A Framework for Adopting Drones to a Logistics Cargo Operator Network

MSc. Thesis

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This thesis is confidential and cannot be made public.

TU Delft

Preface

Everything comes to an end, and so does my amazing period as a student. I am extremely grateful for having the possibility and opportunity to graduate a master's degree in Aerospace Engineering. Something I would have never thought ten years ago.

I couldn't have thought of any other better way than to graduate with this innovative and exciting project. Therefore, I like to show my great appreciation to my supervisor Bruno Santos. He has been so supportive throughout the entire thesis, which allowed me to realize this project in collaboration with Air Canada in the first place. Bruno's feedback was always extremely insightful, clear, and he even supported me in way of communicating with the corporate world. I also like to thank Vito Cerone and Ameet Sareen from Air Canada. Vito's vision for the project was perfectly aligned with mine. He took his time to initiate this project, even during the difficult COVID-19 times that an airline, such as Air Canada, had to go through. Ameet helped me throughout the project to communicate internally and to get the data that was necessary for the project.

My student time wouldn't have been the same without my friends. Bringing laughter and joy made the study time much easier. I like to give a special thank note to my friend Joseph who was willing to give up his free time to share his knowledge in programming with me.

And most importantly, I like to thank my family and my girlfriend for being the absolute best support someone could ever wish for. Special thanks to my parents for all the opportunities they gave me and their constant support. Without them, I would have never graduated a master's degree. The project had definitely some ups and downs, and my girlfriend didn't just support me in the difficult times, she also lived them with me. She was always available whenever I needed someone to talk to, despite how boring my stories and questions sometimes were. And even without some required knowledge she was always able to test me and to let me think in different ways, which really helped me throughout the project. I really want to thank you for the endless talks and calls you had to listen to, but it really helped. I wouldn't have had the same result without you.

M. van Driel - 4296699
Montreal, April 2021

Abstract

Last mile delivery faces challenges in rapid growth in demand for home deliveries, congestion, and restrictions in operations raised by governments, councils, or municipalities. Simultaneously, end-consumers are becoming more demanding in quicker delivery services and how the delivery service are being provided. Which is creating pressure for logistic operators to find sustainable solutions in the last part of the supply chain. Consequently, literature and industry are considering Drones as a Service to provide home delivery services in urban areas. Given the uncertainty and risk factors in a new business model raises questions in the optimal design of a Drone Delivery Network to maximize the distribution efficiency.

This MSc. research describes a sequential framework that addresses the design of a Last Mile Delivery Network. The first part of the Network Design Model formulates a binary integer linear programming model to find the optimal location of intermediate facilities. Following, the sequential framework address problems related to maximizing vehicle load factor, minimizing mileage, and vehicle to package assignment. The framework formulates a package valuation algorithm allowing the model to assign packages with the highest priority first. The Network Design Model aims to minimize the operating costs measured in delivery duration, vehicle ground time, and number of not-delivered packages. A Monte Carlo Simulation is formulated to assess the impact, risk factors, uncertainties, and variation in key network design attributes, have on the performance of the network.
Results from a case study showed that a P2P network is most compatible to provide home delivery services in a metropolitan area. It proved to have the lowest operational cost with less resources.

Nomenclature

$2E-LRP$	Two-Echelon Location Routing Problem
$2E-CLRP$	Two-Echelon Capacitated Location Routing Problem
B2C	Business-to-Consumer
CI	Confidence Interval
CO_2	Carbon Dioxide
DaaS	Drones as a Service
DC	Distribution Center
D.D.	Delivery Duration
DDC	Drone Delivery Canada
DoW	Day of Week
GCD	Great Circle Distance
GHG	Greenhouse Gasses
G.T.	Ground Time
H&S	Hub-and-Spoke
i.i.d.	independent and identically distributed
I.F.	Intermediate Facility
ILP	Integer Linear Programming
I.V.	Inbound Vehicle
KPI	Key Performance Indicator
LLN	Law of Large Numbers
MCS	Monte Carlo Simulation
mlrose	Machine Learning, Randomized Optimization and SEarch
N	Normal Service
O.V.	Outbound Vehicle
P2P	Point-to-Point
pdf	Probability Distribution Function
TSP	Traveling Salesman Problem
VRP	Vehicle Routing Problem
X	Xpress Service
YYZ	Toronto Pearson Airport

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Introduction

This research focuses on the optimal network design of a Drone Delivery Network for logistic operators. The initiative stems from the challenges city logistics are facing which, the industry and literature expect to become more complex from the rising demand for home deliveries in urban areas.

Cities represent about 2% of the geographical space but give housing to 54% of the entire population which, is expected to continue growing [1]. Increase in transport of goods in congested areas has led from urbanization and from globalization with the open web market. Consumers are also becoming more demanding in expectations towards shorter lead times as competition in home delivery services increases. Freight transport that uses mainly road traffic is, therefore, mostly responsible for an increase in pollution and generated emissions [2]. As a result, governments, councils, and municipalities are taking measurements and policies to reduce pollution [3].

An emerging topic as anticipation to deliver more parcels in congested areas in a rather sustainable matter is delivery by drones. Drones do not need couriers nor face congestion issues and thus overcome most of the last mile delivery challenges [4]. The application of drones was limited to military use due to the complexity, technology sensitiveness, and costs of the systems. But, over recent years, as technology has developed, applications of drones have swiftly changed and adopted for civilian applications in disaster relief situations [5], airborne fire sensing [6], in the agriculture industry [7], and most recently in transportation of health services [8], [9]. These successful operations can be considered as a preliminary stage of Drones as a Service (DaaS). As a result, Amazon [10], DHL [11], Google [12], UPS [13], Mercedes-Benz [14], and Antwork [15] are, for example, trying to gradually adopt DaaS to anticipate the challenges city logistics is facing .

The technology to operate drones as a last-mile vehicle is shown to be ready for utilization. As a response, literature raised attention to find ways to operate and utilize drones effectively in a logistics network. Leyerer Et al. [16] focused for example on determining optimal locations of intermediate facilities and allocation of vehicles to the facilities with the objective to minimize operating costs. Troudi et al [17] decided to optimize the fleet sizes and to consider battery management to find an efficient and effective Drone Delivery Network. Hong et al. [18] emphasized on the location of the recharging stations to find a feasible delivery network with the objective to cover the demand in a large urban area. These studies aim to optimize a particular aspect in the network design. In this paper instead, the research aims to find a complete Drone Delivery Network design that can easily be adopted to any existing commercial supply chain providing B2C service in the last part of the supply chain. Resulting in the following research question:

What is the design of a Drone Delivery Network and how should it be configured to ensure delivery to the end-consumer in metropolitan areas under cost minimization such that a profitable Drone Delivery Network can be adopted to the network of logistic operators?

The report describes the scientific paper in *Part I* and the entire thesis report in *Part 2*. The thesis report followed the following structure as a guideline to find the answer to the research question:

From research it is found that there is no study on a Drone Delivery Network that addresses the optimal network strategy to approach commercial utilization of drones. The research focused, therefore, on existing network strategies well established in the aviation industry such as the Point-to-Point (P2P) network and the Hub and Spoke (H&S) network. Finding optimal destination locations for both networks is vital for the coverage of the network, and finding optimal location of the hubs is essential to the performance of the H&S network [19]. Literature also discusses battery management strategies to overcome the limited battery life cycle of drones. The most common suggestions are contactless charging [20], recharging stations [21], and battery swap technologies [22]. These findings are explained in detail in Chapter (1).

Chapter (2) defines the scope of the thesis. It elaborates on the main research question that can be answered by the aid of multiple sub-questions. Subsequently, the eventual project goal is defined by specifying the main objective followed up with sub-goals that are to be accomplished to achieve the ultimate goal.

A network model is presented as a sequential framework that addresses the design of a logistics network in Chapter (3.1). This method is used as it allows to address the Knapsack Problem, Facility Assignment, Travelling Salesman Problem (TSP), and package to drone assignments by using binary decision variables. The objective of the network model is to solve each of the problems individually to minimize the operational costs of the network.
The framework is set-up flexible such that the operator can decide to either configure a P2P network or to design a H&S network. It assumes that the order size, destination locations, hub locations, and vehicles are given. It is a flow-model that uses the pre-determined facility locations to find the optimal hub locations. The operator is also free in tailoring the quality of service it likes to provide for two service types. A package valuation algorithm is implemented in the model to prioritize packages based on due delivery and service type.
The costs are measured in operational costs such as the ground time, delivery duration, and the number of packages not delivered. The formulation of a Monte Carlo Simulation (MCS) allows to observe the impact network attributes have on the costs while considering risk factors and uncertainties. The model distinguishes from literature by allowing any operator to design a P2P or a H&S Drone Delivery Network with tailored services that can be simulated by taking into account risk factors.

The framework is considered in a case study with data of Air Canada in Chapter (4). It is a pioneer in its field and is looking for opportunities to anticipate the rapid increase in demand for home delivery services. Considering the major hub of Air Canada at the Pearson Airport (YYZ), it is decided to find a Drone Delivery Network servicing the City of Toronto.

A sensitivity analysis is performed in Chapter (5). Changing one parameter in the general set-up, obtained from the case study, allows the experimenter to assess the impact the attribute has on the performance of the network. Both network strategies, P2P and H&S, are compared. The outcomes allow to recommend the most competitive Drone Delivery Network that can be adopted by Air Canada's logistics network for this specific scenario in Toronto.

The main elements of the report are discussed and concluded in Chapter (6) and it finishes with suggestions for future research in Chapter (7).

I

Scientific Paper

A Framework for Adopting Drones to a Logistics Cargo Operator Network

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Abstract

City logistics concern solutions in package movements that face challenges in rapid growth in demand for home deliveries, congestion, and expectations from consumers for sustainable solutions. Providing last mile delivery services with drones is considered a promising solution in literature as a response to the raising challenges in urban areas. In this paper, we propose an innovative framework that allows a logistics operator to design a last mile delivery network. The Network Design Model contains two parts. First, a binary integer linear programming model is presented, allowing the operator to find the optimal location of intermediate facilities. It is a flow model that uses pre-located facilities. Secondly, a sequential framework is presented that considers Facility Assignment, Knapsack Problem, Traveling Salesman Problem, and Vehicle Assignment. The Network Design Model aims to minimize the operating costs measured in delivery duration, vehicle ground time, and number of not-delivered packages. A Monte Carlo Simulation is formulated to assess the impact risk factors, uncertainties, and variation in key network design attributes have on the performance of the network.

Keywords: Drone Delivery Network, Last Mile Delivery, Logistics, Network Optimization, Monte Carlo Simulation

1. Introduction

City logistics focuses on optimizing the transportation of goods in urban areas, also called last mile delivery. It is targeted to provide an effective and efficient freight distribution in congested areas taking into account safety, environment, and congestion [1]. Councils and governments are taking measurements to stimulate sustainable solutions for last mile delivery, as global pressure is getting stronger to reduce pollution and generated emissions [2]. Which is a result from global urbanization. It causes a rapid growth in the demand for last mile delivery that uses mainly road traffic. Freight transport is, therefore, mostly responsible for externalities in cities related to delivery. Externality also referred to as external cost, is caused by one group of people that does not compensate or entirely account for the impacts of its economic or social activities on another group. In addition, there are different carriers and logistic service providers that provide last mile delivery services that create an uncoordinated traffic flow of transported goods resulting in high externalities, a high number of routes, low load factors of vehicles, and high operational costs.

Expectations from the consumers to delivery services are changing towards sustainable solutions and the demand for e-commerce is increasing which will impact last mile delivery. Consumers are wealthier and purchase more online. Simultaneously, they are prioritizing to ease their daily tasks and desire to have more input in when, where, and also how the products are being delivered. The consumers prefer a more sustainable and environmentally friendly transport service, even if this means an increase in service price [3].

Many studies discuss solutions to overcome the challenges in last mile delivery. Last mile delivery by freight tricycles, a bicycle that is designed for transporting loads, is one solution that can overcome road restrictions that trucks are facing in urban and congested areas [4]. Other vehicles, such as hybrid and electric vehicles, are also discussed [5]. However, tricycles still face the issue of shortages in couriers, and other vehicles are still limited by traffic flows and congestion. On the contrary, drones do not need couriers nor face congestion issues and thus overcome most of the last mile delivery challenges. It is, therefore, considered a promising solution for last mile delivery in urban areas. From experiments and studies from industry it can be concluded that the design of the drones is not the issue [6], [7], [8], [9], [10], and [11]. Instead, there is little known to the optimal design of a network where drones deliver packages to consumers' homes. It is mandatory for logistic providers to investigate the design of a Drone Delivery Network first, before it is able to to utilize drones efficiently.

Decisions to the design of a logistics network encounter locations, sizing, and the number of facilities [12]. For certain network strategies it is common to have intermediate facilities. Which are facilities located between the origin and the destination where goods are delivered by inbound vehicles and picked up by outbound vehicles to consolidate packages for distance minimization purposes. For such network strategies, it is specifically relevant to optimize the location of intermediate facilities [13]. Other decisions prescribe the functional and physical aspects of the distribution network. It typically encounters fleet management, compositing and sizing of the transportation fleet [14]. The operational decisions consider on-time delivery encompassing scheduling plans and routing. These optimization problems, minimizing vehicle millage and maximizing distribution efficiency are known as Vehicle Routing Problems (VRP). The authors of [15] were the first ones to adopt this concept to a Drone Delivery Network.

The capacity of the vehicle, when replaced by drones, can potentially reduce significantly and inherently have an influence on the fleet size [16]. The operational constraints of the drones introduce other challenges in last mile delivery. Drones have a limited operational range due to the battery life span. They will need to recharge their batteries that can be facilitated by charging stations [17]. Charging time has a long duration relative to the drones' operational time resulting in poor utilization [18].

In this paper we discuss the problems that arise when designing a last mile delivery network for metropolitan areas. The approach is proposed to use drones as city-friendly vehicles to serve last mile deliveries. The approach thereby highlights optimal facility locations, fleet size, and risk factors in demand to compensate for restrictions in city logistics, the operational limitations of drones, and uncertainties in demand.

The remainder of this paper starts by addressing literature that addresses similar problems (2). The following section describes the problem in detail (3) before the mathematical formulation is given in Section (4). The framework is tested through a case study as explained in Section (5). The paper finishes with a discussion on the limitations of the framework and gives suggestions for future research (6).

2. Literature Review

Location Problem

A carrier transports passengers or freight throughout its network. Several strategies exist to define the network structure dependent on the carrier's vision. The vision can, most commonly, be divided between a robust network and an efficient network. The robust network is typically known as the Point-to-Point (PP) network that transports passengers or freight directly from the origin to its destination. Such a network design can improve the stability, flexibility, and security of the operations. The direct flights reduce travel time, but naturally increase operational costs as larger vehicle fleets are required to cover all routes. The efficient network is typically known as a Hub-and-Spoke (H&S) network. It connects the different origin-destination nodes through an intermediate facility, called a hub [19]. The H&S network provides carriers with higher densities, larger scopes, and bigger scales of economies [20]. It allows for better connections between almost all origin-destination nodes with lower number of routes. From Figure 1 it can be observed that a H&S network requires n - 1 routes, n representing the number of airports. On the other hand, utilization of this network implies extended travel times with increased airport and route dependencies.

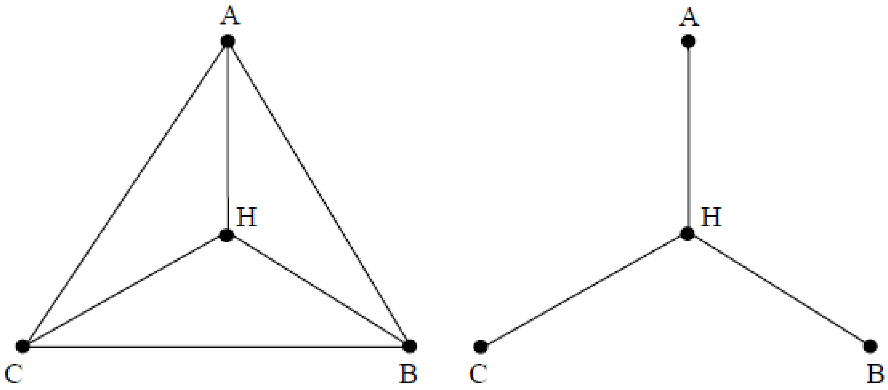


Figure 1: Point-to-Point network versus a Hub-and-Spoke network

Finding optimal destination locations for the P2P network is vital for its performance as the destination locations will determine the coverage of the network. Similar for the H&S network it is vital to find the optimal location of the hub when designing a distribution network to minimize the transportation costs for the incoming and out-going traffic [21]. Covering problems define a static and deterministic approach. If the demand is met within a specified duration, the demand is said to be covered. This problem can be divided into the set covering problem and the maximal covering problem. The covering problem aims to obtain a specified level of coverage while minimizing the facility location costs, and the maximal covering problem determines the possibility of maximizing the demand coverage by considering the available located facilities [22]. In practice, the set covering problems are potentially infeasible due to the usage of an exogenously specified coverage distance. This has led to p-center problems. It implies a minimax problem as it has the objective to minimize the maximum distance between the nearest facility to any demand node [23].

Finding optimal hub locations for a H&S network in city logistics is also commonly discussed as the Two-Echelon Location Routing Problem (2E-LRP). It has known customer locations and seeks for solutions regarding optimal locations of hubs, typically called satellites. This problem is formulated by literature with the following notation $3/\overline{T}/\overline{T}$, $3/T/\overline{T}$, and $3/\overline{T}/T$, where T represents a known location of the satellite, and $\overline{T}$ represents unknown location of the satellite at least at one of the echelons. The problem is further elaborated and expanded to number of facilities, sizes of the fleets, and to route optimization decisions. The most common variation studied, is called the Capacitated 2E-LRP (2E-CLRP). It has the same objective as the classical 2E-LRP, but with additional constraints. Each echelon consists of a fleet with capacity constraints. The authors of [24], expanded the 2E-LRP to also consider fleet sizes while simultaneously minimize transportation costs. More recently, Nguyen [25] introduced the common second stage location problem with capacity constraints that contains one Distribution Center (DC) of which its position is known prior. They formulated the model with Integer Linear Programming (ILP) and with a Greedy Randomized Adaptive Search Procedure (GRASP), including machine learning. The two-echelon problem is further elaborated by considering the following three constraints simultaneously on the second level, pick-up and delivery, multi-product, and usage of processing centers as satellites [26]. The first level aims at finding the location of the satellites, based on a set of potential locations, at minimum costs. The second level has the objective to minimize the route costs and to assign customers to the satellites. This problem is proposed to solve smaller-scale instances with an MILP model in a Cplex solver.

Battery Management

The limited battery cycle of a drone is a significant factor that negatively affects the drones' utilization. Moreover, the inability could cause damage to the drone, or worse, it could injure people when flying over populated and highly congested areas. It is, therefore, essential to take into account a battery management strategy to be able to create a profitable UAV delivery network.

Several methods are discussed in literature to anticipate the limited battery life cycle. Hu et al. [27]

discuss the possibility of contactless charging, for example. The method is, however, constrained in line-of-sight operations, high system costs, and low charging efficiencies [28]. A more common discussed topic in literature is supplying the network with recharging stations. The authors of [29], aimed to find the optimal locations of the refueling stations by using three heuristic algorithms. A greedy-algorithm, together with a genetic-algorithm, is applied to the model that shows efficient and effective results. [30] applied the FRLM in Korea to optimize the vehicle-flow of electrical cars. They define a case study to discuss the formulated multi-period optimization model, the backward-myopic method, and the forward-myopic method. In general, the multi-period optimization model performs better but shows longer computational times as the model increases. Therefore, the authors advise the backward-myopic method for large problems. Hong et al. [**?**] applied the FRLM method to a UAV delivery network. They designed a delivery network with recharging stations in its infrastructure. The network is based on a coverage model. In other words, the ground stations and recharging stations are located such that all customers are covered within the drones' vicinity. A spatial heuristic solution technique is used to find the optimal locations of the recharging stations.

Literature raised attention to battery swapping to improve utilization of drones in response to the demanding charging times discussed in FRLM methods. Suzuki et al. [31] propose a ground station that can swap batteries of a heterogeneous fleet under high-coverage requirements. Ure et al. [18] designed a battery maintenance system that allows to automatically swap the depleted battery with a replenished battery at a ground station while charging other batteries simultaneously [32]. Moreover, FRLM methods could be used to find optimal locations of such battery swap facilities.

Knapsack Problem

The Knapsack Problem aims to maximize the number of packages that can be carried by an object. The max capacity weight and max dimensions limit the number of packages the object can carry. The 2D Knapsack Problem 0-1 tries to maximize the value it can carry without exceeding the max capacity in terms of weight. Each item it can carry has a value and a weight (kg), the two dimensions [33]. The 3D Knapsack Problem 0-1 has the same objective but with volume as an extra dimension taken into account. Which is, therefore, more accurate as objects have fixed dimension constraints. The knapsack problem does, however, not consider optimal package placement by taking into account the length, height, and depth individually as well. This is rather a complex study which will be out of the scope for the project. Therefore, it can be assumed that all packages have a perfect fit in the object by only considering the volume. These assumptions allow pyeasyga PyPi to be a suitable Python optimization tool for the project [34].

Traveling Salesman Problem

The optimal route to visit all destination nodes is called in literature Travelling Salesman Problem (TSP) [35]. The goal is to determine the shortest tour of n cities starting and ending in the same city, visiting each city exactly once. It is its most common used application for a tour in cities, but it is also applied in computer wiring [36] and in wallpaper cutting [37]. Dantzig et al. [38] created one of the first formulations of the TSP, and Miller et al. [39] introduced an alternative formulation to reduce the number of subtour elimination. A large number of exact solutions have been proposed for the TSP, but since it is NP-hard, it is common to address the problem by means of heuristic algorithms [40].

Monte Carlo Simulation

Monte Carlo Simulation (MCS) is a type of simulation that uses repeated random sampling to estimate outcomes influenced by uncertain events. In other words, it is a probability simulation that calculates the outcome hundreds, thousands, or ten thousands of times by using each time a different set of random numbers as input. This approach allows one to understand the impact of uncertainty and risk factors which show the most likely outcomes for that specific scenario [41]. It is particularly applicable to experiments for which the outcome is unknown. It allows the experimenter to apply different scenarios to enable a so-called what-if analysis. Each scenario allows the experimenter to methodologically investigate a range of outcomes that applies to a risk scenario without forcing the experimenter to go through each input parameter and the corresponding outcome individually.

The what-if analysis consists of the most likely scenario, the worst possible scenario, and the best possible scenario. The most likely scenario is the base case for which risks factors are not considered for the input parameters. The uncertainty of various external factors that have an influence on the input parameters are considered for the worst case scenario and the best case scenario.

Rather than identifying each input value individually, MCS is used to create a statistical probability distribution for the entire set of input parameters. It creates random samples of the input parameters based on the probability distribution which will be different for every run simulation [42]. It is a realistic way of describing uncertainty in variables of a risk analysis.

The authors of [43] performed a probabilistic analysis for a reduced number of MCSs to optimize the framework of the design of UAV. Y. Jenie et al. [44] applied MCS for safety assessment for UAV operations in a high density airspace environment. A more similar study to this research is presented by the authors of [45]. They aim to maximize the demand served by drones while considering the uncertainties in battery consumption. While doing so, the model is tasked to locate a pre-specified number of facilities with assigned drones considering range constraints. The model uses a given set of spatially distributed demand with drones serving as delivery vehicles and a potential set of facility locations. The drones have a one-mission task, pick-up commodity from facility, deliver at destination, and return to origin until the available battery energy is exhausted. The authors propose an integer linear programming (ILP) formulation with a penalty-based approach for battery energy availability. The ILP outcomes are tested using MCS with coverage under uncertainty to add robustness to the deterministic problem.

The previously described studies aim to optimize a network design. With each study having a different particular focus in the network design optimization changing from P2P versus H&S, optimal facility location, and battery management strategies. In this paper the research aims to find a complete Drone Delivery Network design that can serve as an extension to an existing supply chain. A sequential framework will be proposed that integrates problems such as the Knapsack Problem and TSP to find the optimal design of the network. It is a flow model with pre-located facilities that aims to optimize the efficiency of the network with the objective to minimize costs. A MCS will be formulated to evaluate the impact variation in key model parameters on the design of the network and to perform a risk assessment. The model uses the battery replacement strategy which will be facilitated at intermediate facilities and at the destination locations, assuming that the vehicles have short distances to cover as the research aims for last mile Delivery services in metropolitan areas.

3. Problem Specification

The problem consist on defining a framework that can be used by any logistic provider to find the optimal last mile delivery network. The framework must be cost-efficient and flexible as supply chains can differ between different logistic providers and even between different cities. The optimal design of a last mile delivery network depends on the following inputs:

1. Order size → *flight frequency*
2. Vehicle capacity → *flight frequency*
3. Number of vehicles → *flight frequency*
4. Destination locations → *distance travelled*
5. Intermediate Facility → *network strategy*
6. Quality of Service → *network strategy*

The order size is prone to uncertainties in demand that has a major impact on the design of the network. On the other hand, vehicle capacity, number of vehicles, and destination locations can be chosen by the operator, but are prone to available resources. The network strategy is vastly defined whether the logistics provider decides to operate with intermediate facilities or not and by the service it wants to provide to its customers.

From the perspective of the operator, minimum trips with minimum required resources without having to spill demand is desired. Having small city-friendly vehicles serving the last mile delivery naturally implies low consolidation factors which inherently means a higher flight frequency or bigger fleet sizes. Strategic destination locations can increase the catchment area of the network which could positively increase the demand of orders. Such locations could, however, increase extra opening costs of the network and more distance travelled per day. Another trade-off would be required by the operator, whether the potential of a higher demand would be desired over extra costs. The quality of service includes the operation hours of the network and indicates the desired lead times. A high quality of service would indicate that the operator aims for quick delivery services which would have a large impact on the optimal design of the network. The operator could also decide to define the quality of service for different service types to better tailor the service.

Different network strategies can be used by an operator when utilizing a last mile delivery network. The model should be able to facilitate the operator with design solutions for each network strategy taking into account that each network strategy requires different resources. If the operator desires to design a H&S network, for example. The model should select optimal locations of intermediate facilities that are located closer to the destination locations serving as small consolidation centers. If the operator decides to design a P2P network where there are no intermediate facilities nor Inbound Vehicles. Packages are delivered directly from origin to destination. The model could consider fleet sizing to optimize the design of such a network, for example.

