each customer node were randomly generated such that they would be confined within the area in each problem instance. These instances were designed to capture a range of possible combinations of customers and depots parameters.

The capacity and the fixed cost for opening each depo were randomly generated based on a uniform distribution that has the minimum and maximum values that are specified in Table 5.

Table 5: Validity testing scenarios

Scenario	Area (km x km)	Number of customers	Density (customer/km^2)	Number of Depots	Depot Capacity (min -> max)	Depot Fix Cost ($/day) (min -> max)	Truck Max Capacity
1	4x4	30	1.875	3	(20->40)	(100->200)	10
2	4x4	40	2.5	3	(20->40)	(100->200)	10
3	4x4	50	3.125	4	(20->40)	(100->200)	10
4	4x4	200	12.5	5	(50 -> 100)	(300->500)	25
5	4x4	300	18.75	5	(60 -> 100)	(300->500)	25
6	7.68x7.68	30	0.50847458	3	(20->40)	(400->500)	10
7	7.68x7.68	40	0.6779661	3	(20->40)	(400->500)	10
8	7.68x7.68	50	0.84745763	4	(20->40)	(400->500)	10
9	7.68x7.68	200	3.38983051	5	(50 -> 100)	(600->800)	25
10	7.68x7.68	300	5.08474576	5	(60 -> 100)	(600->800)	25
11	11x11	30	0.24793388	3	(20->40)	(600->700)	10
12	11x11	40	0.33057851	3	(20->40)	(600->700)	10
13	11x11	50	0.41322314	4	(20->40)	(600->700)	10
14	11x11	200	1.65289256	5	(50 -> 100)	(800->1000)	25
15	11x11	300	2.47933884	5	(50 -> 100)	(800->1000)	25

Validation results and discussion:

To validate the MACO model's results, Scenarios 1 through 15 from Table 5 were run using both the exact and the MACO models. First, this test was performed with the truck-only configuration, and then with the truck-drone configuration. Scenarios 4, 5, 9, 10, 14, and 15 were only feasible to compute by the MILP solver in the LRPAM configuration due to their large size and the limited computing resources available. The results are shown in both Table 6 and Table 7. The MACO model ran 10 times for each instance, and the results in the best iteration (yielding the lowest operational cost) and its computational time were reported.

Table 6: Summary of the validation results for truck-only LRP

			Total Operational Cost ($/day)			Run Time (seconds)	
Scenario	**Area (km^2)**	**Customer Nodes**	**MILP**	**MACO**	**% Gap**	**MILP**	**MACO**
1	4x4	30	344	347	0.9%	344	19
2	4x4	40	558	579	3.7%	558	28
3	4x4	50	648	646	0.3%	648	37
4	4x4	200	(*)	1933	-	(*)	514
5	4x4	300	(*)	2698	-	(*)	961
6	7.68	30	887	902	1.7%	887	24
7	7.68	40	1,290	1,306	1.2%	1290	69
8	7.68	50	1,415	1,422	0.5%	1415	48
9	7.68	200	(*)	3202	-	(*)	495
10	7.68	300	(*)	4531	-	(*)	1068
11	11x11	30	1,128	1,144	1.4%	1128	28
12	11x11	40	1,837	1,850	0.7%	1837	37
13	11x11	50	1,938	1,965	1.4%	1938	38
14	11x11	200	(*)	4332	-	(*)	480
15	11x11	300	(*)	5698	-	(*)	886

(*): Due to the large size of the problem instances, the MILP solver was unable to find a solution with less than a 5% optimality gap within a time constraint of 1 hour.

Table 7: Summary of the validation results for truck-drone LRPAM

			Total Operational Cost ($/day)			Run Time (seconds)	
Scenario	Area (km^2)	Customer Nodes	MILP	MACO	% Gap	MILP	MACO
1	4x4	30	345	345	0.0%	1	2
2	4x4	40	573	578	0.8%	51	3
3	4x4	50	625	625	0.0%	34	4
4	4x4	200	1,667	1,692	1.5%	3605	16
5	4x4	300	2,313	2,378	2.8%	3600	23
6	7.68	30	846	846	0.0%	0	2
7	7.68	40	1,221	1,228	0.6%	1	3
8	7.68	50	1,341	1,344	0.2%	7	4
9	7.68	200	2,676	2,755	3.0%	3600	28
10	7.68	300	3,889	3,984	2.4%	3600	27
11	11x11	30	1,094	1,094	0.0%	1	3
12	11x11	40	1,776	1,776	0.0%	2	3
13	11x11	50	1,784	1,784	0.0%	1	3
14	11x11	200	3,496	3,556	1.7%	3600	20
15	11x11	300	4,711	4,830	2.5%	3600	34

By analyzing the results in Table 6 and Table 7, it is noted that while the routes generated through MILP and MACO were not found to be exactly the same, both decision sets resulted in very close values for the objective function of the total cost of operation. The gap was found to range between 0% and 3.7%. Further analysis that compares the operational cost savings between the two validation datasets in Table 6 and Table 7 to uncover the dependence of savings on the problem size follows in Section 4.5.

For illustrative purposes, the implementation of the solution approach in Scenario 13 is explained as follows, starting with solving this problem as a truck-only LRP problem, and then as an LRPAM problem with trucks and drones.

LRP of Scenario 13:

In this problem instance, the inputs to the model are customer locations and the depot locations, along with the rest of the information about trucks and drones physical parameters listed in Section 3.1. A map that illustrates the problem is shown in Figure 7.

