Comparative Evaluation of Drone Delivery Systems in Last-Mile Delivery

by

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ABSTRACT

With the latest technological advancement, the use of drones has emerged as an innovative and viable business solution for last-mile distribution. An efficient drone delivery system has to address the classic vehicle routing problem (VRP): "What is the optimal set of routes for a fleet of drones to serve a given set of customers?." The goal of this research project is to evaluate the optimal design and operational performance of four different drone delivery systems, using real-life last-mile truck delivery data. The authors quantitatively model four different drone delivery systems, from a pure drone delivery system to an unsynchronized drone-truck system and compare their relative benefits and shortcomings under various scenarios. A Memetic Algorithm, an extension of a Genetic Algorithm, is developed and used to optimize delivery routes of truck and drones for all the four delivery models.

Our research shows that Memetic Algorithm is quite robust handling VRP with 50 customers, yielding only 3.7% gap from the optimal solution. Among the four considered delivery models in this research, the Delivery System model 4 - where truck and drone share same area of service - performs superior than other three models, providing 100% coverage to all customers and reducing minimum tour time as high as 80%. The outcome of this research will help shape the quantitative and qualitative comparison of drone delivery systems and set the foundation for modelling and analysis of more advanced systems (e.g. synchronized truck-drone delivery system). It also helps industry to understand the possible use cases for drones in last-mile delivery and the most crucial levers of these models to maximize the performance of such drone delivery systems.

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Antonius

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1 Introduction

1.1 Market scope

E-commerce continues to outgrow offline retail revenues and is expected to reach 15% of global retail share in 2020 as per eMarketer (2016) as seen in Figure 1.1. E-commerce business, growing fast pace at 21% annual growth, is fueling global parcel distribution, and particularly increasing the number of deliveries in the last leg of distribution from suppliers to customers (B2C shipments), known as the last-mile delivery. Last-mile delivery is one of the most complex and inefficient steps in supply chain due to:

- *Fragmentation of deliveries by different players with different business models.* Examples include: integrated logistics players, such as DHL and UPS; same-day logistics providers, such as Deliv; retailers, such as Amazon; and pure tech players, such as UBERRush.

- *Inefficient delivery routes caused by urban congestion.* Shaikh (2016) from United Nations stated that 65% of all humans will live in cities by 2050. This rising urbanization coupled with unprecedented growth in e-commerce is increasing the volume of urban freight deliveries and consequently putting strain on cities grappling with congestion problems.

These inefficiencies make last-mile delivery as the costliest step in supply chain, accounting for 28–53% of the total shipment costs, based on Dolan (2018) and Hochfelder (2017) as can be seen in Figure 1.2. To address these inefficiencies, this research aims to assess the feasibility of using drones in last-mile delivery as a possible solution to the aforementioned complexities and limitations. We will elaborate on how we propose such solutions in Section 3.

1.2 Significance of drones in urban delivery

To be able to handle the future significant volumes of package deliveries efficiently, a recent solution that has been proposed is drone-based delivery systems by Murray and Chu (2015). Drones can be deployed in last-mile delivery systems due to their several advantages as follows:

- *Reduce cost*: Based on research by Deutsche Bank, Kim (2016) stated that for typical small-box delivery, drones' delivery cost is USD 0.05 per mile - compared to USD 2 for USPS last-mile delivery or USD 6-6.5 for premium ground like FedEx or UPS.

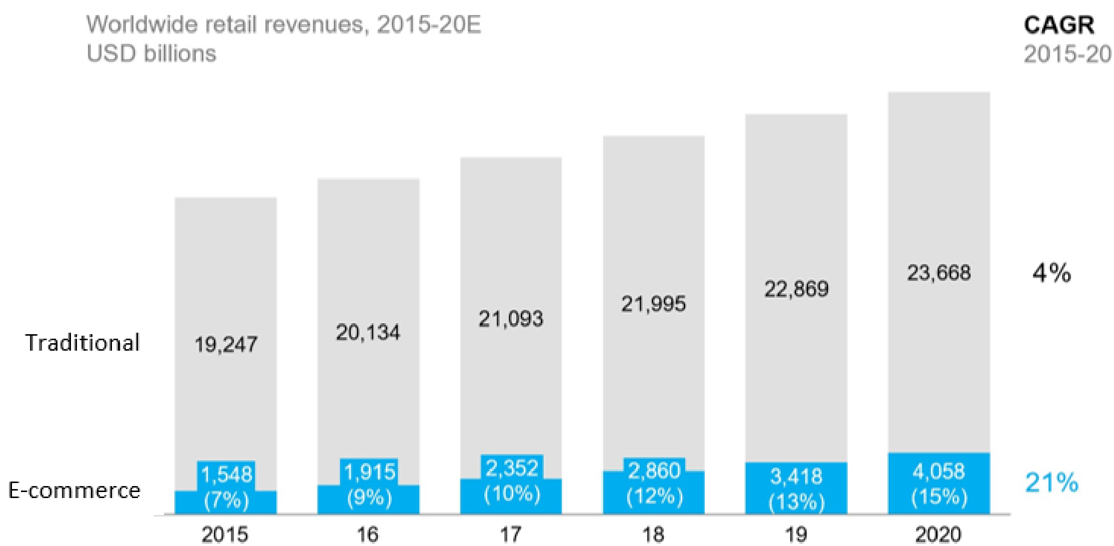


Figure 1.1: **Global retail growth (Traditional and E-commerce)**

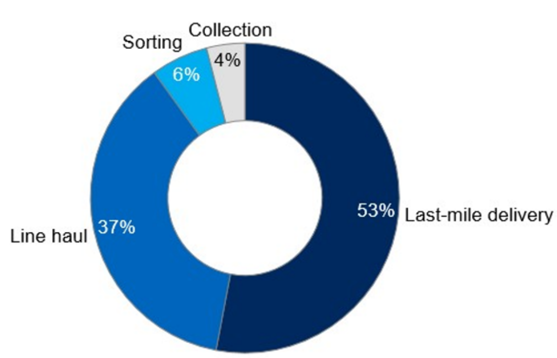


Figure 1.2: **Share of logistic cost based on the journey according to Hochfelder (2017)**

- *Enhance reach area*: In areas with poor infrastructure access, drones can increase reach to remote areas which cannot be served by ground transportation.

- *Reduce delivery time*: Drones significantly reduce delivery transit times compared to those of terrestrial delivery systems, such as trucking. This is because drones are capable of flying in straight lines to their destinations and bypass traffic congestion.

The first attempt to use drones for delivery dated back to 2014, when DHL (2014) launched the first autonomous delivery flights by 'parcelcopter ' to the North Sea island of Juist for emergency delivery of medications. Amazon (2016) followed suit in 2016 when it launched the Prime Air delivery for a bag of popcorn and Amazon Fire TV stick in UK. Currently other major companies are testing more drones deliveries, such as:

- Google (2014): Google is developing Project Wing, an autonomous delivery drone service aiming to increase access to goods in Australia.

- AirBus (2018): Airbus Helicopters partners with SingPost for drone delivery trials around National University of Singapore (NUS) campus.

- UPS (2017): In 2017, UPS tested residential delivery via drone launched from truck-launched drone-maker Workhorse Group in USA.

Although drones have particular advantages over conventional truck-based delivery systems, their widespread adoption is limited by both operational and technical factors, such as:

- *Regulatory issue*: Marcontell and Douglas (2018) from Oliver Wyman stated that in US, most federal regulations on drones still restrict their use: Drones, or unmanned aircraft systems (UAS), cannot fly over most federal facilities or over people; drones cannot fly at night or within five miles of an airport without permission; drones must fly below 400 feet and at less than 100 miles per hour; with some exceptions, they must weigh under 55 pounds (25 kilograms); and they must yield the right of way to manned aircraft

- *Payload*: Payload for most of drones are below 5 – 7 kg.
- *Distance*: Drones' range is still limited to 15 – 20 km.

Despite its limitation, drone delivery is an innovative solution for last-mile delivery operations. Currently, there are several models of drone delivery systems researched: pure drone delivery systems, such as (Dorling et al., 2016; Coelho et al., 2017) and combination of drones and trucks, such as (Murray and Chu, 2015; Kim and Moon, 2018; Ham, 2018).

1.3 Problem scope and assumptions

The objective of this research project is to quantitatively model and analyze four different drone (and truck) delivery systems and to compare their benefits and limitations under various scenarios. We will define these models along with their various components. We will also develop an algorithm based on Memetic Algorithm to optimize the delivery routes for all the four models. Some of the main assumptions of our models are:

- We focus on only the delivery side of operations, i.e., pick-up requests are out of the scope of this project.
- The payload factor limits the drone delivery to one package per trip, therefore after each delivery, drones have to return to the depot to pick up another package.
- The drone travel range (time) will be built into the model in order to replicate realistic conditions. This range will be adjustable to allow for a variable solution range depending on future technology.
- The truck's travel range is assumed to be unlimited.

After we build the model and algorithm, we will identify and conduct a sensitivity analysis on several key parameters of the models, including drone speed and flight limit, the number of available drones, number of trucks, and truck speed. As we change these parameters, we will measure the performance of each system. This performance is measured by three different objective functions, including the latest return time of vehicles to depot, the total costs of distribution, and the total waiting time of all customers. For most of our analyses, we focus on the most popular objective which is minimizing the return time of vehicles to depot. The results are used to determine which and under which circumstances a delivery model is more beneficial than others. Bearing all these objectives in mind, and considering the constraints, a total of four different models have been selected to evaluate the most suitable last-mile delivery setup to tackle the challenges mentioned above:

- *Model 1: Pure drone delivery system*: In this model, only drones are used to delivery packages to customers.

- *Unsynchronized drone-truck system with separate service areas*: This model presents two variants depending on the segmentation of the service area and assignments of them to truck and drones:

  - *Model 2*: Customers which are located close to depot are served by drones, while more distant customers are served by trucks (Drone-inner/Truck-outer).

  - *Model 3*: Customers which are located close to depot are served by trucks, while more distant customers are served by drones (Truck-inner/Drone-outer).

- *Model 4: Unsynchronized drones-trucks system with shared service area between trucks and drones*: Each location can potentially be served by a truck or a drone. The optimization model decides which is the optimal vehicle to deploy.

2 Literature review

The literature review chapter is organized into two separate sections. The first section will discuss case studies of drones in delivery systems – what have been tested and what are the findings so far. Second, we represent a brief review on vehicle routing problems (VRPs) and particularly, VRPs for drone delivery systems. In this section, we will also review research papers on VRPs for multi-modal systems where drones and trucks operate in parallel in the delivery system.

2.1 Drone applications in delivery system

Drone, also commonly known as Unmanned Aerial Vehicle (UAV), is aerial vehicle without on-board human pilots. Drone has historically been limited to military applications dating back to the 1930s, when the British produced a number of radio-controlled aircraft to be used as targets for training purposes. One of the radio-controlled aircraft models was called DH.82B Queen Bee – which is thought to inspire the term "drone" as can be seen in Figure 2.1 (IWM, 2018).

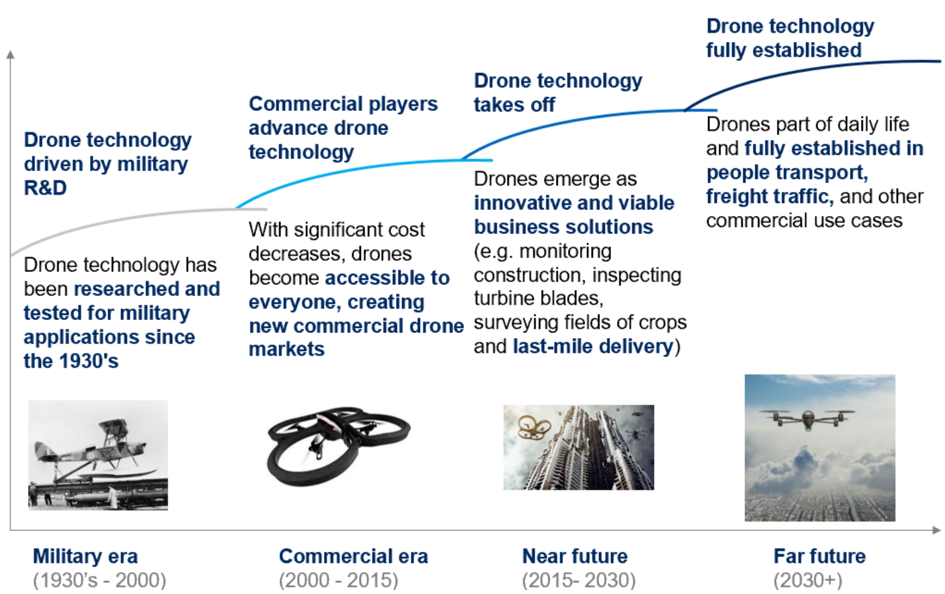


Figure 2.1: **Drones historical and future timeline**

Since the 2000s, with the significant cost decreases, drone becomes accessible to everyone, creating new market for commercial drones. In the last decade, commercial drones have taken off and sales of drones have increased exponentially:

- Schatsky and Ream (2016) from Deloitte show that DJI has the biggest market share in commercial drone market and its revenue skyrocketed from USD 4 million in 2011 to USD 1 billion in 2015
- Goldman-Sachs (2019) stated that commercial drone is the fastest growing segment for UAV and is expected to exceed USD 20 billion by 2021.

With the latest technological advancement, drone emerges as innovative and viable business solution for commercial last-mile operations. As outlined in Figure 2.2, many logistics and e-commerce companies have been testing drones as last-mile delivery system over the past 5 years. More recently in April 2019, Pasztor (2019) from WSJ reported that Google has won first FAA approval for regular drone delivery of consumer items in Virginia. Based on all these experiments, it is essential to note the specific characteristics of drones, such as:

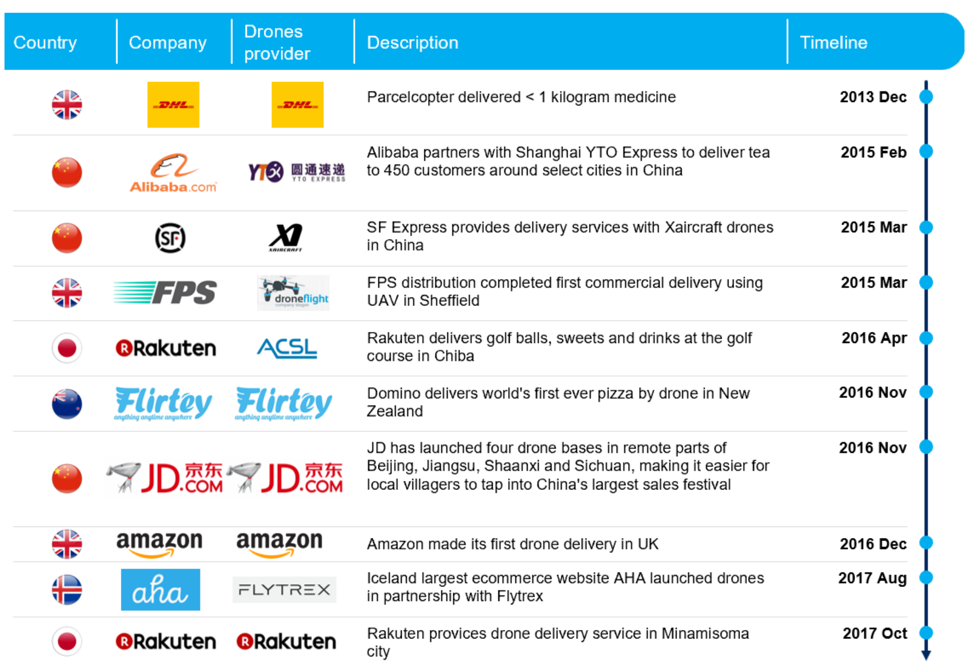


Figure 2.2: **Drones' experiments by major e-commerce and logistic companies**

- Weight: Packages up to 30 kg. JD (2019)
- Variety of packages: medicine, tea, golf balls, food and beverages (pizza, drinks, sweets). Rakuten (2016), Domino's (2016)
- Number of deliveries: 500 parcels per day. Stanton (2015)
- Speed: up to 100 km/hour. JD (2019)

2.2 Vehicle Routing Problem (VRP) for drones delivery system

2.2.1 The Vehicle Routing Problem

To design an efficient drone delivery system, we need to address the classic vehicle routing problem (VRP): "What is the optimal set of routes for a fleet of drones to serve a given set of customers". In this research, an algorithm is developed to determine optimal delivery routes for drones and trucks in various drone delivery system.

VRP was first introduced by Dantzig and Ramser (1959) as the Truck Dispatching Problem, and has retained ever since a steady interest in the academic community. In order to tackle the NP-hardness (non-deterministic polynomial-time hardness) of the VRP, different strategies have been developed over the years in order to solve it. Three of the most successful meta-heuristics were inspired by nature:

1. *Simulated annealing of metal cooling*: Laarhoven and Aarts (1987).