An operator wants to know in advance how the network will perform before investing largely in it. Given the demand, vehicle capacity, number of vehicles, destination or intermediate facility locations, and quality of service do not indicate the operational performance nor the costs of the network. Facility acquisition or rent and insurance are for example costs that are difficult to define upfront. In addition, a network design is prone to certain risk factors and uncertainties. Changes in demand are likely to occur, but are unknown in advance and could negatively impact the performance or the costs of the network. It is undesirable to design a network that will be inefficient shortly after utilization due to the inability to test for different demand scenarios. Due to these uncertainties, it is proposed to measure the operating cost in performance of the network. The objective of the model is to create a flexible framework that aims to minimize the operating costs. A flowchart of the approach for this model is indicated by Figure 2 to clarify how the inputs will be used.

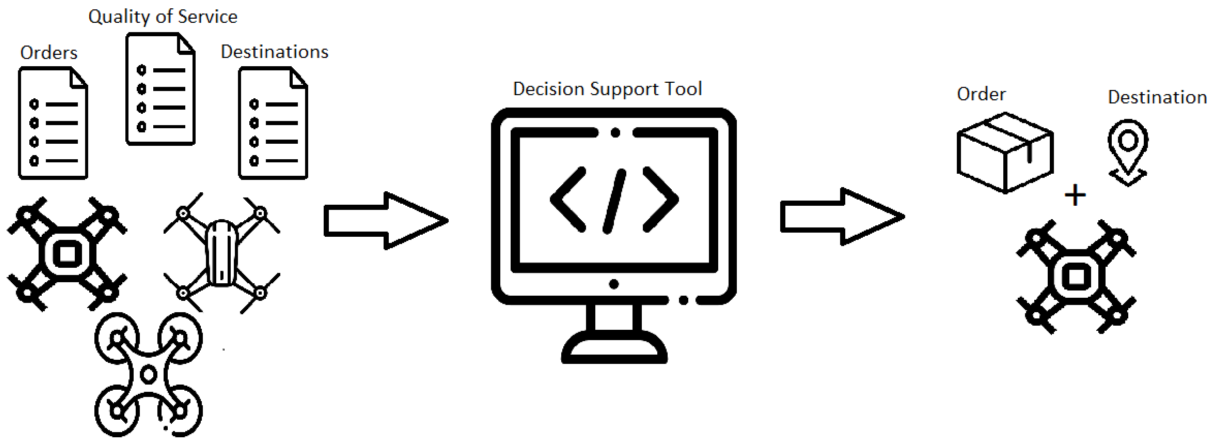


Figure 2: Flowchart of Network Model

The figure illustrates four inputs on the left side which means that the operator selected the P2P network strategy in this example. The size of the orders, quality of service, destination nodes, and vehicles are given.

The destination and service type for each order are, however, unknown due to uncertainties. A probability distribution function could be used to determine the service type and destination of each order. The figure uses drones as an example that can be used as small city-friendly vehicles. Each vehicle has different criteria and availability that the Decision Support Tool (DST), in which the network design model is incorporated, uses to assign a vehicle to an order. It also uses the provided quality of service as given per service type for each order to determine the priority of an order. The order with the highest probability should be assigned first. This is the initial performance of the network that can be tested for multiple scenarios.

If there were intermediate facilities given, the DST would have selected the optimal intermediate facility locations. Subsequently, it would assign orders to a vehicle as explained before at the distribution center and similarly at the intermediate facility.

The network design model supposed to have the following contributions:

1. Allowing a logistic operator to design a last mile delivery network
2. Allowing a logistic operator to test the performance of a delivery network under cost minimization;
3. Providing the operator with flexibility in different network strategies and configurations;
4. Providing the operator with the possibility to analyze the impact of risk factors and uncertainties.

To conclude, the framework should be set-up flexible to allow any logistic operator to design a last mile delivery network under cost minimization.

4. Framework Formulation

In this section, a network model is presented as a sequential framework that addresses the design of a logistics network. This method is used as it allows to address the Knapsack Problem, Facility Assignment, TSP, and package to drone assignments by using binary decision variables. The objective of the network model is to solve each of the problems individually to minimize the operational costs of the network. It is assumed that the:

1. order size;
2. destination locations;
3. quality of service;
4. number of Inbound Vehicles;
5. number of Outbound Vehicles;
6. vehicle capacity; and
7. number and locations of Intermediate Facilities;

are given. The sequential framework allows to address the configuration of a P2P network and to design a H&S network strategy. If there are no intermediate facilities nor inbound vehicles, the model considers the P2P network strategy and delivers packages directly from origin to destination. Otherwise, the model considers the H&S network strategy where packages are distributed over intermediate facilities at which outbound vehicles deliver the packages from the intermediate facility to the destination. The P2P network can, therefore, be considered as a sub-problem of the H&S network, only package to outbound vehicle assignment is relevant, indicated by the yellow box in Figure 3. The remaining part of this section focuses on the sequential framework used for the H&S network.

The framework uses a set of candidate locations of intermediate facilities and a set of destination locations, both given in a csv-file. The locations are selected based on market research with a main focus for population density, employment, and feasibility. The other inputs are manually given to the framework where the operator decides how the demand of orders is distributed over a set of time windows. See box A in the design framework in Figure 3.

This input is used to find the optimal intermediate facility locations which is indicated with box B in Figure 3. A binary integer linear programming model is formulated to assign each order to an intermediate facility. The model selects the intermediate facility based on minimum distance between origin, intermediate facility and destination for each order individually. This approach is chosen to find strategic locations of the facilities to increase efficiency of the network by having a higher catchment area from each intermediate facility without a potential significant increase in operation costs - i.e. distance. The process is done numerous times by the principal of repeated random sampling, which is the formulation of the MCS. The average number of packages distributed per intermediate facility gives the operator a good indication whether the candidate point is selected, if at all, and how frequent.

The operator can change the csv-file to only keep the relevant intermediate facility based on the run MCS. This is the only change in input, at box 1, used for the sequential framework, called configuration, on the right side of Figure 3.

The model is designed to maximize the sum of the values of the packages the inbound vehicle can carry. This integer linear programming problem is known as the Knapsack Problem, see box 2 in Figure 3. It considers the value, weight, and volume of each package. Each order has a value, based on package valuation, to allow the model to prioritize packages. The weight and volume are used to meet the capacity constraints. It does not, however, consider the destination locations. It is assumed that inbound vehicles are designed to carry many packages relative to the outbound vehicles, distances between intermediate facilities are small, and the demand is not big enough that outweighs the first two assumptions. In other words, it is assumed that the number of packages an inbound vehicle has to carry every trip is not large enough for it to be efficient to carry only packages designated to one set of intermediate facilities. The total average delivery duration is assumed to be shorter when the inbound vehicle carries all packages irregardless of the destination locations rather than bringing a part of packages to a set of intermediate facilities and coming back to deliver the remaining part of packages to the other set of intermediate facilities. The Knapsack Problem is an NP-hard combinatorial optimisation problem. The computation time increases with increasing number of packages. It is, therefore, proposed to use pyeasyga, a Genetic Algorithm (GA), to solve multidimensional knapsack problems instead of exact solutions.

The framework uses the destinations of the assigned orders to determine to which intermediate facility each package should be distributed to, see box 3 in Figure 3. The same binary integer linear programming model is used as for the design in box B in Figure 3. Thus, the model assigns the facilities to the inbound vehicle based on the shortest distance per order. Not the shortest distance of all orders together. Because the network would otherwise always assign all orders to only one intermediate facility. It would take away the entire principal of having a H&S network at the first place. Since a H&S network is designed to avoid congestion allowing to scale the network. That is why the Network Model is depicted in two parts where the operator can decide first, based on the MCS, which intermediate facility is the most optimal location while taking into consideration how frequently the intermediate facility is used based on the given scenario. Following, this input is purely used by the configuration to determine to which facility each order should be distributed to individually.

The model aims to find one route with minimum distance given all locations the inbound vehicle must visit to distribute all packages. This integer linear programming problem is known as the TSP indicated by box 4 in Figure 3. The computation time increases significantly when the number of locations to be visited increases. Therefore, instead of using an exact solution. It is proposed to use Machine Learning, Randomized Optimization and SEarch (mlrose), a randomized optimization and search algorithm, for solving the TSP that is NP-hard by nature [46].

The model assigns an available outbound vehicle to the orders that arrived at the designated facility. The binary integer linear programming model is called the Outbound Vehicle Assignment indicated by box 5 in Figure 3. The Vehicle Assignment would have been the only problem if the network was not facilitated with intermediate facilities nor with inbound vehicles.

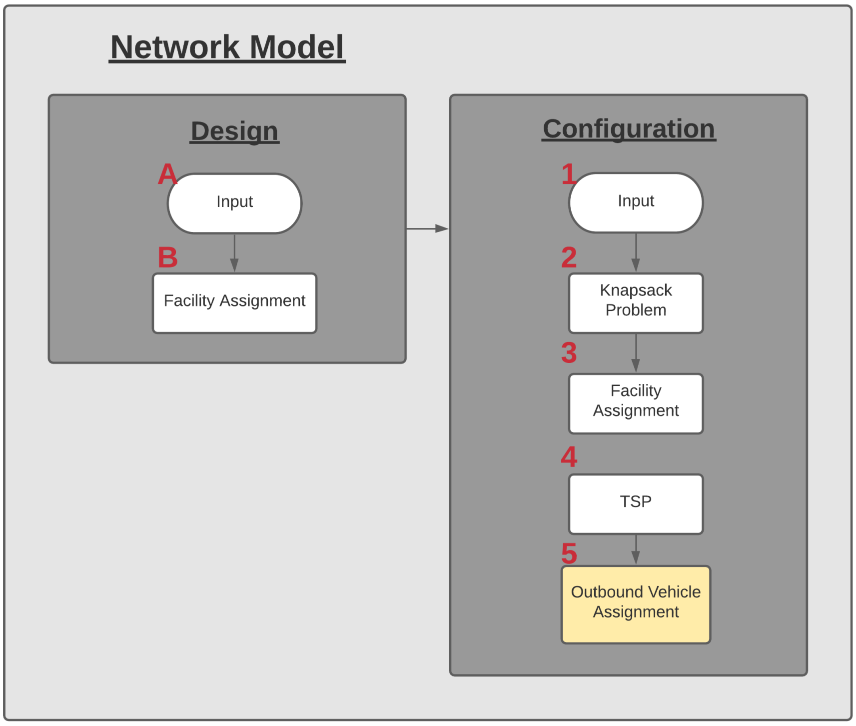


Figure 3: Flowchart Network Model

Package Valuation

The model is facilitated with a package valuation tool to allow the network to prioritize packages at the Knapsack Problem and Vehicle Assignment, box 2 and box 5 respectively, in Figure 3. It is assumed that the network uses two service types, Xpress and Normal. If there is no distribution given, it is assumed that the model has a uniform distribution between Xpress service and Normal service when assigning a service type to an order. The Xpress service is tailored for customers with desires for quicker delivery services. Late deliveries are thus higher penalized for orders with Xpress service than orders with Normal service.

The value is based on the service type and and on the due delivery. Due delivery is the minutes that are remaining before the package should depart from the facility for on-time delivery. Xpress should be prioritized over Normal, and on-time delivery should be prioritized over late-delivery. Bluntly following this approach has, however, the possibility that packages that exceeded the due delivery time will never be delivered. Hence, the model uses a score system. The package with the highest score will be prioritized. Only the order with the highest valuation will be considered to an available drone, else wise the order is put on hold. The package is rewarded with 50 or 10 points for having the Xpress service or Normal service respectively. Both services gain 50 points, if the package has a due delivery bigger than zero - it is estimated to be delivered on time. If the Xpress service package has a delay of x minutes, it is penalized with x^3 points. The package with Normal service is penalized with $(0.5y)^2$ points with y delayed minutes. The red line in the plot shown in Figure 4 indicates the relation between the amount of minutes for each service it is required to be prioritized over the other. In other words, the area above the red line indicates the amount of delay it is required for the package with Normal service to be prioritized over the package with Xpress service.

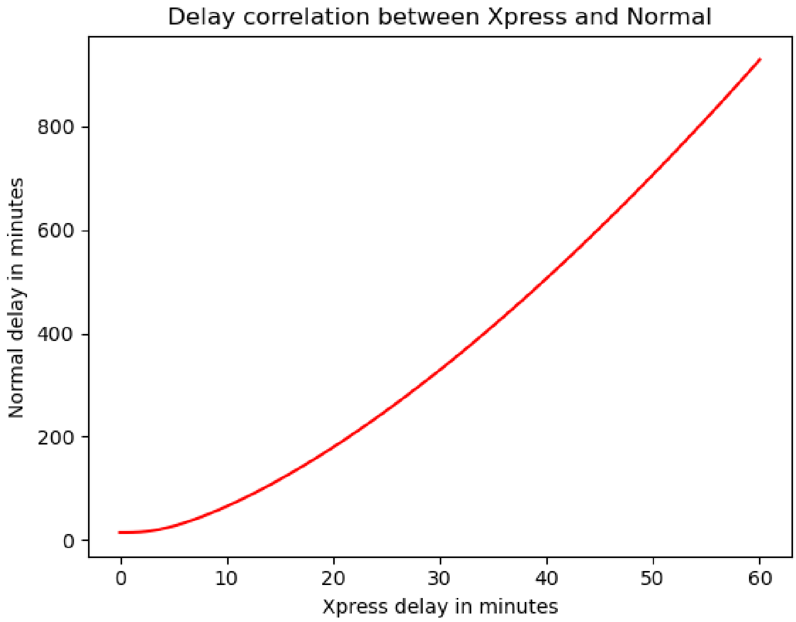


Figure 4: Relation between an Xpress package with delay and a Normal package with delay

Some key examples are withdrawn from the graph, see below:

- Xpress without delay is prioritized over Normal without delay;
- Normal with $\geq$ 20 minutes delay is prioritized over Xpress without delay;
- Normal with $\geq$ 65 minutes delay is prioritized over Xpress with 10 minutes delay;
- Normal with $\geq$ 179 minutes delay is prioritized over Xpress with 20 minutes delay; and
- Normal with $\geq$ 15 hours and 30 minutes delay is prioritized over Xpress with 60 minutes delay;

Mathematical Formulation

The order of the sequential framework indicated by Configuration in Figure 3 will be used in this subsection as a guideline. It covers the Facility Assignment of the design model and it covers the Outbound Vehicle Assignment that is relevant for both P2P and H&S network.

The total number of orders used by the model is indicated by the letter O. The set of orders can be distributed as desired by the operator over different time windows w (w $\in$ W). Each order o (o $\in$ O) has a destination node d (d $\in$ D) and a quality of service q (q $\in$ Q). Depending on the chosen network strategy, the network will be equipped with inbound vehicles I and intermediate facilities F. The set of outbound vehicles is indicated by B.

The model has four binary decision variables. If order o is assigned to outbound vehicle b, the binary decision variable $m_{o,b} = 1$, and 0 otherwise. When the network is facilitated with inbound vehicles and facilities, the decision variable $p_{o,i} = 1$, if order o is assigned to inbound vehicle i, otherwise it is 0. The decision variable $u_{o,f} = 1$ if facility f is assigned to order o, 0 otherwise. When determining the optimal route of the inbound vehicle, the decision variable $x_{k,l} = 1$ if the route goes from facility k to facility l, otherwise it is 0. The objective of the sequential framework is to minimize the operating cost, which is defined in terms of delivery duration c_o, and in terms of ground time of the inbound vehicle and outbound vehicle, e_i and g_b, respectively. The model solves problems sequentially to minimize these costs. The mathematical formulation of the network model is given below and followed with the mathematical formulation of each problem individually.

Sets:

- O: Set of orders
- W: Set of time windows
- D: Set of destination nodes
- Q: Set of service
- I: Set of inbound vehicles
- F: Set of intermediate facilities
- B: Set of outbound vehicles

Subsets:

- J: Subset of F
- S: Subset of O

Decision Variables:

- $m_{o,b}$: 1 if order $\boldsymbol{o}$ is assigned to outbound vehicle $\boldsymbol{b}$, 0 otherwise
- $p_{o,i}$: 1 if order $\boldsymbol{o}$ is assigned to inbound vehicle $\boldsymbol{i}$, 0 otherwise
- $u_{o,f}$: 1 if order $\boldsymbol{o}$ is assigned to facility $\boldsymbol{f}$, 0 otherwise
- $x_{k,l}$: 1 if the path goes from facility $\boldsymbol{k}$ to facility $\boldsymbol{l}$, 0 otherwise

Parameters:

- P_i: max payload inbound vehicle $\boldsymbol{i}$
- P_b: max payload outbound vehicle $\boldsymbol{b}$
- V_i: max volume inbound vehicle $\boldsymbol{i}$
- V_b: max volume outbound vehicle $\boldsymbol{b}$
- R_i: max range inbound vehicle $\boldsymbol{i}$
- R_b: max range outbound vehicle $\boldsymbol{b}$
- N_i: minimum load factor for inbound vehicle $\boldsymbol{i}$
- U_i: minimum number of orders that the inbound vehicle $\boldsymbol{i}$ must carry
- w_o: weight of order $\boldsymbol{o}$
- v_o: volume of order $\boldsymbol{o}$
- $z_{o,i}$: value of order $\boldsymbol{o}$ assigned to inbound vehicle $\boldsymbol{i}$
- $y_{o,b}$: value of order $\boldsymbol{o}$ assigned to outbound vehicle $\boldsymbol{b}$
- $r_{o,f}$: distance of order $\boldsymbol{o}$ from origin to facility $\boldsymbol{f}$ to destination
- r_b: distance of outbound vehicle $\boldsymbol{b}$ from origin to destination
- $h_{k,l}$: distance from facility $\boldsymbol{k}$ to facility $\boldsymbol{l}$
- $a_{o,w}$: arrival time of order $\boldsymbol{o}$ in time window $\boldsymbol{w}$
- d_o: destination node of order $\boldsymbol{o}$
- q_o: quality of service for order $\boldsymbol{o}$

Output:

- c_0: total delivery duration per order $\boldsymbol{o}$
- e_i: total ground time per inbound vehicle $\boldsymbol{i}$
- g_b: total ground time per outbound vehicle $\boldsymbol{b}$

Knapsack Problem

The model is designed to maximize the sum of the values of the packages the inbound vehicle carries, so that the sum of the weight and volume of the assigned packages is less than the weight capacity and volume capacity of the inbound vehicle. However, in the occasion that there are not enough orders to fill the inbound vehicle, the inbound vehicle should stay grounded. Even though it is desired to minimize the ground time of all vehicles, it is not efficient nor optimal to transport the inbound vehicle with a low load factor. The model is, therefore, proposed with a minimum load factor constraint for the inbound vehicle, see Equation 1a.

$$\sum_{o \in S} 1 \geq U_i, \qquad S \subset O, \quad \forall i \in I \tag{1a}$$

$$\text{With } U_i = \frac{N_i}{100\%} \cdot P_i, \qquad \forall i \in I \tag{1b}$$

O is the daily set of orders and S is a subset of O which indicates the orders that are at a specific moment in time present at the facility. U_i is the minimum number of orders that the inbound vehicle should carry at least. It is determined from the given load factor N_i that is a ratio of the max paylaod of the inbound vehicle as shown in Equation 1b. Only, and only if, Equation 1a is met, the model will assign orders to the inbound vehicle according to Problem 2:

$$Max \sum_{o \in O} z_{o,i} \cdot p_{o,i}, \qquad \forall i \in I \tag{2a}$$

$$\text{Subject to} \sum_{o \in O} w_o \cdot p_{o,i} \leq P_i \qquad \forall i \in I \tag{2b}$$

$$\sum_{o \in O} v_o \cdot p_{o,i} \leq V_i \qquad \forall i \in I \tag{2c}$$

The objective function of the Knapsack Problem is explained by Equation 2a. The value of each package is described by z_o, which is valued according to the previous explanation. The decision variable $p_{o,i}$ ensures that only the assigned orders will be taken into account. The sum of the weight w_o and volume v_o of all assigned orders must be within the max payload P_i and max volume V_i capacity of the inbound vehicle as indicated by Equation 2b and Equation 2c, respectively.

The problem is solved sequentially per available inbound vehicle. In other words, the model assigns orders to each inbound vehicle until there are no more available inbound vehicles left. It implicates a better approximate of the network performance than guaranteeing that all packages are transported without a vehicle limit. The performance will be an important indicator reflected in the ground time and delivery duration that can be used as an indicator to determine the number of inbound vehicles required for the network.

Facility Assignment

The model is designed to minimize the total distance travelled per order. In other words, the model aims to choose the facility with the lowest distance from origin to facility to destination. The facility assignment is described below, see Problem 3:

$$Min \sum_{o \in O} \sum_{f \in F} r_{o,f} \cdot u_{o,f} \tag{3a}$$

$$\text{Subject to} \sum_{f \in F} u_{o,f} = 1, \qquad \forall o \in O \tag{3b}$$

The objective function minimizes the distance $r_{o,f}$ from origin to facility f to destination per order o, see Equation 3a. It is assumed that the origin and destination of each order are given. The constraint ensures that only one facility can be assigned to order o as indicated by Equation 3b. However, multiple orders can be assigned to one facility. The decision variable $u_{o,f}$ can only have the value 1 if the facility is assigned to the order, otherwise it is 0.

Traveling Salesman Problem

The inbound vehicle distributes packages over multiple facilities. The TSP aims to minimize the distance travelled when doing such a tour. Given $h_{k,l}$ the distance from facility k to facility l is bigger than zero, the TSP can be formulated as an integer linear programming problem, see Problem 4:

$$Min \sum_{k \in F} \sum_{l \in F, l \neq k} h_{k,l} \cdot x_{k,l} \tag{4a}$$

$$\text{Subject to} \sum_{k \in F, k \neq l} x_{k,l} = 1, \qquad \forall l \in F \tag{4b}$$

$$\sum_{l \in F, l \neq k} x_{k,l} = 1, \qquad \forall k \in F \tag{4c}$$

$$\sum_{k \in J} \sum_{l \in J, l \neq k} x_{k,l} \leq |J| - 1, \qquad J \subset F, \quad |J| \geq 2 \tag{4d}$$

The TSP aims to minimize the distance required to travel to cover only the assigned facilities, which is taken into account by including the decision variable $x_{k,l}$, see Equation 4a. The first constraint requires that the inbound vehicle can reach a facility only from one prior facility, see Equation 4b. The second constraint requires that the departure is exactly to one facility, see Equation 4c. In other words, the two constraints ensure that the inbound vehicle can visit a facility and depart from a facility only once. With J a subset of F, the last constraint ensures that the solution is a single tour and not a combination of multiple sub-tours as indicated by Equation 4d.

The inbound vehicle has typically a larger range compared to the small distances it is required to cover between intermediate facilities in city logistics. It is, therefore, assumed that the inbound vehicle will be able to complete each tour and it will have full range at each start of the tour.

Outbound Vehicle Assignment

The model aims to maximize the value of the package it assigns to the outbound vehicle. The valuation $y_{o,b}$ is defined as explained before in Package Valuation 4. The assignment problem is given by Problem 5:

$$Max \sum_{o \in O} \sum_{b \in B} y_{o,b} \cdot m_{o,b} \tag{5a}$$

$$\text{Subject to} \sum_{b \in B} m_{o,b} = 1, \qquad o \in O \tag{5b}$$

$$\sum_{o \in O} m_{o,b} = 1, \qquad b \in B \tag{5c}$$

The objective function is described by Equation 5a that finds the match for an order o and an outbound vehicle b with the highest valuation. The problem is given two constraints to ensure the objective function indeed finds a match. Equation 5b indicates that each order o needs to be assigned to only one outbound vehicle b, and Equation 5c indicates that each outbound vehicle b needs to be assigned to only one order o. The outbound vehicle has limited space to carry packages. It is, therefore, assumed that it cannot carry more than one package per trip. The decision variable $m_{o,b}$ can only have the value 1 if it is assigned and 0 otherwise.

Outbound vehicles are typically smaller vehicles with lower payload and lower volume capacity. The orders must meet the requirements of the outbound vehicles as described by Equation 6 and Equation 7:

$$\sum_{o \in O} w_o \cdot m_{o,b} \leq P_b, \quad \forall b \in B \tag{6}$$

$$\sum_{o \in O} v_o \cdot m_{o,b} \leq V_b, \quad \forall b \in B \tag{7}$$

The weight of the assigned order and the volume of the assigned order must be within the payload capacity P_b and volume capacity V_b of the outbound vehicle. The weight of the order and the volume of the order are described by w_o and v_o, respectively.

The distance r_b required for the outbound vehicle to transport the order o from its origin to the destination must be smaller than the range R_b of the corresponding outbound vehicle, see Equation 8.

$$\sum_{o \in O} r_b \cdot m_{o,b} \leq R_b, \quad \forall b \in B \tag{8}$$

The origin is a given at this point in the sequential framework. For the P2P network it would be the distribution center, and for the H&S network it would be the facility as assigned by the model.

Assumptions

The network design model is assumed to be utilized with one-mission vehicles. The vehicles deliver all assigned packages at the designated destination and return to their origin for as long as the network is operative. The operator can indicate the desired operation hours of the network with the quality of service. The model will stop running once it reached the closing time, irregardless where the vehicles are. The assumption is chosen to understand how many packages the network is able to deliver until closing time including the entire demand. All made assumptions are summed up below:

- Ground Time is calculated by subtracting Arrival Time from Departure Time ;
- Delivery Duration is calculated by subtracting Arrival Time Distribution Center from Arrival Time Destination;
- Not delivered packages are all packages that did not arrive at the destination at the ultimate operation time of the network, which is calculated by subtracting the total number of delivered packages from the entire set of orders;
- Origin is fixed and known;
- Inbound vehicle departs only if it meets the minimum load factor constraint;
- Outbound vehicle departs only if it has at least one and at most one order assigned;
- Outbound vehicle cannot carry more than one order;
- All vehicles have one mission;
- All intermediate facilities can handle each an infinite number of orders simultaneously;
- All destinations are located next to a warehouse, it can store infinite number of packages ;
- Two or more vehicles can deliver a package at the same time at the same facility - at intermediate facility and at destination;

- Outbound vehicle has full range after each trip;
- Total tour of the inbound vehicle is always within its range;
- Inbound vehicle has full range after completion of each tour;
- Set of facility locations, destination locations, and demand are given;
- All assigned packages to the inbound vehicle have a perfect fit - no optimal placement;
- The quality of service that the network provides is divided by an Xpress service and a Normal service;

Monte Carlo Simulation

It is assumed that the logistic operator has historical data available that can be used as a guideline for the daily order size. A MCS is formulated to incorporate the impact of uncertainties and risk factors on the order size by repeated random sampling for different scenarios. The simulation creates a set of orders based on the given demand by the operator, indicated by O. Such data can be difficult to obtain by an operator, but it is assumed that the logistic operator is able to extract historical data on a daily level. The simulation is provided with a set of time windows, W, to allow the operator to have a more accurate estimate of arrival flows during a day. The number of time windows and the size of each time window depends on the accuracy of the provided data and the desired operating hours of the network. The probability distribution of order arrivals per time window can be uniform, unless the operator has more accurate historical data. The random arrival time is indicated by $a_{o,w}$, with o the order and w a time window.