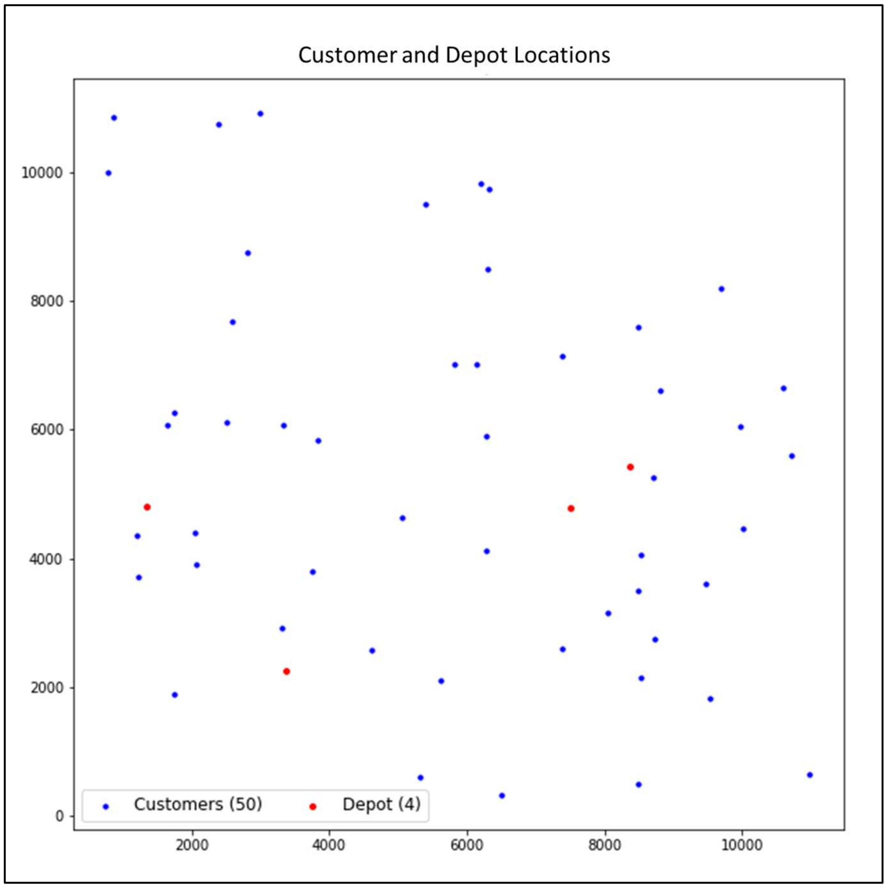

Figure 7: Customer and Depot locations map for Scenario 13

As no drones are present in this operation, this LRP requires no clustering. The problem has been solved using a MILP solver and the MACO model separately, giving the results shown in Figure 8. In this scenario, the cost difference between the two solutions is 1.4% (MILP solver: $1,938/day, MACO: $1,965/day). Both solutions yielded the same number of trucks routes and depots to be opened. The only difference is the sequence of truck routes, which contributes to the small difference in the cost of the operations (1.4% gap). However, this difference is compromised by a significant improvement in solving time, amounting to 98%. While it took the MILP solver 1,938 seconds to find the solution, the MACO model only took 38.

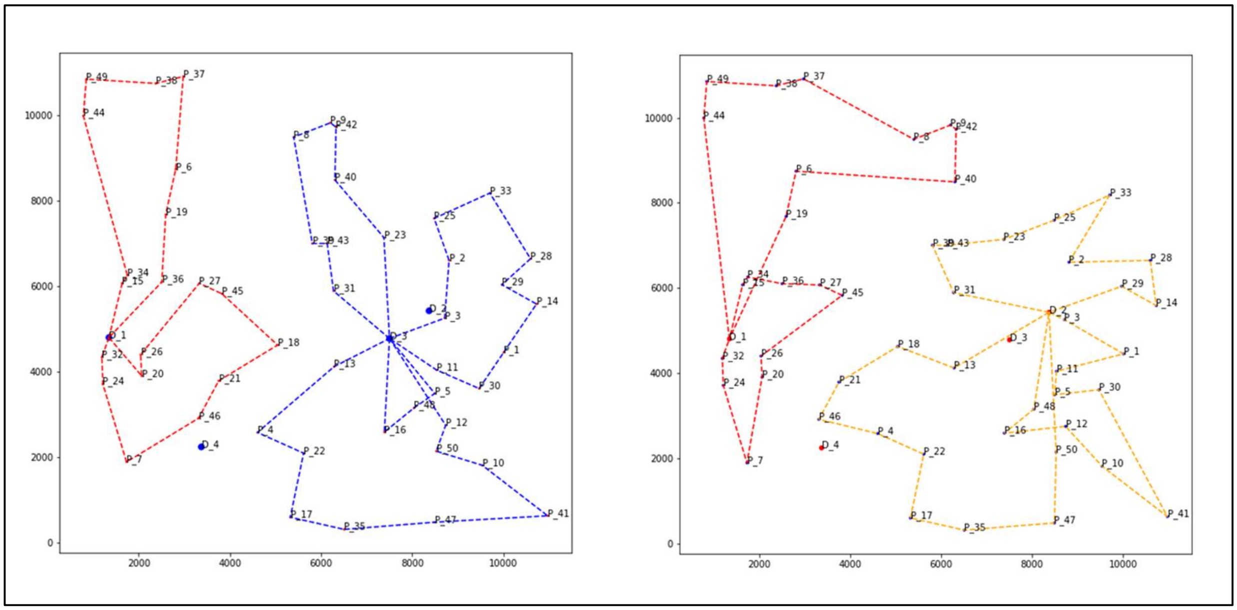

Figure 8: LRP solution. Left: MILP. Right: MACO

LRPAM of Scenario 13:

In this instance, the same inputs are taken, as described in the LRP. However, the problem is solved under a truck-drone configuration. The depots and customers are mapped as shown previously in Figure 7, and all customers are grouped into clusters, as shown in Figure 9.

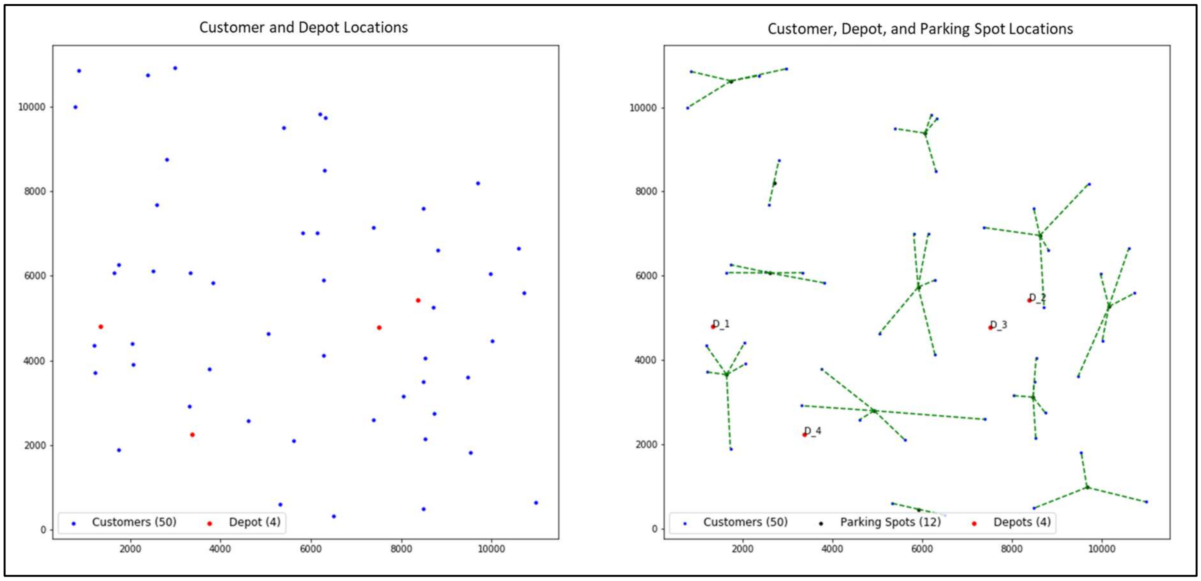

Figure 9: Customer locations before (left) and after (right) clustering

Following clustering, the number of nodes to be visited by the trucks is greatly reduced. The MILP and the MACO models are both applied to the clustered maps to generate the results shown in Figure 10.