   Simulated annealing is a probabilistic method that emulates physical process of annealing in metal works whereby a metal cools down over time. The algorithm reduces the probability of finding local optima by allowing worse solutions when the temperature is still high.

2. *Genetic Algorithm*: Goldberg (1989)

   Genetic algorithm is a numerical optimization technique that uses evolution concept of survival of the fittest. The algorithm will perform natural selection where the fittest individuals (the most optimum solutions) are selected to produce offspring for next generation.

3. *Ant-Colony Optimization (ACO)*: Dorigo and Di Caro (1999)

   Ant-Colony Optimization (ACO) is a probabilistic technique to determine most optimal path by emulating the behaviour of ants following paths from their colony to source of food. Ants drop a chemical substance called pheromone when they travel. Ants behaviour is to travel along the paths that have strongest pheromone scent, hence the more pheromone on a particular path means a higher probability that a particular path is optimal.

Additionally several extensions of the original VRP have been proposed to limit or adapt the problem to specific situations in order to find the best fitting solution. Some of these are the VRP with time-windows (VRPTW) by Bräysy and Gendreau (2005), or VRP with mixed fleet and size (FSMVRP) by Tan et al. (2006). Our research also adopts mix fleet concept where we have drones and trucks in last-mile delivery.

2.2.2 Pure drone delivery systems

Despite a wealth of knowledge and literature that exists for classical vehicle routing problem (VRP), the literature on drone delivery routing problems tends to be limited because drone delivery concept only emerged recently. In addition, a drone routing problem needs to consider several specific constraints, such as operational limit of the drones (e.g. distance covered, flight limit, payload, etc), and unique technical characteristics of drone delivery (e.g. one package per trip, no pick-up, no night-time operation, etc).

Dorling et al. (2016) solved drone delivery routing problem with two different objective functions: one minimizes costs subject to a delivery time limit and second minimizes overall delivery time subject to a budget constraint via Mixed Integer Linear Program (MILP) that considers battery weight, payload weight and drone reuse. In order to solve practical scenarios with hundreds of locations, simulated annealing algorithm was used to solve the problem. The study found that optimizing battery weight and reusing drones are important considerations for drones delivery.

Choi and Schonfeld (2016) approached the drone delivery routing problem by exploring sensitivity of four variables (working period, drone operating speed, demand density of service area and battery capacity) to determine optimal costs of drone delivery system. The study assumed that a drone can lift multiple packages within its maximum payload and serve customers within a given radius. Battery capacities were analyzed to relate parcel payloads and flight ranges. The study indicated that extended working periods would benefit both providers and customers. Furthermore, increased of drone operating speed would reduce total costs at the expense of increasing cost for supplier. Finally, the research concluded that drone deliveries were more economical in areas with high demand densities and that larger battery capacities would reduce number of drones require to satisfy a service area.

2.2.3 Multi-modal truck and drone systems

Among multi-modal truck and drone systems, Murray and Chu (2015) considered drone as part of the integrated trucks-drones delivery system in which trucks are responsible for large parcels or customers outside of drones flight range. The research introduces Parallel Drone Scheduling TSP (PDSTSP) and Flying Sidekick Travelling Salesman Problem (FSTSP), in which trucks and drones work in tandem for an optimized drone-assisted parcel delivery via two scenarios. The first scenario is that the drone serves customers near depot/distribution center (PDSTSP) and the second is that the drone is launched from a delivery truck when customers are located far-away from drone flight range (FSTSP).

Ham (2018) extended PDSTSP problem by incorporating two different type of drone tasks: drop and pickup. After a drone delivers its package, the drone can either fly back to the depot to pick up and deliver next package or fly directly to another customer for pickup. This problem is modelled as unrelated parallel machine scheduling. A constraint programming (CP) was proposed and tested with problem instances of m-truck, m-drone, m-depot and hundred-customer distributed across an 8-mile square region. The study concluded that CP proved to be a promising technology for the UAVs scheduling problem because it found optimality majority of the time for PDSTSP problems with 20-50 instances.

Kim and Moon (2018) proposed a multi-modal truck and drone system to overcome drones flight-range limitation, especially where customers are located far from distribution center. Kim and Moon recommended mixed integer programming to solve traveling salesman problem with a drone station (TSP-DS). Two-stage traveling salesman and modified parallel machine scheduling problem (TSMPMS) is developed to find a schedule that minimizes the number of drones used at a station. The research revealed that TSP-DS is more effective in serving customers than PDSTSP when a majority of customers are located far from distribution.

3 Methodology

Drone delivery systems exhibit classical vehicle routing problem (VRP) characteristics, where we need to find optimal set of routes for a fleet of vehicles to deliver packages to customers. The goal of our research project is to evaluate the optimal design and operational performance of four different drone delivery systems, using real-life last-mile truck delivery data. We model four different drone delivery systems and compare their relative benefits and shortcomings under various scenarios. A Memetic Algorithm, an extension of a Genetic Algorithm, is developed and used to optimize delivery routes of drones and trucks in all models.

This section outlines our methodology and is organized into two sub-chapters. In Section 3.1 we introduce the four different drone delivery systems used in this project, from pure drone delivery system to unsynchronized drones-trucks system with both separated and shared areas. Then, in Section 3.2, we lay out the approach we use to optimize the delivery routes for all delivery models.

3.1 Drone delivery models

Based on our research, there are various models for drone delivery systems, from pure drone delivery system: Dorling et al. (2016), Coelho et al. (2017) to truck-drone tandem: Murray and Chu (2015), Kim and Moon (2018), Ham (2018).

In our paper, we modelled four different drone delivery systems. These systems are developed based on the types of available vehicles and the assignment of areas to vehicles based on their proximity to the depot (Figure 3.1).

3.1.1 Model 1: Pure drone delivery

In the pure drone delivery (Model 1 - Figure 3.2a), all the deliveries are carried out by drones. Due to drone capacity being restricted to a single payload, this model boils down to scheduling single return trips to the depot. There is no truck involved in this delivery

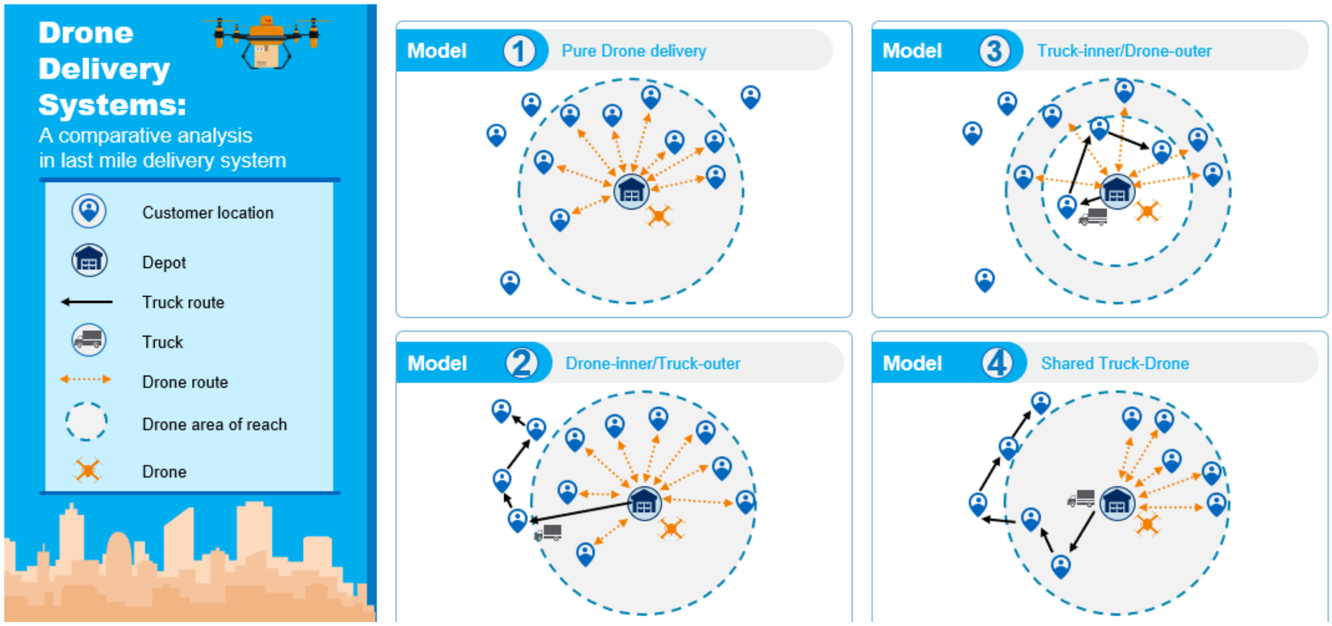


Figure 3.1: **Drone delivery models: (1) Pure drone delivery (2) Drone-inner/Truck-outer (3) Truck-inner/Drone-outer (4) Shared Truck-Drone**

system.

3.1.2 Model 2: Drone-inner/Truck-outer

This model splits service areas into two based on proximity to the depot: (1) Inner: area close to the depot (2) Outer: area farther from the depot. Model 2 assigns drone to serve the inner area and truck to serve the outer area (Figure 3.2b).

3.1.3 Model 3: Truck-inner/Drone-outer

Model 3 (Figure 3.2c) is the reverse of model 2, where in model 3 the inner area is assigned for truck and the outer area is assigned for drone. In this model, a threshold is set to split the area of service between truck and drone. Beyond this threshold, drones will serve the outer area. In this model locations outside of the drone range will then be out of reach and cannot be served.

3.1.4 Model 4: Shared Truck-Drone

The shared area between trucks and drones (Model 4 - Figure 3.2d) better reflects real-life model in which the drones and trucks share same area for delivery service. The algorithm will determine optimal routes for both drones and trucks.

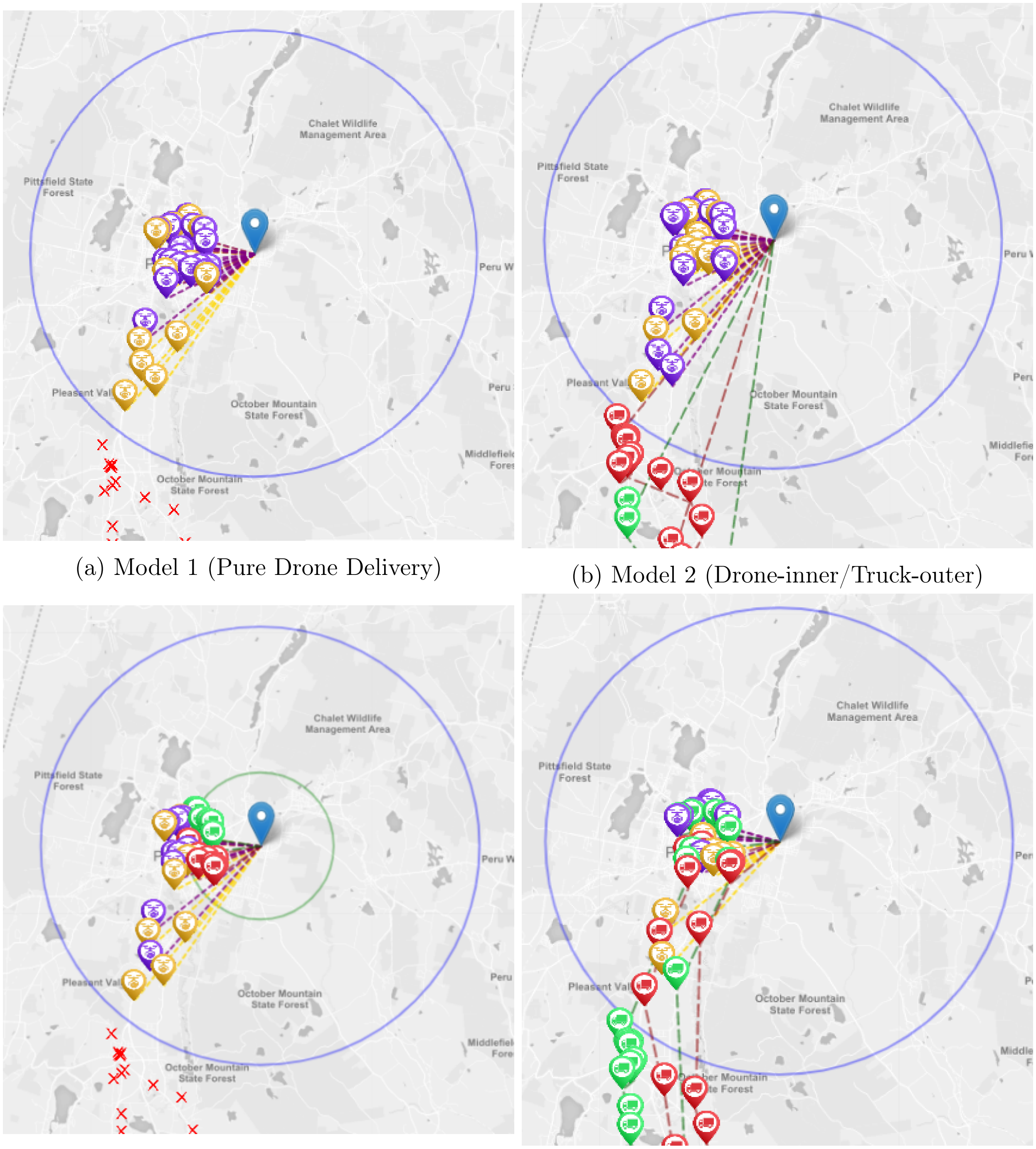
3.2 Proposed approach

In order to determine the optimal design and operational performance of different drone delivery systems, we developed an optimization algorithm to obtain optimal (or near-optimal) delivery routes for drones and trucks. In this section, we describe the problem and algorithm briefly.

3.2.1 Problem notation

We modelled our problem based on the notation shown in Table 3.1. A fleet of drones $D = \{d_1, d_2, ..., d_j\}$ and trucks $T = \{t_1, t_2, ..., t_k\}$ deliver packages to customers $C = \{c_1, c_2, ..., c_i\}$. A truck can perform multiple packages deliveries per trip, that is, the truck's capacity is large enough to serve all customers, whereas drones can deliver only one package per trip. Each customer receives one package per delivery and there is no customer delivery time window. There is only one depot, from which the fleet of drones and trucks dispatch. Truck speed, drone speed and drone flight limit are built into the model and sensitivity analyses are conducted on these parameters for understanding the effect of these on the performance of the models. Finally, a truck threshold is also defined for Model 3 (Truck-inner/Drone-outer) to determine cut-off areas between drone and truck.

The developed algorithm is able to optimize the routing problem of truck and drones with different objective functions. In this project, we seek to minimize the latest return time of all trucks or drones to the depot. This objective function is the most common objective in the literature (Murray and Chu, 2015).



(a) Model 1 (Pure Drone Delivery)

(b) Model 2 (Drone-inner/Truck-outer)

(c) Model 3 (Truck-inner/Drone-outer)

(d) Model 4 (Shared Truck-Drone)

Figure 3.2: Drone Delivery Models representation example

Table 3.1: Drone Delivery System Problem Notation

Notation	Description
i	Number of customers
j	Number of drones
k	Number of trucks
$X = \{x_1\}$	Depot
$C = \{c_1, c_2, ..., c_i\}$	Customers
$D = \{d_1, d_2, ..., d_j\}$	Drones
$T = \{t_1, t_2, ..., t_k\}$	Trucks
V_t	Truck speed
T_t	Truck threshold - for Model 3 (Truck-inner/Drone-outer)
V_d	Drone speed
D_a	Drone flight limit

3.2.2 Proposed algorithm

Drone delivery is a variant of Vehicle Routing Problem (VRP). Exact algorithms such as Branch-and-cut and Branch-and-price are available to solve for VRP as outlined by Ropke (2005). However, in last-mile delivery problems, there is a relatively high number of nodes that will expand VRP solution space exponentially which leads to intractable computation times. Hence, most algorithms for the VRP in last-mile delivery problems rely on heuristics. Heuristics do not guarantee optimal solution; however, they are able to find near optimal solutions in relatively short time with an acceptable gap.

In this project, we propose a Memetic Algorithm to optimize delivery routes of drones and trucks. Memetic Algorithm, was developed by Moscato (1999), and is a meta-heuristic approach that introduces local search to Genetic Algorithm. Genetic algorithm is a numerical optimization technique, first introduced by John Holland in 1960 and extended by his student Goldberg (1989). It is based on the concept of Darwin's theory of evolution: survival of the fittest individuals. Genetic Algorithm will perform natural selection where the fittest individuals (the most optimum solutions) are selected to produce offspring for next generation. Moscato (1999) argued that Genetic Algorithm does not consider a step of self-improvement within the cycle (only based on randomized variation). Hence Memetic

Algorithm introduces a stage of individual learning (rather than population), so a new better solution that has higher fitness can be selected, independent from the rest of the population. A Memetic Algorithm pseudocode and flowchart can be seen in Algorithm 1.