Even though the destination of each order is unknown, it is assumed that a set of destination locations is given. The model selects a destination node for each order based on a probability distribution function (pdf). The pdf will be determined by the population density and by the number of destination locations, D. Clustering each of these matters per district allows the operator to determine the pdf of the destination locations. The probability is a ratio of the population density relative to the total population density of all districts together. The district probability is divided by the number of destination locations in the district assuming that the population density within each district is homogeneous and thus the definition of Uniform Distribution applies. The randomly generated destination location d_o is given to each order o .

The system allows the operator to tailor the quality of service provided to its customers, Q. It is assumed that the quality of service a logistic provider wants to offer is given. Depending on how much the operator wants to tailor its service to its consumers' desires, the system will have a set of service types to assess the impact a quality of service can have on the network. The operator can create a pdf based on the operator's expectations towards consumers' desires per service type. Else wise, a uniform distribution is assumed. The simulation assigns a service type $q_o$to each order o based on the chosen pdf.

Assumptions MCS

The following assumptions apply to the distributions used by the MCS:

- If there is no distribution given, the model uses a uniform distribution for arrival times within a time window;
- The model uses a uniform distribution for destination locations within the same district;
- If there is no distribution given, the model uses a uniform distribution between Xpress service and Normal service.

5. Case Study

The proposed framework is tested through a case study with Air Canada in the City of Toronto. Historical demand data of Air Canada and all proposed destination locations are used as input for the model. The locations are based on an elaborate market research and are separately entered in the model via a csv-file containing all coordinates. Air Canada collaborates with a drone manufacturer and operator called Drone Delivery Canada (DDC). It is proposed to use their manufactured drones as the small city-friendly vehicles, Sparrow and Robin XL. Each drone has different specifications which the model uses as input. The model uses the different specifications to determine the better choice of drone for a specific scenario. Together with Air Canada, it is proposed to approach the problem by using a P2P and a H&S network strategy.

Internal data platforms of Air Canada allows to analyse historical data from 2016 to 2019. The provided data is on day-level with precise arrival times in Toronto. It is proposed to aggregate the package arrivals per three hour time frame to get a better grasp on the flow of package arrivals per day. It is proposed that the logistic network will be operative from 7 am to 7 pm due to expected restrictions in drone operations by night. As such, the simulation has 4 sets of time windows per day, 7 am - 10 am (early morning), 10 am - 1 pm (late morning), 1 pm - 4 pm (early afternoon), and 4 pm - 7 pm (late afternoon). It is assumed that the arrival times per three hour time frames are independent and identically distributed (i.i.d.). Therefore, the simulation uses an equally divided probability per three hour time frames to determine at which hour a package arrives in that particular time window. The packages received outside operation hours do not have to be randomized as these packages will be ready to be distributed at 7 am by the network.

Two service types, Xpress and Normal, are proposed to provide a certain quality of service to the consumer. With the Xpress service a delivery before 12 pm and the Normal service a delivery before 7 pm if in both cases the package arrived before 7 am, otherwise the next day. The probability distribution between Xpress and Normal is also assumed to be i.i.d..

The destination of each order is, however, uncertain. The probability of a package's destination depends on population density. The pdf can be determined as described in (4). The pdf indicates the probability that an incoming order will be delivered at a specific depot location per district, see Table 1.

Destination probability distribution function - City of Toronto				
District	Population in millions	Population Density	Number of destinationss	pdf
York	0.146	4%	3	1.4%
Etobicoke	0.365	10%	1	10.2%
Old Toronto	0.798	22 %	51	0.4%
North York	0.869	24%	18	1.3%
Scarborough	0.632	18%	17	1.0%
East York	0.118	3%	5	0.7%
Markham	0.343	10%	2	4.8%
Richmond	0.208	6%	1	5.8%
Thornhill	0.112	3%	2	1.6%
Total	3.591	100%	100	

Table 1: Case Study

Assumptions

It is assumed that the drones fly directly from origin to destination without obstacle avoidance consideration. This is done, because the drones of DDC have these algorithms already available with additional traffic controllers to control safe flight operations. Their systems are designed to find the shortest path, that is not the goal of this project. So, the distance can be determined by using the Great Circle Distance (GCD) based on the coordinates of the facility locations. In addition to calculate the flight duration, the drones are also assumed to fly at constant max speed. Having the distance and speed allows to calculate the flight duration. DDC provides a general timeline for landing and unloading of the package of ten minutes for Sparrow and Robin XL, and 15 minutes for Condor. The additional minutes are added to the flight duration to estimate a more accurate total flight duration.

Air Canada is expecting to continue receiving packages 24/7 based on historical data. Regulators do not allow drones to operate in populated areas. Excessive flight test programs are needed for the regulators to build trust in safe and harmonized operation of drones in the society. The Drone Delivery Network is, therefore, designed with operation hours between 7 am and 7 pm. See below for the complete set of assumptions:

- It takes an hour for the packages to be ready to depart from the DC after aircraft landing at YYZ;
- Drones fly directly from origin to destination measured in GCD;
- All drones fly at a constant max speed;
- Condor can refuel the tank at all satellites and at the DC;
- Condor takes in total 15 minutes for landing, package unloading, required visual check, and gas refuel;
- Robin XL and Sparrow can both swap old batteries with replenished batteries at all facilities;
- Robin XL and Sparrow take both in total 10 minutes for landing, package unloading, and battery swap;
- Time window packages retrieval: 24/7;
- Operation times drone: 7am – 7pm;
- P2P network: all drones start at DC;
- H&S network: all Condors start at DC and all RXL and Sparrows are divided by ratio over the satellites;
- Fleet of the P2P network, and the inbound and outbound fleet of the H&S network are all homogeneous.
- All packages meet either the Sparrow or Robin XL dimension criteria - depending on the fleet configuration;
- The entire demand of Air Canada to YYZ is assumed to have the City of Toronto as end-destination;
- The number of missing packages in the data is higher than the number of packages that do not have the City of Toronto as actual end-destination.

Results

The network design model is made in the programming language Python 3.8 (64-bit), because of its flexibility and the many public libraries. It reads a csv-file with coordinates of all facilities. The flow of package arrivals per time window is given in the model with a multiplier as a parameter to allow to check for different scenarios, see Table 2. Each scenario considers packages that meet the criteria of the Sparrow (small packages) and the Robin XL (big packages).

Table	Scenario 1: Base Case		Scenario 2: Better Case		Scenario 3: Bull Case	
Time Frame	1.1) Small Packages	1.2) Big Packages	2.1) Small Packages	2.2) Big Packages	3.1) Small Packages	3.2) Big Packages
Opening	24	43	34	60	48	86
Morning 1	5	10	7	14	10	20
Morning 2	6	11	8	15	12	22
Afternoon 1	8	15	11	21	16	30
Afternoon 2	9	17	13	24	18	34
Total	52	96	73	134	104	192

Table 2: Scenarios

DDC manufactured a drone called Condor that can serve as an inbound vehicle. It is able to fit at least 77 Sparrow packages and 59 Robin XL packages considering the volume capacity of the Condor and the max dimensions of the packages that Robin XL and Sparrow can carry, assuming perfect fit of the packages. Consequently, only the Better Case (Scenario 2.2) and the Bull Case (Scenario 3.2) for bigger packages are considered relevant for the H&S network to avoid high ground times and low load factors. Scenario 2.2 is selected to present a complete comparison of the results between the P2P and the H&S network.

Key Performance Indicators

The experimenter selected the following Key Performance Indicators (KPI)s:

- Average Ground Time (G.T.) in minutes;
- Average Delivery Duration (D.D.) in minutes;
- Average D.D. Xpress in minutes;
- Average D.D. Normal in minutes;
- Number of packages not delivered the same day;
- Average number of packages outside range;

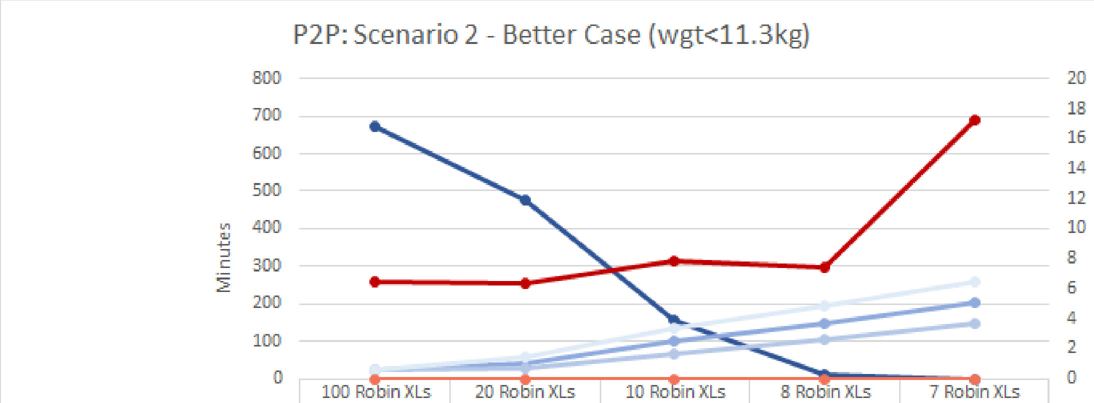
The ground time is a good indicator to determine the required number of drones. An excess in drones could be indicated by a high ground time, and vice versa. The average delivery duration indicates how quickly the network delivers packages from origin to the end-consumer. A low delivery duration would indicate a quick delivery service which could be desired by customers. However, it is plausible to have a high ground time when the delivery duration is low. It requires a quality of service versus cost trade-off to determine what is desired. The average delivery duration is also distinguished per service type. Allowing the operator to determine how quickly the network should be able to deliver packages for each service type. It should help the operator to define the quality of service requirements. The simulation runs a daily demand set. It is, therefore, not possible to observe the overall performance of the network over an entire week. For better understandings, the simulation indicates the number of packages that were not delivered the same day. A backlog could result in poor network performance of the next day and the day after due to accumulation. There are nine DroneSpots located outside the range of the Sparrow for the P2P network. When the final output indicates a high number of packages outside the drone's range. It could be another trade-off for Air Canada to configure its fleet with Robin XLs.

The only additional KPIs for the H&S network are ground time, that is distinguished per echelon level, and delivery duration that is distinguished per satellite. Ground time per echelon level allows to get a better grasp on the number of vehicles required for each echelon. Additionally, a big difference in delivery duration per satellite could indicate a discrepancy in how the outbound vehicles are distributed over the satellites.

P2P: Results

The performance of the P2P network for this scenario is presented in Figure 5. The x-axis displays the number of Robin XLs used and the y-axis displays minutes. The ground time of the Robin XLs, indicated with the dark blue line, drop while the average delivery duration per package increases as the number in used Robin XLs decrease. The average delivery duration is 24 minutes and has an insignificant change in duration between the service types when the network uses 100 Robin XLs. As the network is facilitated with more drones than it has to deliver packages, there is always a drone available. Having said that, it can be concluded that the P2P network has the quickest delivery on average in 24 minutes. Note that 6.5 packages are not delivered with the 100 Robin Xl configuration. That is due to the assumption that packages can still arrive at 7 pm exactly, but the drones will stop operating irregardless of their location. The network has an average of zero ground time when it is utilized with seven Robin XLs. It has, however, ten more packages it was not able to deliver by the end of the day compared to the configuration with eight Robin XLs. The eight Robin XLs have a total average ground time of 11 minutes. The ground time can be considered insignificant and the one extra drone can allow more flexibility to the network with better growth opportunities. The risk reward could be considered favorable enough. Therefore, the best configuration is with eight Robin XLs.

Scenario 2.2 reaches zero ground time with seven Robin XLs, see Figure 5. It has, however, an increase of 10 not delivered packages with respect to eight Robin XLs. The ground time is only 11 minutes with relative quick deliveries. It can be concluded that the P2P network should be utilized with eight Robin XLs for this specific scenario.



	100 Robin XLs	20 Robin XLs	10 Robin XLs	8 Robin XLs	7 Robin XLs
Average Ground Time	671.5	477.3	156.4	10.9	0
Average Delivery Duration	24.1	42.4	100	149.6	202.6
Average D.D. Xpress	24.1	29	67.3	104.4	149.2
Average D.D. Normal	24.1	56.3	133	194	259
Not delivered	6.5	6.4	7.8	7.4	17.3
Outside range	0	0	0	0	0

Figure 5: P2P: Results of Scenario 2.2

H&S: Results

From Graph 6 to Graph 9 it can be observed that the model for the H&S network selects only four satellites based on the MCS Satellite Selection that was run 10,000 times for Scenario 2.2. Satellite 1 and Satellite 2 follow a normal distribution. For a normally distributed random variable Y, the Confidence Interval (CI) can be defined as follows:

$$\mathrm{P}(\mu - 1.96\sigma \leq Y \leq \mu + 1.96\sigma) = 0.95 \tag{9}$$

with μ the mean and σ the standard deviation. 1.96 is derived from the standard normal z distribution for a 95% confidence interval. In other words, it can be said with 95% confidence that Satellite 1 will distribute between 90 and 109 packages a day, and Satellite 2 between 16 and 33 packages a day for this specific scenario. The 95% CI interval is indicated with the grey area and the two red zones indicate the area outside the CI interval. The other two satellites have an insignificant number of packages it distributed a day, see Figure 8 and Figure 9. Satellite 4 and Satellite 10 distribute approximately more than three quarter of the times less than 5% of the total packages. It can be concluded that these two satellites will not be relevant for the H&S network.

From these observations it is expected that Satellite 1 distributes 80% of all packages and Satellite 2, 20% of all packages. Because of the nature of i.i.d., it can be concluded that the ratio of packages distributed per satellite is constant and independent of the size of orders. The ratio is used as an input in the configuration model of the H&S model to test the network for its performance, see Figure 10.

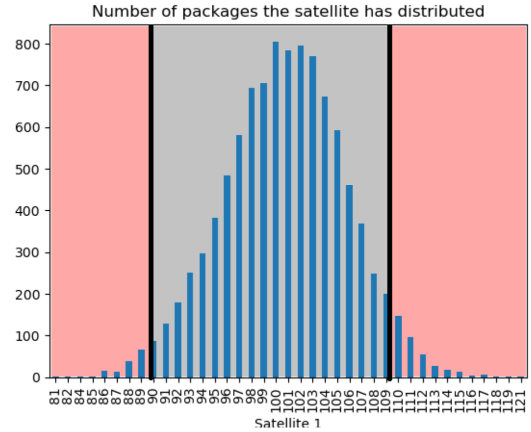


Figure 6: Simulation Satellite 1 - 10.000 runs

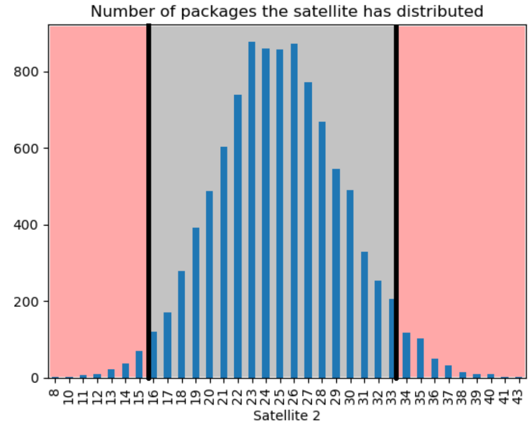


Figure 7: Simulation Satellite 2 - 10.000 runs

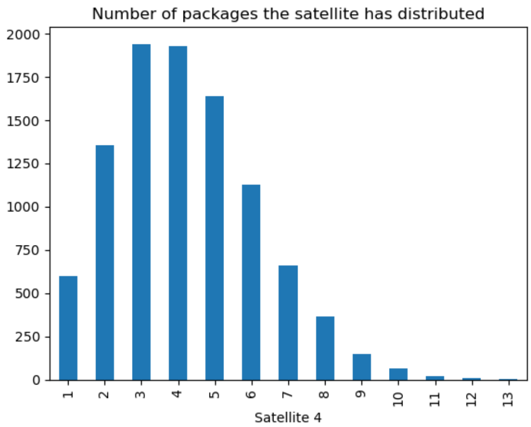


Figure 8: Simulation Satellite 4 - 10.000 runs

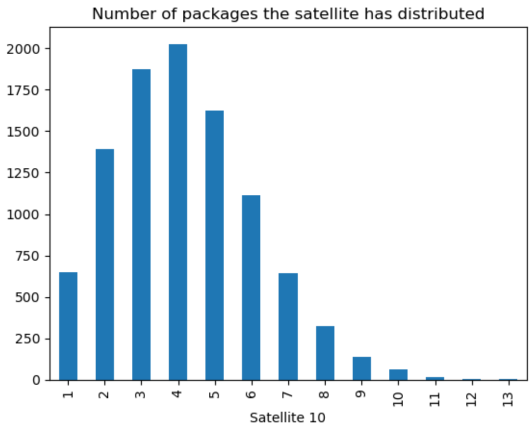
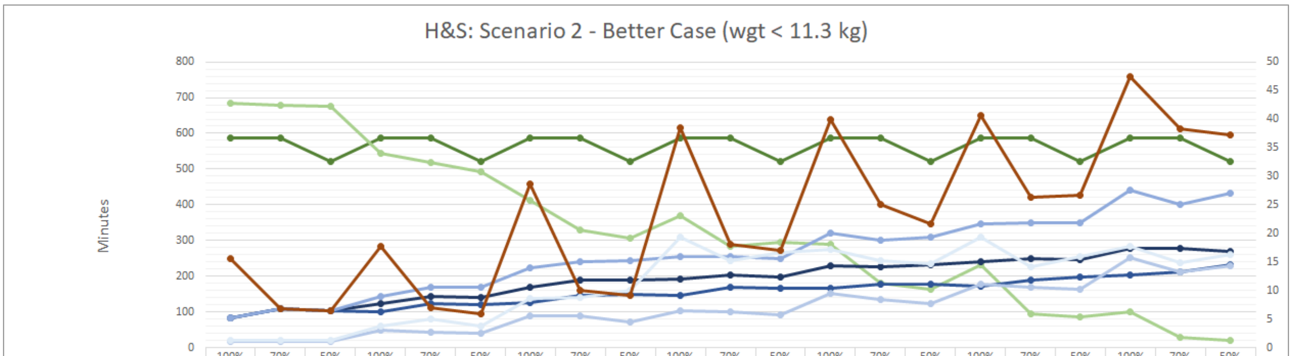


Figure 9: Simulation Satellite 10 - 10.000 runs



	100% Capacity 100 Robin XL	70% Capacity 100 Robin XL	50% Capacity 100 Robin XL	100% Capacity 20 Robin XL	70% Capacity 20 Robin XL	50% Capacity 20 Robin XL	100% Capacity 10 Robin XL	70% Capacity 10 Robin XL	50% Capacity 10 Robin XL
Ave G.T. inbound	588	588	522	588	588	522	588	588	522
Ave G.T. outbound	683.1	679.3	675.8	544.5	517.3	491.8	413	329.5	306
Ave D.D.	82.3	109.2	102.3	122.2	143.6	141.7	170	189.3	188.6
Ave D.D. Xpress	82.6	109.8	102.2	101.4	122.2	119.8	125.4	146.1	150.2
Ave D.D. Normal	82.1	109.3	103	144.6	168	168.1	222.5	241.2	242.6
Ave D.D. sat 1	18	18.1	17.8	48.8	44	40.1	88.5	89.7	72.8
Ave D.D. sat 2	19.9	20.4	20.2	60.4	79.7	61.2	137.4	141.2	160.4
Ave #packages not delivered	15.5	6.9	6.4	17.8	7	5.9	28.6	10.1	9.2

	100% Capacity 8 Robin XL	70% Capacity 8 Robin XL	50% Capacity 8 Robin XL	100% Capacity 6 Robin XL	70% Capacity 6 Robin XL	50% Capacity 6 Robin XL	100% Capacity 5 Robin XL	70% Capacity 5 Robin XL	50% Capacity 5 Robin XL	100% Capacity 4 Robin XL	70% Capacity 4 Robin XL	50% Capacity 4 Robin XL
Ave G.T. inbound	588	588	522	588	588	522	588	588	522	588	588	522
Ave G.T. outbound	369.9	284.8	295.8	288.3	181.7	162.8	232.6	93.5	85.7	99.1	29.8	19.1
Ave D.D.	191.4	204.4	198.6	229	225.9	231.8	241.4	250.2	247.4	277.6	276.8	269.6
Ave D.D. Xpress	146.8	170.6	165.4	165.2	177.9	177.7	172.5	189.9	197.3	203.5	212.2	231.7
Ave D.D. Normal	254.9	254.9	250	321.5	299.7	308.6	345.5	348.9	348.5	441.4	402	433.7
Ave D.D. sat 1	104.1	100.9	91.2	153	133.9	124.1	178.7	168.1	163.4	251.9	213.4	228.8
Ave D.D. sat 2	308.3	244.3	267.8	276.4	243.8	233.8	310.3	225.4	255.9	284.3	236.9	260.1
Ave #packages not delivered	38.4	18	17.1	39.9	25.1	21.6	40.6	26.3	26.6	47.5	38.3	37.2

Figure 10: H&S: Results Scenario 2.2

The results of Scenario 2.2 are presented in Figure 10. The ground time is distinguished by the inbound vehicle and the outbound vehicles, represented by the green lines. The average delivery duration is distinguished by Xpress service and Normal service and per satellite, indicated by the blue lines. Each simulation is run 50 times. The x-axis indicates the configuration of the H&S network for each simulation. The configuration changes in the number of outbound vehicles, or in the minimum required load factor of the Condor. The network contains a fixed constraint that the Condor will transport the packages only if its capacity is at least 50%, 70%, or 100%. For all three set-ups, the number of outbound vehicles are decreasing from left to right with a starting point of 100 Robin XLs. The y-axis indicates the minutes on the left side for the previously discussed KPIs. The right side of the y-axis indicates quantities measured in number of non-delivered packages. This KPI is displayed with the red line.
Observing the figure shows that the ground time of the outbound vehicles is decreasing with decreasing number of Robin XLs and with lower load factors of the Condor. It is self-explanatory that less outbound vehicles implies less ground time. A lower load factor could indicate a more frequent package delivery to the satellites, which could explain the lower ground time with lower load factors. The average number of not delivered packages has a strong peak whenever the Condor has a minimum load factor of 100%. It takes longer until the Condor meets the minimum load factor criteria which could explain this peak.
The overall quickest delivery of the network is reached with 100 outbound vehicles at a 100% load factor. The average delivery duration is approximately 80 minutes for both services with an average delivery duration of less than 20 minutes from the satellites. However, regarding the high ground times of the vehicles it is not considered the best configuration set-up.
Instead, a minimum of 50% load factor for the Condor together with a total of five outbound vehicles is considered the best configuration of the H&S network for Scenario 2.2. The delivery criteria of Xpress and Normal are met. The ground time of the outbound vehicles are approximately half of the ground time with six outbound vehicles while the average delivery duration increases by only 15 minutes. Just five more packages, a total of 26.6, are not delivered by the end of the day with five outbound vehicles compared to six outbound vehicles. Which is increased to 37.2 packages when the network is utilized with 4 outbound vehicles. 37.2 not-delivered packages by the end of the day plus the expected 60 packages at opening time of the next day, together with the higher delivery duration implicate that four outbound vehicles is too low. Especially considering the low ground time of the outbound vehicles when it is utilized with four Robin XLs. Indicating that there is not much safety margin left for this configuration to cope with backlogged packages. It is, therefore, concluded that the optimal H&S network configuration for Scenario 2.2 contains five Robin XLs with a minimum inbound vehicle load factor of 50%.

P2P versus H&S

The P2P network is able to achieve package deliveries in 24 minutes with its quickest performing configuration. The H&S network achieves its quickest delivery in 80 minutes. Both networks have a high excess in used vehicles, for these configurations, indicated by the high number of ground time. It was concluded that the optimal network set-up of the P2P network should have eight outbound vehicles and the H&S network five outbound vehicles. Even though, the H&S network needs less outbound vehicles, it requires more resources such as an inbound vehicle and two satellites. For this specific scenario, the P2P network has a better performance and is more costly efficient. From these conclusions the best network strategy for Air Canada tends to be the P2P network. The benefit of a H&S network is, however, its ability to scale. It is perhaps possible to observe a cross-over point at which the H&S network becomes more efficient by analyzing the required resources with increasing demand for both networks, see Figure 11.

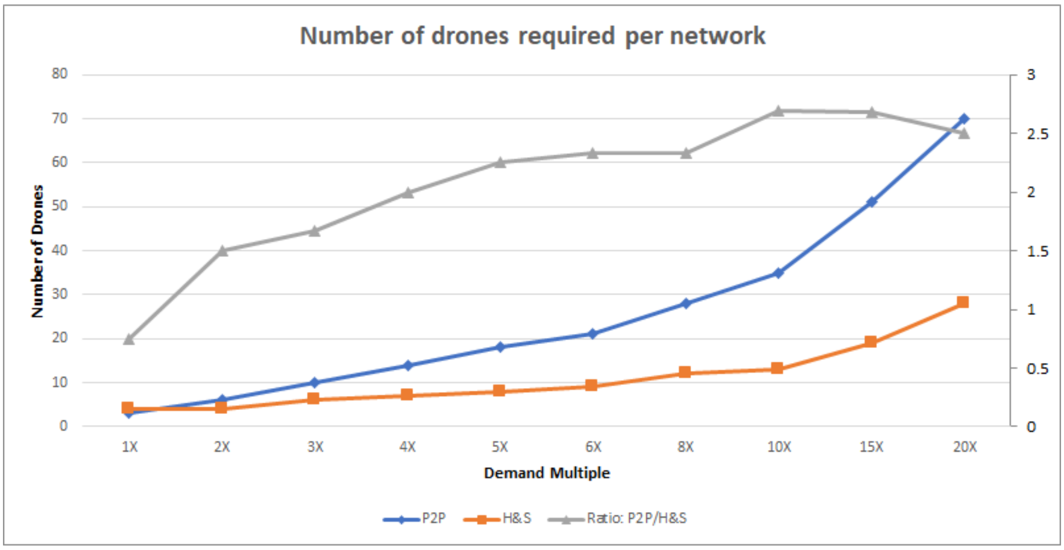


Figure 11: P2P versus H&S

The x-axis indicates the multiple of Scenario 1.1 and the left side of the y-axis indicates the optimal number of outbound vehicles required per network strategy. The graph shows that the number of drones required by the P2P network, indicated by the blue line, increases quicker than the H&S network, indicated by the orange line. The grey line is a ratio of the blue line over the orange line to get a better grasp of the relation between them. The ratio reaches a peak at a 10X multiple. So, the graph is indicating what was expected and could confirm that the H&S network becomes more interesting when there is a demand for network scalability. Observing the performance of both networks at this configuration for a 10X multiple is essential to make any conclusions. Both performances are summed in Table 3, with Inbound Vehicle (I.V.), Outbound Vehicle (O.V.), Xpress (X), and Normal (N).