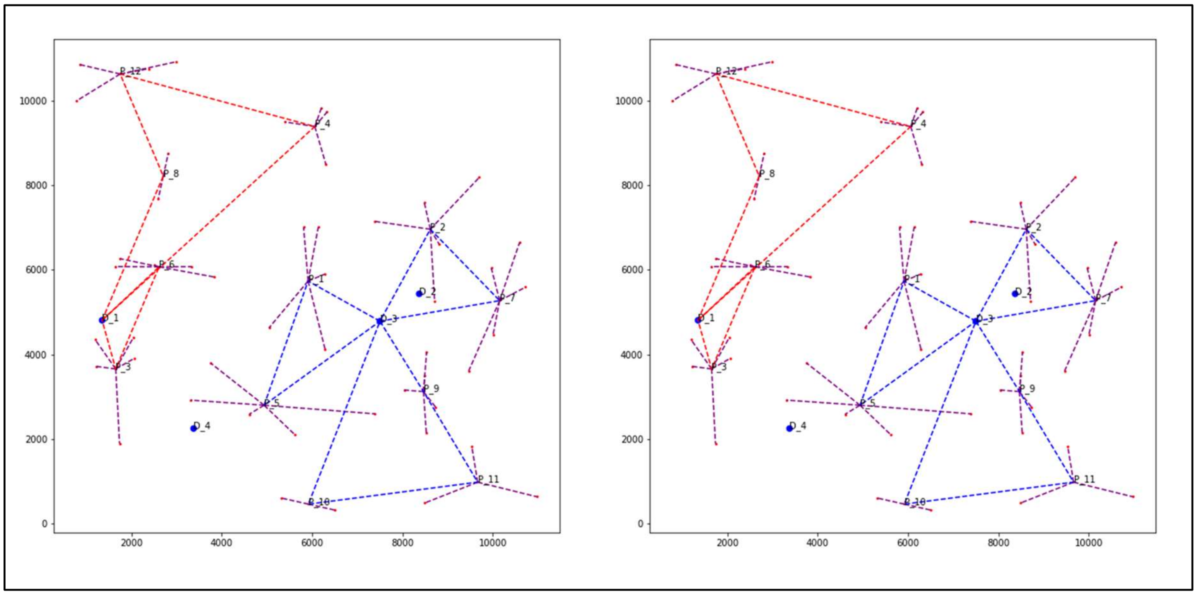

Figure 10: LRPAM solution. Left: MILP. Right: MACO

In this scenario and under the truck-drone configuration, both the MILP and the MACO solutions yielded the same results, which may not always be the case, as the rest of the scenarios in Table 7 show. It is also noted that while the number depots to be opened and the number of truck routes are the same in both LRP and LRPAM, the operating cost of the LRPAM is 7.9% lower than that of the LRP (LRP: $1,938/day, LRPAM: $1,784/day). This is a promising indication for the benefit of the truck-drone system, which is further discussed in Chapter 4.

In summary, the results of the validation scenarios showed that the solutions obtained from the developed MACO model are consistent with those from MILP solver. The solution gap was at most 3.7% for LRP and 3% for LRPAM. There was also a noticeable difference in solution run time, where the MACO model took significantly less to find the best solution, compared to the MILP solver. For large problem sets, the difference in solving time was more than a hundred folds. Based on the analysis of the results, the conclusion is that the developed MACO model is sufficiently reliable and provide an appropriate compromise between the solution optimality and the computing time. The model is therefore used to analyze the LRPAM in a more realistic distribution dataset, as outlined in Chapter 4.

4. Results, Analysis, and Discussion

This chapter applies the developed MACO model, as described in Chapter 3, to a realistic and large distribution dataset that is taken from an actual map of a metropolitan area. It then proceeds to analyze and discuss the findings to quantify the economic significance of implementing the truck-drone distribution mode, and to uncover managerial insights of interest.

4.1. Base Case of Manhattan

In the validity testing that Section 3.5.3 establishes, a Euclidean plane is used as a basis for generating random instances, rather than a map of an actual location. This approach was followed because it allowed for scaling the problem size as required. In quantifying the savings by implementing the truck-drone configuration, however, a base case with the actual road map of Manhattan is used to calculate the actual truck traveling distance, rather than using a circuity factor. The case of Manhattan is based on an anonymized dataset for a distribution network that was developed by the MIT Megacity Logistics Lab (MLL) (Winkenbach, 2020). It contains 200 unique customers and 5 depots, with their locations plotted on the map as shown in Figure 11. In this case, the distances take into account the actual path that the trucks will follow turn-for-turn, instead of the Euclidean distance. Such instances require the pre-computation of a distance matrix between all nodes before the LRPAM solving begins. In addition, the selected values for all physical parameters are listed in Table 3.

Only the heuristic model with the MACO is applied to this case, in order to satisfy computational feasibility. Because the main interest is to compare the total cost of distribution, with and without the drones, this problem is first solved as an LRP, and then as an LRPAM.