Algorithm 1: Memetic Algorithm heuristic in pseudocode.

Initialize population with random individuals;
Evaluate each individual;
repeat
    Select parents;
    Crossover pairs of parents to create offspring;
    Mutate the resulting offspring;
    Improve individuals with local search;
    Evaluate new individuals;
    Select individuals for the next generation;
until *Termination condition is satisfied*;

We selected a Memetic Algorithm to solve the drone delivery system problem because it is based on Genetic Algorithm that is quite mature and widely used in researches for Vehicle Routing Problem (VRP). Memetic Algorithms generally perform better to solve the combinatorial problem that our drone delivery system presents. This is achieved through a local search technique that reduces the likelihood of premature solution. Prins and Bouchenoua (2005) and Ngueveu et al. (2010) used Memetic algorithm to solve VRP in their research. Below we describe the terminology for a Memetic Algorithm (also illustrated in Figure 3.3):

- *Initial population.* A set of individuals at the beginning of the process is called initial population. Each individual is a solution of the problem, which in our case is a set of truck and drone routes. An individual has a set of variables known as Genes. Genes are then combined into a string (analog to a DNA sequence) to form a Chromosome that represents an individual (solution).

- *Fitness function.* The fitness function determines how good a solution is. In this step, Memetic Algorithm calculates a fitness score to each potential solution based on a predefined objective function (e.g. duration in minutes until the latest vehicle return

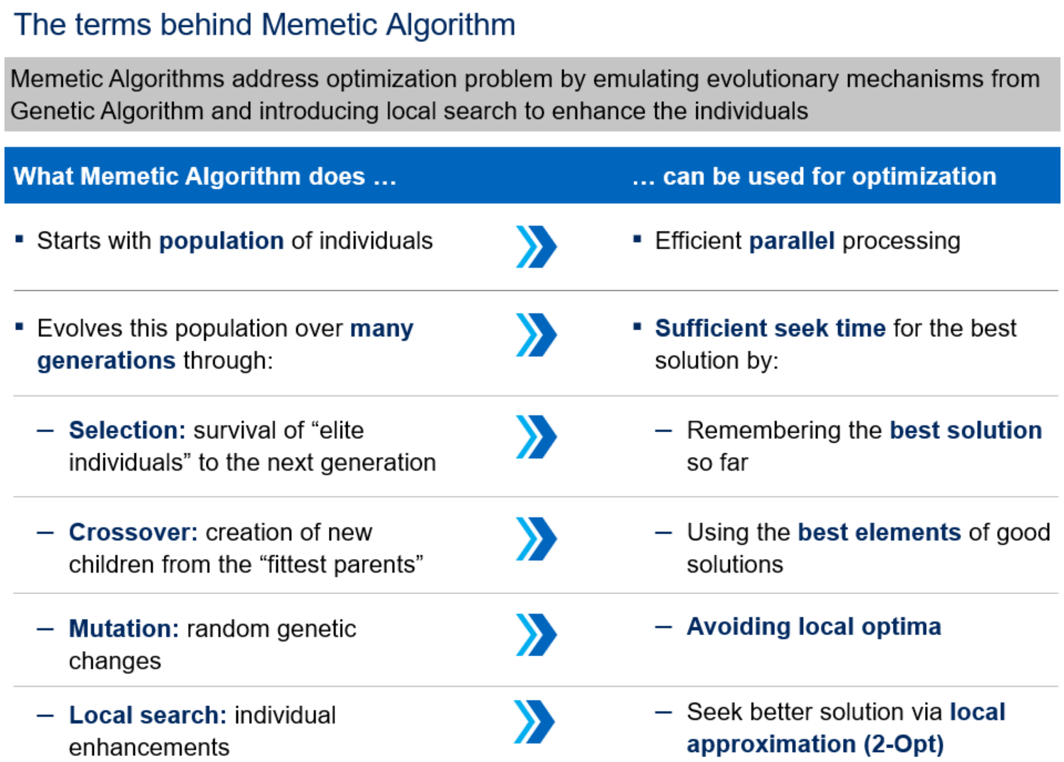


Figure 3.3: **Memetic Algorithm terms and their relation to optimization**

to depot). The probability of that solution surviving into the future generations is based on its fitness score.

- *Selection*. Selection will select the fittest solutions to pass their genes to the next generation of population. Multiple parents are selected based on their fitness scores and the higher solutions fitness scores are, the higher chance to be selected for reproduction.

- *Crossover*. Crossover is a process to split and combine the parents' genes to create offspring for the next generation.

- *Mutation*. Mutation is a process to change some of the genes. Mutation probability is very low and it exists to sustain the diversity of the population

- *Local Search*. Local search is a technique to enhance performance of the algorithm by building local approximation to capture local behavior. In our model, we will use 2-opt local search to find and fix routes that cross each other.

4 Proposed solution

This chapter outlines the solution and implementation of Memetic Algorithm to find optimum route for drone delivery system.

4.1 Initialization

The first step of a Memetic Algorithm is to initialize the population. A population is a set of individual solutions that represent the routing of the vehicles (trucks/drones) to customers (Figure 4.1). Each route is a chromosome and is represented as a list of customers (genes) that is grouped based on vehicles (trucks/drones) and this solution is encapsulated in a class Schedule with list variables (truck_schedules and drone_schedules). The pseudocode of this step is shown in Algorithm 2.

During the first initialization, the algorithm separates customers into drone and truck assignments. For the customers assigned to truck, the algorithm applies K-means clustering to build cluster of customers and assign each cluster to each truck. The number of cluster (K) is determined based on number of trucks. For the remaining drone customers, the algorithm then sorts the customers by distance and assigns successively to each vehicle to have an even distribution (e.g. farthest customer assigned to drone 1, second farthest customer assigned to drone 2 and so on).

The rest of solutions will be generated based on the population size parameter (population_size) using random mutation of the initial individual solution. For example, if the population size is 40, then the algorithm will clone the best solution as the first element of population and mutate this best solution to generate 39 other solutions to be included in the initial population.

	Vehicle	Solution
List of Drones	Drone 1	[Customer 3, Customer 7]
	Drone 2	[Customer 2, Customer 4, Customer 8]
List of Trucks	Truck 1	[Customer 5, Customer 1]
	Truck 2	[Customer 9, Customer 10]

Figure 4.1: **Solution representation example**

Algorithm 2: Initialize in pseudocode.

Inputs: C_i (Customer nodes), D_1 (Depot position)
Build *distance matrix* for all customers
Generate first routing/schedule based on minimum completion time (or based on sorting of customers distance and k-means clustering for first generation)
Clone the first/routing schedule (best solution) to *new_population* (at index 0)
Generate the rest of initial population from random mutation of best solution
for $p \leftarrow 1$ **to** *population_size*-1 **do**
    Mutate best solution
end
return *new_population*

4.2 Selection

The second step of Memetic Algorithm is to (randomly) select individuals for reproduction and add children to the population (Algorithm 3). The parameter to determine reproduction probability is reproduce_probability and this algorithm is using 80% probability rate. If the population size is 40, the algorithm will generate 32 additional solutions to the population. Before adding these solutions to the population, the algorithm will perform cross over between the solutions as explained in next chapter.

4.3 Crossover

During crossover, the algorithm performs the reproduction of additional solutions before adding them into the population. Cross-over or recombination is a function to (re)arrange genes in the chromosome of two parents to generate new children (Algorithm 4).

Algorithm 3: Selection.

for $p = 1$ **to** *reproduce_probability * population_size* **do**
  Assign individual to *fertile_list*
end
Shuffle $fertile\_list$
for $f = 1$ **to** *len(fertile_list)* **do**
  Perform crossover between $fertile\_list_i$ and $fertile\_list_{i+1}$
  Add $fertile\_list_i$ and $fertile\_list_{i+1}$ to the *population*
  $f = f + 2$
end

The cross-over or recombination function switches a number of genes between the two parents based on reproduce_segment_size parameter. That is, we rearrange customers assigned to a particular vehicle (truck or drone) to another vehicle, respecting the flight time constraints. In this case, the parameter is set to 3. Example of the cross-over function is illustrated in Figure 4.2.

Algorithm 4: Crossover.

for $r = 1$ **to** *reproduce_segment_size in Parent 1 chromosome* **do**
  Assign individuals for cross-over operation
end
for $r = 1$ **to** *reproduce_segment_size in Parent 2 chromosome* **do**
  Assign individuals for cross-over operation
end
Perform cross-over operation
Return new chromosomes as children

4.4 Mutation

After reproduction and cross-over of new population, the algorithm is going to perform mutation to random chromosomes in the population (Algorithm 5). All chromosomes, both parents and children, have same probability to be mutated, however the first chromosome – which is the best solution – is not going to be mutated. Probability of mutation is set by parameter mutation_probability and it is currently set at 15%

Mutation algorithm will pick-up randomly a particular customer from a particular vehicle

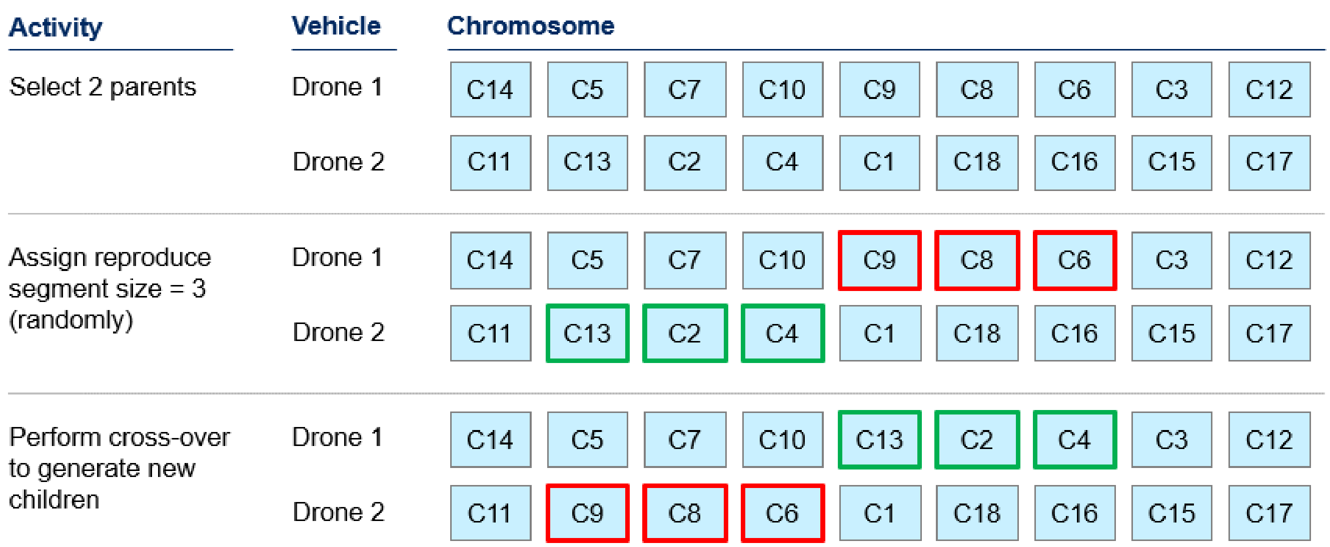


Figure 4.2: **Crossover example**

route and insert it to other random vehicle of the solution, respecting flight limit restrictions (i.e. a customer out of the drone range, cannot be mutated into a drone route). Example of mutation is illustrated in Figure 4.3.

Algorithm 5: Mutation.

for $individual = 1$ **to** $population\_size$ **do**
  if $individual \neq best\_solution$ **then**
    if $random\_probability < mutation\_probability$ **then**
      Perform mutation operation;
end

4.5 Local search

Local search 2-opt is implemented in memetic algorithms to optimize the solution by rearranging a section of nodes in a route that crosses itself as per Figure 4.4. Pseudocode of local search 2-opt is shown in Algorithm 6.

4.6 Termination

The algorithm will terminate based on two main conditions:

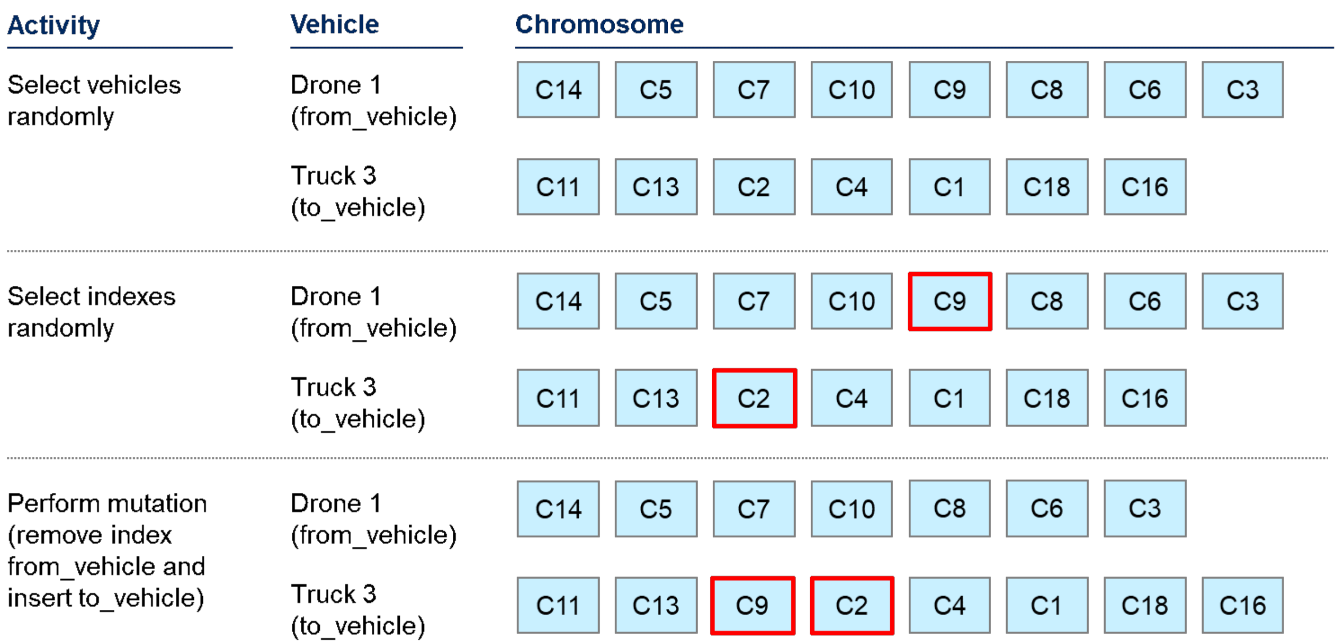


Figure 4.3: **Mutation example**

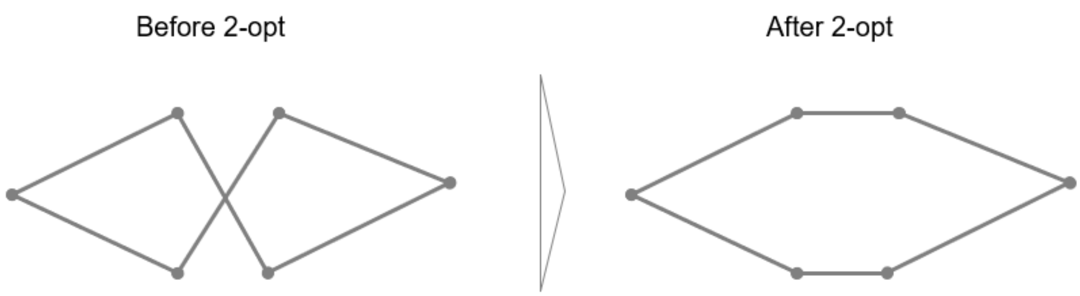


Figure 4.4: **2 opt illustration**

1. Condition 1: no improvement in the population for a certain amount of iterations determined in parameter exit_condition, for example 200.

2. Condition 2: number of generations has been achieved as per parameter generation_size

Algorithm 6: Local search 2-Opt.

Inputs: Route, i, k
for 0 **to** $i-1$ **do**
    $New\_Route_i = Route_i$
end
for i **to** k **do**
    $Temp\_Route_i = Route_i$
end
Reverse $Temp\_Route$
Append $Temp\_Route$ to New_Route
for $k+1$ **to** *len(Route)* **do**
    $New\_Route_i = Route_i$
end

5 Result

This section outlines the results of our experiments and is organized into four sub-chapters. In Section 5.1, we introduce algorithm parameters tuning to identify best parameters for Memetic algorithm. Then, in Section 5.2, we test this algorithm to solve for Travelling Salesman Problem (TSP) with known solution. We want to identify the gap of our solution to the optimum solution. In Section 5.3, we run the algorithm across different drone delivery models to gain insights of different drone delivery model. Finally, in Section 5.4, we conducted sensitivity analysis for different operating parameters such as number of trucks/drones, drone speed, etc.

We use real-life problem instances to test our algorithm. We deploy drone delivery system program on Google Cloud Platform, utilizing most basic computation offered by Google's infrastructure: single core CPU setting with 3.75 GHz memory (Figure 5.1).