	P2P 35 O.V.	H&S 13 O.V.
Average G.T. I.V.	N/A	86.4
Average G.T. O.V.	27.8	20
Average D.D.	143.4	219.5
Average D.D.X	99.4	202.3
Average D.D.N	189.4	301.3
Not delivered	30.4	98.6
D.D. Satellite 1	N/A	121.5
D.D. Satellite 2	N/A	212.32

Table 3: Performance of P2P and H&S network for 10X multiple

The ground time of the outbound vehicle for the H&S network is lower than the average ground time of the outbound vehicle of the P2P network. The delivery duration is on average about 70 minutes slower for the H&S network and it delivers approximately 60 packages less per day. It uses, however, 22 outbound vehicles less than the P2P network. The costs are, unfortunately, unknown which makes the trade-off of costs versus quality of service difficult between the two network strategies. It could be concluded that the

P2P network has a better performance, purely looking at the shorter lead times of the network strategies. Whether this is desired, depends entirely on the desired quality of service that Air Canada wants to provide its customers with.

Note, the framework is not able to apply consolidation of packages at satellites, nor did it include the possibilities of having other inbound vehicles serving the satellites from different locations, nor did it include the increased catchment area from each satellite for the H&S network. Data of small packages that could be consolidated at the satellites, data of incoming trucks to Toronto from different cities, and potential demand from different regions was either unknown or out of the scope of the project. Having such abilities could substantially increase the efficiency of the H&S network.
In addition, the strategy discussed so far is mainly based on the initial goal of finding a competitive Drone Delivery Network for Air Canada in Toronto. A different approach, however, would be by considering the available products, technology, and resources. The Condor might be more efficient for long haul distances considering its max payload and its max range of 200 kilometers. Therefore, the second strategy could focus on increasing the catchment area of the network by finding candidate locations for the satellites in different cities, see Figure 12. The blue balloons represent the candidate locations for the satellites, with an additional indication of a 30 kilometer vicinity by the purple circles. The red balloons indicate the 100 DroneSpot locations discussed for the City of Toronto. Similar candidate locations for the DroneSpots should be looked for in the other purple circles. The network increases its catchment area by 2.3 million people by adding a satellite in London (404,699), Hamilton (924,078), Niagara (447,888), and Whitby (519,178) to the network. Which potentially almost doubles the catchment area compared to the City of Toronto only.

A potential solution would be a H&S network on provincial level. The City of Toronto would still be serviced by a P2P network, and the Condor would transport packages from the distribution center at the Pearson Airport to the satellites located at the edge of different cities. Numerous outbound vehicles transport the packages individually from each of these satellites to the end-consumer.

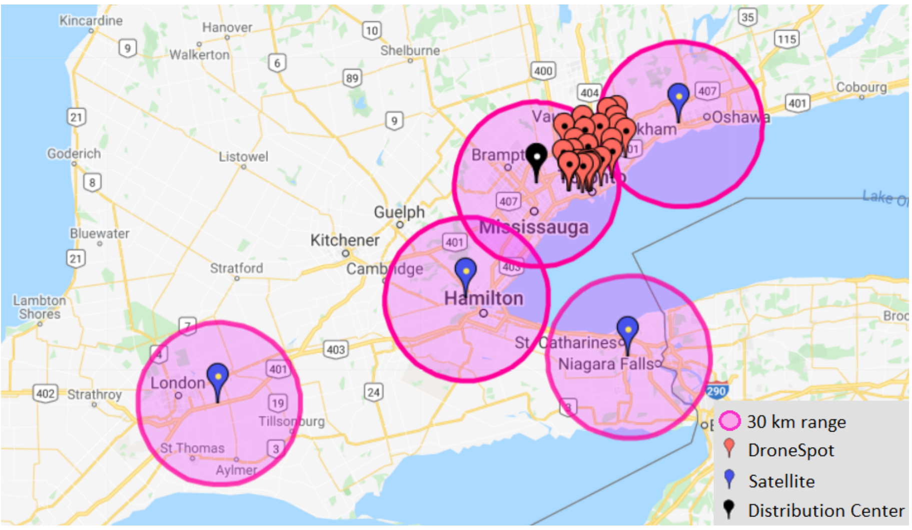


Figure 12: H&S Network: Ontario

6. Discussion and Conclusion

There are clear trends in demand for sustainable solutions regarding last mile delivery, which is being challenged due to urbanization and e-commerce growth. As a response, literature raised attention to find ways to operate and utilize drones effectively in a logistics network. Leyerer Et al. [13] focused for example on determining optimal locations of satellites and allocation of vehicles to the satellites with the objective to minimize operating costs. Troudi et al [16] decided to optimize the fleet sizes and to consider battery management to find an efficient and effective Drone Delivery Network. Hong et al. [**?**] emphasized on the location of the recharging stations to find a feasible delivery network with the objective to cover the demand in a large urban area. These studies aim to optimize a particular aspect in the network design. In this paper instead, the research aims to find a complete Drone Delivery Network design that can easily be adopted to any existing commercial supply chain providing B2C service in the last part of the supply chain.

The first step of the research was to formulate a sequential framework and a Monte Carlo Simulation with a focus on designing a last mile delivery network. It allows to design a P2P and a H&S network under cost minimization. Research clearly illustrated, when utilizing drones as delivery vehicles, that the P2P network was more cost efficient compared to the H&S network measured in ground time, quality of service, and number of required resources. But, it also raised questions towards its ability to scale at which the H&S network was able to show its competitiveness to the P2P network. The H&S network is, however, limited in assigning optimal intermediate facilities based on minimum distance, a fixed minimum load factor constraint, and no consolidation at intermediate facilities. Implementing these factors in the model could substantially increase the efficiency of the H&S network, which could result in preferences for the H&S network with lower demands.

Research has proved through implementation of the framework that it is able to find the best fitted design of different network strategies. The main contribution of the research follows from the fact that the framework can help the operator finding the optimal network strategy under cost minimization whilst allowing to consider different fleet configurations, destination locations, number of destinations, size of daily orders, and the quality of service as desired per service type. Different scenarios and repeated random sampling used by the Monte Carlo Simulation allow to consider the impact of risks and uncertainties, and to assess the performance of the network with confidence. In other words, it allows the operator to utilize the network with a scenario it is confident with. And after utilization, the operator can use real-life data and the results from the model to continuously develop the network design.

Future research could consider a two-mission fleet with operation between any two sets of facilities. A two-mission fleet would allow a drone to make profit on any route instead of making purely costs going back to its origin. Operation between any two sets of facilities would greatly benefit the potential utilization of the network. Rather than providing long-haul B2C services only, it would allow the logistic provider to provide short-haul Consumer to Consumer services as well, which would increase the demand and directly impact the fleet size. Considering a weekly demand rather than a daily demand would allow the experimenter to assess the impact of backlogged packages from the previous day to the performance of the network as a whole. Better fleet sizing estimates would result by considering such uncertainties in the network. Expanding the MCS formulation to assess the delivery duration of each service type would allow the operator to observe the quality of service the network would be able provide with certainty. More specifically, besides designing the network, it would help the operator to define the product it is able serve its customers with. The performance of the H&S network design could benefit by considering consolidation at intermediate facilities, finding the optimal minimum load factor, and by clustering destination locations. Consolidation of orders would increase the efficiency by decreasing the total distance travelled. Finding the optimal minimum load factor could decrease the ground time and destination clustering could avoid inefficient routes by only assigning orders of one cluster to the inbound vehicle. These matters could improve the network design model by allowing the logistic operator to configure a more optimized network design.

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II

Thesis Report

1

Literature Review

Already graded under AE4020

Globalization and the open web market have led to an increase in the transport of goods. It allows people to order goods from anywhere, to anywhere in the world. It caused an exponential rise in the demand for product deliveries. Together with urbanization and higher demand for e-commerce, traffic in cities increase, which naturally causes higher carbon dioxide (CO_2) emissions. Sustainable public transport networks are initiated, addressed, and even operative in some cities with progressive forward-thriving policies. However, the initiatives taken in the sustainable delivery of goods is lagging (1.1). An emerging topic as anticipation to deliver more parcels in congested areas in a rather sustainable matter is delivery by drones (1.2). Creating a new business model involves many uncertainties. Observing such uncertainties and risk factors that come along can be observed by using the repeated random sampling technique (1.3). The chapter is concluded to determine the main focus of this project (1.4).

1.1. City logistics

City logistics focuses on optimizing the transportation of goods in urban areas, also called last mile delivery. It is targeted to provide an effective and efficient freight distribution in congested areas taking into account safety, environment, and congestion [23]. Knowing the expected trends to occur in city logistics will enable the transport industry to anticipate on the challenges it is facing. Councils and governments are taking measurements to stimulate sustainable solutions for last mile delivery, as global pressure is getting stronger to reduce pollution and generated emissions [2]. Which is a result from global urbanization. Cities represent about 2% of the geographical space, produce 80% of Greenhouse Gasses (GHG) and emissions, and use 80% resources [24]. Currently, 54% of the population live in cities that are expected to rise to about 66% by 2050 [1]. By 2100, it is even expected that the world's urbanization goes up to 85%. From this, the demand for smart cities rises (1.1.1). However, anticipating just on the expected change in policies will not cover the complete change in last mile delivery. Expectations from the consumers are changing as well (1.1.2) as the strong increase in demand for e-commerce that both will impact last mile delivery (1.1.3).

1.1.1. Smart City

Smart cities are often referred to as the integration of technology in the development of cities [25]. Smart cities are used to overcome the issues from urbanization and global climate change [26]. A liveable and sustainable city would be the main long term objectives.

Smart city projects are generally large capital investments that tend to change societal and environmental matters [27]. Therefore, these projects are hard to realize. They cannot be adopted abruptly by the cities as they can have an impact on the safety and habitats of people [28]. Hence, these projects are naturally ad hoc projects to transform cities into smart cities in a gradual manner. It is, therefore, hard to accurately identify and produce the desired social outcomes [29]. For example, Songdo City (Korea) is considered as the first smart city that started investing in sustainable solutions for over a decade ago, but they still have not seen the desired outcomes yet [30].

Urbanization is a dominant influencer on the needs of resources and services in dense areas [1]. It causes a rapid growth in the demand for last mile delivery that uses mainly road traffic. Freight transport is, therefore, mostly responsible for externalities in cities related to delivery. According to the EU definition, externality also referred to as external cost, is caused by one group of people that does not compensate or entirely account for the impacts of its economic or social activities on another group. In addition, there are different carriers and logistic service providers that provide last mile delivery services that create an uncoordinated traffic flow of transported goods resulting in high externalities, a high number of routes, low load factors of vehicles, and high operational costs.

As a result, councils and governments are taking measurements and policies to fight the externalities [31]. The European Commission, for example, formulated the objective of a free CO2 urban logistics system by 2030 [3]. As a result, the government of Hamburg took a free-diesel zone policy in notion, and Paris created a number plate scheme to determine which cars are allowed to transport in some time windows. These policies can have a significant impact on the delivery services of freight transporters. Hence, their demand to find sustainable solutions regarding last mile delivery is rising as a response to the market changes and governmental policies.

1.1.2. Urban trend

Over the past ten years there changed three independent factors that influenced the expectations of the consumers 1) 20 times more people carry a phone in 2018 relative to 2008; 2) global urbanization, and; 3) internet retail sales increased in ten years from $290.4 billion to $1.6 trillion in 2018. All these three facts importantly contribute to the way the transport and logistics industry is trying to adapt to meet the rising expectations of the consumers. The accessibility provided by the internet that is available on the phone has created unprecedented connectivity that generated new business models. Companies seek new opportunities to capitalize by anticipating the connectivity that has resulted in new markets that are indispensable today, for example, online food delivery. Consumers are wealthier and purchase more online. Simultaneously, they are prioritizing to ease their daily tasks and desire to have more input in when, where, and also how the products are being delivered. The consumers prefer a more sustainable and environmentally friendly transport service, even if this means an increase in service price [32].

1.1.3. E-commerce trend

Brick-and-mortar retail is the gratification of consumers to touch and feel their purchases in advance. Services of online retailers, large product selection for lower prices, made consumers shift more towards e-commerce. Canada saw a growth rate in e-commerce of 21.1% in 2020 [33]. Globally, over the past five years, online purchases have grown annually with a rate of 20%, and estimates show that this trend will continue to grow. These numbers did not even take into account the pandemic of 2020, which was or still is a major stimulus for e-commerce growth. This boost is changing the logistics industry resulting in new business models. Some retailers already started shifting towards the strategy of omnichannel retailing. According to [34], omnichannel retailing is defined as a strategy to meet the consumers' demand by using and synchronizing inventory with its logistics distribution and other available channels. Amazon is adopting this strategy by anticipatory shipping and local warehousing to reduce lead times. They are trying to change their supply chain to an anticipatory mechanism such that products are being transported to consumers before they have been purchased. The other strategy that is being pursued by Amazon is the integration of local distribution centers to realize one hour delivery in the United Kingdom [35].

DHL is also considering the changing trends and published in 2019 its award-winning white paper about shortening the last mile delivery [36]. It presented four different strategies that, in the opinion of DHL, should be taken into account considering the e-commerce trends. They suggest to adopt flexible delivery services, that is a demand-driven change, to overcome courier shortages in the final stage of the supply chain, the last mile delivery. In particular during national holidays and commercial holidays to cope with the-commerce purchases peaks. As stated before, consumers start to have higher demands for transportation services. To anticipate this trend, DHL suggests to adopting flexible delivery services that will transform and innovate the service of logistic providers in the final stage of the supply chain, the last mile delivery. Parcel lockers, service points, and electric vehicles are some examples that could facilitate this change. It is a demand-driven change, that becomes a higher priority considering courier shortages and the fact that the last mile delivery is the least efficient and the most expensive leg of the total supply chain [37]. The second trend is shown by considerably higher e-commerce purchases during national holidays and commercial holidays. As a result, DHL suggests creating a more agile operating model to anticipate the challenges that come along with seasonal logistics. They call it an elastic business model where the last mile should encounter more resources and couriers supplied by the internal inventory management. The changing behavior of consumers is expected to be more demanding. DHL concludes, similar like Amazon, to shift more to a localized distribution network to shorten the lead team as a response to the changing trend in consumers' behaviour.

A logistic provider can benefit from decentralizing its network to better its connectivity and its flexibility. Besides the challenge in inventory management that comes along with decentralizing the one big warehouse to multiple smaller warehouses. It also results in more frequent delivery transports that can be undesired in congested areas [38].

1.2. Drone Delivery Network

Many studies discuss solutions to overcome the challenges in last mile delivery. Externalities, as discussed before, is one of these common issues in urban areas that can be reduced with sustainable urban delivery alternatives. Last mile delivery by freight tricycles, a bicycle that is designed for transporting loads, is one solution that can overcome road restrictions that trucks are facing in urban and congested areas [39]. Other vehicles, such as hybrid and electric vehicles, are also discussed [40]. However, tricycles still face the issue of shortages in couriers, and other vehicles are still limited by traffic flows and congestion. On the contrary, drones do not need couriers nor face congestion issues and thus overcome most of the last mile delivery challenges. It is, therefore, considered a promising solution for last mile delivery in urban areas. However, before drones can be utilized as an efficient freight transporter in last mile delivery, it is mandatory to investigate and exploit the design of a Drone Delivery Network first. Network strategies used by logistics operators are used as inspiration for the Drone Delivery Network (1.2.1). Different design aspects discussed in literature are explained in Subsection (1.2.2). The operational constraints of drones introduce other challenges in last mile delivery such as a limited operational range (1.2.3). An optimal network design operates efficiently only if the resources are utilized to their potentials. For example, maximizing the load factor of each vehicle (1.2.4) and minimizing the distance travelled of each vehicle (1.2.5) should be considered.

1.2.1. Network Strategies

A carrier transports passengers or freight throughout its network. Several strategies exist to define the network structure dependent on the carrier's vision. The vision can, most commonly, be divided between a robust network and an efficient network. The robust network is typically known as the P2P network that transports passengers or freight directly from the origin to its destination. Such a network design can improve the stability, flexibility, and security of the operations. The direct flights reduce travel time, but naturally increase operational costs as larger vehicle fleets are required to cover all routes. The efficient network is typically known as a H&S network. It connects the different origin-destination nodes through an intermediate facility, called a hub [41]. The H&S network provides carriers with higher densities, larger scopes, and bigger scales of economies [42]. It allows for better connections between almost all origin-destination nodes with lower number of routes. From Figure 1.1 it can be observed that a H&S network requires n - 1 routes, n representing the number of airports. On the other hand, utilization of this network implies extended travel times with increased airport and route dependencies.

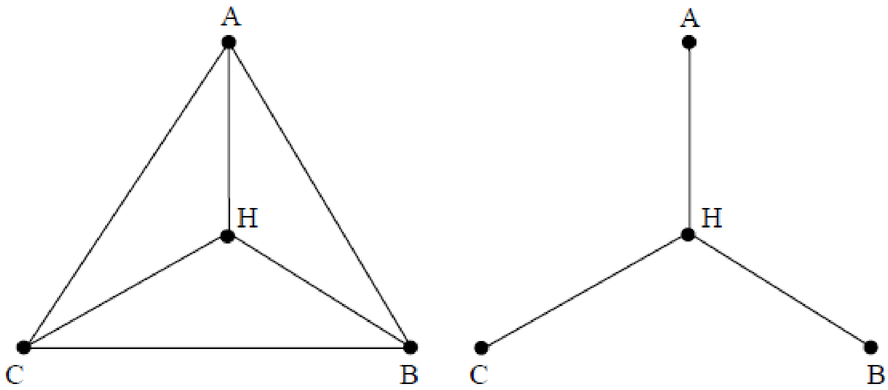


Figure 1.1: Point-to-Point network versus a Hub-and-Spoke network

1.2.2. Drone Delivery Network Design Aspects

Finding optimal destination locations for the P2P network is vital for its performance as the destination locations will determine the coverage of the network. Similar for the H&S network it is vital to find the optimal location of the hub when designing a distribution network to minimize the transportation costs for the incoming and out-going traffic [19]. Covering problems define a static and deterministic approach. If the demand is met within a specified duration, the demand is said to be covered. This problem can be divided into the set covering problem and the maximal covering problem. The covering problem aims to obtain a specified level of coverage while minimizing the facility location costs, and the maximal covering problem determines the possibility of maximizing the demand coverage by considering the available located facilities [43]. In practice, the set covering problems are potentially infeasible due to the usage of an exogenously specified coverage distance. This has led to p-center problems. It implies a minimax problem as it has the objective to minimize the maximum distance between the nearest facility to any demand node [44]. Another common approach is finding a set of potential sites which is then used as input in a model to determine the best sites [45]. There are numerous strategic decision approaches, but the most common approach for urban areas is a multi-criteria decision-making concept for location optimization of distribution centers [46]. Besides identifying the potential locations, this approach also includes evaluation criteria to determine the optimal site.
Finding optimal hub locations for a H&S network in city logistics is also commonly discussed as the Two-Echelon Location Routing Problem (2E-LRP). It has known customer locations and seeks for solutions regarding optimal locations of hubs, typically called satellites. This problem is formulated by literature with the following notation $3/\overline{T}/\overline{T}$, $3/T/\overline{T}$, and $3/\overline{T}/T$, where T represents a known location of the satellite, and $\overline{T}$ represents unknown location of the satellite at least at one of the echelons. The problem is further elaborated and expanded to number of facilities, sizes of the fleets, and to route optimization decisions. The most common variation studied, is called the Capacitated 2E-LRP (2E-CLRP). It has the same objective as the classical 2E-LRP, but with additional constraints. Each echelon consists of a fleet with capacity constraints. The authors of [47], expanded the 2E-LRP to also consider fleet sizes while simultaneously minimize transportation costs. More recently, Nguyen [48] introduced the common second stage location problem with capacity constraints that contains one Distribution Center (DC) of which its position is known prior. They formulated the model with Integer Linear Programming (ILP) and with a Greedy Randomized Adaptive Search Procedure including machine learning. The two-echelon problem is further elaborated by considering the following three constraints simultaneously on the second level, pick-up and delivery, multi-product, and usage of processing centers as satellites [49]. The first level aims at finding the location of the satellites, based on a set of potential locations, at minimum costs. The second level has the objective to minimize the route costs and to assign customers to the satellites. This problem is proposed to solve smaller-scale instances with an MILP model in a Cplex solver.

Designing a logistics network should consider the functional and physical aspects of the distribution network. Such aspects consider fleet management, compositing, and sizing of the transportation fleet [50]. Each of these matters can interchangeably influence each other. It is worth regarding these interdependencies to optimize the efficiency of the network. Optimizing the flow of goods is another aspect that can increase the efficiency of the network by taking into account different parts of the supply chain. The cross-docking strategy optimizes the flow of goods by considering interdependencies between the incoming and outgoing goods, for example [51]. It uses intermediate facilities where goods are directly loaded from inbound vehicles to outbound vehicles, it does not contain inventory [52]. The capacity of the outbound vehicle, when replaced by drones, will significantly reduce and inherently have an influence on the fleet size [17].

1.2.3. Battery Management

The limited battery cycle of a drone is a significant factor that negatively affects the drones' utilization. Moreover, the inability could cause damage to the drone, or worse, it could injure people when flying over populated and highly congested areas. It is, therefore, essential to take into account a battery management strategy to be able to create a profitable UAV delivery network.
Several methods are discussed in literature to anticipate the limited battery life cycle. Hu et al. [20] discuss the possibility of contactless charging, for example. The method is, however, constrained in line-of-sight operations, high system costs, and low charging efficiencies [53]. A more common discussed topic in literature is supplying the network with recharging stations. The authors of [21], aimed to find the optimal locations of the refueling stations by using three heuristic algorithms. A greedy-algorithm, together with a genetic-algorithm, is applied to the model that shows efficient and effective results. [54] applied the FRLM in Korea to optimize the vehicle-flow of electrical cars. They define a case study to discuss the formulated multi-period optimization model, the backward-myopic method, and the forward-myopic method. In general, the multi-period optimization model performs better but shows longer computational times as the model increases. Therefore, the authors advise the backward-myopic method for large problems. Hong et al. [18] applied the FRLM method to a UAV delivery network. They designed a delivery network with recharging stations in its infrastructure. The network is based on a coverage model. In other words, the ground stations and recharging stations are located such that all customers are covered within the drones' vicinity. A spatial heuristic solution technique is used to find the optimal locations of the recharging stations.
Literature raised attention to battery swapping to improve utilization of drones in response to the demanding charging times discussed in FRLM methods. Suzuki et al. [22] propose a ground station that can swap batteries of a heterogeneous fleet under high-coverage requirements. Ure et al. [55] designed a battery maintenance system that allows to automatically swap the depleted battery with a replenished battery at a ground station while charging other batteries simultaneously [56]. Moreover, FRLM methods could be used to find optimal locations of such battery swap facilities.

1.2.4. Knapsack Problem

The Knapsack Problem aims to maximize the number of packages that can be carried by an object. The max capacity weight and max dimensions limit the number of packages the object can carry. The 2D Knapsack Problem 0-1 tries to maximize the value it can carry without exceeding the max capacity in terms of weight. Each item it can carry has a value and a weight (kg), the two dimensions [57]. The 3D Knapsack Problem 0-1 has the same objective but with volume as an extra dimension taken into account. Which is, therefore, more accurate as objects have fixed dimension constraints. The knapsack problem does, however, not consider optimal package placement by taking into account the length, height, and depth individually as well. This is rather a complex study which will be out of the scope for the project. Therefore, it can be assumed that all packages have a perfect fit in the object by only considering the volume.

1.2.5. Vehicle Mileage

Decisions that ensure on-time delivery encompassing scheduling plans and routing encounter the operational aspects of a logistics network. These optimization problems, minimizing vehicle millage and maximizing distribution efficiency, are well known and categorized as Vehicle Routing Problems (VRP). There are many different VRP models, each with other constraints and different approaches. The majority focuses on cost minimization and the authors of [58] were the first ones to adopt this concept to a drone delivery network. They presented a VRP problem, similar to Mercedes-Benz's experiment [14], where drones pick-up parcels and return after delivery to mobile depots, such as trucks. Some scientific researches consider the different decision levels and analyze the impact on the distribution network. They recommend locating the distribution centers outside the city center [61]. An alternative approach in minimizing the vehicle mileage is by considering a single tour, rather than allowing the vehicle to perform a multiple route [62]. The optimal single route to visit all destination nodes without vehicle capacity is called in literature TSP [63]. The goal is to determine the shortest tour of n cities starting and ending in the same city, visiting each city exactly once.

It is its most common used application for a tour in cities, but it is also applied in computer wiring [64] and in wallpaper cutting [65]. Dantzig et al. [66] created one of the first formulations of the TSP, and Miller et al. [67] introduced an alternative formulation to reduce the number of subtour elimination. A large number of exact solutions have been proposed for the TSP, but since it is NP-hard, it is common to address the problem by means of heuristic algorithms [68].

1.3. Monte Carlo Simulation

MCS is a type of simulation that uses repeated random sampling to estimate outcomes influenced by uncertain events. In other words, it is a probability simulation that calculates the outcome hundreds, thousands, or ten thousands of times by using each time a different set of random numbers as input. This approach allows one to understand the impact of uncertainty and risk factors which show the most likely outcomes for that specific scenario [69]. It is particularly applicable to experiments for which the outcome is unknown. It allows the experimenter to apply different scenarios to enable a so-called what-if analysis. Each scenario allows the experimenter to methodologically investigate a range of outcomes that applies to a risk scenario without forcing the experimenter to go through each input parameter and the corresponding outcome individually.
The what-if analysis consists of the most likely scenario, the worst possible scenario, and the best possible scenario. The most likely scenario is the base case for which risks factors are not considered for the input parameters. The uncertainty of various external factors that have an influence on the input parameters are considered for the worst case scenario and the best case scenario.
Rather than identifying each input value individually, MCS is used to create a statistical probability distribution for the entire set of input parameters. It creates random samples of the input parameters based on the probability distribution which will be different for every run simulation [70]. It is a realistic way of describing uncertainty in variables of a risk analysis.
The authors of [71] performed a probabilistic analysis for a reduced number of MCSs to optimize the framework of the design of UAV. Y. Jenie et al. [72] applied MCS for safety assessment for UAV operations in a high density airspace environment. A more similar study to this research is presented by the authors of [73]. They aim to maximize the demand served by drones while considering the uncertainties in battery consumption. While doing so, the model is tasked to locate a pre-specified number of facilities with assigned drones considering range constraints. The model uses a given set of spatially distributed demand with drones serving as delivery vehicles and a potential set of facility locations. The drones have a one-mission task, pick-up commodity from facility, deliver at destination, and return to origin until the available battery energy is exhausted. The authors propose an ILP formulation with a penalty-based approach for battery energy availability. The ILP outcomes are tested using MCS with coverage under uncertainty to add robustness to the deterministic problem.