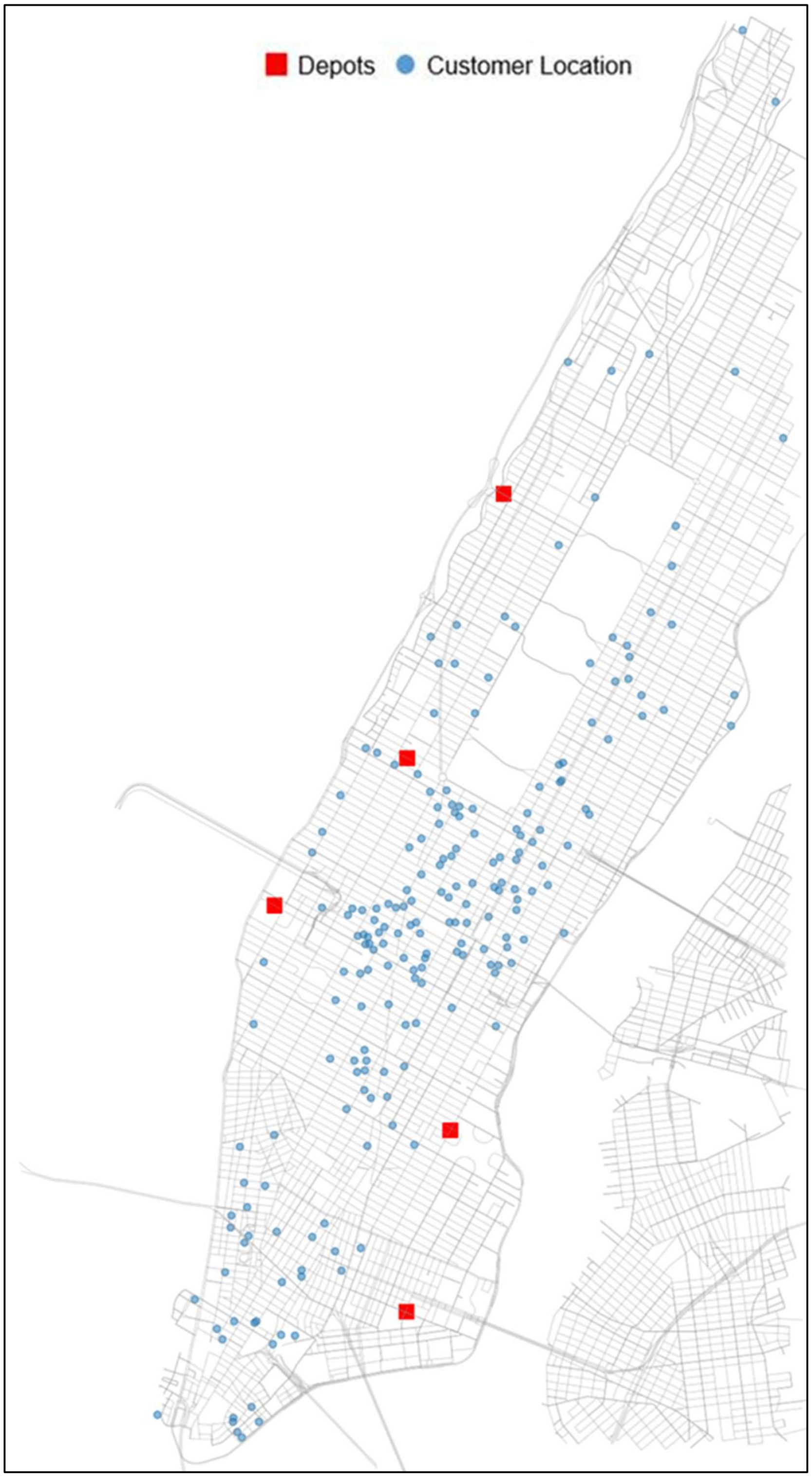

Figure 11: Base case scenario used for the analyses

4.2. Graphical Results of the LRP

The distribution is considered with trucks only and no drones. As such, there is no value in clustering, and the problem is solved using the MACO directly. The results are mapped and shown in Figure 12.

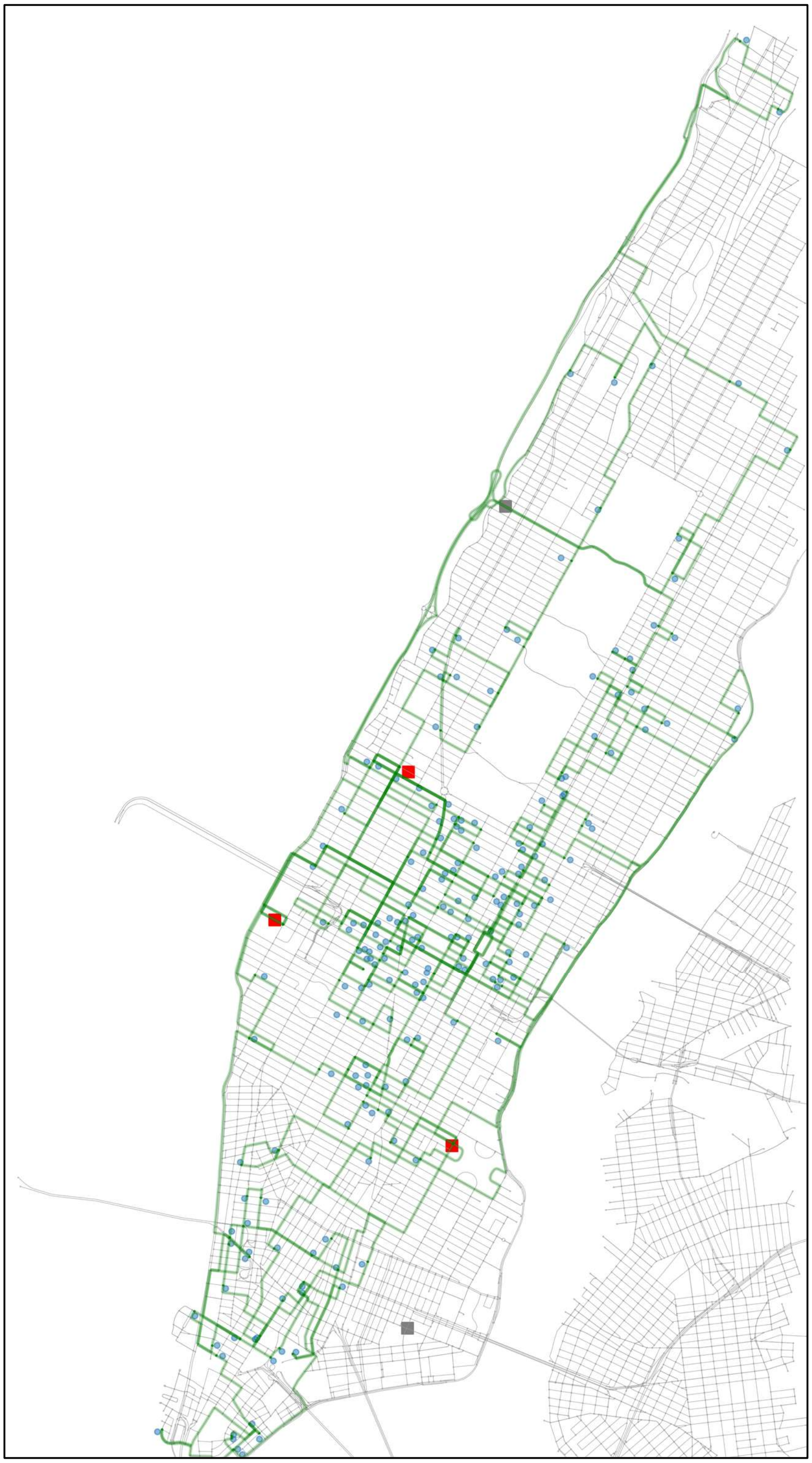

Figure 12: LRP solution for the base case

4.3. Graphical Results of the LRPAM

The base case is solved again as an LRPAM, with truck-drone distribution. With this method, clustering the customer nodes around parking locations is performed first. Figure 13 shows a map of Manhattan before and after clustering.