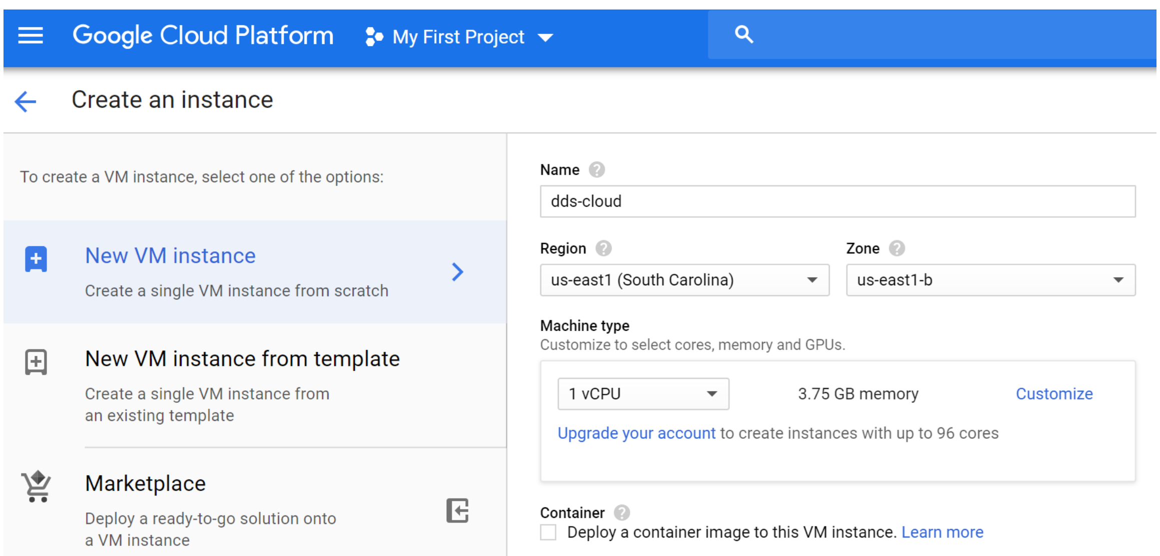


Figure 5.1: **Setting of Google Cloud Platform for DDS cloud**

5.1 Algorithm parameters tuning

In order to obtain the best performance of the algorithm, we conducted tuning of the algorithm parameters. We selected six parameters and started experimenting with base values for each parameter. The baseline values are number of generations: 1000, population size: 40, elite size 10% of population, reproduce rate of 80%, 2-opt percentage of 40% and mutation rate of 15%. Then for tuning, we considered 2 different values for each parameter and performed 10 runs for each parameter value against real-life last-mile delivery data from West Massachusetts. This data contains 50 customers locations in the form of latitude and longitude. The algorithm will determine the duration to serve all these customers, measured in the last vehicle return time to the depot in minutes.

The results of parameter tuning are as follow and more detailed results are available in Appendix A:

1. *Number of generations* (Figure A.1): With 1000 generations as baseline, our average solution is 148.28 minutes - whereas 800 generations and 1200 generations result in 144.93 minutes and 145.03 minutes, respectively.

2. *Population size* (Figure A.2): Typical population size for the algorithm is 30-60 and we set our baseline parameter at 40. Based on the analysis performed, 60 population size yielded better result in term of average, as well as range of the obtained solutions.

3. *Elite size* (Figure A.3): Baseline parameter for elite size is 20 % from the population size. This parameter produced better results with less variance compared to elite size of 10% and 5%.

4. *Reproduce rate or Crossover probability* (Figure A.4): Crossover probability is set to 80% as baseline value - producing average solution of 148.28 minutes. The results of 80% probability are compared with 65% and 95% respectively, both have similar average solution of 144.00 minutes and 144.32 minutes. Crossover probability of 65% yielded more results with less variance.

5. *2-Opt percentage* (Figure 4.4): 2-Opt analysis demonstrated that percentage of 2-Opt correlated with the optimum results of the solutions. Reducing 2-Opt from 40% to

30% increased average solution by around 1 minute. Increasing 2-Opt to 50% reduced average solution by around 6 minutes.

6. *Mutation rate* (Figure A.6): Analysis is done for mutation rate of 5%, 15% and 25%. The results of various mutation rate are relatively similar, hence baseline parameter of 15% for mutation rate will be used.

In total, we conducted 130 runs and obtained the median, minimum, and maximum result for each parameter tuning. These results are plotted into box-whisker graph (Figure 5.2). Based on the analyses, the algorithm parameters are selected as follow: number of generations (800), population size (60), elite size (20%), reproduce rate (65%), 2-opt percentage (50%) and mutation rate (15%).

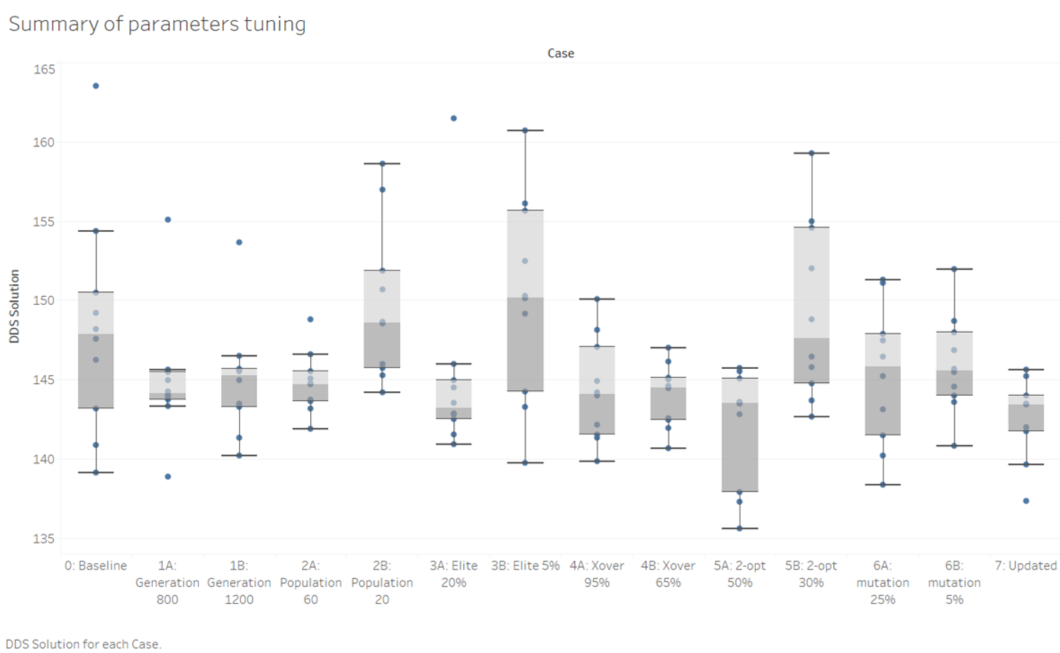


Figure 5.2: **Parameter tuning - Summary**

5.2 Algorithm performance evaluation

After setting up the parameters, we tested our algorithms to benchmark against problem instance "eil51" for the Travelling Salesman Problem (TSP) that is commonly used in routing

Table 5.1: DDS solution results of 30 runs for eil51 TSP

DDS solution for TSP-51	
Mean	441.8223333
Standard Error	0.991856576
Median	441.445
Mode	#N/A
Standard Deviation	5.432622205
Sample Variance	29.51338402
Kurtosis	-0.010357619
Skewness	0.074425423
Range	23.96
Minimum	430.24
Maximum	454.2
Sum	13254.67
Count	30
Confidence Level(95.0%)	2.02857447

research. *eil51* is a 51-city TSP problem developed by Christofides and Eilon (1969), it has a single depot and 50 customers located in Eucledian plane with optimum routing solution of 426.

We tested our algorithm by setting up the operating parameters to only have a single truck without any drones. We conducted 30 runs in order to have statistically significant data and the results of this testing can be seen in Table 5.1.

Average result of our algorithm is 441.82 - which has 3.7% gap with optimum solution of 426. Considering that the algorithm is set to solve vehicle routing problem, the result shows that the algorithm is quite robust to solve TSP. All the results of the runs are also plotted in a box-whisker plot as can be seen in Figure 5.3.

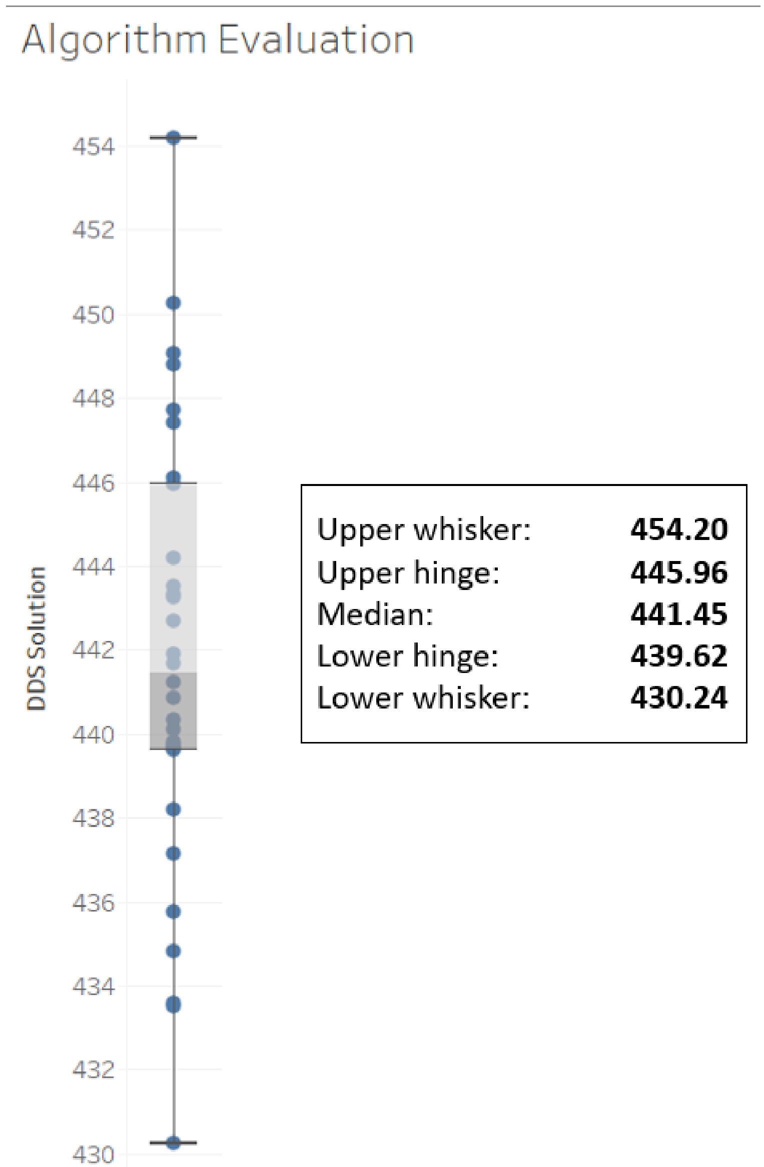


Figure 5.3: **Evaluation results of Memetic Algorithm on problem instance "eil51" for a Traveling Salesman Problem**

5.3 Analysis of drone delivery model

As outlined in previous chapter (Figure 3.1), we developed four different drone delivery models:

1. *Pure drone delivery*: drones will serve all customers

2. *Drone-inner/Truck-outer*: drones will serve customers closer from the depot and truck serve customers farther from the depot

3. *Truck-inner/Drone-outer*: trucks will serve customers closer from the depot and drones serve customers farther from the depot

4. *Shared Truck-Drone*: trucks or drones can serve any customers

In this section, we use our algorithm to solve our four models on six problem instances. Each of these problems has 100 customers with different locations detailed in Appendix B (Figure B.1 to B.6). The customer locations are from a real case study from a major package delivery company in the state of Massachusetts, USA. Baseline operating parameters that we use are 2 drones (flight speed of 45 km/h and flight limit of 30 mins) and 2 trucks (truck speed of 30 km/h).

The result of the analysis is shown in Figure 5.4. The bar chart at the top is last return time to depot (minimum tour time) in minutes. There are 6 bar-charts representing 6 problem instances for each of the four drone delivery models. Correspondingly, the line chart at the bottom shows the number of customers not served for that particular problem instance and drone delivery model. We can derive insights as follow from our analysis:

- Model 1 (pure drone delivery) and model 3 (truck-inner/drone-outer) did not manage to serve all the 100 customers in each of the 6 problem instances due to drone flight limit. These models performed relatively acceptable in problem instance 4, where we have most customers located near the depot

- Model 2 (drone-inner/truck-outer) and model 4 (shared truck-drone) managed to serve all the customers in all the 6 problem instances, indicating that these models are more adaptable for different scenarios.

- Model 4 (shared truck-drone) was expected to yield the most optimum result because there is no restriction as to which customer is served by truck/drone. The result of model 4 performed especially well in problem instance 3 and 4 where model 4 only needed 1/3 to 1/5 of time required by model 2 to serve all customers.

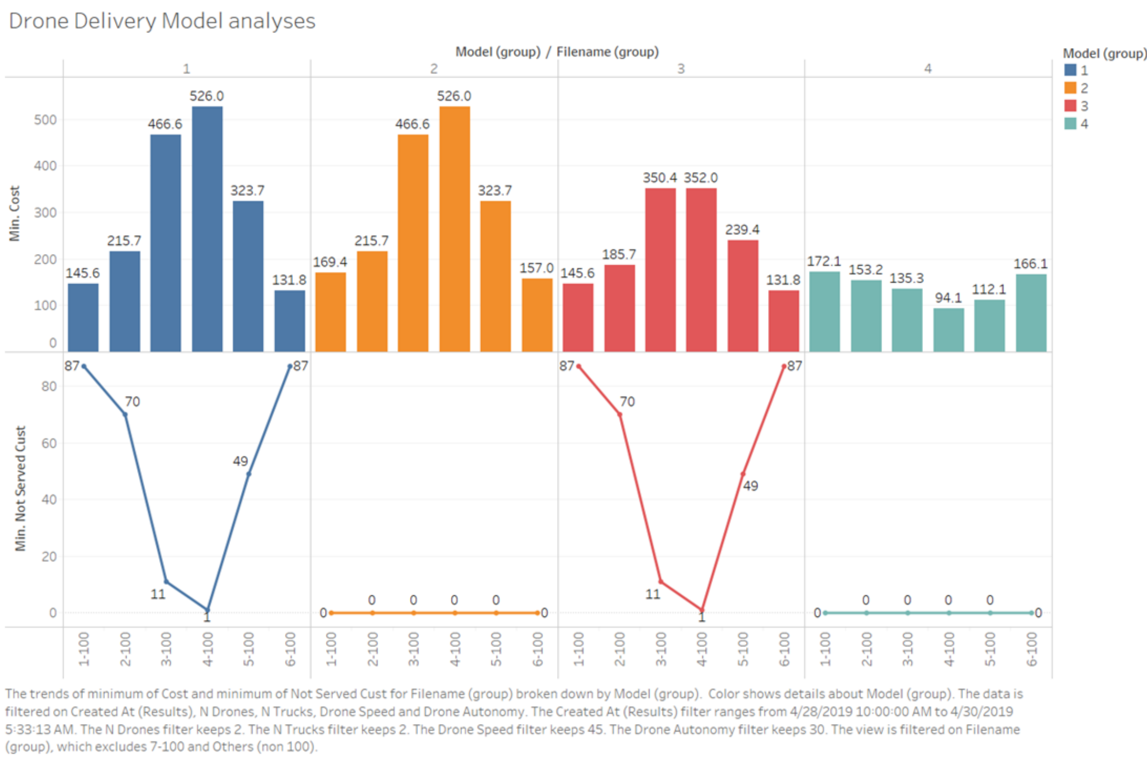


Figure 5.4: **Summary of drone delivery model performance**

5.4 Effect of operating parameters

In this section, we conducted a comprehensive sensitivity analysis for different operating parameters: number of trucks, number of drones, drones speed and flight limit. By conducting this analysis, we hope to provide insights to decision makers to understand the sensitivity of each the proposed models to each parameter for better design of their drones delivery systems.

We ran these various operating parameters against real-life last-mile delivery data of 100 customers (problem instance 2) for the four drone delivery models. The operating parameters used for sensitivity analysis and the insights are described below:

1. *Number of trucks* (Figure 5.5): Sensitivity analysis is done with number of trucks 1, 2 and 3. Number of trucks has obviously no impact to Model 1 (pure drone delivery) because there is no truck in this model. There is also no impact in Model 2 (drone-inner/truck-outer) and Model 3 (truck-inner/drone-outer) because the drone is the bottleneck in both models. Model 3 also has 70 unserved customers due to drone flight range limitation. Increasing number of trucks from 1 to 2 has the most positive impact in Model 4, reducing time required to serve all customers by around 32 minutes (17% time reduction). Further increasing the number of trucks to 3 also reduces time by 12 minutes (9% time reduction).