1.4. Conclusion

The logistics industry is facing the challenge of finding new last mile delivery solutions considering urbanization, e-commerce growth, and sustainability [32]. However, the decreasing size of packages and direct-to-consumer deliveries increase freight movements [23]. Hence, the logistics industry is investigating in last mile delivery services executed by drones for over seven years. From studies, experiments, and investigations from industry it can be concluded that the design of the drones is not the issue [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], and [15]. Instead, there is little known to the optimal design of a Drone Delivery Network.

Long-term decisions to the design of a logistics network incorporate network strategies. Such high-level decisions define the necessity of facilities, potential locations, sizing, and the number of facilities [16]. Warehouse planning becomes important if it is decided that facilities are desired. At such facilities it is essential to consolidate freight and to merge operations to improve the provided service and to reduce costs [74]. A cross-docking strategy is commonly used to improve the flow of goods in distribution networks [52]. Finding the optimal location and size of such facilities are key factors to an optimal delivery network.

Mid-term decisions relate to the functional matters of the logistics network, such as fleet management. Fleet sizing and composition of the fleets ensure the logistics provider to meet the demand with its fleet. However, the limited battery life span of drones could negatively impact the utilization of the fleets [55]. Contactless charging, battery swap, or facilitating the network with recharging stations are proposed to compensate for the operational constraints of the drones.

Short-term decisions aim to maximize the distribution efficiency of the network. Efficient utilization of a network involves maximizing a vehicle's load factor, called Knapsack Problem, and minimizing vehicle mileage [58]. Minimizing vehicle mileage can be addressed by either allowing the vehicle to perform a multiple route with capacity constraints, called VRP, or by allowing the vehicle to find the shortest single tour without capacity constraints, called TSP.

2

Research Formulation

Based on a report already graded under AE4010

This section defines the scope of the thesis. It describes the main research question that can be answered by the aid of multiple sub-questions that each can be subdivided into higher detailed questions (2.1). Subsequently, the eventual project goal is defined by specifying the main objective followed up with sub-goals that are to be accomplished to achieve the ultimate goal of the project (2.2).

2.1. Research Question(s)

The main goal of this project is to define a Drone Delivery Network that can be used as an extension to the supply chain of a logistics operator's network. The Drone Delivery Network is specifically aimed for utilization of drones with the purpose of parcel delivery to end-consumers. Therefore, the main research question, that has to be answered to reach the project goal, can be defined as follows:

What is the design of a Drone Delivery Network and how should it be configured to ensure delivery to the end-consumer in metropolitan areas under cost minimization such that a profitable Drone Delivery Network can be adopted to the network of logistic operators?

Trying to solve the main research question requires to answer the following sub-questions first:

1. What network strategy, P2P or H&S, would be the best fit for the Drone Delivery Network?
2. What facilities are needed for the UAV delivery network?
    - What is the most convenient location of the facility, or facilities?
    - How many facilities are needed to meet the demand?
    - Does the UAV delivery network require inventory facilities, or is cross-docking operations more desired?
3. What is the best fleet composition, and how should it be set-up to ensure a profitable fleet that can meet the demand?
    - How many drones are needed to meet the demand?
    - Is the fleet going to be homogeneous or heterogeneous?
    - Are the drones going to be subdivided and assigned to different districts?
        - If so, how many drones per district?
4. What is the strategy to maximize the vehicle utilization regarding battery life span?

- Is it needed to facilitate the network with mini charging depots, or are the drones going to be charged at the warehouse(s)?
- Is it feasible to conduct battery swapping rather than charging?
- How many batteries are required in stock in order to facilitate either the swapping strategy, or in case of failures?

5. How to improve utilization efficiency of the network?
    - How is the network able to maximize the vehicle's load factor?
    - How is the network able to minimize the vehicle mileage?

2.2. Research Objective

The main research objective of this thesis is to achieve a profitable Drone Delivery Network that can easily be adopted to any existing commercial supply chain providing B2C service in the last part of the supply chain. By means of identifying the network strategy, different facilities, compositing the fleet management, battery strategy, and optimal utilization matters.

The main objective of this thesis can be achieved by accomplishing the following sub-goals:

- understanding city logistics;
- understanding different available facilities and their pros and cons;
- finding feasible location(s) for the facilities;
- understanding the differences in pros and cons between inventory management versus cross-docking;
- understanding the drones' capabilities and constraints;
- understanding different battery management strategies;
- finding a framework to design the Drone Delivery Network;
- formulating framework to assess feasibility and profitability of the Drone Delivery Network design.

3
Model Formulations

This chapter is used to explain the generic framework that allows to find the optimal design of a Last Mile Delivery Network. The model is presented as a sequential framework that addresses the design of a logistics network in Section (3.1). The assigning algorithm is explained by the hand of a flowchart in Section (3.2).

3.1. Framework Formulation

A sequential framework is used as it allows to address the Knapsack Problem, Facility Assignment, TSP, and package to drone assignments by using binary decision variables. The objective of the network model is to solve each of the problems individually to minimize the operational costs of the network. It is assumed that the:

1. order size;
2. destination locations;
3. quality of service;
4. number of Inbound Vehicles;
5. number of Outbound Vehicles;
6. vehicle capacity; and
7. number and locations of Intermediate Facilities;

are given. The sequential framework allows to address the configuration of a P2P network and to design a H&S network strategy. If there are no intermediate facilities nor inbound vehicles, the model considers the P2P network strategy and delivers packages directly from origin to destination. Otherwise, the model considers the H&S network strategy where packages are distributed over intermediate facilities at which outbound vehicles deliver the packages from the intermediate facility to the destination. The P2P network can, therefore, be considered as a sub-problem of the H&S network, only package to outbound vehicle assignment is relevant, indicated by the yellow box in Figure 3.1. The remaining part of this section focuses on the sequential framework used for the H&S network.
The framework uses a set of candidate locations of intermediate facilities and a set of destination locations, both given in a csv-file. The locations are selected based on market research with a main focus for population density, employment, and feasibility. The other inputs are manually given to the framework where the operator decides how the demand of orders is distributed over a set of time windows. See box A in the design framework in Figure 3.1.
This input is used to find the optimal intermediate facility locations which is indicated with box B in Figure 3.1. A binary integer linear programming model is formulated to assign each order to an intermediate facility. The model selects the intermediate facility based on minimum distance between origin, intermediate facility and destination for each order individually. This approach is chosen to find strategic locations of the facilities

to increase efficiency of the network by having a higher catchment area from each intermediate facility without a potential significant increase in operation costs - i.e. distance. The process is done numerous times by the principal of repeated random sampling, which is the formulation of the MCS. The average number of packages distributed per intermediate facility gives the operator a good indication whether the candidate point is selected, if at all, and how frequent.
The operator can change the csv-file to only keep the relevant intermediate facility based on the run MCS. This is the only change in input, at box 1, used for the sequential framework, called configuration, on the right side of Figure 3.1.
The model is designed to maximize the sum of the values of the packages the inbound vehicle can carry. This integer linear programming problem is known as the Knapsack Problem, see box 2 in Figure 3.1. It considers the value, weight, and volume of each package. Each order has a value, based on package valuation, to allow the model to prioritize packages. The weight and volume are used to meet the capacity constraints. It does not, however, consider the destination locations. It is assumed that inbound vehicles are designed to carry many packages relative to the outbound vehicles, distances between intermediate facilities are small, and the demand is not big enough that outweighs the first two assumptions. In other words, it is assumed that the number of packages an inbound vehicle has to carry every trip is not large enough for it to be efficient to carry only packages designated to one set of intermediate facilities. The total average delivery duration is assumed to be shorter when the inbound vehicle carries all packages irregardless of the destination locations rather than bringing a part of packages to a set of intermediate facilities and coming back to deliver the remaining part of packages to the other set of intermediate facilities. The Knapsack Problem is an NP-hard combinatorial optimisation problem. The computation time increases with increasing number of packages. It is, therefore, proposed to use pyeasyga, a Genetic Algorithm, to solve multidimensional knapsack problems instead of exact solutions [59].
The framework uses the destinations of the assigned orders to determine to which intermediate facility each package should be distributed to, see box 3 in Figure 3.1. The same binary integer linear programming model is used as for the design in box B in Figure 3.1. Thus, the model assigns the facilities to the inbound vehicle based on the shortest distance per order. Not the shortest distance of all orders together. Because the network would otherwise always assign all orders to only one intermediate facility. It would take away the entire principal of having a H&S network at the first place. Since a H&S network is designed to avoid congestion allowing to scale the network. That is why the Network Model is depicted in two parts where the operator can decide first, based on the MCS, which intermediate facility is the most optimal location while taking into consideration how frequently the intermediate facility is used based on the given scenario. Following, this input is purely used by the configuration to determine to which facility each order should be distributed to individually.
The model aims to find one route with minimum distance given all locations the inbound vehicle must visit to distribute all packages. This integer linear programming problem is known as the TSP indicated by box 4 in Figure 3.1. The computation time increases significantly when the number of locations to be visited increases. Therefore, instead of using an exact solution. It is proposed to use Machine Learning, Randomized Optimization and SEarch (mlrose), a randomized optimization and search algorithm, for solving the TSP that is NP-hard by nature [60].
The model assigns an available outbound vehicle to the orders that arrived at the designated facility. The binary integer linear programming model is called the Outbound Vehicle Assignment indicated by box 5 in Figure 3.1. The Vehicle Assignment would have been the only problem if the network was not facilitated with intermediate facilities nor with inbound vehicles.

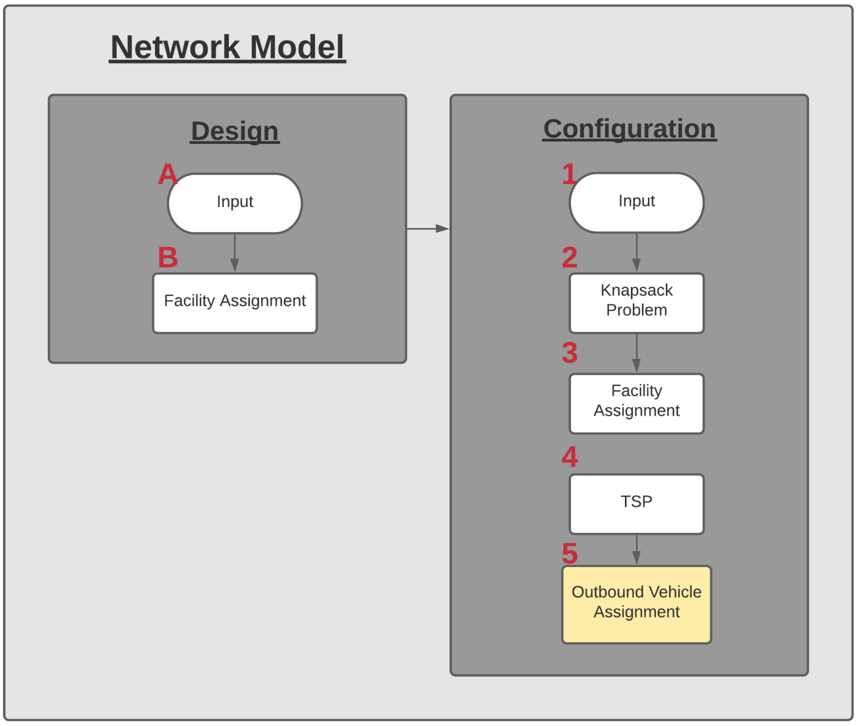


Figure 3.1: Flowchart Network Model

3.1.1. Package Valuation

The model is facilitated with a package valuation tool to allow the network to prioritize packages at the Knapsack Problem and Vehicle Assignment, box 2 and box 5 respectively, in Figure 3.1. It is assumed that the network uses two service types, Xpress and Normal. If there is no distribution given, it is assumed that the model has a uniform distribution between Xpress service and Normal service when assigning a service type to an order. The Xpress service is tailored for customers with desires for quicker delivery services. Late deliveries are thus higher penalized for orders with Xpress service than orders with Normal service.
The value is based on the service type and and on the due delivery. Due delivery is the minutes that are remaining before the package should depart from the facility for on-time delivery. Xpress should be prioritized over Normal, and on-time delivery should be prioritized over late-delivery. Bluntly following this approach has, however, the possibility that packages that exceeded the due delivery time will never be delivered. Hence, the model uses a score system. The package with the highest score will be prioritized. Only the order with the highest valuation will be considered to an available drone, else wise the order is put on hold. The package is rewarded with 50 or 10 points for having the Xpress service or Normal service respectively. Both services gain 50 points, if the package has a due delivery bigger than zero - it is estimated to be delivered on time. If the Xpress service package has a delay of x minutes, it is penalized with x^3 points. The package with Normal service is penalized with $(0.5y)^2$ points with y delayed minutes. The red line in the plot shown in Figure 3.2 indicates the relation between the amount of minutes for each service it is required to be prioritized over the other. In other words, the area above the red line indicates the amount of delay it is required for the package with Normal service to be prioritized over the package with Xpress service.

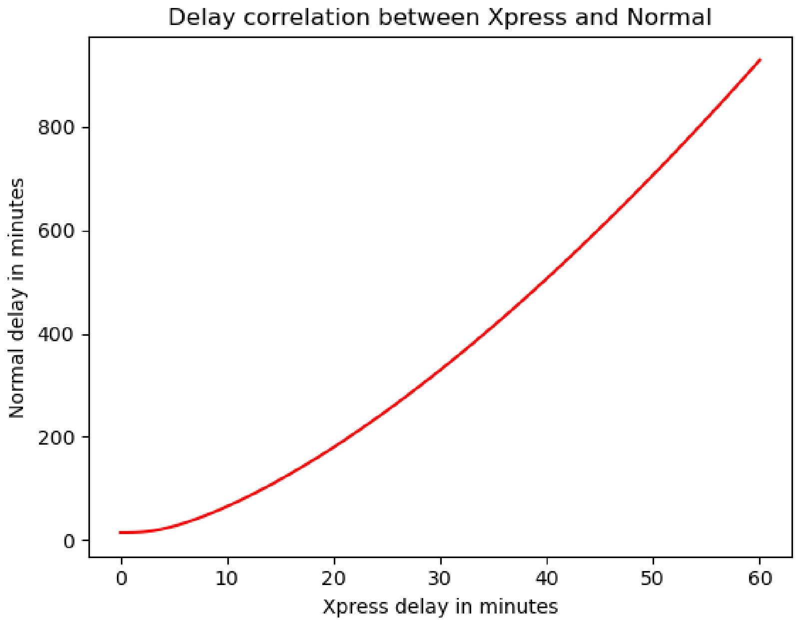


Figure 3.2: Relation between an Xpress package with delay and a Normal package with delay

Some key examples are withdrawn from the graph, see below:

- Xpress without delay is prioritized over Normal without delay;
- Normal with ≥ 20 minutes delay is prioritized over Xpress without delay;
- Normal with ≥ 65 minutes delay is prioritized over Xpress with 10 minutes delay;
- Normal with ≥ 179 minutes delay is prioritized over Xpress with 20 minutes delay; and
- Normal with ≥ 15 hours and 30 minutes delay is prioritized over Xpress with 60 minutes delay;

3.1.2. Mathematical Formulation

The order of the sequential framework indicated by Configuration in Figure 3.1 will be used in this subsection as a guideline. It covers the Facility Assignment of the design model and it covers the Outbound Vehicle Assignment that is relevant for both P2P and H&S network.

The total number of orders used by the model is indicated by the letter O. The set of orders can be distributed as desired by the operator over different time windows w (w ∈ W). Each order o (o ∈ O) has a destination node d (d ∈ D) and a quality of service q (q ∈ Q). Depending on the chosen network strategy, the network will be equipped with inbound vehicles I and intermediate facilities F. The set of outbound vehicles is indicated by B.

The model has four binary decision variables. If order o is assigned to outbound vehicle b, the binary decision variable $m_{o,b} = 1$, and 0 otherwise. When the network is facilitated with inbound vehicles and facilities, the decision variable $p_{o,i} = 1$, if order o is assigned to inbound vehicle i, otherwise it is 0. The decision variable $u_{o,f} = 1$ if facility f is assigned to order o, 0 otherwise. When determining the optimal route of the inbound vehicle, the decision variable $x_{k,l} = 1$ if the route goes from facility k to facility l, otherwise it is 0. The objective of the sequential framework is to minimize the operating cost, which is defined in terms of delivery duration c_o, and in terms of ground time of the inbound vehicle and outbound vehicle, e_i and g_b, respectively. The model solves problems sequentially to minimize these costs. The mathematical formulation of the network model is given below and followed with the mathematical formulation of each problem individually.

Sets:

O: Set of orders
W: Set of time windows
D: Set of destination nodes
Q: Set of service
I: Set of inbound vehicles
F: Set of intermediate facilities
B: Set of outbound vehicles

Subsets:

J: Subset of F
S: Subset of O

Decision Variables:

$m_{o,b}$: 1 if order ***o*** is assigned to outbound vehicle ***b***, 0 otherwise
$p_{o,i}$: 1 if order ***o*** is assigned to inbound vehicle ***i***, 0 otherwise
$u_{o,f}$: 1 if order ***o*** is assigned to facility ***f***, 0 otherwise
$x_{k,l}$: 1 if the path goes from facility ***k*** to facility ***l***, 0 otherwise

Parameters:

P_i: max payload inbound vehicle ***i***
P_b: max payload outbound vehicle ***b***
V_i: max volume inbound vehicle ***i***
V_b: max volume outbound vehicle ***b***
R_i: max range inbound vehicle ***i***
R_b: max range outbound vehicle ***b***
N_i: minimum load factor for inbound vehicle ***i***
U_i: minimum number of orders that the inbound vehicle ***i*** must carry
w_o: weight of order ***o***
v_o: volume of order ***o***
$z_{o,i}$: value of order ***o*** assigned to inbound vehicle ***i***
$y_{o,b}$: value of order ***o*** assigned to outbound vehicle ***b***
$r_{o,f}$: distance of order ***o*** from origin to facility ***f*** to destination
r_b: distance of outbound vehicle ***b*** from origin to destination
$h_{k,l}$: distance from facility ***k*** to facility ***l***
$a_{o,w}$: arrival time of order ***o*** in time window ***w***
d_o: destination node of order ***o***
q_o: quality of service for order ***o***

Output:

c_0: total delivery duration per order ***o***
e_i: total ground time per inbound vehicle ***i***
g_b: total ground time per outbound vehicle ***b***

3.1.3. Knapsack Problem

The model is designed to maximize the sum of the values of the packages the inbound vehicle carries, so that the sum of the weight and volume of the assigned packages is less than the weight capacity and volume capacity of the inbound vehicle. However, in the occasion that there are not enough orders to fill the inbound vehicle, the inbound vehicle should stay grounded. Even though it is desired to minimize the ground time of all vehicles, it is not efficient nor optimal to transport the inbound vehicle with a low load factor. The model is, therefore, proposed with a minimum load factor constraint for the inbound vehicle, see Equation 3.1a.

$$\sum_{o \in S} 1 \geq U_i, \qquad S \subset O, \quad \forall i \in I \tag{3.1a}$$

$$\text{With} \quad U_i = \frac{N_i}{100\%} \cdot P_i, \qquad \forall i \in I \tag{3.1b}$$

O is the daily set of orders and S is a subset of O which indicates the orders that are at a specific moment in time present at the facility. U_i is the minimum number of orders that the inbound vehicle should carry at least. It is determined from the given load factor N_i that is a ratio of the max paylaod of the inbound vehicle as shown in Equation 3.1b. Only, and only if, Equation 3.1a is met, the model will assign orders to the inbound vehicle according to Problem 3.2:

$$Max \sum_{o \in O} z_{o,i} \cdot p_{o,i}, \qquad \forall i \in I \tag{3.2a}$$

$$\text{Subject to} \sum_{o \in O} w_o \cdot p_{o,i} \leq P_i \qquad \forall i \in I \tag{3.2b}$$

$$\sum_{o \in O} v_o \cdot p_{o,i} \leq V_i \qquad \forall i \in I \tag{3.2c}$$

The objective function of the Knapsack Problem is explained by Equation 3.2a. The value of each package is described by z_o, which is valued according to the previous explanation. The decision variable $p_{o,i}$ ensures that only the assigned orders will be taken into account. The sum of the weight w_o and volume v_o of all assigned orders must be within the max payload P_i and max volume V_i capacity of the inbound vehicle as indicated by Equation 3.2b and Equation 3.2c, respectively.

The problem is solved sequentially per available inbound vehicle. In other words, the model assigns orders to each inbound vehicle until there are no more available inbound vehicles left. It implicates a better approximate of the network performance than guaranteeing that all packages are transported without a vehicle limit. The performance will be an important indicator reflected in the ground time and delivery duration that can be used as an indicator to determine the number of inbound vehicles required for the network.

3.1.4. Facility Assignment

The model is designed to minimize the total distance travelled per order. In other words, the model aims to choose the facility with the lowest distance from origin to facility to destination. The facility assignment is described below, see Problem 3.3:

$$Min \sum_{o \in O} \sum_{f \in F} r_{o,f} \cdot u_{o,f} \tag{3.3a}$$

$$\text{Subject to} \sum_{f \in F} u_{o,f} = 1, \qquad \forall o \in O \tag{3.3b}$$

The objective function minimizes the distance $r_{o,f}$ from origin to facility f to destination per order o, see Equation 3.3a. It is assumed that the origin and destination of each order are given. The constraint ensures that only one facility can be assigned to order o as indicated by Equation 3.3b. However, multiple orders can be assigned to one facility. The decision variable $u_{o,f}$ can only have the value 1 if the facility is assigned to the order, otherwise it is 0.

3.1.5. Traveling Salesman Problem

The inbound vehicle distributes packages over multiple facilities. The TSP aims to minimize the distance travelled when doing such a tour. Given $h_{k,l}$ the distance from facility k to facility l is bigger than zero, the TSP can be formulated as an integer linear programming problem, see Problem 3.4:

$$Min \sum_{k \in F} \sum_{l \in F, l \neq k} h_{k,l} \cdot x_{k,l} \tag{3.4a}$$

$$\text{Subject to} \sum_{k \in F, k \neq l} x_{k,l} = 1, \qquad \forall l \in F \tag{3.4b}$$

$$\sum_{l \in F, l \neq k} x_{k,l} = 1, \qquad \forall k \in F \tag{3.4c}$$

$$\sum_{k \in J} \sum_{l \in J, l \neq k} x_{k,l} \leq |J| - 1, \qquad J \subset F, \quad |J| \geq 2 \tag{3.4d}$$

The TSP aims to minimize the distance required to travel to cover only the assigned facilities, which is taken into account by including the decision variable $x_{k,l}$, see Equation 3.4a. The first constraint requires that the inbound vehicle can reach a facility only from one prior facility, see Equation 3.4b. The second constraint requires that the departure is exactly to one facility, see Equation 3.4c. In other words, the two constraints ensure that the inbound vehicle can visit a facility and depart from a facility only once. With J a subset of F, the last constraint ensures that the solution is a single tour and not a combination of multiple sub-tours as indicated by Equation 3.4d.

The inbound vehicle has typically a larger range compared to the small distances it is required to cover between intermediate facilities in city logistics. It is, therefore, assumed that the inbound vehicle will be able to complete each tour and it will have full range at each start of the tour.

3.1.6. Outbound Vehicle Assignment

The model aims to maximize the value of the package it assigns to the outbound vehicle. The valuation $y_{o,b}$ is defined as explained before in Package Valuation 3.1.1. The assignment problem is given by Problem 3.5:

$$Max \sum_{o\in O}\sum_{b\in B} y_{o,b}\cdot m_{o,b} \tag{3.5a}$$

$$\text{Subject to} \sum_{b\in B} m_{o,b} = 1, \qquad o\in O \tag{3.5b}$$

$$\sum_{o\in O} m_{o,b} = 1, \qquad b\in B \tag{3.5c}$$

The objective function is described by Equation 3.5a that finds the match for an order o and an outbound vehicle b with the highest valuation. The problem is given two constraints to ensure the objective function indeed finds a match. Equation 3.5b indicates that each order o needs to be assigned to only one outbound vehicle b, and Equation 3.5c indicates that each outbound vehicle b needs to be assigned to only one order o. The outbound vehicle has limited space to carry packages. It is, therefore, assumed that it cannot carry more than one package per trip. The decision variable $m_{o,b}$ can only have the value 1 if it is assigned and 0 otherwise.

Outbound vehicles are typically smaller vehicles with lower payload and lower volume capacity. The orders must meet the requirements of the outbound vehicles as described by Equation 3.6 and Equation 3.7:

$$\sum_{o\in O} w_o\cdot m_{o,b} \leq P_b, \quad \forall b\in B \tag{3.6}$$

$$\sum_{o\in O} v_o\cdot m_{o,b} \leq V_b, \quad \forall b\in B \tag{3.7}$$

The weight of the assigned order and the volume of the assigned order must be within the payload capacity P_b and volume capacity V_b of the outbound vehicle. The weight of the order and the volume of the order are described by w_o and v_o, respectively.

The distance r_b required for the outbound vehicle to transport the order o from its origin to the destination must be smaller than the range R_b of the corresponding outbound vehicle, see Equation 3.8.

$$\sum_{o\in O} r_b\cdot m_{o,b} \leq R_b, \quad \forall b\in B \tag{3.8}$$

The origin is a given at this point in the sequential framework. For the P2P network it would be the distribution center, and for the H&S network it would be the facility as assigned by the model.