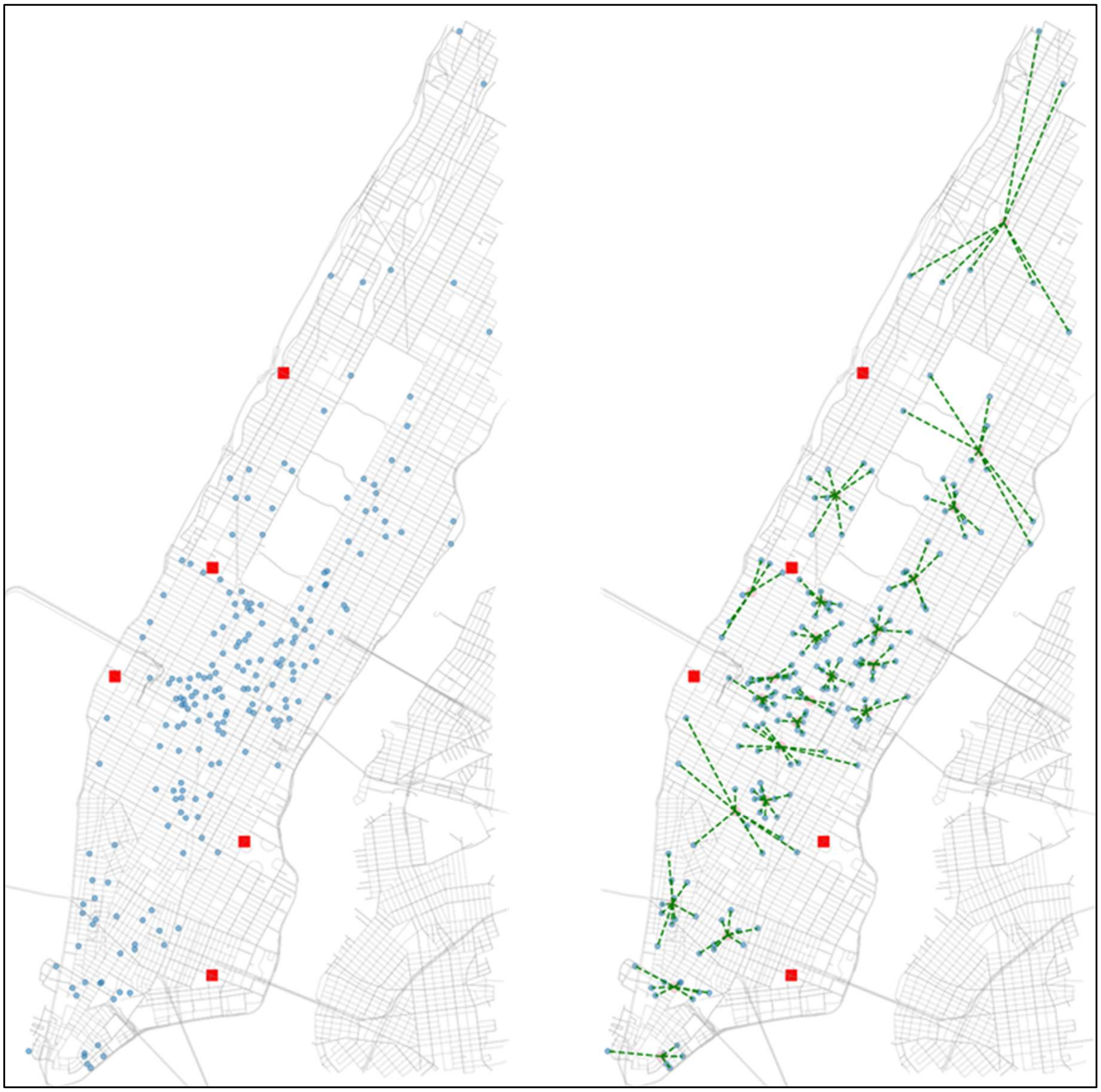

Figure 13: Base case before (left) and after (right) clustering

Following clustering, the facility selection and routes construction were completed, and the results are as shown in Figure 14. It can visually be noted that truck travelling distance in Figure 14 is significantly lower in comparison with Figure 13.

