Is your last-mile delivery ready for drone?

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Summary: With the latest technological advancement, the use of drones has emerged as an innovative and viable business solution for last-mile distribution. There are various operating models for a drone-based last-mile delivery system from a pure drone delivery model where customers are served by drones (no trucks) to a shared truck-drone delivery model where customers can be served by either trucks/drones. This thesis quantitatively models these different drone-based last-mile delivery systems and compare their relative benefits and shortcomings under various operating models. The goal of the thesis is to help the industry understand potential use cases of drones in last-mile delivery systems.

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KEY INSIGHTS

1. Adding a drone to a traditional last-mile delivery system that uses trucks only can reduce minimum tour time by up to 10%.
2. Among the four considered drone delivery models in this research, shared truck-drone model — where truck and drone share same area of service — performs superior to other three models, providing 100% coverage to all customers and reducing minimum tour time as high as 80%.
3. A Memetic Algorithm used for our routing optimization proves to be quite robust in handling Vehicle Routing Problem (VRP) with 50 customers, yielding only 3.7% gap from the optimal solution.

Introduction

E-commerce continues to outgrow offline retail revenues and is expected to reach 15% of global retail share in 2020. 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 the 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. The 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 a strain on cities grappling with congestion problems.

These inefficiencies make last-mile delivery as the costliest step in the supply chain, accounting for 28–53% of the total shipment costs.

With the latest technological advancement, the use of drones has emerged as an innovative and viable business solution for last-mile distribution. Compared to traditional last-mile distribution with a truck, a drone has competitive advantages such as lower cost structure, reduced delivery time, farther reach in poor infrastructure areas and less CO2 emission.

This thesis evaluates the optimal design and operational performance of different drone delivery models to help the industry understand potential use cases of drones in last-mile delivery systems

Methodology

There are various operating models for a drone-based last-mile delivery system from pure drone delivery model to unsynchronized/synchronized truck-drone delivery system. This thesis focuses on and quantitatively models four main drone delivery system as shown in Figure 1:

1. Pure drone delivery: customers are served by drones (no trucks)
2. Drone-inner/Truck-outer: drones to serve customers closer from the depot and trucks to serve customers farther from the depot
3. Truck-inner/Drone-outer: trucks to serve customers closer from the depot and drones to serve customers farther from the depot
4. Shared Truck-Drone: trucks or drones can serve any customers, depending on the optimality of objective function (e.g. minimizing tour time)

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?". We developed a Memetic Algorithm, an extension of a Genetic Algorithm, to optimize delivery routes of truck and drones in all the four delivery models.

A Memetic Algorithm is a meta-heuristic approach that introduces local search to a Genetic Algorithm. We selected a Memetic Algorithm to solve the drone delivery system problem because it is based on a Genetic Algorithm that is quite mature and widely used in researches for the Vehicle Routing Problem (VRP).

Genetic Algorithm is a numerical optimization technique, 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 the next generation. The drawback of a Genetic Algorithm is that it does not consider a step of self-improvement within the cycle (only based on randomized variation). Hence, a 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.

In our drone delivery model, we also consider several specific constraints of the drones, such as the operational limit of the drones (e.g. distance covered, endurance, payload) and unique technical characteristics of drone delivery (e.g. one package per time, no pick-up).

Developed solution

In order to conduct an evaluation of the drone delivery system, we built a complete solution deployed on Google Cloud, along with a complete setup of the SQL database to record the results of the experiments. The solution was built using Python programming language and the database was deployed with PostgresSQL.