3.1.7. Assumptions

The network design model is assumed to be utilized with one-mission vehicles. The vehicles deliver all assigned packages at the designated destination and return to their origin for as long as the network is operative. The operator can indicate the desired operation hours of the network with the quality of service. The model will stop running once it reached the closing time, irregardless where the vehicles are. The assumption is chosen to understand how many packages the network is able to deliver until closing time including the entire demand. All made assumptions are summed up below:

- Ground Time is calculated by subtracting Arrival Time from Departure Time ;
- Delivery Duration is calculated by subtracting Arrival Time Distribution Center from Arrival Time Destination;
- Not delivered packages are all packages that did not arrive at the destination at the ultimate operation time of the network, which is calculated by subtracting the total number of delivered packages from the entire set of orders;
- Origin is fixed and known;
- Inbound vehicle departs only if it meets the minimum load factor constraint;
- Outbound vehicle departs only if it has at least one and at most one order assigned;
- Outbound vehicle cannot carry more than one order;
- All vehicles have one mission;
- All intermediate facilities can handle each an infinite number of orders simultaneously;
- All destinations are located next to a warehouse, it can store infinite number of packages ;
- Two or more vehicles can deliver a package at the same time at the same facility - at intermediate facility and at destination;
- Outbound vehicle has full range after each trip;
- Total tour of the inbound vehicle is always within its range;
- Inbound vehicle has full range after completion of each tour;
- Set of facility locations, destination locations, and demand are given;
- All assigned packages to the inbound vehicle have a perfect fit - no optimal placement;
- The quality of service that the network provides is divided by an Xpress service and a Normal service;

3.1.8. Monte Carlo Simulation

It is assumed that the logistic operator has historical data available that can be used as a guideline for the daily order size. A MCS is formulated to incorporate the impact of uncertainties and risk factors on the order size by repeated random sampling for different scenarios. The simulation creates a set of orders based on the given demand by the operator, indicated by O. Such data can be difficult to obtain by an operator, but it is assumed that the logistic operator is able to extract historical data on a daily level. The simulation is provided with a set of time windows, W, to allow the operator to have a more accurate estimate of arrival flows during a day. The number of time windows and the size of each time window depends on the accuracy of the provided data and the desired operating hours of the network. The probability distribution of order arrivals per time window can be uniform, unless the operator has more accurate historical data. The random arrival time is indicated by $a_{o,w}$, with o the order and w a time window.
Even though the destination of each order is unknown, it is assumed that a set of destination locations is given. The model selects a destination node for each order based on a probability distribution function (pdf). The pdf will be determined by the population density and by the number of destination locations, D. Clustering each of these matters per district allows the operator to determine the pdf of the destination locations. The probability is a ratio of the population density relative to the total population density of all districts together. The district probability is divided by the number of destination locations in the district assuming that the population density within each district is homogeneous and thus the definition of Uniform Distribution applies. The randomly generated destination location d_o is given to each order o .
The system allows the operator to tailor the quality of service provided to its customers, Q. It is assumed that

the quality of service a logistic provider wants to offer is given. Depending on how much the operator wants to tailor its service to its consumers' desires, the system will have a set of service types to assess the impact a quality of service can have on the network. The operator can create a pdf based on the operator's expectations towards consumers' desires per service type. Else wise, a uniform distribution is assumed. The simulation assigns a service type $q_o$to each order o based on the chosen pdf.

3.1.9. Assumptions MCS

The following assumptions apply to the distributions used by the MCS:

- If there is no distribution given, the model uses a uniform distribution for arrival times within a time window;
- The model uses a uniform distribution for destination locations within the same district;
- If there is no distribution given, the model uses a uniform distribution between Xpress service and Normal service.

3.2. Assigning Algorithm

This subsection explains how the assigning algorithm works and how it incorporates the problems formulated by the sequential framework. The objective of the assigning algorithm is to assign an order to a vehicle and subsequently to assign a facility to the vehicle's destination. It is assumed that the input, shown in Section (3.1), and the created list of orders, with each their corresponding service type and destination location as explained in Subsection (3.1.8), are given to the assigning algorithm, see level 1 in Figure 3.3. The algorithm uses the input to determine which network strategy is used by the operator at level 2. If there are no Intermediate Facilities (I.F.) nor Inbound Vehicles (I.V.), the algorithm skips the first four steps and goes to the process before box 7. If there are I.F. and I.V. the algorithm puts the order in a queue with all orders that are present at the facility at that time. Afterwards, the algorithm checks for the availability of an I.V. at level 3. If there is no available I.V. the algorithm puts the order back in the queue. When there is an available I.V., it assigns a value to the order. Depending on the quality of service as desired and given by the operator, the algorithm will assign different values to each order as explained in Subsection (3.1.1). The algorithm fits as many packages as possible to the available I.V. based on the highest valuation of each package, at level 4. If it does not fit, the algorithm puts the order back in the queue, otherwise the algorithm assigns the order to the I.V.. The algorithm finds the facility closest between the origin and the destination and assigns this facility to the I.V.. Subsequently, it checks if the vehicle has arrived at the designated facility, at level 5. If it did not arrive it sends out the I.V. to its destination and drops all orders that are assigned to that facility. The algorithm determines if the I.V. has another location to drop off packages. If so, it sends out the I.V. to the next destination, else wise it moves the I.V. back to its origin, at level 6.
The algorithm puts all orders in the queue that are present at that moment in time for that specific facility, which would have been the starting point for the algorithm if there were no I.F. nor I.V.. Following, the algorithm gives a value to the orders present at the facility as described in Subsection (3.1.1). The O.V. can carry only one package, so the algorithm assigns the order with the highest valuation only, see level 7. If there is another order with a higher valuation it puts the order back in the queue. The order with the highest valuation will be assigned to an available drone at level 8. If there is no O.V. available, the algorithm puts the order back in the queue. After O.V. assignment, the algorithm sends the O.V. to the designated destination if the O.V. has not arrived yet, see level 9. Upon arrival, the O.V. drops the order at the destination and returns to its origin.

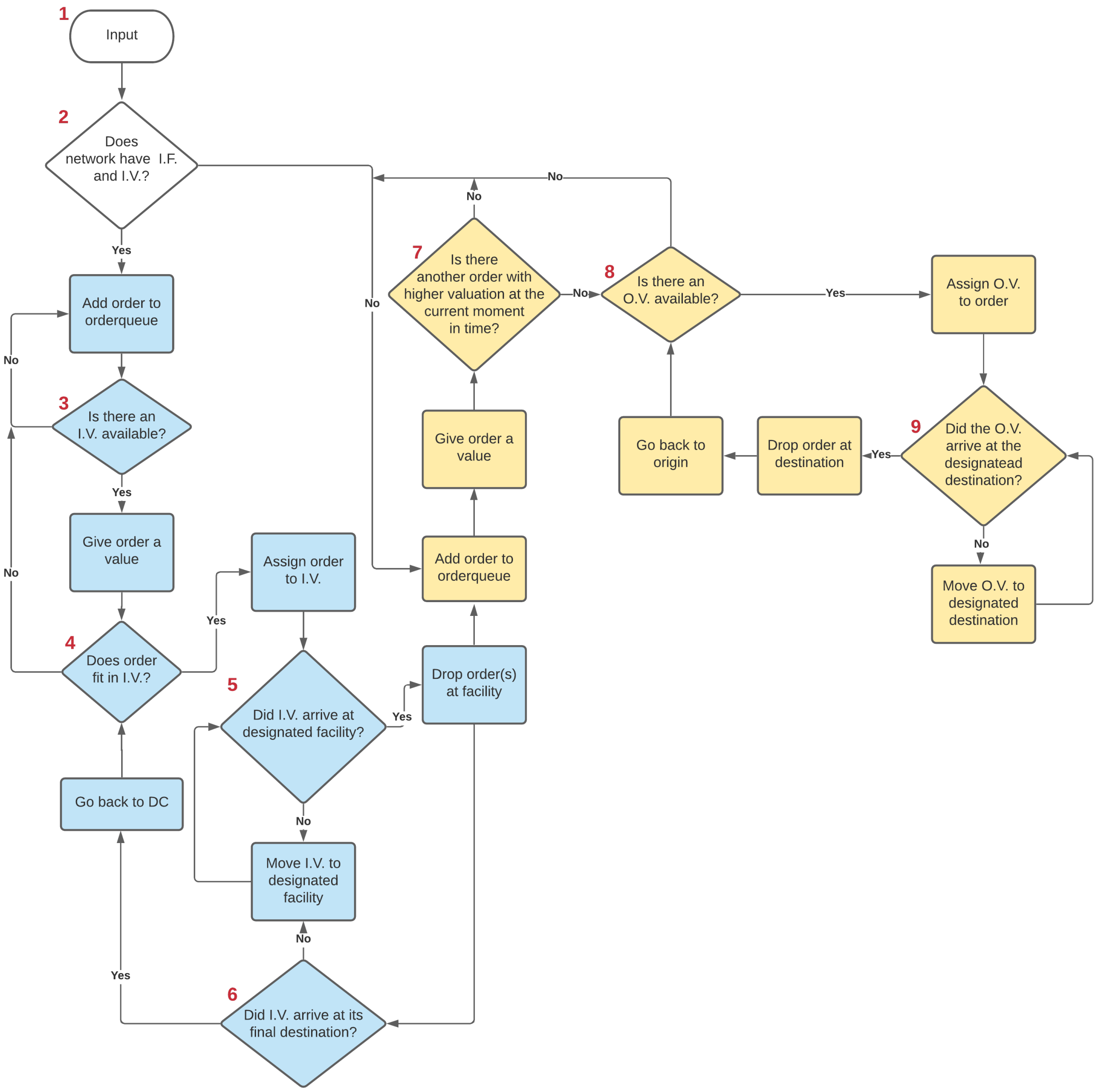


Figure 3.3: Flowchart assigning algorithm

4 Case Study

As of writing, there are no Drone Delivery Networks servicing the last part of a supply chain of an airline. Moreover, it is more common for airlines to provide only airport-to-airport services or warehouse-to-warehouse services. It is observed that the demand for e-commerce rises rapidly. Air Canada as a pioneer in its field, continuously strives for innovation and sustainable solutions while aiming to be the market leader. To anticipate the growth in demand for e-commerce, the changing customer behavior and expectations, and the possibility to potentially be the first in utilizing a Drone Delivery Network, made Air Canada decide to collaborate with the researcher to find a competitive Drone Delivery Network in the City of Toronto.

Air Canada is currently not providing Business to Consumer (B2C) service, and transports only a small portion of the e-commerce market. Considering the total addressable market in Canada as well as globally will give a better understanding of the underlying opportunities (4.1). The origin and destination of the demand are essential pieces of information to create an efficient network. The demographics of the city will, therefore, give a relative good insight in the demand nodes (4.2). Drones that deliver packages are designed to be quick and efficient which makes the drones more competitive for home delivery services than other vehicles in metropolitan areas. The beneficial characteristics come with a price. Drones have to compensate with its maximum payload that is significantly smaller than that of airplanes and controversial trucks. It is able to carry only a very specific part of the airline's demand. The current demand of Air Canada is, therefore, carefully considered to get a better grasp of the demand that should be addressed by the Drone Delivery Network (4.3). City logistics, airline networks, and other existing logistic providers network strategies are considered for the Drone Delivery Network (4.4). Each network strategy requires different resources to facilitate the network to meet the demand. It is essential to find optimal locations for the resources to create an efficient network (4.5). The following two sections describe the applicable network strategies along with the required components and how they are set-up (4.6), and (4.7). All assumptions are summed up in Section (4.8) and the chapter is concluded in Section (4.9)

4.1. Market Research

From Section (1.1) key reasons were given to improve and invest in last mile delivery due to the increasing expectations of consumers towards a seamless experience as they desire faster and more frequent deliveries. In addition to the expectations, the consumers' behaviour is also changing as they are moving more towards online purchases. As a result, e-commerce has seen continuous growth over the past years, and its market share of the total global retail sales is expected to grow up to 22% in 2023, see Figure A.1 in Appendix (A). When considering the Canadian e-commerce market, an expected growth is anticipated per year reaching a total $33 billion USD market by 2022, see Figure A.2 in Appendix (A). Which is 10% of the total market size of courier, express and parcel of the year 2019, see Figure A.3 in Appendix (A). In addition to understanding the growth potentials, it is vital to understand where the demand is coming from. It is interesting to observe, from Figure A.4 and from Figure A.5 in Appendix (A), that the online purchases in Canada are mainly driven by consumers in urban areas that desire home delivery services [75]. The growth in e-commerce is clear, but it is only relevant for the project if the demand meets the package criteria that drones can carry. Figure

A.6 in Appendix (A) indicates the distribution of package weights of online purchases. The results are found from the survey with 34,500 respondents that show that half of the cross-border purchases weigh less than 0.5 kilograms and 90% of of the cross-border purchases are below five kilograms [76].
Even though the online purchases are rapidly growing every year. There is still a large group of people that avoid cross-border purchases. More than 25% of this group does not proceed with cross-border purchases, because they prefer lower to no shipping costs, see Figure A.7 in Appendix (A). Other barriers that concern the consumers are long delivery times, uncertainty in actual deliveries, difficulties in returning products, and international taxes. Long delivery times can be fastened by providing home deliveries with drones, and lower charging shipping costs can be achieved by loyalty programs. Anticipating on these consumer barriers can help Air Canada to gain significant market share in e-commerce.

Historical data of package distribution flows throughout the city would make the analysis even more complete. Unfortunately, DHL, UPS, FedEx, Canada Post, and Purolator were not able to provide such data. They were either not willing to collaborate, or they were simply not keeping track of this data. It was mentioned that data measuring the distance travelled before making another stop is more relevant. In other words, courier services focus more on route optimization and do not care as much where the truck is going to relative to its previous location.

Besides the commercial resources, consultation with University of Toronto, McMaster University, the Ministry of Transportation of Ontario, and the municipality of Toronto was conducted. Unfortunately, none of the resources were able to provide insights in the distribution of small parcels in the city of Toronto. The municipality, however, was focused on a project related to the flow of cargo goods in the city, but they were not successful with gaining enough meaningful data. As a result they started focusing on bigger packages transported by heavy trucks which was easier to track data from their GPS as heavy trucks are required to keep track of its routes. Since drones are not able to carry heavy packages, this data is not considered meaningful. Additionally, package deliveries to warehouses could potentially be gathered, but warehouses are typically used to distribute packages to different regions, and hence this data would also not be relevant for the project. It could rather provide misguidance.

4.2. City of Toronto demographics

The city of Toronto is the largest economic center, the most populous city of Canada, and the fourth-largest city in North-America. The city has 2.93 million people and is divided in 6 areas as shown in Appendix (B). YYZ is located outside the city in Mississauga next to the Etobicoke region which is, therefore, known to have many warehouses and consolidation centers. Scarborough contains the biggest surface, but does not contain the highest population. Observing Figure 4.1 shows that North York has the highest population. Old Toronto has the second highest population, but it has the highest population density. Etobicoke has the smallest population density.

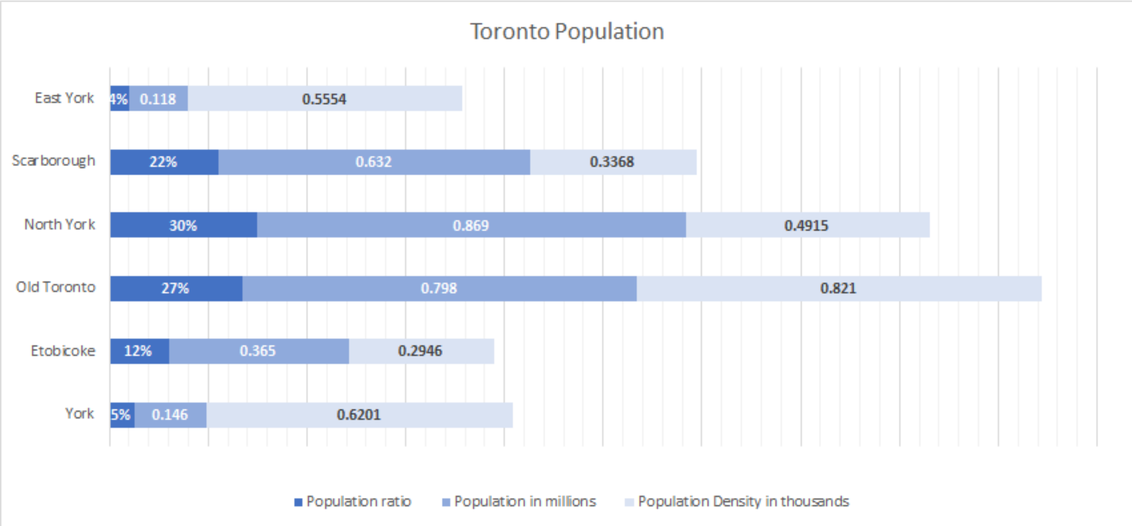


Figure 4.1: Population in millions and population density by region

Toronto has a ten year average employment growth rate of 2.0%, a five year employment growth rate of 2.5%, and saw a growth rate of 3.1% from 2018 to 2019 [77]. To put total employment rate of Toronto in perspective, Figure 4.2 shows the employment density distributed over the city. The region Old Toronto for example, is the economical hub of the city and country. It has more than half a million jobs which accounts for 37.2% of Toronto's total employment with an average employment density of 30,000 jobs per km^2. A small area inside the Old Toronto area, called Downtown, is located south east and contains a total of 101,950 jobs in 2019. The region saw an compound annual growth rate of 4.2% since 2014. North York is Toronto largest centre with 35,920 jobs. Etobicoke has the smallest employment, but has grown the fastest with an average of 3.1% per year since 2014 to a total of 10,850 jobs in 2019.

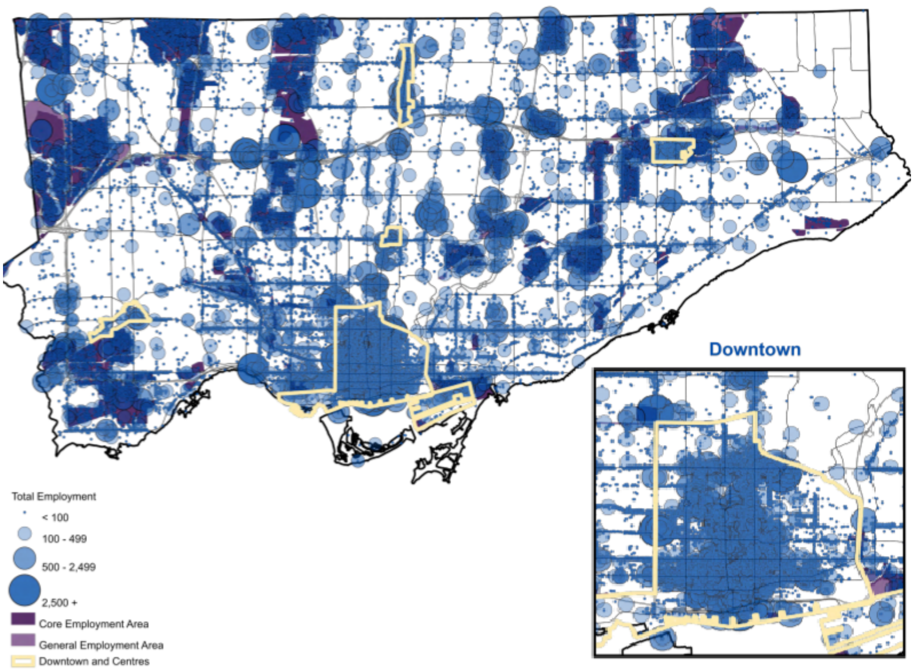


Figure 4.2: Employment concentration November 2019 [77]

The distribution of population and employment is a good indication for potential higher demands of package deliveries and pick-ups. From Figure A.5 it was observed that 66% of the online purchases are delivered to the consumer's home and 11% to the office/workplace. In addition, The historical employment growth could attract more people to the city as well. More people could indicate again a higher demand for home deliveries of e-commerce.

4.3. Air Canada

Two different data sets are extracted from internal data platforms of Air Canada. One data set contains flights with a total maximum cargo weight of 11.3 kilogram - from here on referred to as the bigger packages. The other data set contains flights with a total maximum cargo weight of 4.5 kilogram - from here on referred to as the smaller packages. It must be noted that these maximum cargo weights are on flight level, not on individual package level. It is not possible to drill down to package level to extract details of each individual package of all flights over the five year period to determine exactly how many of this total cargo weight were packages with a specific maximum weight. Therefore, the conservative approach is chosen to guarantee that the observations and conclusions do not consider any package that exceeds the weight limit. Subsection (4.3.1) elaborates the demand for package arrivals in Toronto, which can be translated in potential demand for home deliveries in the City of Toronto. The entire demand of Air Canada to YYZ as destination is assumed to have the City of Toronto as end-destination. The reader is referred to Appendix (C) for the analysis of packages departing from Toronto. Home pick-ups in Toronto for the Drone Delivery Network could be translated from the demand of small parcels that depart from Toronto. It is noted in Section (3.1.7) that the Network Design Model considers one mission fleets only - all vehicles return back to their origin once it delivered all assigned packages. However, analyzing the pick-up demand could indicate the impact a two-mission fleet could have on a Drone Delivery Network. Different scenarios are designed to allow the experimenter to conduct a what-if analysis on the data to anticipate the hidden packages and uncertainties in demand (4.3.2).

4.3.1. Demand: Package arrivals Toronto

Both data sets for smaller packages and bigger packages contain data from 2016 to 2020. The flights of 2020 are considered to be less representable due to the pandemic. These flights are, therefore, not taken into account. Subsequently, both data sets are filtered with flights to Toronto only. The demand for package arrivals in Toronto can be considered as the demand for home deliveries for the Drone Delivery Network in Toronto. From observations it is concluded that both data sets follow approximately the same distribution. The drone with a payload of up to 11.3 kilogram is not commercially operative yet in contrary to the other drone with a payload of 4.5 kilograms. Hence, the observations of the data set with a maximum of 4.5 kilogram is shown below. Only anomalies with the bigger packages are discussed, the reader is referred to Appendix (D) to see the full big package analysis. So, for further reference, whenever packages are mentioned in this section, it is referring to packages with a weight of 4.5 kilogram or less, unless mentioned otherwise.

On average per year, Air Canada transports 37 packages a day to Toronto. This is a very rough estimation which will give a general idea of the business of the Drone Delivery Network throughout the year. However, it does not give a clear understanding about the distribution flow of package arrivals during the week and day which is necessary to find potential bottlenecks in the network.
A drill down to the Day of Week (DoW) is considered to find arrival peaks during the average week per year, see Figure 4.3. The figure shows a clear pattern with a lower number in arrivals on Sundays and Mondays with a range between 24 and max 31 a day. Which is a drop of more than 30% compared to Tuesday, Wednesday, Thursday, and Friday, that have an average of 43 package arrivals a day. The rate of change between the four different years tends to be low, and not correlated between the different days either.

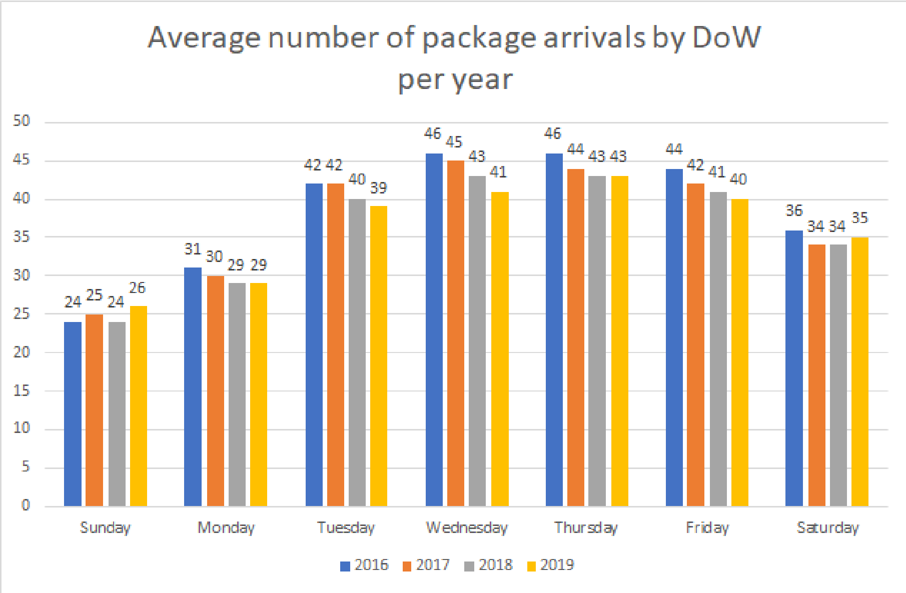


Figure 4.3: Average number of package arrivals by DoW per year

The next potential bottleneck can occur by strong peaks in arrivals during one day. Therefore, the flow distribution of the average of 37 package arrivals over one day is necessary to understand. To find the distribution, the day is divided in eight time frames of three hours, early night (00:00 – 03:00), late night (03:00 – 06:00), early morning (06:00 – 09:00), late morning (09:00 – 12:00), early afternoon (12:00 – 15:00), late afternoon (15:00 – 18:00), early evening (18:00- 21:00), and late evening (21:00 – 00:00). Note, it is assumed to have an equal distribution of package arrivals in each time frame of three hours.
The distribution of package arrivals is not constant over the different time frames, see Figure 4.4. As expected, a lower number of arrivals can be observed during the night with a small range between two and four arrivals, and one peak of five arrivals in 2016. The busy hours are shown to occur during the afternoon and the beginning of the evening with the highest peak in the late afternoon with a constant average of seven arrivals for each year. The demand is also observed to be relatively constant over the four years.

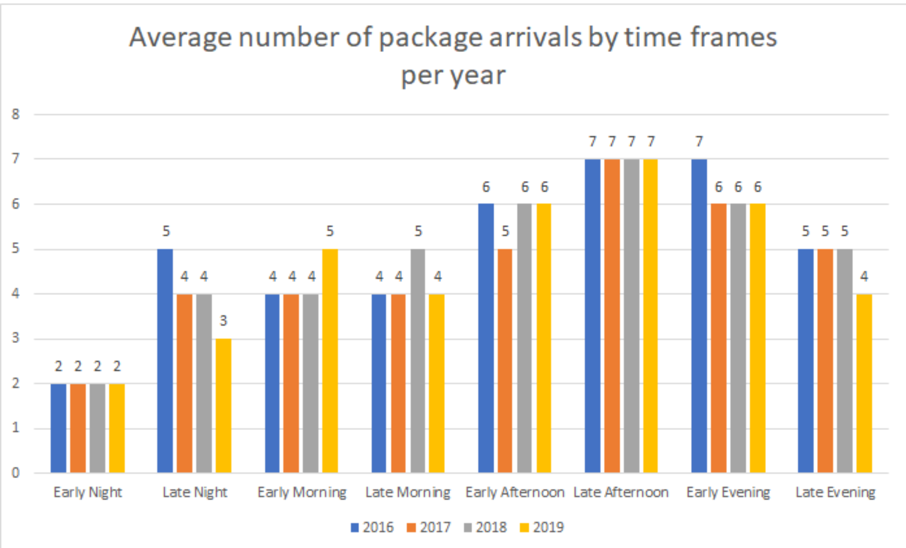


Figure 4.4: Average number of package arrivals by time frames per year

It is concluded, however, that Tuesday, Wednesday, Thursday, and Friday are the busiest days of the week. It is therefore more likely to find bottlenecks in the distribution of package arrivals on each of these days, see

Figure 4.5. The number of arrivals during the night sees only a small change in its peak in 2016 to six arrivals. In contrary to the other time frames which almost all see a small increase in arrivals relative to the previous Figure 4.4. The pattern stayed relatively the same with also a peak during the late afternoon of up to eight arrivals.