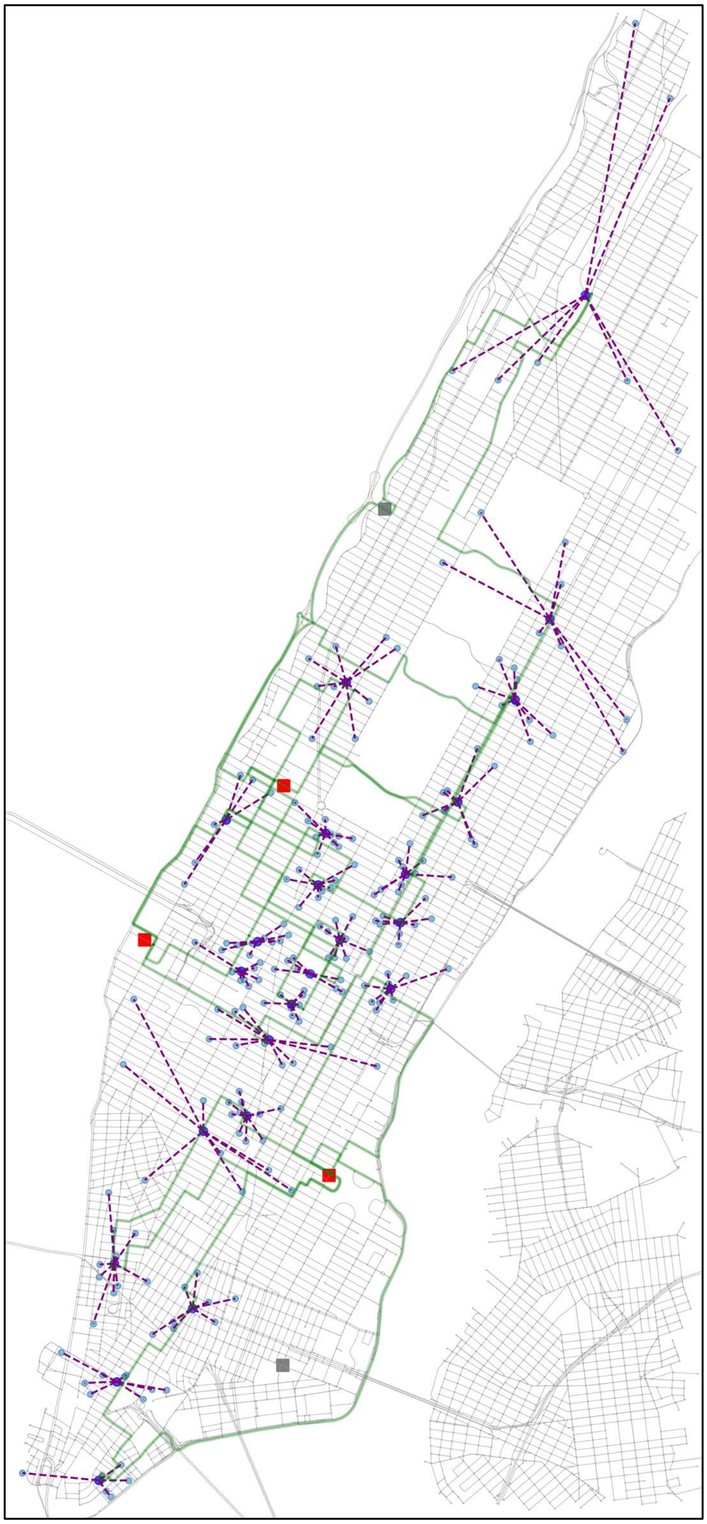

Figure 14: LRPAM solution to the base case

4.4. Numerical Results for Manhattan Base Case

Based on the two methods of distribution for the base case, with trucks only (Section 4.2) and with trucks and drones (Section 4.3), the results are summarized in Table 8 and Figure 15.

Table 8: Cost summary for the base case as an LRP and as an LRPAM

Problem type	LRP	LRPAM	Change
Transportation modes	Trucks	Trucks + Drones	-
Solver	MACO	MACO	-
Fixed cost: Depot opening	640.00	640.00	0.0%
Fixed cost: Truck deployment	166.85	166.85	0.0%
Fixed cost: Drone deployment	-	73.85	New cost
Variable cost: Truck traveling	548.17	187.57	-65.8%
Variable cost: Drone traveling	-	4.70	New cost
Variable cost: Truck waiting	107.50	39.52	-63.2%
Total Cost	1,462.52	1,112.47	-23.93%

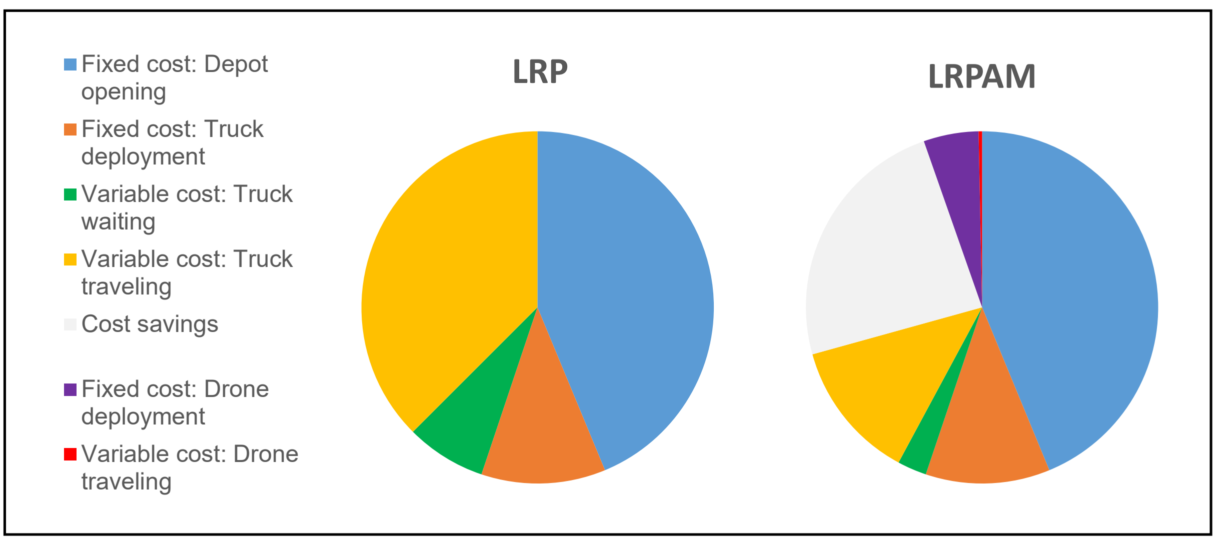

Figure 15: Distribution cost. Left: LRP. Right: LRPAM

Table 8 and Figure 15 Figure 15: Distribution cost. Left: LRP. Right: LRPAMreveal that introducing the truck-drone system would result in a cost reduction of approximately 23.93%, close to a quarter of the total distribution cost, including that of opening the depots. The most significant savings come from the elimination of two-thirds of the truck travel, which costs a little above a third of all costs in the LRP case. This finding is supported by a noticeable decrease in truck travel when comparing Figure 12 and Figure 14. In addition, the truck waiting cost was reduced significantly. This reduction in waiting was accounted for by the accumulated difference between the time it took the truck to stop at each individual customer node in the LRP, and the time it required for the drones to be loaded and to travel to each customer node in the LRPAM. Because there are multiple drones per truck, drones can be deployed to travel in parallel, and the parallel delivery reduced the accumulated truck waiting time at the parking spots.

4.5. Sensitivity Analysis

As the base case revealed that 23.93% savings could be realized from implementing the truck-drone system, this section tests how different input parameters could affect the total operation cost in both the LRP and the LRPAM modes. The varied parameters are shown in Table 9.

Table 9: Varied parameters in the sensitivity analysis

Parameter	Base Value	Units of Measurement	Tested values
Number of drones per truck	3	-	1, 2, 3, 4, 5
Drone travel speed	16	m/s	12, 14, 16, 18, 20

Parameter	Base Value	Units of Measurement	Tested values
Truck travel speed	7	m/s	3, 5, 7, 9, 11
Drone travel cost	0.05	USD/mile	0.05, 0.25, 0.50, 1, 3, 4

The results of varying these parameters are shown in Table 10, where the cost savings from implementing the LRPAM are taken as a percentage of the LRP cost.

Table 10: Results of the sensitivity analysis runs. Green: Same parameter and result as the base case

					Operational Cost (USD/day)		
Sensitivity Test no.	Drones per truck	Drone Speed (m/s)	Truck Speed (m/s)	Drone Travel Cost (USD/Mile)	LRP	LRPAM	LRPAM cost savings over LRP
1	1					1,117	23.61%
2	2					1,105	24.43%
3	3	16	7	0.05	1,463	1,112	23.93%
4	4					1,136	22.35%
5	5					1,147	21.60%
6		12				1,120	23.42%
7		14				1,120	23.43%
8	3	16	7	0.05	1,463	1,112	23.93%
9		18				1,111	24.03%
10		20				1,102	24.66%
11			3		1,756	1,190	32.21%
12			5		1,543	1,130	26.75%
13	3	16	7	0.05	1,463	1,112	23.93%
14			9		1,382	1,109	19.75%
15			11		1,365	1,094	19.80%
16				0.05		1,112	23.93%
17				0.25		1,139	22.11%
18	3	16	7	0.50	1,463	1,161	20.64%
19				1.00		1,211	17.17%
20				3.00		1,406	3.85%
21				4.00		1,482	-1.36%

The plots in Figure 16 illustrate and summarize how the savings generated by applying the LRPAM change based on the shift in parameters.