The interface of the solution is shown in Figure 2. In this solution, a user can change various variables such as Memetic Algorithm parameters (e.g., the number of generations, population, etc.), Drone Delivery operating parameters (e.g., the number of

Figure 1 – Four different drone delivery models

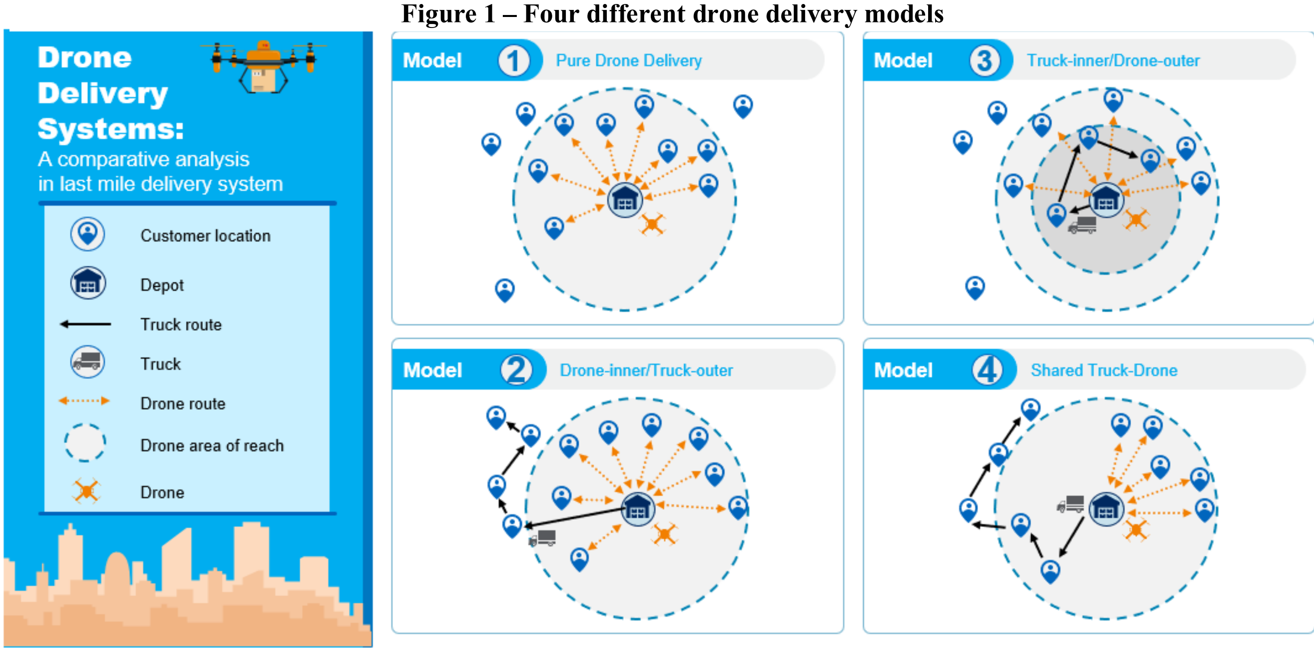
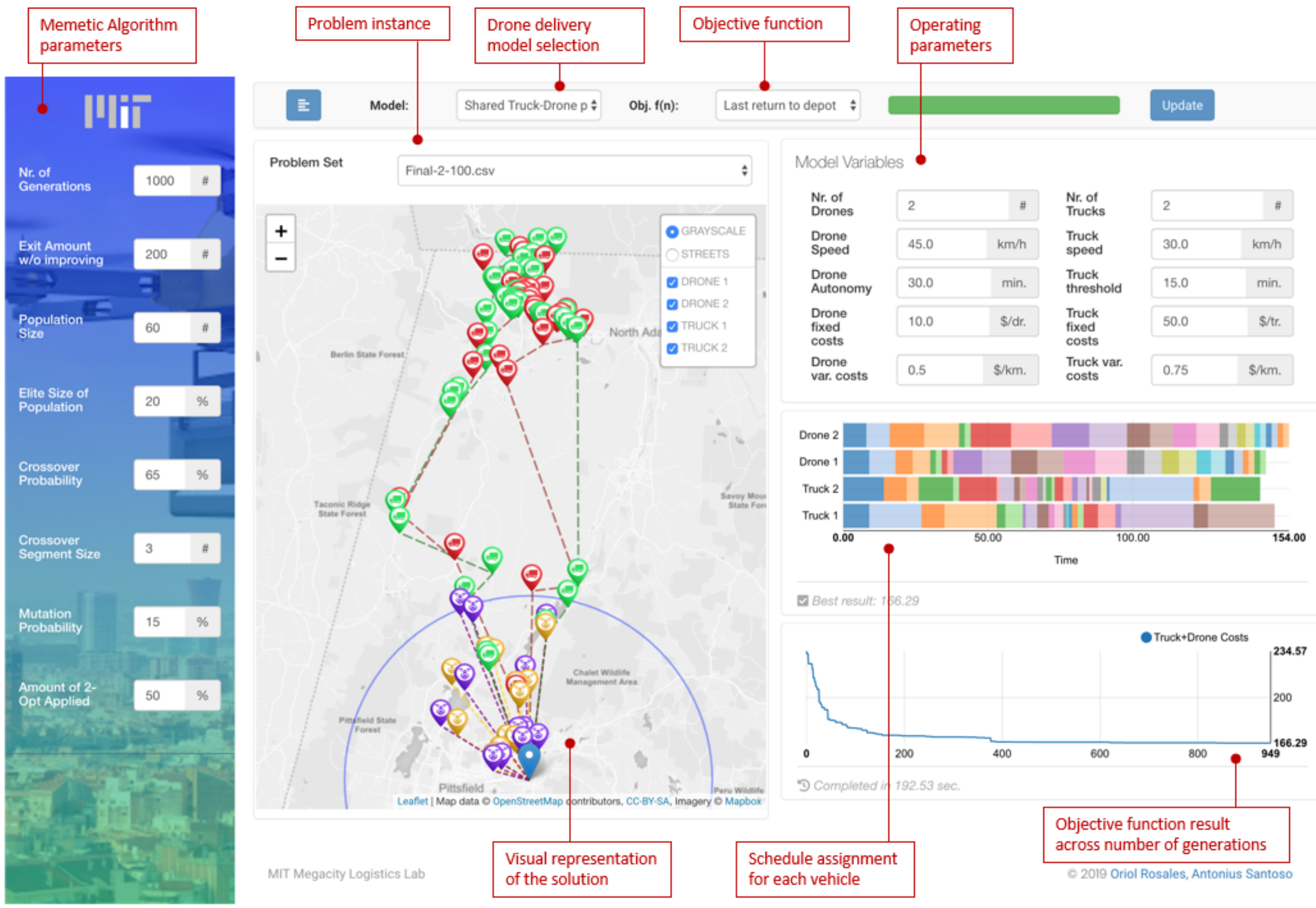