2. *Number of drones* (Figure 5.6): We also conducted experiments with 1, 2 and 3 drones. Increasing the number of drones has a similar positive impact in Model 1 (pure drone delivery) and Model 3 (truck-inner/drone-outer) because we reach the customers faster with more drones. However in both these models, the unserved customers stay the same at 70 customers because the range of the drone is still limited. In Model 2 (drone-inner/truck-outer), we can see a positive impact as increasing number of drones from 1 to 2 reduces minimum tour time by 50% (from 431.5 minutes to 215.7 minutes) and further increasing number of drones to 3 reduces time by 29% (from 215.7 minutes to

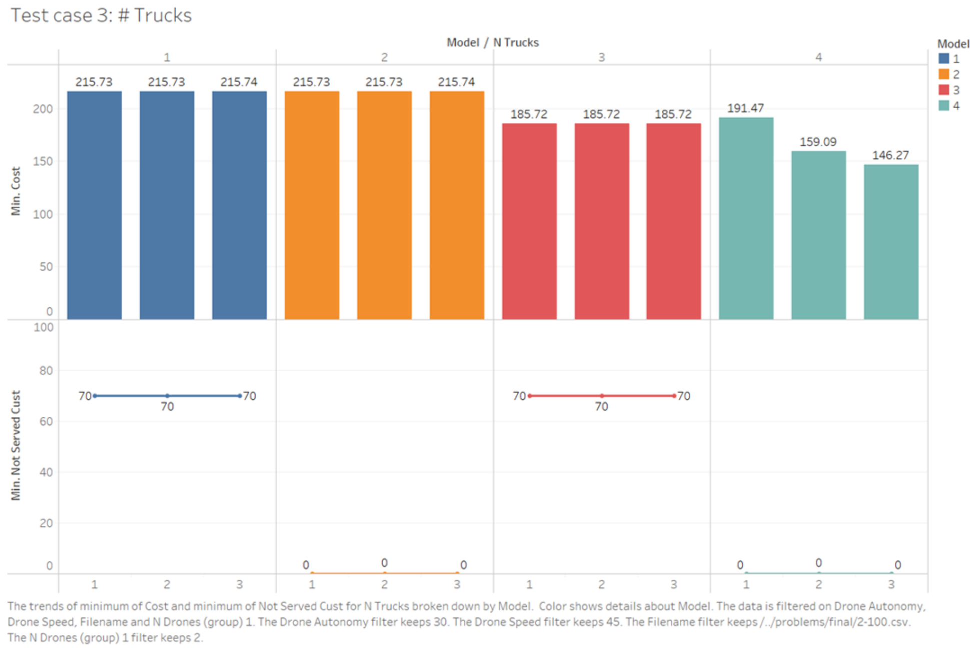


Figure 5.5: **S**ensitivity analysis for number of trucks

154.2 minutes). We don't see any major improvement for Model 4 (shared truck-drone) because the bottleneck is mainly with the truck.

3. *Drone speed* (Figure 5.7): We performed experiments with drone speed of 30 km/h, 45 km/h and 60 km/h. Increasing drone speed has visible impact to Model 1 (pure drone delivery) and Model 3 (truck-inner/drone-outer), reducing the number of unserved customers due to farther drone range. However, an increase in speed is not enough as with 60 km/h, we still have 64 unserved customers (out of 100 customers). In Model 2 (drone-inner/truck-outer), increasing drone speed has an adverse effect because the drone starts to take customers originally assigned for the truck, resulting in longer minimum tour time. In Model 4 (shared truck-drone), increasing drone speed from 45 km/h to 60 km/h reduces time required from 159 minutes to 154 minutes (around 4% improvement).

4. *Drone flight limit* (Figure 5.8): Finally, we also tested with drone flight limit of 30 minutes and 60 minutes. Doubling drones flight limit from 30 minutes to 60 minutes

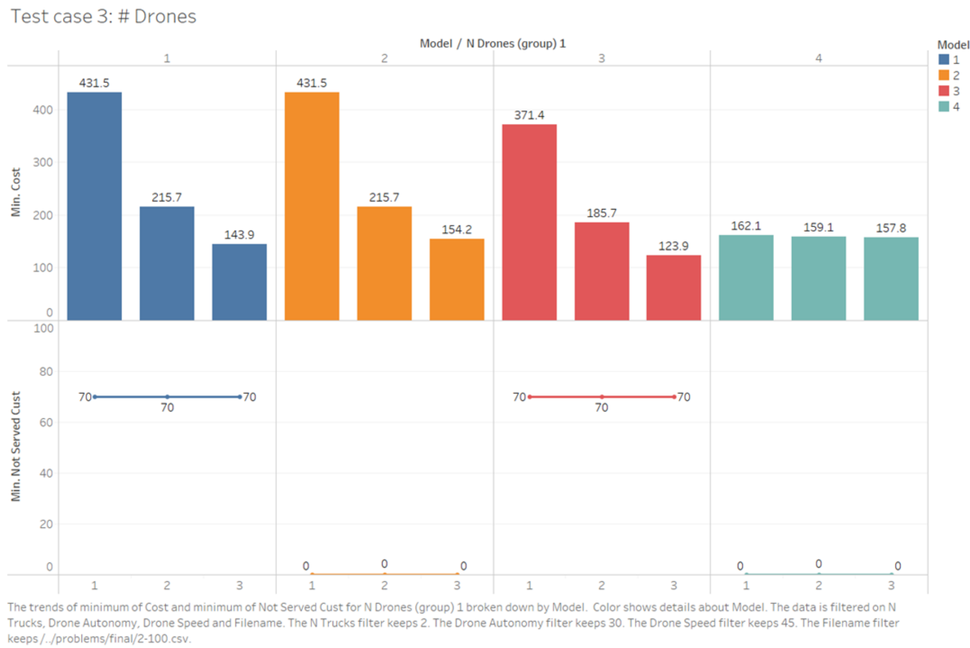


Figure 5.6: **Sensitivity analysis for number of drones**

expands drones area of service, hence it has positive impact to Model 1 (pure drone delivery) and Model 3 (truck-inner/drone-outer), reducing the number of unserved customers to 61 customers. Similar to drone speed sensitivity analysis, increasing drone flight limit has negative effect to minimum tour time in Model 2 (drone-inner/truck-outer) because drones are starting to serve farther customers, taking up customers originally assigned by trucks. Drone is not as efficient as truck for longer distances, as it needs to make return trip every time it delivers a package to a customer, creating a sub-optimal solution. Finally in Model 4 (shared truck-drone), there is no impact because the bottleneck is with the truck.

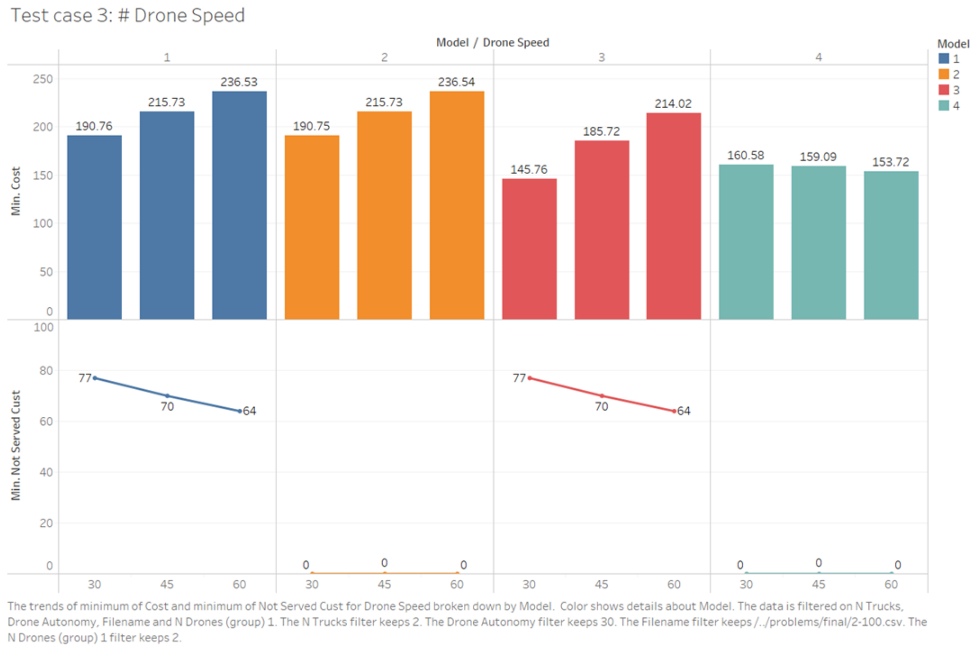


Figure 5.7: **Sensitivity analysis for drone speed**

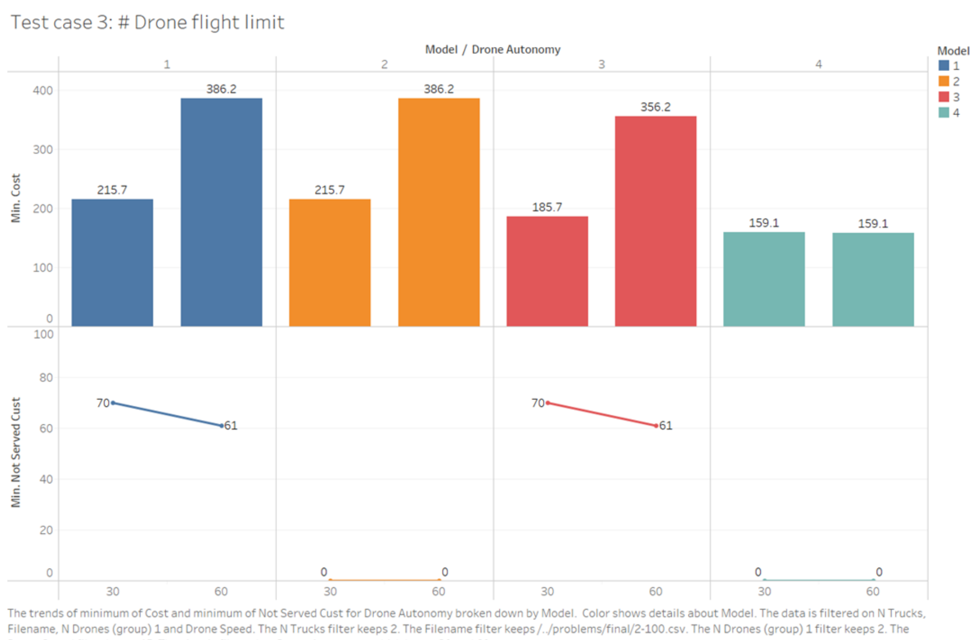


Figure 5.8: **Sensitivity analysis for drone flight limit**

6 Conclusions

In our research, we evaluated the optimal design and operational performance of four different drone delivery models (pure drone, drone-inner/truck-outer, truck-inner/drone-outer and shared area). We proposed a Memetic Algorithm to optimize delivery routes for drones and trucks with objective function to minimize latest return time of all vehicles to the depot. We developed a software package to evaluate drone delivery models. This software package is deployed on the cloud and can be accessed by any web browser. Interface and solutions of the software package are elaborated in Appendix E.

The algorithm is tested to solve eil51 Travelling Salesman Problem (TSP) and it produces robust result, averaging only 3.7% gap from the optimum solution. Analysis for different drone delivery model also shows that Model 2 (drone-inner/truck-outer) performs better than Model 3 (truck-inner/drone-outer) because Model 3 restricts drones from serving customers at farther areas, limiting total number of customers that can be served. In various problem instances with 100 customers that we tested, we also observed that Model 4 (shared truck-drone) performs the best with up to around 80% reduction in return time to depot compared to Model 2 (drone-inner/truck-outer). Sensitivity analyses to various operating parameters also yields several interesting insights. Increasing drone speed and flight time limit has adverse impact for Model 2 (drone-inner/truck-outer) because more customers at farther distances are assigned to drones instead of trucks. Therefore, we can conclude that trucks are more suitable to serve farther customers since drones are limited to deliver one package per trip. We also found that increasing number of trucks (from 2 to 3) and drone speed (from 30 km/h to 45 km/h) has positive impact to the best model, Model 4 (shared truck-drone) as it reduces minimum tour time by 8% and 3%, respectively.

Finally, we also conducted the analysis to understand the impact of introducing drones to pure truck delivery system. We found that adding 2 drones in the pure truck delivery system can reduce minimum tour time by 1 to 11%, as per Figure 6.1.

For future research areas, in order to make more holistic review of drone delivery system,

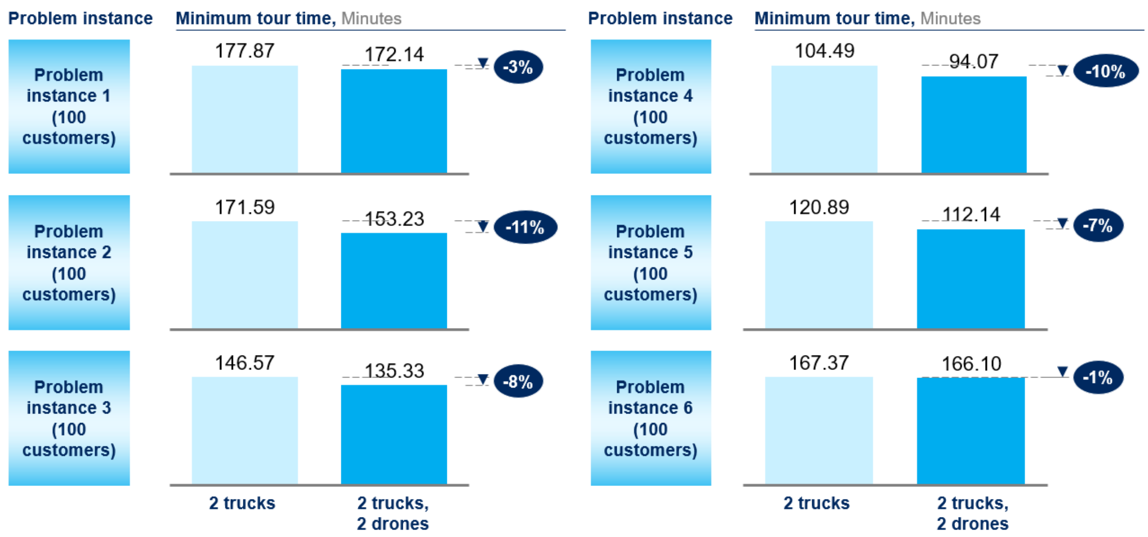


Figure 6.1: **Introducing drones to traditional truck-only delivery system reduces minimum tour time by 1 to 11% in various problem instances**

we can take into accounts vehicle capacity. Our research assumed uncapacitated truck and single package capacity for drone. In real life, the truck has space limitation in the amount of packages it carries. Drone even has more limitation in the packages it can carry (e.g. limited by weight, dimension or package type). Another extension of this research is to consider different customers' delivery windows. This constraint should be incorporated into the model, and the algorithm has to be able to optimally conduct vehicle assignment to deliver all packages within specific customers delivery window.