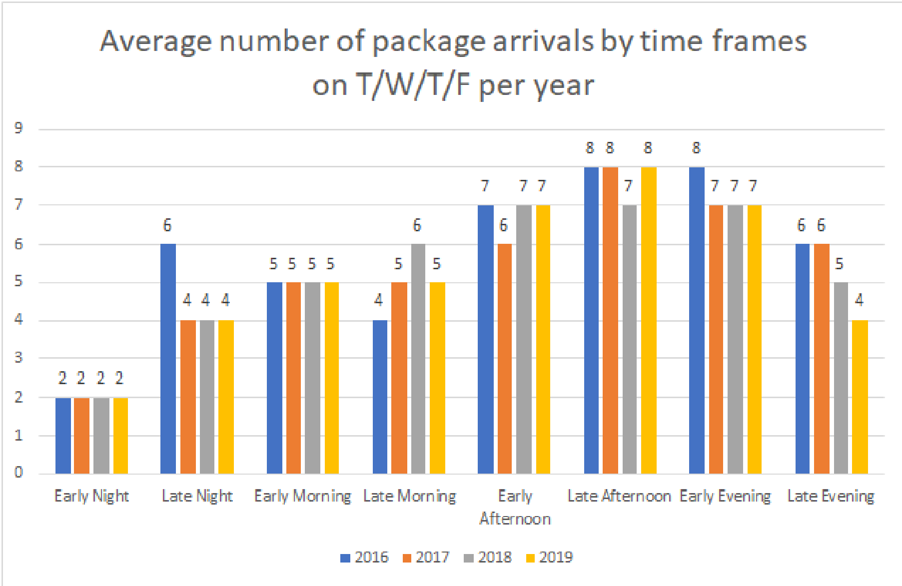


Figure 4.5: Average number of package arrivals by time frames on Tuesday, Wednesday, Thursday and Friday per year

During the previous analysis, seasonal peaks are not considered. Distribution of package arrival over the different months is, hence, considered to find seasonal peaks, see Figure 4.6. The graph shows a lower number of arrivals in February and December and the highest number of arrivals on average in May. More surprisingly, the average number of package arrivals tends to decrease form 2016 to 2019 with the biggest decrease during the summer months. However, the decrease is not significant. Also, the trend over four years can be considered too small to conclude that this trend is continuous.

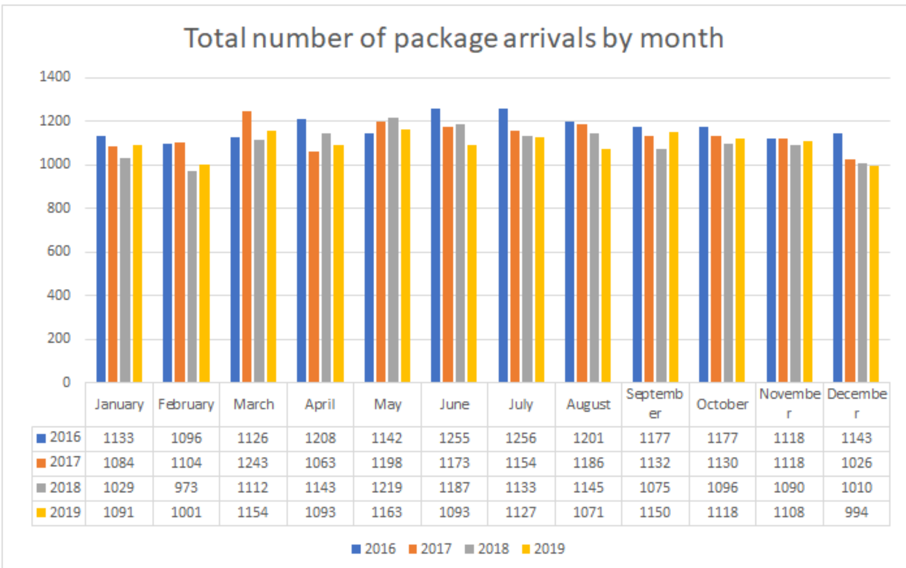


Figure 4.6: Total number of package arrivals by month

So, the next drill down is in month May to find the seasonal peaks in this particular month, see Figure 4.7.

The graph shows similar trends as before without strong trends between the four years, but with more arrivals during the midweek with the highest peak on Thursdays in May 2018. This peak is relative high considering the other years on Thursday. On Wednesday however, there is a constant peak relative to the other days over the four years. This will be the next drill down since the average peaks are the most relevant to find the bottlenecks. Packages smaller than 11.3 kilograms see a constant peak on Thursdays in May, see Figure D.5, which is the first anomaly between the two data sets.

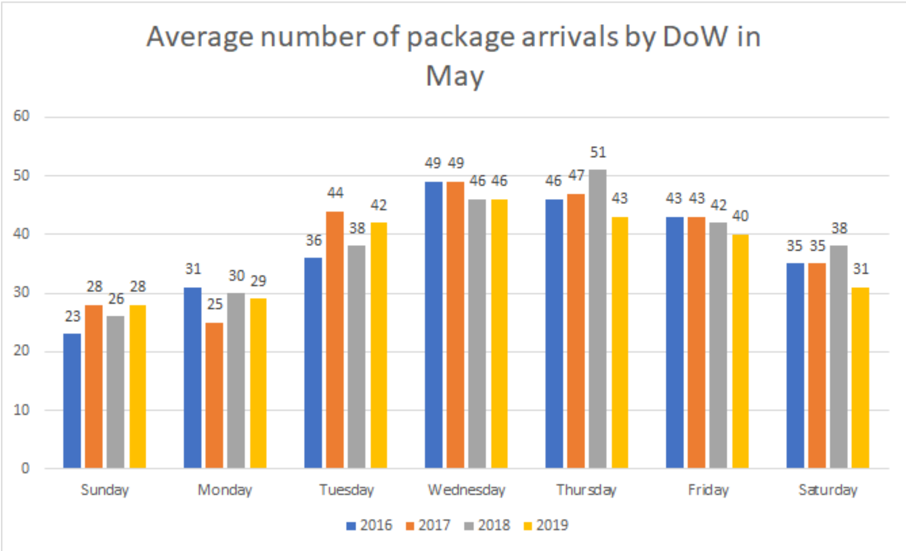


Figure 4.7: Average number of package arrivals by DoW in May

From Figure 4.8 there is no clear constant pattern of package arrivals on Wednesdays in May over the four years. The average peak is found on both late afternoon and early evening with eight package arrivals. Early evening seems to be more influenced by the higher peak from 2016. Observing the bigger packages shows, however, a constant increase in demand for all time frames on Thursdays in May from 2016 to 2019, see Figure D.6. To conclude, the highest peak of package arrivals is expected to be 9 in the late afternoon on Wednesdays for the smaller packages, but no more than 50 package arrivals over the entire day. The bigger packages are expected to see a peak of 17 arrivals in the late afternoon on Thursdays in May, with a total expected arrivals around 88 packages on this day.

Regulators do not allow drones to operate in populated areas so far. Excessive flight test programs are needed for the regulators to build trust in safe and harmonized operation of drones in the society. It is unknown when this will happen, but it is expected that once drone operations are accepted, it will be restricted to operate during night or even without daylight. It is, therefore, expected that the Drone Delivery Network will be operative between 7 am and 7 pm. This will cause an accumulation of package arrivals at the opening time. From analysis, it is concluded that the average retrieval time, time it takes for smaller packages after landing to be processed to get shipped at the warehouse, takes approximately 49 minutes, see Appendix (E). Therefore, packages that arrive during the evening and night will not get distributed until the next opening day at 7 am, to include an 11 minute buffer for the packages to get loaded onto the drone.

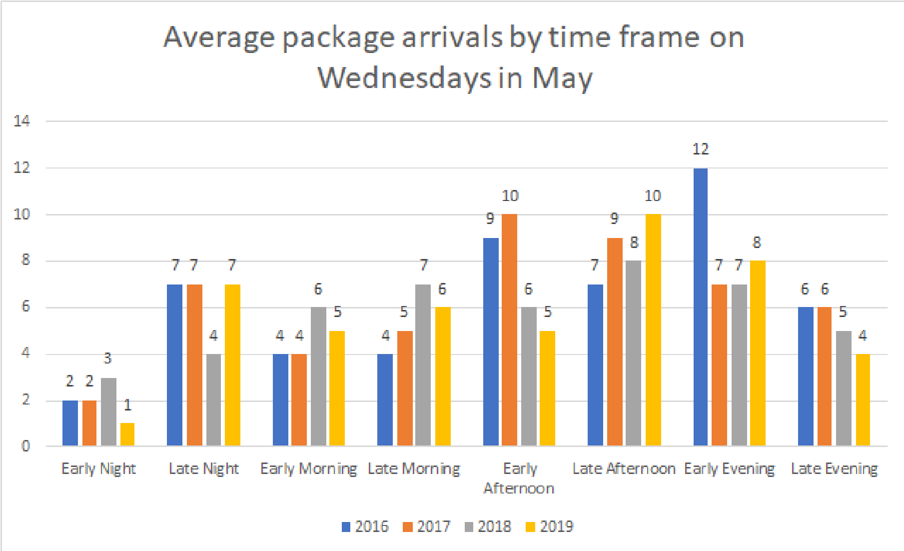


Figure 4.8: Average number of package arrivals by time frames on Wednesdays in May

Considering the previous analysis on Figure 4.8, means that at the opening time of the Drone Delivery Network, there are on average 22 packages waiting to be distributed – nine (early evening), five (late evening), two (early night), and on average six (late night). To conclude, not the early afternoon, but the morning at opening time will be the real bottleneck of the network.

So, a similar analysis on just the four time frames outside operating hours is performed to find the peak, see Figure 4.9. Over the four different years and all months, Air Canada sees an average of 16 package arrivals per day during the evening and night at YYZ, with June the highest average of 17 package arrivals. Again, observing the figure shows a decrease in package arrivals over the four years.The trend seems to be stronger than previously, which could be explained from changes in Air Canada's flight schedule considering more strict guidelines regarding flying by night. Observing Figure D.7 shows a peak in August, with an average of 32 package arrivals. It is an increase of 3 packages compared to the average over the entire year. No strong seasonality can be concluded from both data sets.

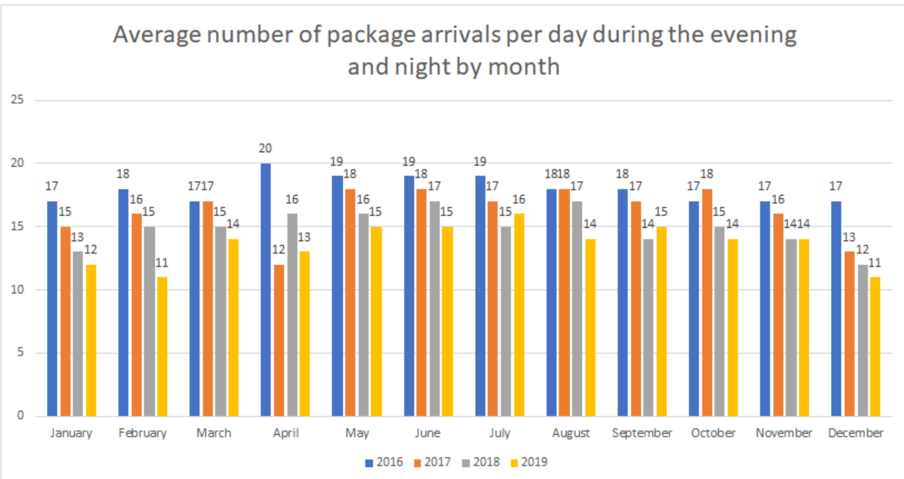


Figure 4.9: Average number of package arrivals by month during the evening and night

Wednesday has an average of 20 package arrivals, and Friday an average of 22 package arrivals when excluding the year 2019, see Figure 4.10. The same analysis on packages smaller than 11.3 kilograms show a high average of 43 package arrivals during the evening and night on Wednesdays in August 2018, see Figure D.8.

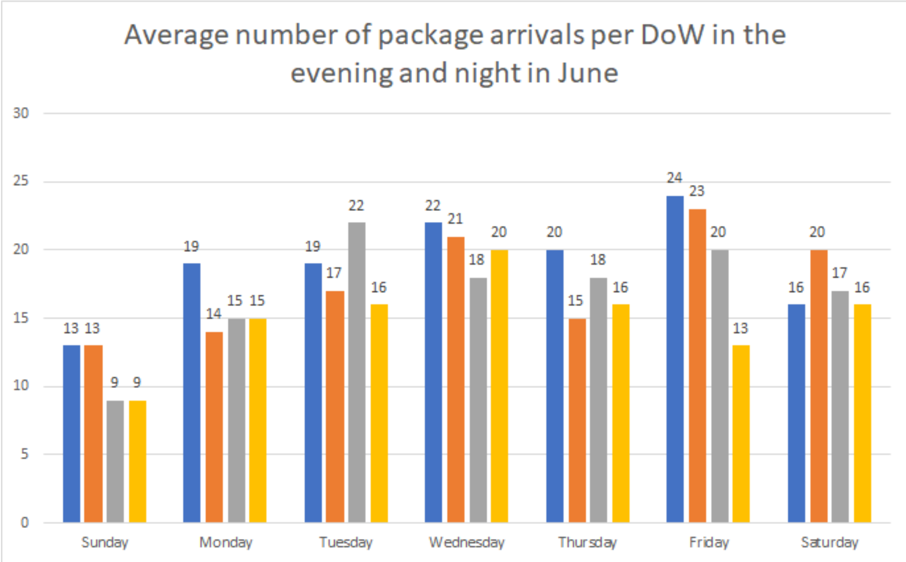


Figure 4.10: Average number of package arrivals by DoW during the evening and night in June

To conclude 37 packages arrive on average every day with a lower demand during the weekends and on Monday, and an average of 70 package arrivals for packages of up to 11.3 kg. The distribution of package arrivals on each day is observed to have a higher demand in the afternoon and the early evening. Due to the constraint in operating hours of the drones, however, the highest number of packages that have to be distributed at once will be in the morning at opening time at 7 am. The warehouse is open 24/7 and will receive packages all evening and night. The analysis shows an average of 16 smaller package arrivals during the evening and night with a peak on Fridays in June with an average of 22 packages. The bigger packages have an average of 29 package arrivals during these time frames with a peak of 43 package arrivals on Wednesdays in August 2018. The reader is referred to Appendix (F) to see the analysis regarding the trend of Air Canada Cargo.

4.3.2. Scenarios

From Section (4.3.1) it was observed that Air Canada receives on average 17, 4, 4, 6, and 7 small packages and 30, 8, 8, 12, 13 big packages before 7 am, in the early morning, late morning, early afternoon and late afternoon respectively. A seasonal peak was found on Wednesdays in May with a distribution of small package arrivals over the same time frames of 22, 5, 6, 8, and 9. The big package arrivals saw a peak on Thursdays in May with a distribution of 34, 10, 11, 15, and 17 over the time frames. Focusing on the bottleneck of the Drone Delivery Network, it was found that Air Canada can expect a peak of 24 small packages in June and a peak of 43 big packages in August at the opening time. It is desired for Air Canada to be able to distribute the demand at any time according to its quality of service. Therefore, the demand of the seasonal peaks is considered as the most likely scenario that the Drone Delivery Network should be able to distribute, Scenario 1 - Base Case. The scenario is defined for the smaller and bigger packages, Scenario 1.1 and Scenario 1.2, respectively, see Table 4.1.

It is, however, noted that the data available by Air Canada is limited to flight level. Numerous packages applicable to the Drone Delivery Network are thus hidden in the data. To anticipate on the conservative approach there is not a worst case scenario with a lower demand. Instead, scenario 2 a better case is chosen. A 20% increase in demand would not be significant enough. As it would imply a total demand of ten packages more with only one package more per time frame from morning to afternoon - assuming a linear increase over the time frames. Therefore, scenario 2 is chosen with a linear demand increase of 40%. It implies a total increase of 21 arrivals and 38 arrivals for the small and big packages, Scenario 2.1 and Scenario 2.2, respectively.

A bullish scenario is chosen to anticipate on the potential rapid increase in demand. Scenario 3 the Bullish Case implies an increase of 100% for the small and big packages, Scenario 3.1 and Scenario 3.2, respectively.

The assumption that the entire demand to YYZ has the City of Toronto as end-destination is noted. It is, however, assumed that the number of missing packages in the data is much higher than the number of packages arriving in Toronto that have different end-destinations. For this reason the better case scenario and the bullish case scenario are not considered for even higher demands. See Table 4.1 below for the summary of all scenarios.

Table	Scenario 1: Base Case		Scenario 2: Better Case		Scenario 3: Bull Case	
Time Frame	1.1) Small Packages	1.2) Big Packages	2.1) Small Packages	2.2) Big Packages	3.1) Small Packages	3.2) Big Packages
Opening	24	43	34	60	48	86
Morning 1	5	10	7	14	10	20
Morning 2	6	11	8	15	12	22
Afternoon 1	8	15	11	21	16	30
Afternoon 2	9	17	13	24	18	34
Total	52	96	73	134	104	192

Table 4.1: Scenarios

Comparing the distribution of package arrivals in Toronto, explained by Scenario 1.1 and Scenario 1.2 in Table 4.1, with the distribution of package departures in Toronto, explained by Scenario 1.1 and Scenario 1.2 in Table C.3 in Appendix (C). Shows that the demand for package arrivals in the early afternoon is relatively, percentage wise of total packages, two times higher than the demand for package departures in the early afternoon. For all other time frames, the demand for package arrivals is slightly lower than the demand for package departures, this account for both data sets - small and big packages.

4.4. Network Strategies

The P2P network and the H&S network are both considered for a Drone Delivery Network. The efficiency of the network depends highly on the characteristics of each network. It is, however, unknown in advance how multiple factors can influence the efficiency the network. Both networks should, therefore, be considered to understand the pros, and cons and set-up similarly for better comparisons. Drones have a limited battery cycle, which can negatively affect the efficiency of the drones' utilization. It is, therefore, essential to take into account a battery management strategy to be able to create a profitable Drone Delivery Network (4.4.1). A delivery network has different customers with different desires. Providing different services allows the logistics operator to tailor the service to a customer's needs (4.4.2).

4.4.1. Battery Management Strategy

Each drone must be capable of completing its mission without power loss. The inability could cause damage to the drone, or worse, it could injure people when flying over populated and highly congested areas. Hence, literature describes the necessity of predicting the drone's capability of completing its mission [78]. Apart from preventing a drone from not completing its mission, and cause harm, it is also essential to carefully define a battery management strategy to increase its utilization. Otherwise, it is difficult to provide a profitable delivery service in large urban areas. As such, scientific research addresses contactless charging, recharging stations, and battery swapping as potential battery management strategies. Contactless charging is constrained in line-of-sight operations, high system costs, and low charging efficiencies. Recharging stations require extra facilities and potential detours of the drones resulting in higher costs. Battery swapping requires also challenging technology, but is proven to be most efficient [56]. Moreover, Drone Delivery Canada (DDC), the partner of Air Canada, has a proprietary technology for battery swapping. The customer is able to purchase or lease a DroneSpot which is a mini-depot at which the drones can drop-off their packages and execute a battery swap to replace the old battery with a replenished one. The estimation for landing, package drop-off, and battery swap is ten minutes. Because of the available battery swap technology and the proven efficiency of the technology in literature, it is chosen to move forward with this strategy for the Drone Delivery Network.

4.4.2. Quality of Service

The Drone Delivery Network might be very efficient and profitable, but if the network does not meet the desires of the consumers, it is not sustainable. The network will provide two different services to anticipate on the different needs of the many consumers:

- **Xpress**: Delivers before 12 pm if the package is received before 7 am, otherwise the next day before 12 pm.
- **Normal**: Delivers the same day if the package is received before 7 am otherwise the next day.

In the event of urgent deliveries for medical care for example, the consumer is willing to pay more for a quicker service. To anticipate on such events, the Drone Delivery Network will provide an Xpress service that delivers packages before noon if the package arrived before opening hours of the Drone Delivery Network. Elsewise, a service called Normal will be provided. This service delivers packages the same day if the package arrived before opening time of the Drone Delivery Network.

4.5. Site Selection

The rise of population in urban areas inherently increases the movements of goods creating even bigger traffic congestion issues. The flying capabilities of the drones will decrease the traffic congestion, but it does not take away the importance of site selection as it does influence external costs. A drone flying every minute over someone's house will not be considered an improvement for the person's living conditions. It increases risks to the person's health and it can cause noise disturbances. The negative impacts on the residents and on the environment from controversial trucks resulted in new sustainable freight regulations for municipalities like dedicated delivery zones, and restricted delivery timing [46]. Selecting a site close to the consumers will increase external costs, but selecting a site far from the consumer will increase distribution costs for the operator. The optimal site selection is, therefore, of interest of several stakeholders like the operator, municipality, and the citizens, and thus requires multiple criteria.

The selection of criteria to assess the applicability and feasibility for evaluating potential locations depends on different desires per stakeholder. The operator, Air Canada, wants the locations to be optimal in terms of maximum customer coverage, low costs, and good accessibility. The urban residents want a quick delivery service without impacting their living conditions. The municipality focuses on the bigger picture and wants the negative impact to be minimal for all stakeholders considering the operator, residents, strategic city planning, environment, and perhaps other operators as well. Seven criteria are chosen such that the different stakeholders are taken into consideration, see Table 4.2.

Criteria for Location Selection		
Criteria	Definition	Criteria Type
Accessibility	Access for operator's vehicles and by public and private transport	Benefit, more is better
Customer proximity	Distance to customers	Benefit, more is better
Supplier proximity	Distance to Distribution Center	Benefit, more is better
Costs	Acquiring/lease land, or facility	Cost, lower is better
Externalities	Environmental impact, noise, and pollution i.e.	Cost, lower is better
Expansion	Possibility to expand to meet increasing demand	Benefit, more is better
Security	Safe location, no high risks for vandalism, theft, or accidents	Benefit, more is better

Table 4.2: Criteria for location selection

The criteria accessibility, customer and supplier proximity, and costs have a direct impact on Air Canada. Accessibility allows the drones to easily reach the facility without special obstacle manoeuvres or detours for restricted flight zones. A big catchment area improves the proximity to customers and a facility located close to the Distribution Center allows shorter delivery times. Lower costs will improve the competitiveness and profitability of the Drone Network. The other criteria focus more on other stakeholders, but will influence indirectly the efficiency of the chosen facility location. For example, a policy towards flight manoeuvres restrictions could result from a poor selected location that has a negative impact on the environment.

The following step involves selecting potential locations for the facilities. Normally, the decision maker uses prior experience and knowledge on restricted fly zones and other transportation conditions of the city to select candidate sites. The drones are, however, not allowed to operate anywhere in the city. Hence, the criteria are followed as a guideline to select candidate points which can later on be used as an input to assess the impact of the facility's location on the network.

4.6. P2P Network

The Drone Delivery Network with a P2P strategy delivers packages to consumers in Toronto from the DC of Air Canada at YYZ. The DroneSpot of DDC is chosen as the facility for the P2P network serving as the mini-depot to deliver packages to the consumers and as recharging stations (4.6.1). Different drones will be available by DDC with each its own intrinsic value for delivering packages (4.6.2). Finally, the chosen destination locations are selected (4.6.3).

4.6.1. DroneSpot

The DroneSpot is typically 20 x 20 ft in linear dimensions. Under any circumstance, at least one person - typically a trained member of the customer's staff, is required to load the drones and swap the battery packs for recharging at the DroneSpot. There is an optional cargo drop capability for the drones which does not require a trained staff member at the out-station. However, an individual will need to retrieve the dropped package. When using cargo drop capability, the customer may opt for a secure netted enclosure to further protect the goods being air dropped. A customer staff member would need to retrieve the package following being air dropped. The DroneSpot can also be equipped with a retractable roof and can be heated. Drone handling time at the DroneSpots varies according to the drone, but typically a turnaround (package load/unload & battery swap) can be achieved quickly in 5-10 minutes.

Customarily, the customer will store packages in a warehouse or a vehicle adjacent to the DroneSpot. The

DroneSpots require a clear area for drone air maneuvering. The DroneSpots are equipped with a weight scale to verify payload compliance by the shipper. The scale face features a QR code which is used by a small camera equipped in the drone base to aid the drone to precisely set down in the middle of the scale. The DroneSpots are also equipped with a micro-weather station, a security surveillance camera, required communications equipment, keypad entry and a package bar code reader.

4.6.2. Drones

DDC designed and manufactured two electrical drones called Sparrow and Robin XL, see Figure 4.11 and Figure 4.12 respectively, and below their specifications in Table 4.3. Robin XL is still going through flight test programs and is expected to entry-into-service by summer 2021. In preparation, the Robin XL is being certified with an emergency parachute as standard as a regulatory precaution in the unlikely event of a mechanical failure, which may help in obtaining authorization to overfly urban areas. The Sparrow on the other hand is already commercially operative. It is capable to fly fully autonomously, but the operator is required to provide remote oversight of the drone operations. The Sparrow is currently used by customers on their logistic centers between different warehouses and facilities, for example. For one of the customers it is approved to fly over highway 401, the world's busiest highway, in an area densely built up with warehouses. Operation in urban areas such as the City of Toronto is, however, still restricted by the regulator, Transport Canada. These restrictions are expected to ease over time as experience is gained with commercial drone delivery operations. It is not known yet, if the authorization will vary by drone model.

Figure 4.11: Sparrow

Figure 4.12: Robin XL

Drone Specifications	
Sparrow	Robin XL
Max. Range = 30 km	Max. Range = 60 km
Max. Speed = 80 km/h	Max. Speed = 105 km/h
Max. Payload = 4.5 kg	Max. Payload = 11.3 kg
Noise L & T/O = 100 dB	Noise L & T/O = 100 dB
Noise cruise = 70-80 dB	Noise cruise = 85 dB
Max. WxDxH = 310mm x 201mm x 140mm	Max. WxDxH = 330mm x 229mm x 150mm
Powerplant = 8 electric motors	Powerplant = 8 electric motors
Navigation = GPS-based	Navigation = GPS-based

Table 4.3: Outbound Vehicles - Characteristics

4.6.3. Selected Sites

The key factor for an efficient and profitable P2P network is finding the optimal destination locations. The criteria given in (4.5) are followed to find these locations. The decision maker does not have enough information to assess the criteria costs, externalities, expansion, and security for each location. It requires a thorough market research which is outside the scope of the project. The remaining four criteria decide whether the location of the DroneSpot is a good strategy for a competitive network.