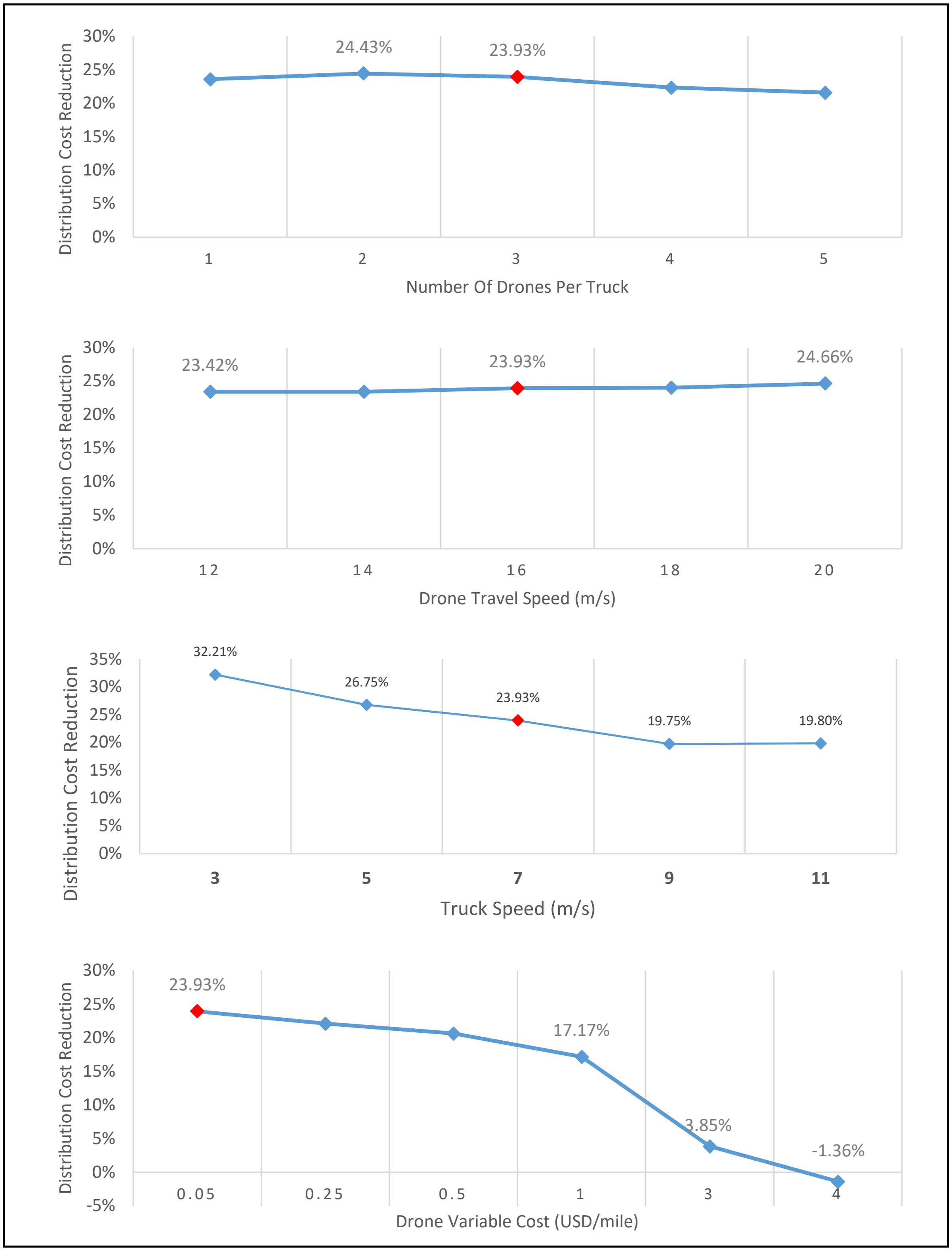

Figure 16: The sensitivity of the cost savings by truck-drone mode to the modeling parameters. Red marker: Base case

Further analysis of the first chart in Figure 16 suggests that the optimal number of drones per truck is two. It is worth noting, however, that the amount of savings is not very sensitive to the number of drones. This insight gives the organizations more freedom to select the number of drones that suit their operations the most with regards to other aspects besides the direct cost of distribution. Having more drones per truck means that the distribution operation can be completed faster, as trucks would spend less time parked, and more drones are deployed in parallel to save more customers concurrently. On the other hand, having more drones in operation will add to the complexity in navigating the drones, managing a larger fleet, and designing a truck that can accommodate more drones without a significant loss in the parcel carrying capacity.

The second chart of Figure 16 shows that an increase in the drone traveling speed barely has an impact on the cost and is therefore not a technological advancement worth pursuing for commercial delivery drones. The analysis of this case also confirms that the traveling range for the drone is not a binding constraint and that today's average range for roundtrip flight far exceeds the requirement to serve a metropolitan area.

The third chart of Figure 16 indicates that an increase in the speed of trucks has a negative impact on the cost savings from the truck-drone configuration. The lower the speed of trucks, the more savings are realized. This finding suggests that the application of LRPAM is more suitable for cities where traffic congestion is high, causing trucks to travel slower, especially in cities like Manhattan, where average vehicle speed has dropped steadily over the past years (Hinds, 2015).

The chart at the bottom of Figure 16 shows that there is a strong business case for introducing the truck-drone system, even if the variable cost per mile for drone travel of \$0.05, as estimated by Deutsche Bank and reported by Kim (2016), was off by a factor of 20. The estimated cost reduction was calculated to be around 17% at a \$1.00/mile drone traveling cost, and the savings were observed to decline sharply from that point after. The business case is no longer viable if the drone travel costs \$4/mile or more, as drone travel would then be more costly than the last-mile delivery cost by vans for an average mid-tier courier (Kim, 2016).

To understand how the problem size affects the savings, the scenarios from the validity testing that were used in Section 3.5.3 are revisited, as they allowed scaling the problem size as required, and adding randomly generated locations for both depots and customers. The calculated savings are shown in Table 11.