A Appendix A: Parameters tuning results

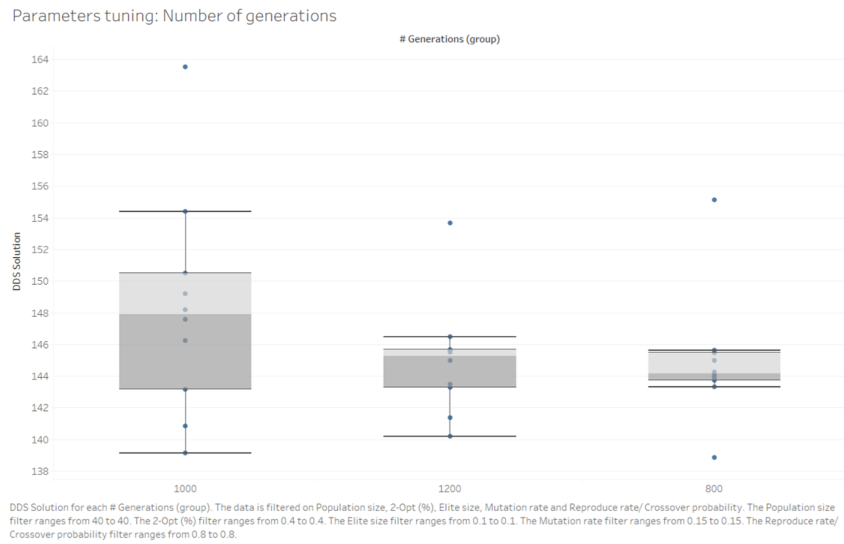


Figure A.1: **Parameter tuning - Number of generations**

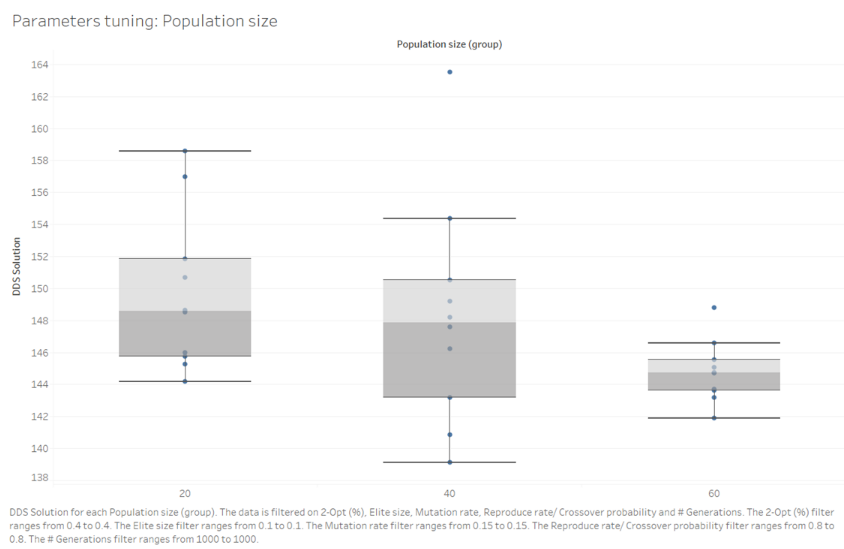


Figure A.2: **Parameter tuning - Population size**

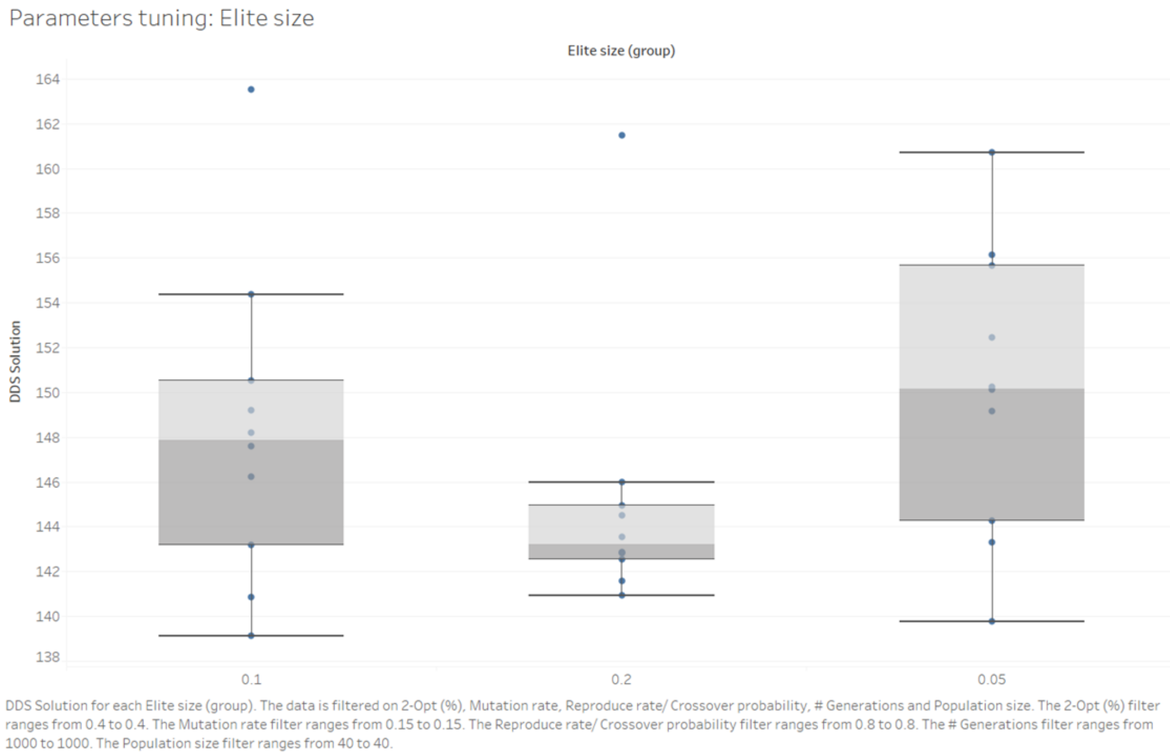


Figure A.3: **Parameter tuning - Elite size as percentage of population**

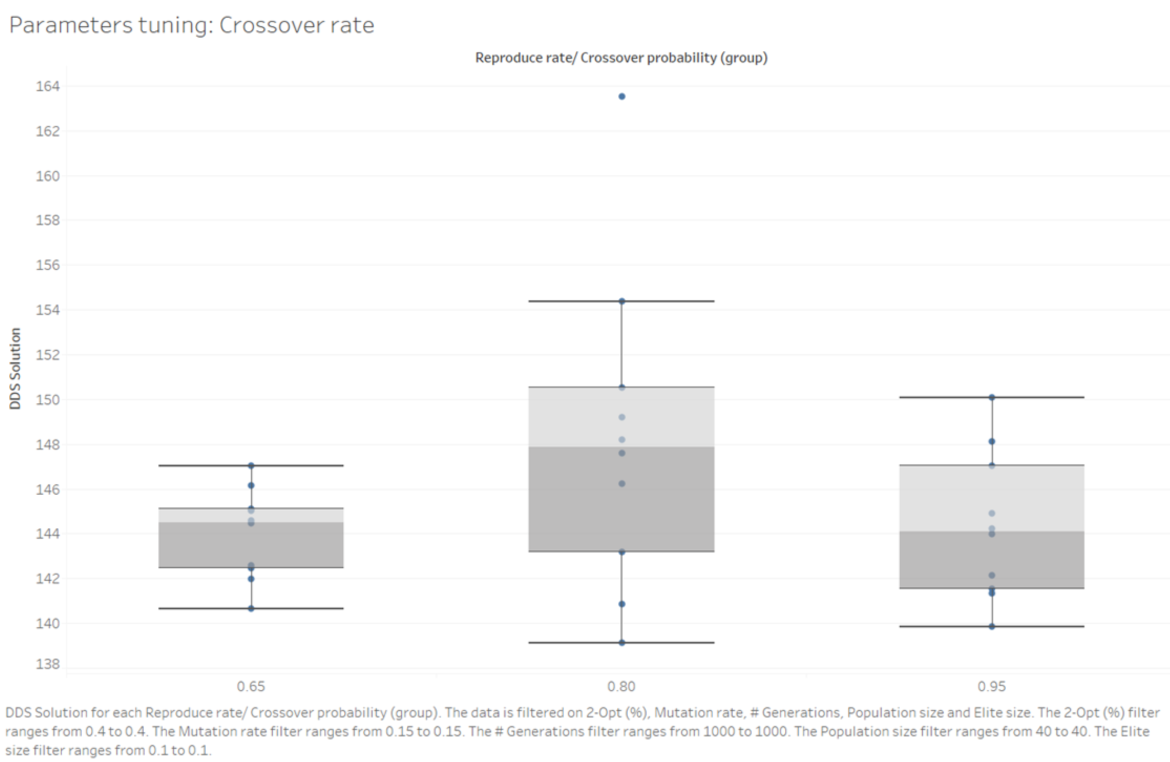


Figure A.4: **Parameter tuning - Reproduce rate or crossover probability**

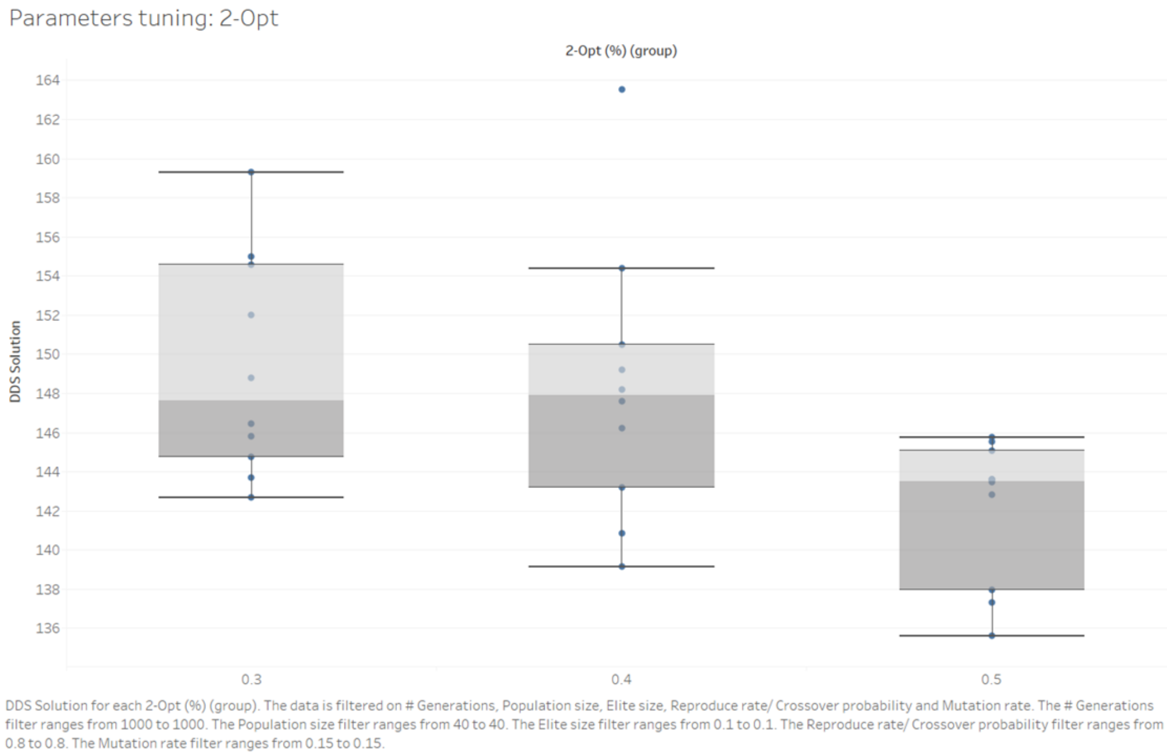


Figure A.5: **Parameter tuning - 2-Opt percentage**

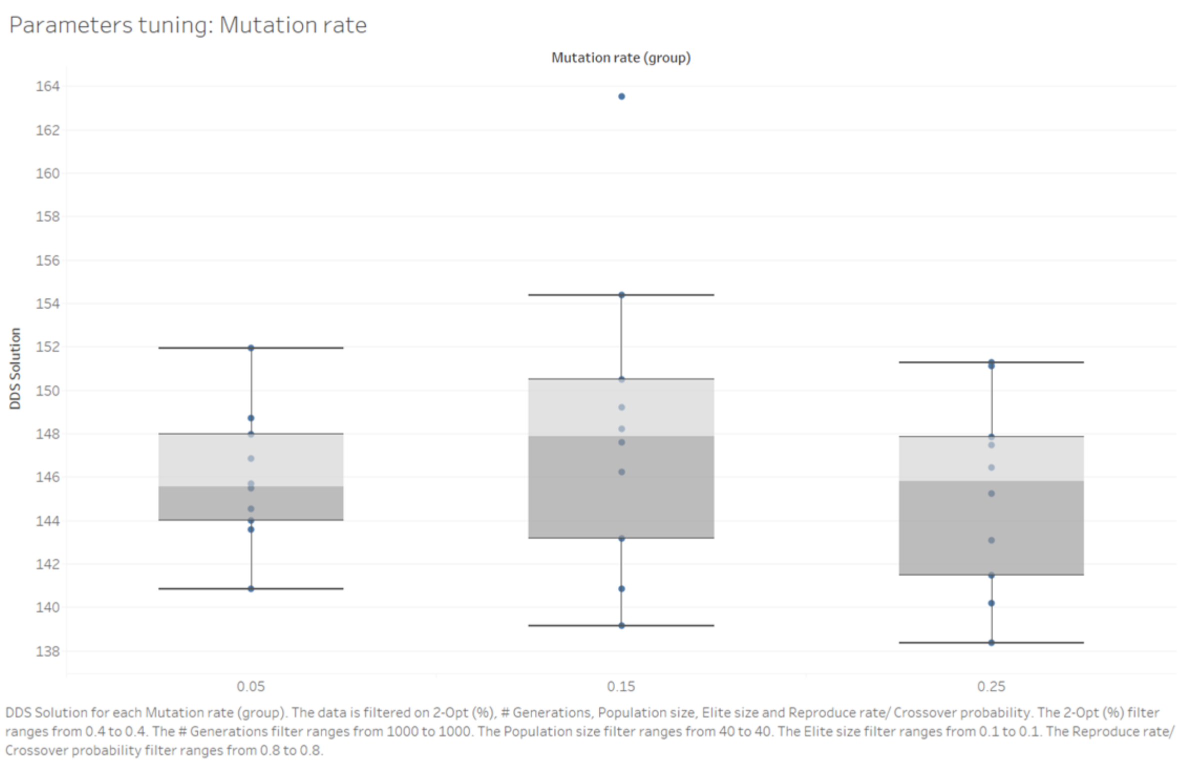


Figure A.6: **Parameter tuning - Mutation rate**

B Appendix B: Problem instances

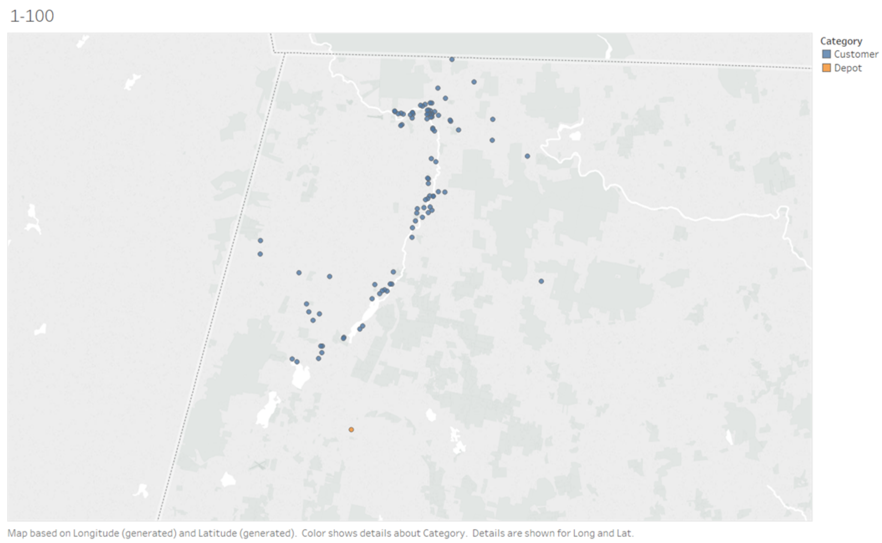


Figure B.1: **Problem instance 1 (100 customers)**

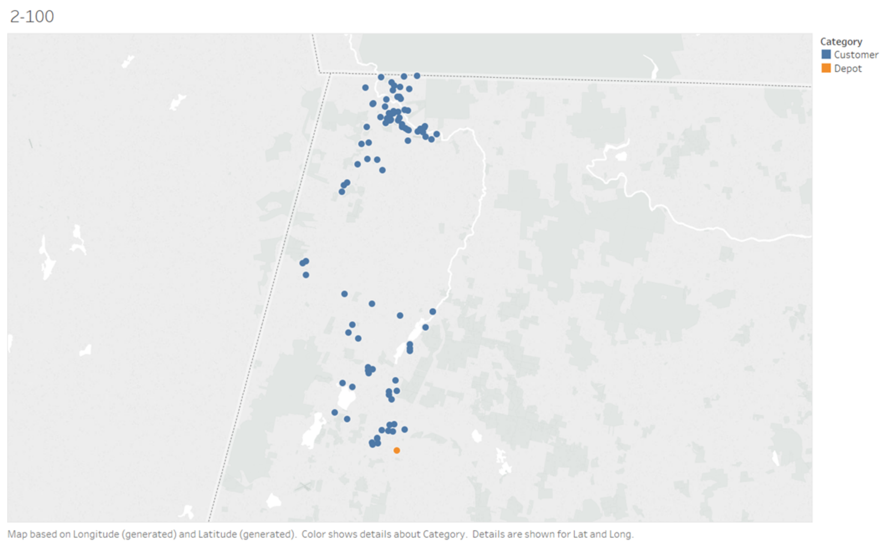
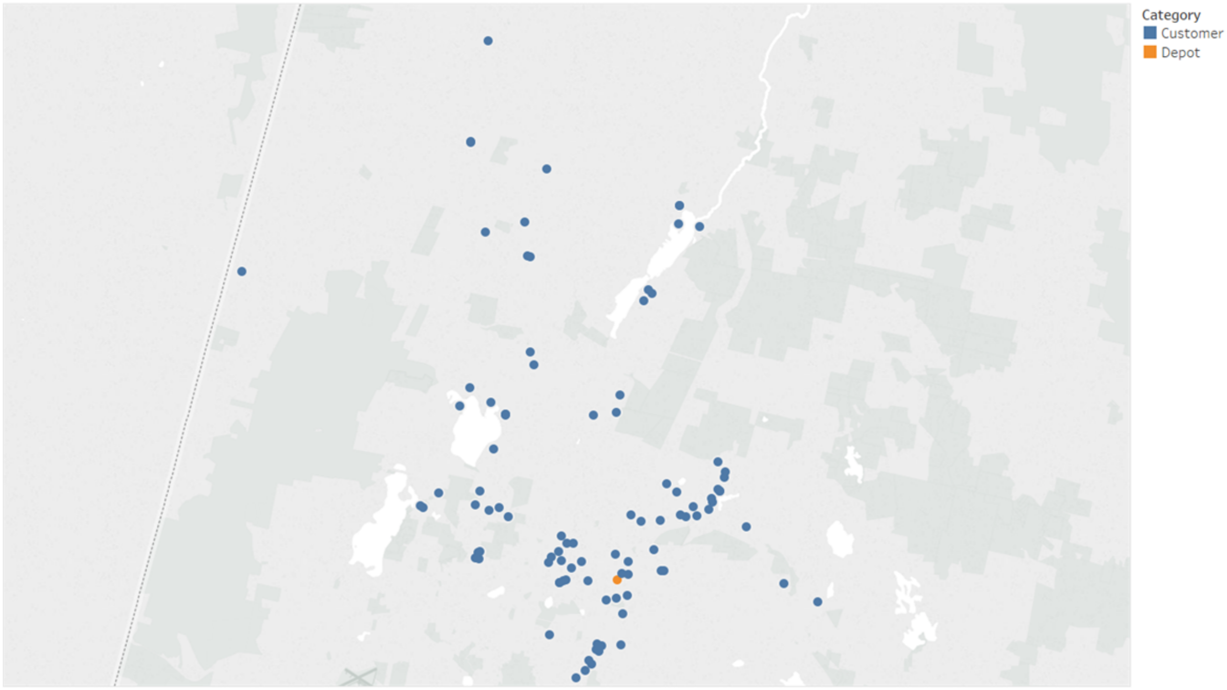