Figure 2 – Interface of developed solution: Drone delivery evaluation in last-mile delivery



drones/trucks, speed or flight limit of drone, etc.) as well as the four different drone delivery systems outlined above.

Results

Our research shows that our Memetic Algorithm is quite robust in handling "*eil51*" Travelling Salesman Problem (TSP) that is commonly used in routing research. *eil51* is a 51-city TSP problem with a single depot and 50 customers located in Euclidean space with optimum routing solution of 426. We tested our algorithm against this problem, yielding only 3.7% gap from the optimal solution.

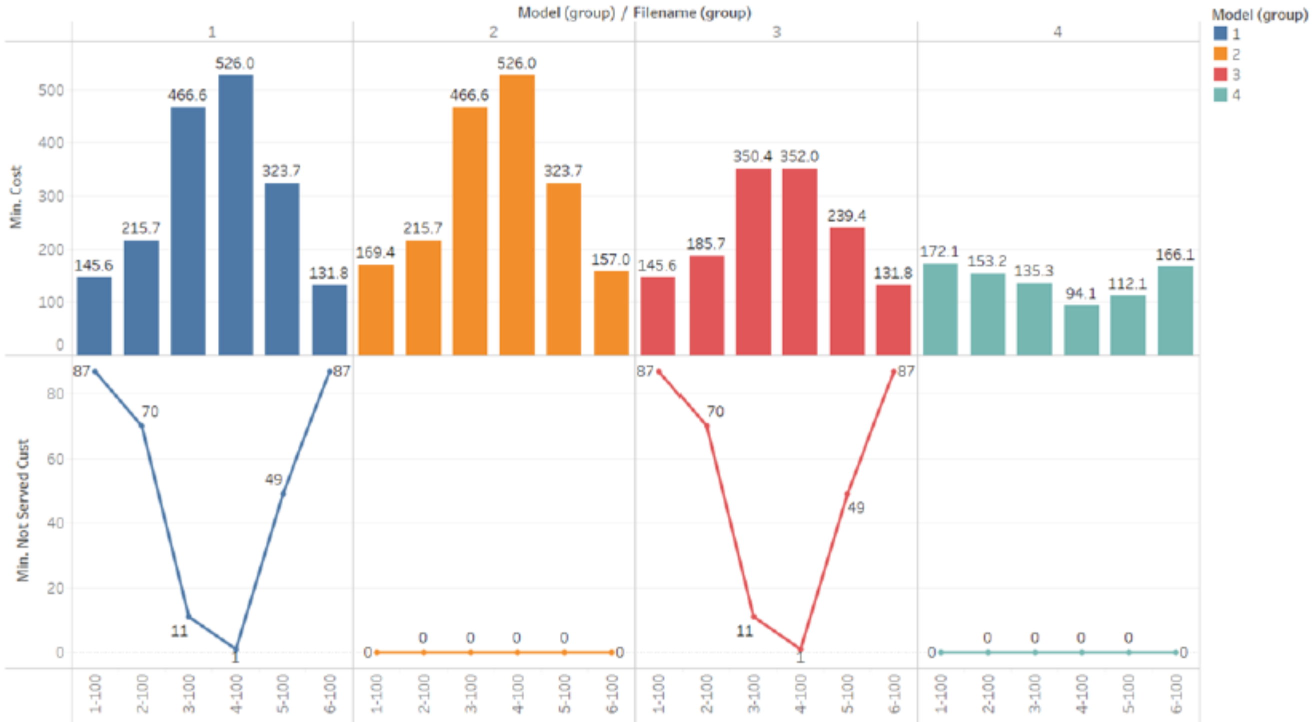
We then use this algorithm to solve four different drone delivery models on six problem instances. Each of these problems has 100 customers with different locations. The customer locations are from a real case study from a major package delivery company in the state of Massachusetts, USA. Baseline operating 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 3. The bar chart at the top is the last return time to a depot (minimum tour time) in minutes. There are six bar-charts representing six 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 six 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 3 – Drone delivery model performance



Sensitivity analyses for various operating parameters also yield several interesting insights, particularly on Model 2 (drone-inner/truck-outer) and Model 4 (shared truck-drone).

Increasing drone speed and flight time limit has an adverse impact on 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 in Model 2 (drone-inner/truck-outer), increasing number of drones has positive impacts because increasing drones from 1 to 2 reduces minimum tour time by 50% and further increasing number of drones to 3 reduces time by 29%.

In Model 4 (shared truck-drone), increasing drone speed from 45 km/h to 60 km/h reduces minimum tour time by 4%. We also doubled the drone flight limit from 30 minutes to 60 minutes, however there is no impact because the bottleneck is with the trucks.

Finally, we also conducted an analysis to understand the impact of introducing drones on a pure truck delivery system. We found that adding a drone in the pure truck delivery system can reduce minimum tour time by up to 10%.

For future research areas, in order to make a more holistic review of the drone delivery system, we can take into accounts vehicle capacity. Our research assumed uncapacitated truck and single package capacity for the drone. In real life, the truck has space limitation in the number of packages it carries. A 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 a specific customers delivery window.