Table 11: Savings in operational costs by implementing the truck-drone system for various problem sizes

Scenario	Area (km^2)	Customer nodes	LRP Cost (\$)	LRPAM Cost (\$)	LRPAM Savings
1	16	30	347	345	0.4%
2	16	40	579	578	0.2%
3	16	50	646	625	3.2%
4	16	200	1,933	1,692	12.5%
5	16	300	2,698	2,378	11.8%
6	59	30	902	846	6.3%
7	59	40	1,306	1,228	6.0%
8	59	50	1,422	1,344	5.5%
9	59	200	3,202	2,755	14.0%
10	59	300	4,531	3,984	12.0%

Scenario	Area (km^2)	Customer nodes	LRP Cost ($)	LRPAM Cost ($)	LRPAM Savings
11	121	30	1,144	1,094	4.4%
12	121	40	1,850	1,776	4.0%
13	121	50	1,965	1,784	9.2%
14	121	200	4,332	3,556	17.9%
15	121	300	5,698	4,830	15.2%

Figure 17 summarizes the savings data from Table 11, as seen below, where the size of the bubble represents the amount of savings realized.

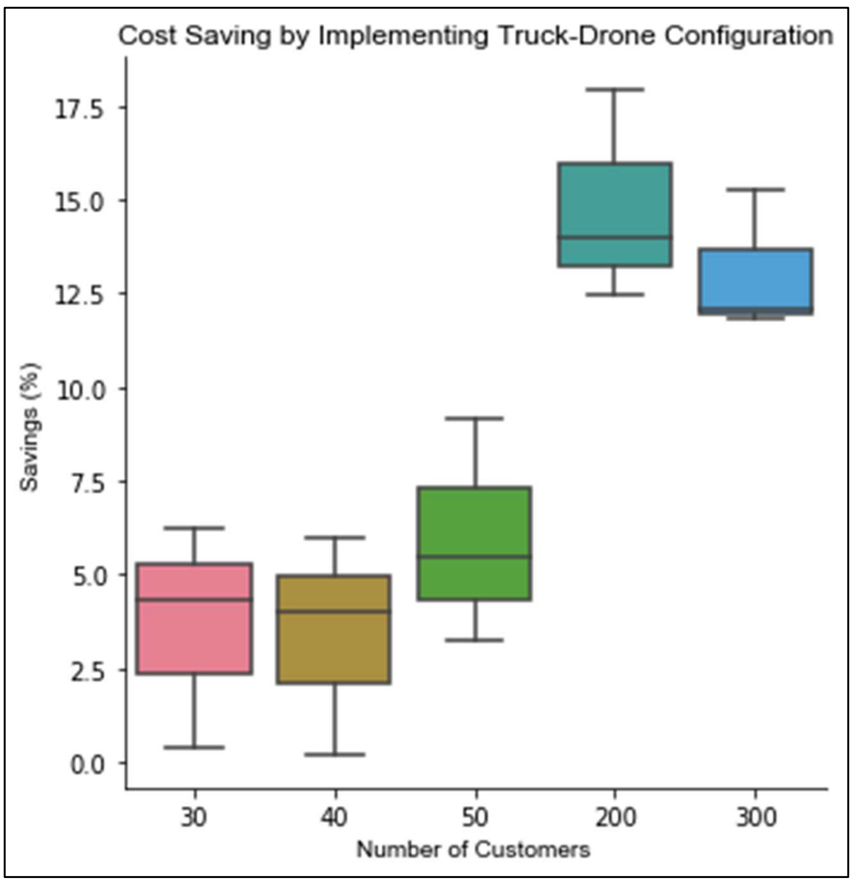

Figure 17: Results of varying the problem size on the savings generated by the truck-drone system.

The data from Table 11 and Figure 17 suggest that the operational savings from implementing the truck-drone system generally increase as the number of customers grows, and then stagnate at around 200 customers per region. For a small problem set of 50 customers or under, while the truck-drone system still generates savings, these savings relatively low.

4.6. Effect of Truck-Drone on Facility Location

Using the optimization model that was developed for this project, two sets of instances were tested to obtain the LRP and the LRPAM solutions: The “Validation Set” (Table 5), and the “Sensitivity Testing Set” (Table 9). In no instance did the depot opening decision change between the truck-only (LRP) and the truck-drone (LRPAM) modes of distribution. Since the fixed cost of opening depots represent an amount comparable with truck and drone fixed and variable cost (44% versus 56% as shown Figure 15), it is an indication that the testing sets used are sensitive enough to detect whether a change in depot could result in a better solution. Therefore, the conclusion that can be drawn is that, at least within the testing scope of this project, introducing drones as an ancillary mode does not affect the depot decision.

Not having to vary the facilities is fortunate for organizations considering the truck-drone system, because it indicates the lack of significance for revising any facility selection decisions that were previously made based on truck distribution alone.

5. Conclusion

This capstone project has developed a model to solve the Location Routing Problem with Ancillary Modes (LRPAM), which has been implemented to solve several instances of drone-assisted delivery with trucks, including a realistic case for Manhattan. The model used a metaheuristic approach that relied on pre-clustering and then the Multiple Ant Colony Optimization (MACO) method to recommend the choice of depots and the route that should be followed to serve each customer. The model performed well, with an optimality gap averaging around 1% for the LRPAM when compared to an exact Mixed Integer Linear Program (MILP) solver.

Using this model, it was possible to estimate the savings in the daily cost of parcel distribution if drones are introduced as a secondary mode that departs from trucks and delivers to customers. For the theoretical case, the savings in comparison to traditional truck-only delivery, which reached 17%, were found to be highly dependent on the problem size. However, for the realistic case that modeled distribution in Manhattan, the savings were found to be even higher, reaching 24%.

The experiments showed that increasing the speed of drones increases the savings, however, the amount of improvement is negligible and amount to a 1% improvement at best. They also showed that there should be no need to reconsider the facility locations if current distribution networks are to be modified for the truck-drone distribution system. In addition, there is no direct cost benefit to adding more than two drones onboard each truck. Moreover, truck-drone solution does not appear to be viable for serving a small number of customers. However, it remains extremely significant for serving higher numbers of customers over greater service regions. While the amount of savings shrinks with an increase in the variable cost of drone travel, the case remains strong given that the most-widely cited value of drone cost per mile is $0.05. Moreover, drones continue to produce significant savings at much higher variable costs, as long as the value does not exceed that of truck travel, which is estimated to be $4.00/mile on average for last-mile delivery.

The major roadblocks to the use of drones in commercial parcel delivery are societal and regulatory, rather than technological or financial. The findings of this project show that there is an excellent financial opportunity, even with today's drone specifications. Suggestions for future work can focus on either applying this project's model to more realistic problems and testing its robustness or improving the algorithm by exploring more efficient clustering techniques such as density-based or hierarchical clustering.

At the time this report was completed, the world was witnessing a disruption unlike anything that has ever happened in the past century. The epidemic caused by the Coronavirus Disease 2019 (COVID-19) placed stringent restrictions on human-to-human contact to combat the spread of the virus, which in turn increased the demand for contact-free methods of doing business. Perhaps these difficult times will drive the societal change needed for the wide adoption of unmanned delivery of goods using drones.

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