Figure B.2: **Problem instance 2 (100 customers)**

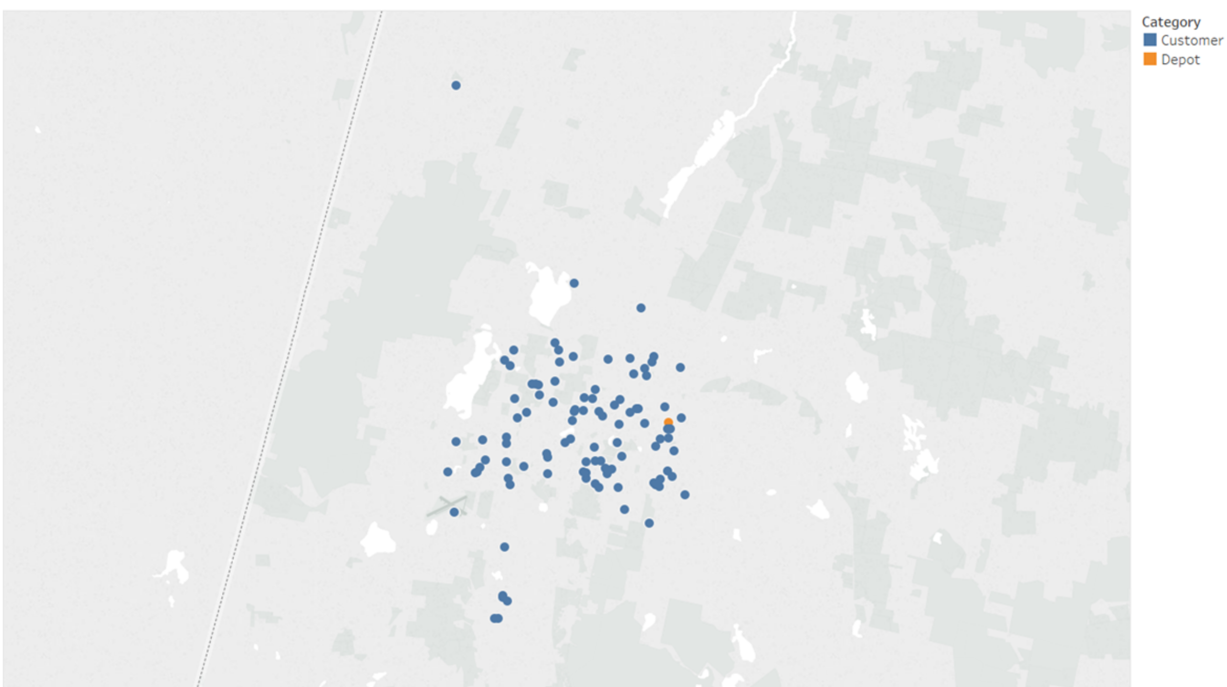
3-100



Map based on Longitude (generated) and Latitude (generated). Color shows details about Category. Details are shown for Long and Lat.

Figure B.3: **Problem instance 3 (100 customers)**

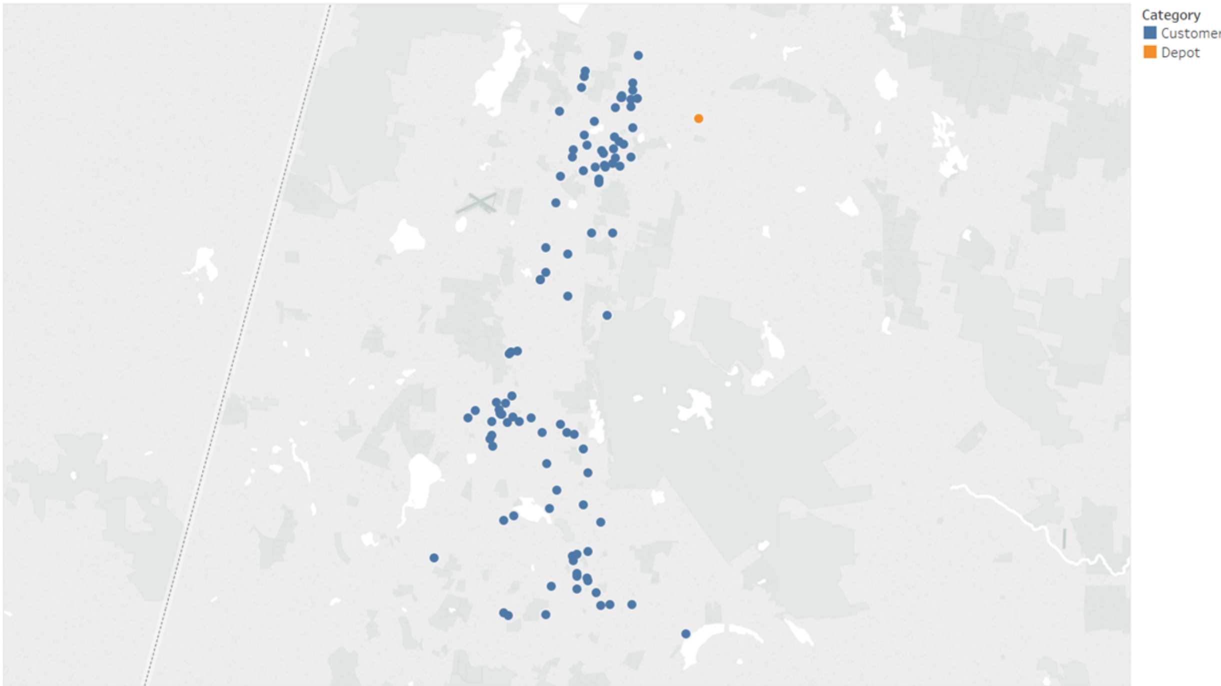
4-100



Map based on Longitude (generated) and Latitude (generated). Color shows details about Category. Details are shown for Long and Lat.

Figure B.4: **Problem instance 4 (100 customers)**

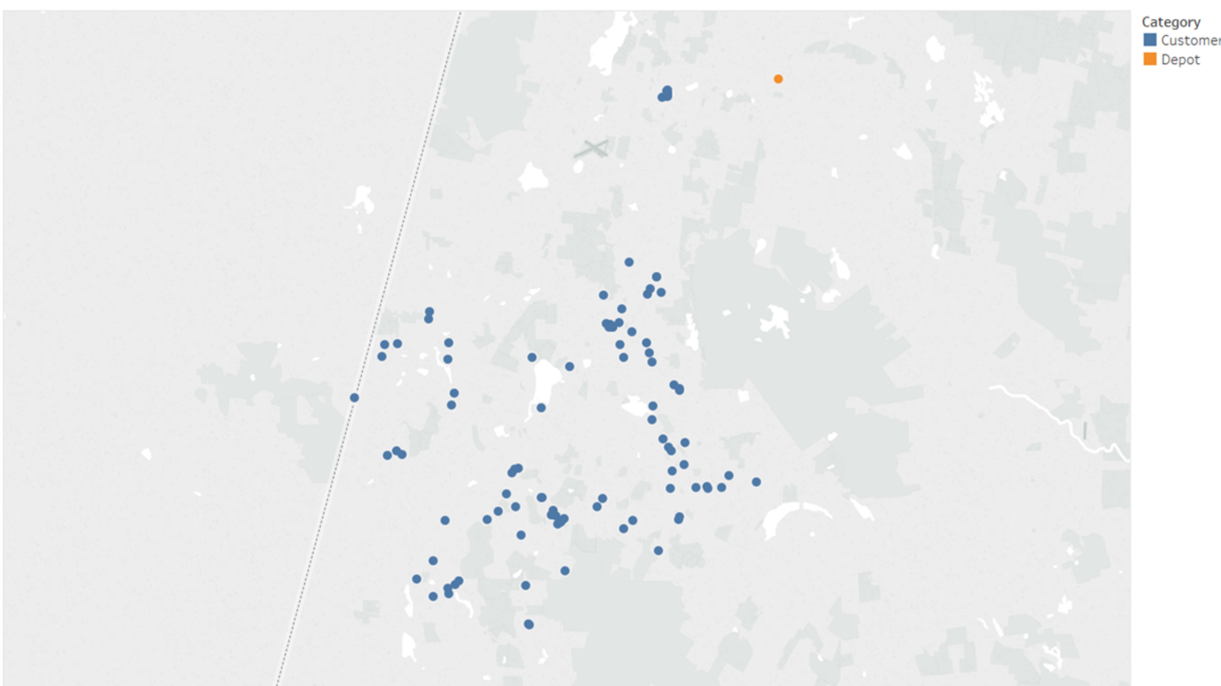
5-100



Map based on Longitude (generated) and Latitude (generated). Color shows details about Category. Details are shown for Lat and Long.

Figure B.5: **Problem instance 5 (100 customers)**

6-100



Map based on Longitude (generated) and Latitude (generated). Color shows details about Category. Details are shown for Lat and Long.

Figure B.6: **Problem instance 6 (100 customers)**

C Appendix C: Raw data of drone delivery model analysis

Problem instance	Model	DDS Solution	Timing to reach solution (seconds)	Customers not served	Generations reached
Final-1-50	1: pure drone	105.75	4.16	41	256
Final-1-50	1: pure drone	105.75	4.86	41	301
Final-1-50	1: pure drone	105.75	4.81	41	293
Final-1-50	1: pure drone	105.75	3.67	41	226
Final-1-50	1: pure drone	105.75	4.09	41	256
Final-1-50	2: drone-inner/truck-outer	145.21	26.62	-	363
Final-1-50	2: drone-inner/truck-outer	139.62	39.27	-	643
Final-1-50	2: drone-inner/truck-outer	141.75	46.26	-	749
Final-1-50	2: drone-inner/truck-outer	137.33	43.26	-	695
Final-1-50	2: drone-inner/truck-outer	143.50	39.59	-	534
Final-1-50	2: drone-inner/truck-outer	145.64	42.28	-	626
Final-1-50	2: drone-inner/truck-outer	143.99	33.49	-	501
Final-1-50	2: drone-inner/truck-outer	141.75	27.34	-	413
Final-1-50	2: drone-inner/truck-outer	141.98	37.03	-	578
Final-1-50	2: drone-inner/truck-outer	143.45	28.95	-	390
Final-1-50	3:truck-inner/drone-outer	105.75	4.60	41	239
Final-1-50	3:truck-inner/drone-outer	105.75	5.45	41	279
Final-1-50	3:truck-inner/drone-outer	105.75	5.87	41	304
Final-1-50	3:truck-inner/drone-outer	105.75	7.64	41	394
Final-1-50	3:truck-inner/drone-outer	105.75	5.27	41	274
Final-1-50	4:shared	139.88	56.79	-	749
Final-1-50	4:shared	142.78	41.45	-	539
Final-1-50	4:shared	141.26	23.75	-	318
Final-1-50	4:shared	143.05	46.48	-	599
Final-1-50	4:shared	140.59	36.71	-	471
Final-1-50	4:shared	139.96	57.60	-	749
Final-1-50	4:shared	145.18	25.56	-	335
Final-1-50	4:shared	143.52	52.54	-	675
Final-1-50	4:shared	141.73	46.96	-	620
Final-1-50	4:shared	142.44	31.53	-	417

Figure C.1: **Drone Delivery Model Analyses: Model 1 (pure drone delivery), Model 2 (drone-inner/truck-outer), Model 3 (truck-inner/drone-outer) and Model 4 (shared truck-drone)**

D Appendix D: Raw data of operating parameters analysis

Model setup		Result				DDS variables					
Problem	**Model**	**DDS Solution**	**Timing to reach solution (seconds)**	**Customers not served**	**Generations reached**	**# Trucks**	**Truck speed (km/h)**	**Truck threshold (mins)**	**# Drones**	**Drone speed (km/h)**	**Drone autonomy (mins)**
Baseline with updated parameters											
Final-1-50	2: drone-inner/truck-outer	145.21	26.62	-	363	2	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	139.62	39.27	-	643	2	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	141.75	46.26	-	749	2	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	137.33	43.26	-	695	2	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	143.50	39.59	-	534	2	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	145.64	42.28	-	626	2	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	143.99	33.49	-	501	2	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	141.75	27.34	-	413	2	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	141.98	37.03	-	578	2	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	143.45	28.95	-	390	2	30	15	2	45	30
Trucks: 2, 3, 1											
Final-1-50	2: drone-inner/truck-outer	126.67	28.62	-	382	3	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	126.25	48.54	-	709	3	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	132.55	39.32	-	549	3	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	132.56	41.80	-	599	3	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	136.80	44.30	-	570	3	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	135.45	28.42	-	396	3	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	126.25	35.19	-	490	3	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	134.12	51.18	-	749	3	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	128.06	51.07	-	749	3	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	126.67	51.70	-	734	3	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	194.28	28.30	-	299	1	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	173.22	64.26	-	749	1	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	194.41	24.38	-	258	1	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	194.28	29.42	-	379	1	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	194.66	31.30	-	317	1	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	194.79	27.68	-	289	1	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	173.22	37.74	-	421	1	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	194.28	31.91	-	343	1	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	194.41	29.11	-	311	1	30	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	194.28	40.30	-	446	1	30	15	2	45	30

Figure D.1: **Operating Parameter Sensitivity Analyses: Number of trucks**

Model setup		Result				DDS variables					
Problem	Model	DDS Solution	Timing to reach solution (seconds)	Customers not served	Generations reached	# Trucks	Truck speed (km/h)	Truck threshold (mins)	# Drones	Drone speed (km/h)	Drone autonomy (mins)
Trucks speed: 45, 15											
Final-1-50	2: drone-inner/truck-outer	105.75	51.75	-	749	2	45	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	105.75	47.31	-	665	2	45	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	105.75	39.88	-	538	2	45	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	105.75	48.39	-	685	2	45	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	105.75	50.30	-	656	2	45	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	105.75	35.00	-	441	2	45	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	105.75	48.45	-	676	2	45	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	105.75	44.62	-	638	2	45	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	105.75	31.20	-	416	2	45	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	105.75	52.72	-	749	2	45	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	282.39	52.64	-	749	2	15	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	288.23	50.93		749	2	15	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	281.22	52.01		749	2	15	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	285.04	33.70		464	2	15	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	279.52	44.24		618	2	15	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	283.72	44.69		614	2	15	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	271.99	36.43		488	2	15	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	286.93	47.92		655	2	15	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	288.43	47.59		664	2	15	15	2	45	30
Final-1-50	2: drone-inner/truck-outer	287.18	30.66		396	2	15	15	2	45	30

Figure D.2: **Operating Parameter Sensitivity Analyses: Speed of trucks**

Model setup		Result				DDS variables					
Problem	Model	DDS Solution	Timing to reach solution (seconds)	Customers not served	Generations reached	# Trucks	Truck speed (km/h)	Truck threshold (mins)	# Drones	Drone speed (km/h)	Drone autonomy (mins)
Drones: 2, 3, 1											
Final-1-50	2: drone-inner/truck-outer	142.31	53.70	-	363	2	30	15	3	45	30
Final-1-50	2: drone-inner/truck-outer	143.15	39.82		518	2	30	15	3	45	30
Final-1-50	2: drone-inner/truck-outer	142.35	36.50		477	2	30	15	3	45	30
Final-1-50	2: drone-inner/truck-outer	143.55	44.70		538	2	30	15	3	45	30
Final-1-50	2: drone-inner/truck-outer	142.89	52.73		626	2	30	15	3	45	30
Final-1-50	2: drone-inner/truck-outer	141.67	40.49		539	2	30	15	3	45	30
Final-1-50	2: drone-inner/truck-outer	144.03	53.55		749	2	30	15	3	45	30
Final-1-50	2: drone-inner/truck-outer	138.81	55.32		749	2	30	15	3	45	30
Final-1-50	2: drone-inner/truck-outer	143.46	42.85		562	2	30	15	3	45	30
Final-1-50	2: drone-inner/truck-outer	139.82	43.40		590	2	30	15	1	45	30
Final-1-50	2: drone-inner/truck-outer	208.91	33.69		475	2	30	15	1	45	30
Final-1-50	2: drone-inner/truck-outer	208.91	33.58		468	2	30	15	1	45	30
Final-1-50	2: drone-inner/truck-outer	208.91	39.27		576	2	30	15	1	45	30
Final-1-50	2: drone-inner/truck-outer	208.91	33.90		477	2	30	15	1	45	30
Final-1-50	2: drone-inner/truck-outer	208.91	36.47		522	2	30	15	1	45	30
Drones autonomy: 45 mins, 15 mins											
Final-1-50	2: drone-inner/truck-outer	210.54	31.67	-	430	2	30	15	2	45	45
Final-1-50	2: drone-inner/truck-outer	210.54	49.19		749	2	30	15	2	45	45
Final-1-50	2: drone-inner/truck-outer	210.52	48.22		638	2	30	15	2	45	45
Final-1-50	2: drone-inner/truck-outer	210.57	22.69		309	2	30	15	2	45	45
Final-1-50	2: drone-inner/truck-outer	210.55	49.79		733	2	30	15	2	45	45
Final-1-50	2: drone-inner/truck-outer	145.54	58.84		749	2	30	15	2	45	45
Final-1-50	2: drone-inner/truck-outer	148.38	44.73		570	2	30	15	2	45	45
Final-1-50	2: drone-inner/truck-outer	146.17	60.19		749	2	30	15	2	45	45
Final-1-50	2: drone-inner/truck-outer	143.64	59.01		749	2	30	15	2	45	45
Final-1-50	2: drone-inner/truck-outer	141.09	59.14		749	2	30	15	2	45	45

Figure D.3: **Operating Parameter Sensitivity Analyses: Number of drones and flight limit**

E Appendix E: Developed software package for evaluation of drone delivery models

In order to conduct evaluation of drone delivery system, we built a complete solution deployed on Cloud, along with complete setup of a SQL database to record the results of the experiments. The solution was built using Python programming language and the database was deployed with PostgreSQL. The solution is available in Google Cloud (http://bit.ly/dronecloud/) and can be accessed by any web browser to perform the experiments.

The interface of the solution is shown in Figure E.1. In this solution, user can change various parameters such as Memetic Algorithm parameters and Drone Delivery operating parameters as well as select various Drone Delivery models, objective functions and problem instances.

Examples of the solutions for different drone delivery models are shown in Figure E.2 to Figure E.5.

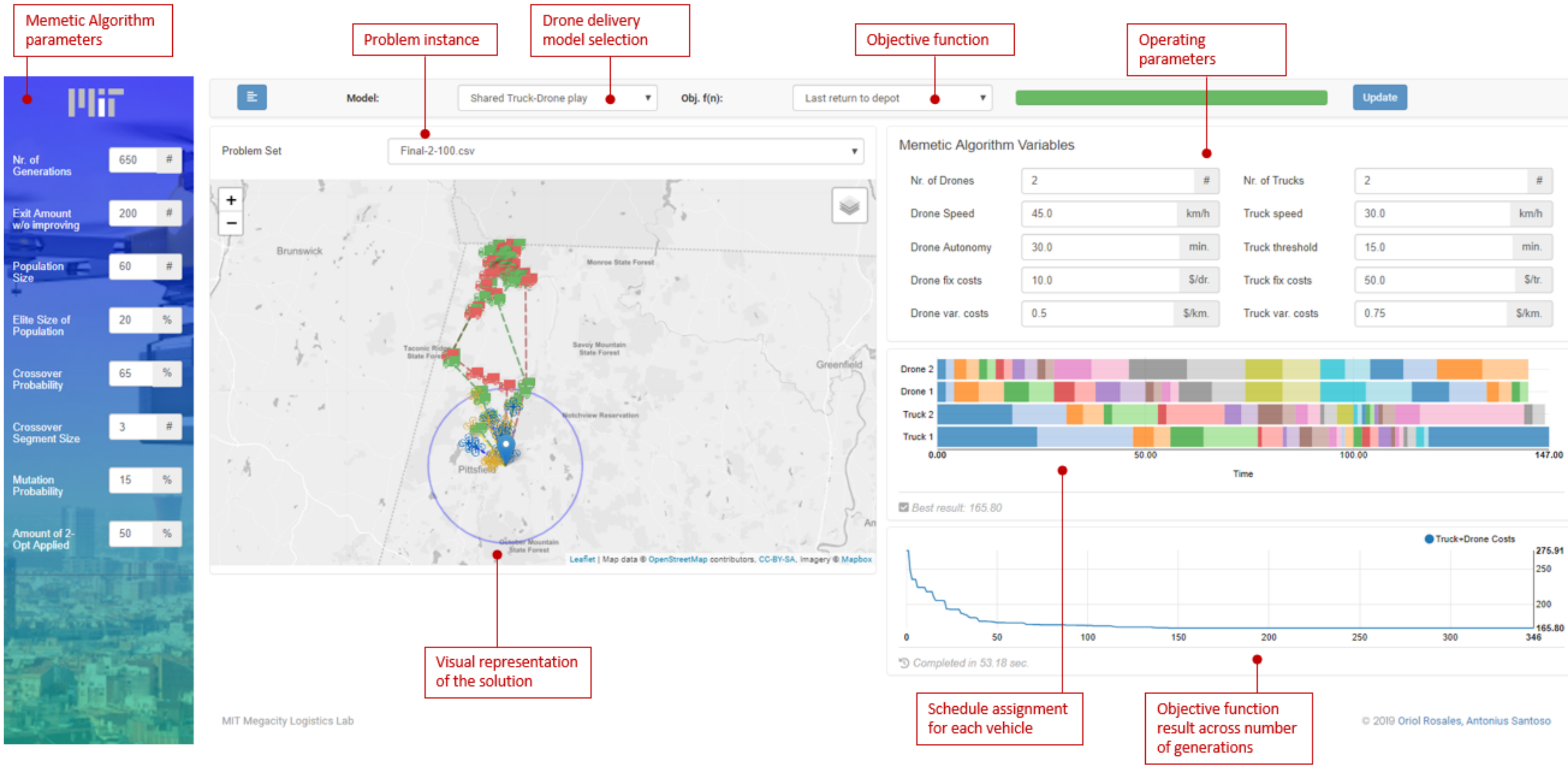


Figure E.1: **Interface of developed software package: Drone Delivery Evaluation in Last-Mile Delivery**

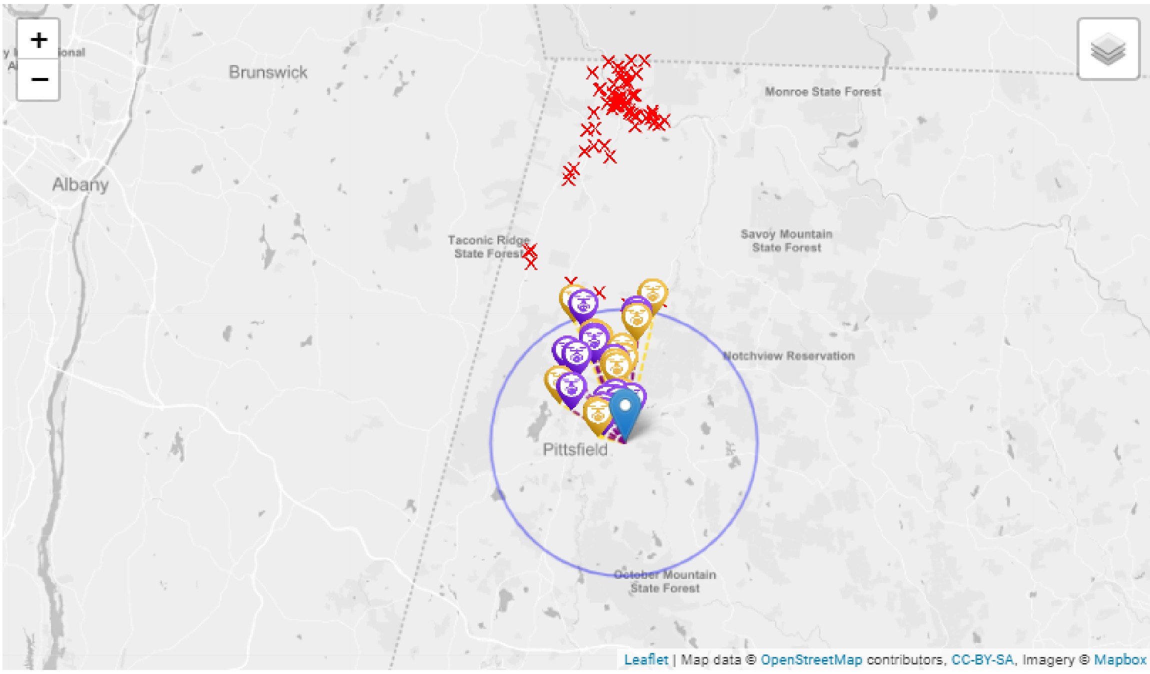


Figure E.2: **Drone Delivery Model-1 (pure drone delivery) in problem instance 2 with 100 customers: Customers beyond drone flight range are unreachable**

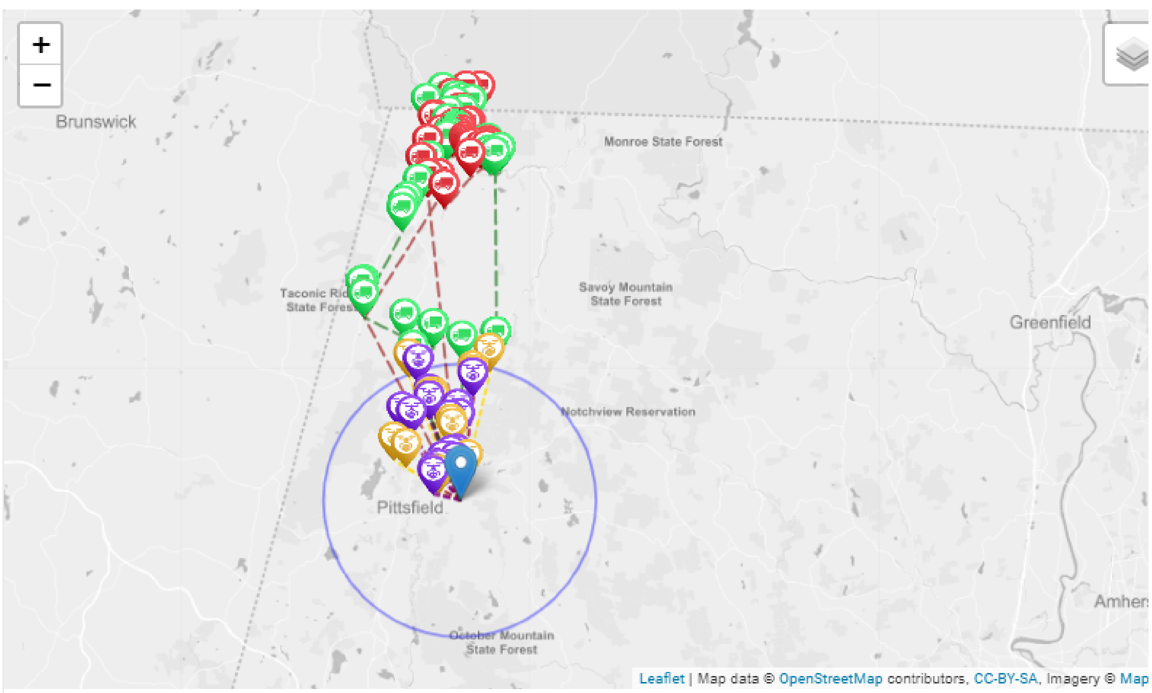


Figure E.3: **Drone Delivery Model-2 (drone-inner/truck-outer) in problem instance 2 with 100 customers: Customers inside drone flight range (inside circle) are served by drones and the customers outside circle are served by trucks**

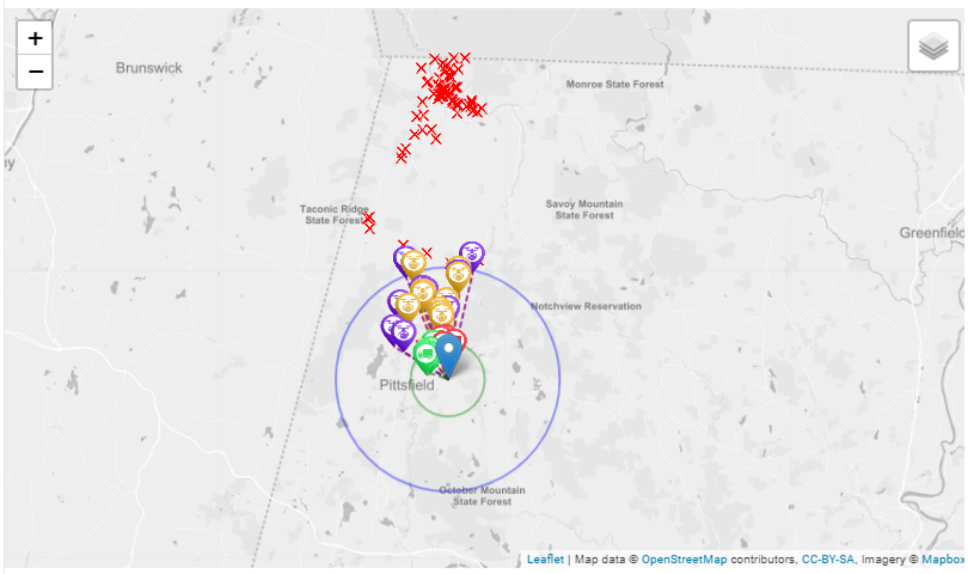


Figure E.4: **Drone Delivery Model-3 (truck-inner/drone-outer) in problem instance 2 with 100 customers: Customers inside truck coverage area (inside green circle) are served by trucks and customers outside green circle are served by drones. Customers beyond drone flight range (outside purple circle) are unreachable**

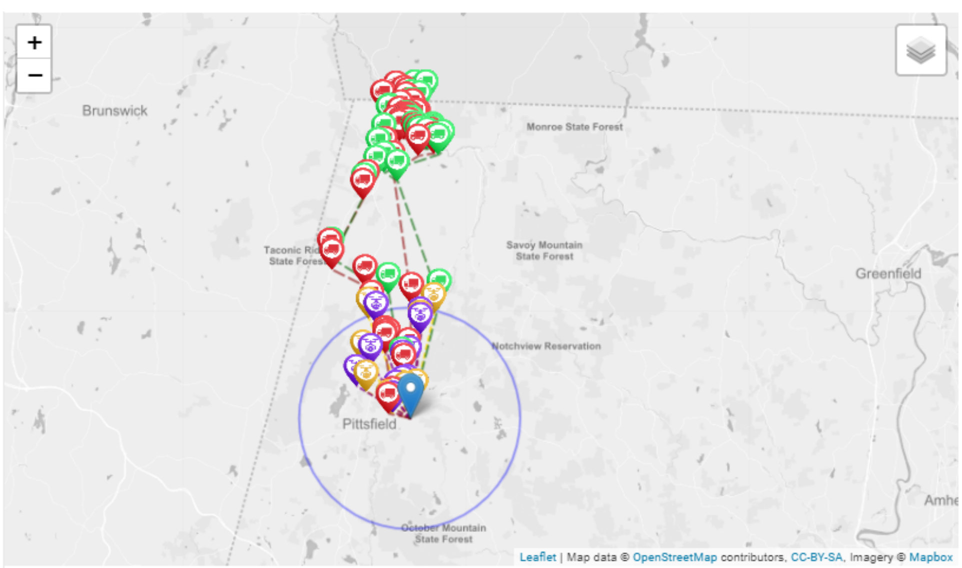


Figure E.5: **Drone Delivery Model-4 (shared truck-drone) in problem instance 2 with 100 customers: Customers are served by drones and trucks based on the most optimum routing as per algorithm**

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