Open space that allows drones to freely manoeuvre is the main factor when considering the accessibility criteria per location. The network is, however, competitive when each DroneSpot has a high catchment area, or a good customer proximity. Considering the fact that Toronto is the fourth most populated city after Mexico City, New York City, and Los Angeles, doesn't go hand in hand. As a result, the decision maker had to be creative and come up with solutions such as placing the DroneSpots on top of buildings. It is still a preliminary idea that has to be consulted with the regulator. Otherwise, big parking spots, petrol stations, and warehouses of other carrier services like UPS, DHL, and FedEx are considered good accessible locations. To improve the accessibility, connectivity to the candidate locations by main roads are considered as well. Section (4.2) is used as a guideline to find good customer proximity locations for the DroneSpots. The candidate locations are also mainly chosen at locations within a 30 km to improve supplier proximity. All selected candidate locations are displayed on the map of Toronto, see Figure 4.13.

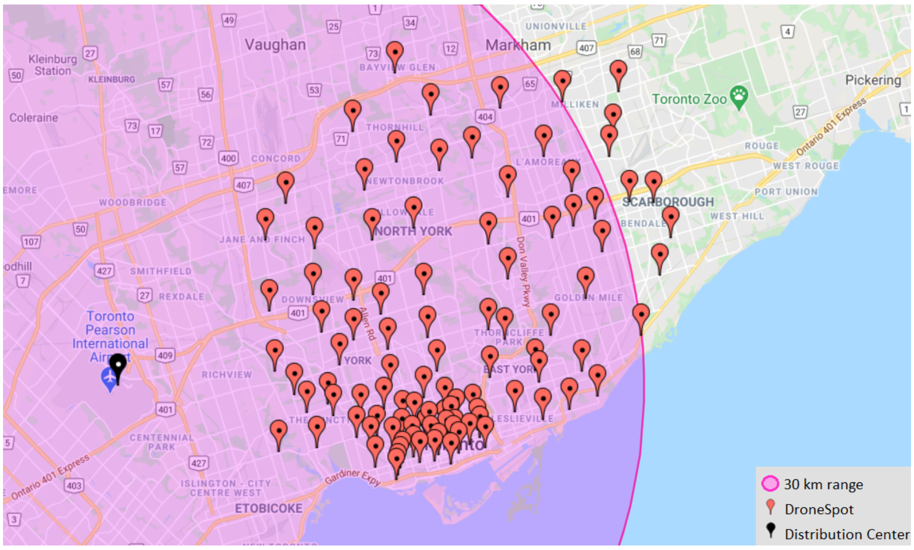


Figure 4.13: Case Study P2P

The purple area indicates the range of 30 kilometers from YYZ. Note that the project is focused on providing service to the City of Toronto. Other places that are in the vicinity of the drones, like Mississauga (South-West on the figure), are left out. The red balloons indicate the selected locations of the DroneSpots with a total of 100 different locations. More Candidate points are located in Old Toronto with specifically a higher concentration in the Downtown area considering the high population density and employment growth as explained in Section 4.2. Other DroneSpots are located further away from the Downtown area to increase the catchment area. Travel distance of five to ten minutes by car is followed as guideline to avoid ambiguous locations. Observing the figure also indicates that nine DroneSpots are located outside the 30 kilometer range. Robin XL would be able to reach these destination locations which implies an additional customer reach of approximately + 160,000 people, which is more than 5% of the entire population of Toronto. Such trade-offs can help to assess the impact that different drones can have on the network.

4.7. H&S Network

The H&S network uses intermediate facilities between the origin and destination nodes to distribute packages. It is called a hub, and for city logistics it is typically called a satellite. The satellite can be a different type of facility depending on the strategy of the network (4.7.1). The satellite receives packages from the inbound vehicle and loads the packages onto the outbound vehicle. It is considered a two-level fleet. Each fleet serves the network differently and thus requires different types of vehicles (4.7.2). The location of the satellite is essential for the efficiency of the network (4.7.3).

4.7.1. Satellites

Satellites are facilities that serve as sorting, transshipment, and switching points between origin and destination nodes. The goods are unloaded at the satellite and loaded onto city freighters, smaller and more environmentally friendly vehicles, that will serve the end-consumers [79]. Depending on the satellite, it is possible to store the goods, or to directly load the goods on the outbound vehicles without storage. Satellite with storage capability needs more space and labor compared to the satellite without storage. Satellite with a storage is similar to a traditional DC. Such facilities are more common for retailers, the goods can be stored until the customer requests a delivery [80]. A satellite without storage, called a cross-dock, is less costly, reduces the risk for loss and damage, and shortens the delivery lead time. Air Canada is not a retailer and only transports goods by demand. A cross-dock is, therefore considered a better fit for the needs of the Drone Delivery Network. The cross-dock that receives the package and directly loads the package onto an outbound vehicle is called a one-touch cross-dock. A two-touch cross-dock allows the package to be stored temporarily until it is loaded onto the outbound vehicle. It is used to anticipate on imbalance between the inbound and outbound of goods, caused by a peak in deliveries that the outbound vehicles are not able to meet.

4.7.2. Fleets

The H&S network consists of a two-level fleet. The inbound vehicles, also called the first echelon, and the outbound vehicles, also called the second echelon. Each echelon serves the network differently with different goals. The first echelon aims to distribute as many packages as possible to the satellites. The second echelon aims to deliver the package from the satellite as quickly as possible to the destination. The previously discussed drones, Sparrow and Robin XL shown respectively in Figure 4.11 and Figure 4.12 are small, light and agile. They cannot serve the network efficiently as inbound vehicles with the limited payload capacity. They are suitable as outbound vehicles instead. With the battery swapping technology, the drones are able to have a high utilization factor, low transport costs, but still quick deliveries. The network needs a bigger drone to serve as an inbound vehicle. DDC designed and manufactured a small helicopter with a payload of 180 kilograms, see Figure 4.14, and its specifications below in Table 4.4, that suits better the needs of an inbound vehicle.

Figure 4.14: Condor

Condor Characteristics
Max. Range = 200 km
Max. Speed = 120 km/h
Max. Payload = 180 kg
Noise L & T/O = TBD
Noise cruise = TBD
Max. WxDxH = 61cm x 122cm x 91cm
Powerplant = 2 Stroke Gasoline
Fuel Tank = 45.4 liters
Navigation = GPS-based

Table 4.4: Inbound Vehicle - Characteristics

The Condor is currently also in flight test programs and expected to entry-into-service by Summer 2021. It is unlike the other drones, though, gasoline powered resulting in more expensive flights. Consequently, it is even more essential to use the Condor in the most efficient way by using its max payload as much as possible. The Condor is very heavy compared to the other drones, and requires a visual check after every flight. Unloading the packages, conducting the visual check, and refueling the gas is anticipated to take approximately 15 minutes.

4.7.3. Selected Sites

The H&S network will use the same destination locations for the DroneSpots as the P2P network (4.6.3) and uses the same four criteria from Table 4.3 to select candidate locations for the satellites. Unlike the DroneSpot, the satellites either need an old warehouse, DC, or an empty field to build the satellite as desired. The availability of existing facilities are limited, and mostly poorly located. The decision maker chose, therefore, to find open fields or areas where a satellite can be built. When looking for open fields and areas, infrastructure of gas availability was mainly considered. In accordance with the desire to facilitate the Condor with gas at

the satellite. A good location would be on an open field close to a road that connects two petrol stations of the same company. Otherwise, an open field close to a petrol station was chosen.
The accessibility criteria is mainly relevant for drones and operators since there are no consumers or other stakeholders that need access to the satellite. The location must have enough free space, no obstacles like electricity cables, or high buildings in its surroundings to allow air manoeuvring of drones. For the operators it is considered to have main roads that are well connected to the location.
The criteria customer proximity is taken into account by considering the distances between the candidate point and the different DroneSpot locations. The supplier proximity is considered by taking into account the distances from the candidate locations to the DC.
Candidate points that meet these criteria were looked for in areas located close to the DroneSpots but outside high population density areas. This strategy aims to create a scalable network dedicated to the City of Toronto, see Figure 4.15. The red balloons are the previously selected DroneSpots locations, and the blue balloons are the selected candidate points for the satellites. The DroneSpots are all well surrounded by multiple satellite locations. Each satellite can potentially be dedicated to one area of DroneSpots allowing the network to be scalable. The decision maker purposely picked more than necessary locations to help finding more accurately the final desired locations of the network.

Figure 4.15: Case Study H&S Toronto

4.8. Assumptions

It is assumed that the drones fly directly from origin to destination without obstacle avoidance consideration. This is done, because the drones of DDC have these algorithms already available with additional traffic controllers to control safe flight operations. Their systems are designed to find the shortest path, that is not the goal of this project. So, the distance can be determined by using the Great Circle Distance (GCD) based on the coordinates of the facility locations. In addition to calculate the flight duration, the drones are also assumed to fly at constant max speed. Having the distance and speed allows to calculate the flight duration. DDC provides a general timeline for landing and unloading of the package of ten minutes for Sparrow and Robin XL, and 15 minutes for Condor. The additional minutes are added to the flight duration to estimate a more accurate total flight duration. See below for the complete set of assumptions:

- It takes an hour for the packages to be ready to depart from the DC after aircraft landing at YYZ - see Appendix (E);
- Drones fly directly from origin to destination measured in GCD;
- All drones fly at a constant max speed;
- Condor can refuel the tank at all satellites and at the DC;
- Condor takes in total 15 minutes for landing, package unloading, required visual check, and gas refuel;

- Robin XL and Sparrow can both swap old batteries with replenished batteries at all facilities;
- Robin XL and Sparrow take both in total 10 minutes for landing, package unloading, and battery swap;
- Time window packages retrieval: 24/7;
- Operation times drone: 7am – 7pm;
- P2P network: all drones start at DC;
- H&S network: all Condors start at DC and all RXL and Sparrows are divided by ratio over the satellites;
- Fleet of the P2P network, and the inbound and outbound fleet of the H&S network are all homogeneous.
- All packages meet either the Sparrow or Robin XL dimension criteria - depending on the fleet configuration;
- The entire demand of Air Canada to YYZ is assumed to have the City of Toronto as end-destination;
- The number of missing packages in the data is higher than the number of packages that do not have the City of Toronto as actual end-destination.

4.9. Conclusion

Demand for e-commerce, globally as well as domestically, is growing rapidly. Even though the potentials are significant in the market of e-commerce, there is a lot to gain for logistic providers to attract even more consumers by providing lower shipping costs, quicker delivery times, and guaranteed deliveries.

Due to shortage in data it is not possible to find a flow of package distribution throughout the City of Toronto. Consequently, demographics of the city are considered. The highest population density and the highest number of employment are found in Old Toronto. It could be a reasonable approximation to expect higher demands from this area.

Data of Air Canada is used to approximate the demand for small parcel arrivals for the City of Toronto. Three different scenarios are created to anticipate risk factors and uncertainties that come along with the demand. The demand of Air Canada is used as the base case, and the two other scenarios are a better (+40%) and a bullish (+100%) case scenario, to anticipate the hidden packages in the demand.

It is concluded to use battery swapping technology to improve utilization of the vehicles. To meet the demanding expectations of the customers it is proposed to utilize the network with an Xpress and a Normal service. Both network strategies should improve the quality of service that can be applied to a P2P network and a H&S network. Each network will use the same 100 destination locations in the City of Toronto at which battery swapping is supported. The drones from DDC, Sparrow and Robin XL, will serve both networks as outbound vehicles, and the Condor will serve the H&S network as the inbound vehicle. The transition to unload the package from the inbound vehicle to load onto the outbound vehicle will happen at the intermediate facility, called a satellite. A two-touch cross-dock satellite is considered most suitable for the network to compensate for the inconsistent distribution of package arrivals. 19 candidate locations of the satellites are chosen at the surroundings of the city.

These are the general set-up of the P2P network and the H&S network that will be used to find the optimal design of each network for this specific business case for Air Canada. The candidate locations of the satellites will be used in the framework to find the optimal locations, which will be the final set-up for the H&S network.

5
Results

The Drone Delivery Network has the goal to distribute packages in the most optimal way for Air Canada. It should be commercially competitive such that the costs are minimized and the demand can be fully met. Many costs are, however, unknown partly due to the new business model of delivering packages by drones, and partly by a lack of information. Costs like drone and facility enquiries, drone and facility maintenance, insurance, and labor costs are unknown. Instead, it is possible to anticipate on operational costs to increase the efficiency of the network. It is where the design of the network comes mainly into place. The previous chapter discusses the general set-up per network strategy. Now it is mandatory to finalize the complete design.

The different scenarios allow the experimenter to observe the impact risk factors and uncertainties have. It is, therefore, important that the scenarios have the same general network set-up with some fixed parameters. Changing one parameter in the general set-up allows the experimenter to assess the impact the attribute has on the performance of the network, which is called a sensitivity analysis. The impact can be assessed by analysing certain Key Performance Indicators (KPI) (5.1). Observing the attribute's impact per network design can be used as a tool to conclude the optimal network design for the P2P network in Section (5.2) and the H&S network in Section (5.3). Subsequently, the two network strategies are compared to each other in Section (5.4). The chapter finishes with a conclusion in Section (5.5).

5.1. Key Performance Indicators

The experimenter selected the following KPIs:

- Average Ground Time (G.T.) in minutes;
- Average Delivery Duration (D.D.) in minutes;
- Average D.D. Xpress in minutes;
- Average D.D. Normal in minutes;
- Average number of packages not delivered the same day;
- Average number of packages outside range;

The ground time is a good indicator to determine the required number of drones. An excess in drones could be indicated by a high ground time, and vice versa. The average delivery duration indicates how quickly the network delivers packages from origin to the end-consumer. A low delivery duration would indicate a quick delivery service which could be desired by customers. However, it is plausible to have a high ground time when the delivery duration is low. It requires a quality of service versus cost trade-off to determine what is desired. The average delivery duration is also distinguished per service type. Allowing the operator to determine how quickly the network should be able to deliver packages for each service type. It should help the operator to define the quality of service requirements. The simulation runs a daily demand set. It is, therefore, not possible to observe the overall performance of the network over an entire week. For better understandings, the simulation indicates the number of packages that were not delivered the same day. A backlog could result in poor network performance of the next day and the day after due to accumulation. There are nine DroneSpots located outside the range of the Sparrow for the P2P network as discussed in Section 4.6.3. When the final output indicates a high number of packages outside the drone's range. It could be another trade-off for Air Canada to configure its fleet with Robin XLs.

The only additional KPIs for the H&S network are ground time, that is distinguished per echelon level, and delivery duration that is distinguished per satellite. Ground time per echelon level allows to get a better grasp on the number of vehicles required for each echelon. Additionally, a big difference in delivery duration per satellite could indicate a discrepancy in how the outbound vehicles are distributed over the satellites.

5.2. P2P Network Design

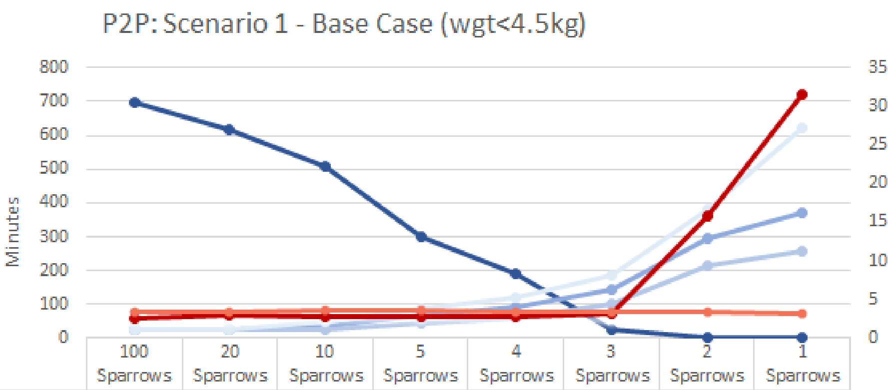
Figure 5.1 shows the results of Scenario 1.1. All simulations are run 50 times. For each simulation, the P2P network is utilized with a different number of Sparrows as indicated on the x-axis. The left side of the y-axis indicates the number of minutes related to the blue KPIs. The ride side of the y-axis indicates the quantities of the red KPIs.

The ground time of the Sparrows drop as the number in used Sparrows decrease, as expected. The average delivery duration is 24 minutes for both service types when the network uses 100 Sparrows. As the network is facilitated with more drones than it has to deliver packages, there is always a drone available. Having said that, it can be concluded that the overall performance of the P2P network, with this specific set-up, accomplishes the quickest delivery in 24 minutes. Note that 2.6 packages are not delivered with the 100 Sparrow configuration. That is due to the assumption that packages can still arrive at 7 pm exactly, but the drones will stop operating irregardless of their location.

The number of not delivered packages has a substantial increase when the network is configured with two Sparrows instead of three Sparrows. This could result in a strong accumulation of backlogged packages which could indicate a poor performance of the network. From this, it can be concluded that the P2P network for this scenario should be facilitated with at least three Sparrows.

The network is able to deliver Xpress packages within 100 minutes and Normal packages in approximately three hours when three Sparrows are used. The Xpress packages are aimed to be delivered before 12 pm if they arrived before opening time and Normal packages before closing. Considering the average delivery duration of both package services. It can be concluded that the network is able to deliver all packages on time when three Sparrows are used with a demand of 52 packages on one day.

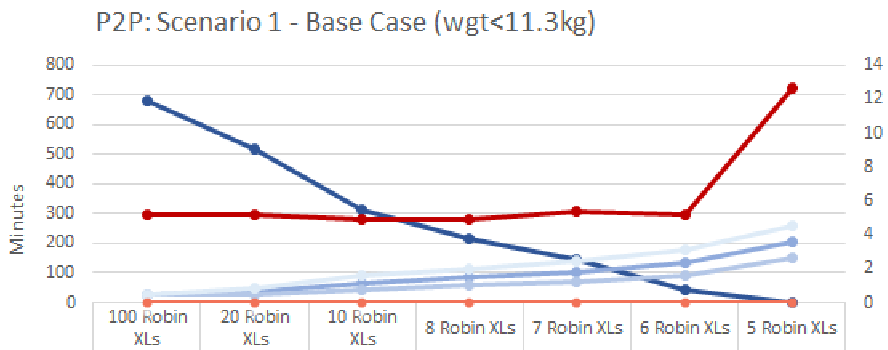
Over all run scenarios, the network allocated on average 3.4 packages to DroneSpots located outside the range of the Sparrow. A spill of three packages a day does not seem to be significant enough to consider Robin XL utilization for this specific scenario. Therefore, it is concluded that the P2P network should be facilitated with three Sparrows for this specific scenario.



	100 Sparrows	20 Sparrows	10 Sparrows	5 Sparrows	4 Sparrows	3 Sparrows	2 Sparrows	1 Sparrows
Average Ground Time	698.8	614.7	508.4	300.8	192.1	24.8	0	0
Average Delivery Duration	24.1	24.8	37.1	67.1	90.3	142.4	296.1	371.8
Average D.D. Xpress	24.1	24.2	26.6	44.5	60.9	99.8	213.1	256.4
Average D.D. Normal	24.2	25.3	47.7	89.1	121.4	184.8	382.5	622.2
Not delivered	2.6	2.9	2.7	2.8	2.8	3.2	15.9	31.5
Outside range	3.46	3.44	3.51	3.5	3.36	3.47	3.49	3.2

Figure 5.1: P2P: Results of Scenario 1.1

The Drone Delivery Network should be able to meet a demand of 96 packages if the network is facilitated with Robin XL drones. All destinations are within the vicinity of Robin XL considering the range of the drone, see Figure 5.2. Six of these drones would allow Air Canada to meet the demand entirely - excluding the packages received at 7 pm. Although, the drones would have a total of 43.3 minutes ground time. One drone less would imply zero ground time, but a substantial increase in the number of packages not delivered. The delivery duration of the network with six Robin XLs is also within the desired criteria and more than an hour quicker than with seven drones. From these observations it can be concluded that the P2P network should be facilitated with six Robin XLs for this specific scenario. The ground time might be relative high, but it gives also a safety margin for strong peaks during the day or an increase in demand.

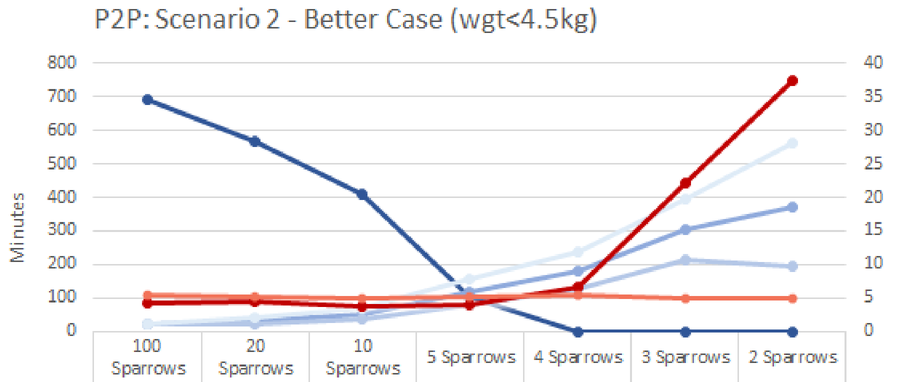


	100 Robin XLs	20 Robin XLs	10 Robin XLs	8 Robin XLs	7 Robin XLs	6 Robin XLs	5 Robin XLs
Average Ground Time	679.5	516.7	312.8	213.8	145.3	43.3	0
Average Delivery Duration	24.1	36.6	67	86	104.1	135.4	202.9
Average D.D. Xpress	24.1	26.2	44.9	57.8	69.7	92.3	150
Average D.D. Normal	24.1	47.2	89.2	114.2	137.8	178.4	258.1
Not delivered	5.2	5.2	4.9	4.9	5.4	5.2	12.6
Outside range	0	0	0	0	0	0	0

Figure 5.2: P2P: Results of Scenario 1.2

Following the same analysis principles allows the experimenter to observe similar patterns for Scenario 2.1, see Figure 5.3. The network is on average not able to deliver five packages due to the range of the Sparrow, which can be considered insignificant. It is noted that positive ground time reaches zero from the moment the network is utilized with four Sparrows. The average delivery duration equals three hours, with normal

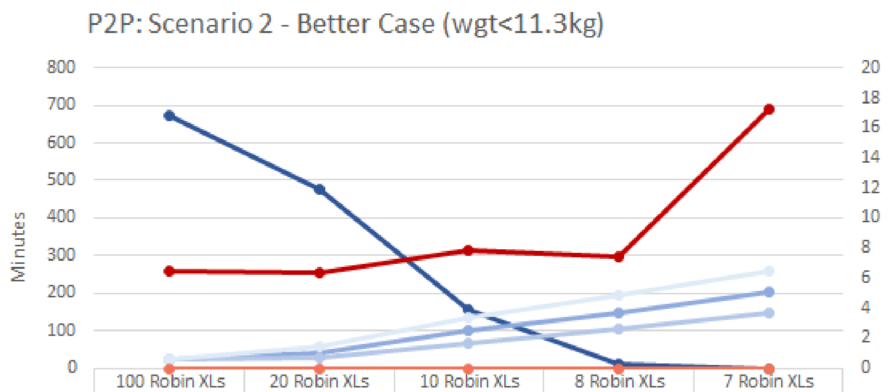
packages up to four hours, and Xpress packages in just more than two hours. Whereas the delivery duration almost doubles when the network is utilized with three Sparrows. It can be concluded that a utilization of three Sparrows is to slim considering the significant longer delivery duration and the strong increase in not delivered packages.
Five Sparrows do not have spill, but imply a total ground time of more than one and a half hour. Even though the P2P network does not have any spill with five Sparrows with respect to some non-delivered packages with four Sparrows. A fleet with four Sparrows seems to be more efficient as it is able to meet the quality of service criteria with zero ground time. The network might be considerably more profitable. It would just be more prone to peaks in package arrivals during the day.



	100 Sparrows	20 Sparrows	10 Sparrows	5 Sparrows	4 Sparrows	3 Sparrows	2 Sparrows
Average Ground Time	689.5	567.1	411	103.4	0	0	0
Average Delivery Duration	24.1	32.1	54	119.8	182.1	303.1	370.2
Average D.D. Xpress	24.1	24.2	35.6	81.3	127.9	215	197.1
Average D.D. Normal	24.1	40.2	72.4	157.7	237.9	397.4	560.9
Not delivered	4.3	4.4	3.8	4	6.6	22.2	37.5
Outside range	5.38	5.11	4.99	5.12	5.46	5.04	4.92

Figure 5.3: P2P: Results of Scenario 2.1

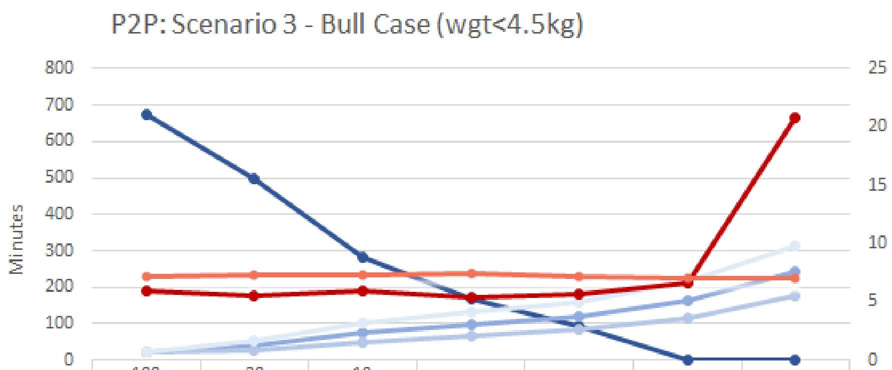
Scenario 2.2 reaches zero ground time with seven Robin XLs, see Figure 5.4. It has, however, an increase of 10 not delivered packages with respect to eight Robin XLs. The ground time is only 11 minutes with relative quick deliveries. It can be concluded that the P2P network should be utilized with eight Robin XLs for this specific scenario.



	100 Robin XLs	20 Robin XLs	10 Robin XLs	8 Robin XLs	7 Robin XLs
Average Ground Time	671.5	477.3	156.4	10.9	0
Average Delivery Duration	24.1	42.4	100	149.6	202.6
Average D.D. Xpress	24.1	29	67.3	104.4	149.2
Average D.D. Normal	24.1	56.3	133	194	259
Not delivered	6.5	6.4	7.8	7.4	17.3
Outside range	0	0	0	0	0

Figure 5.4: P2P: Results of Scenario 2.2

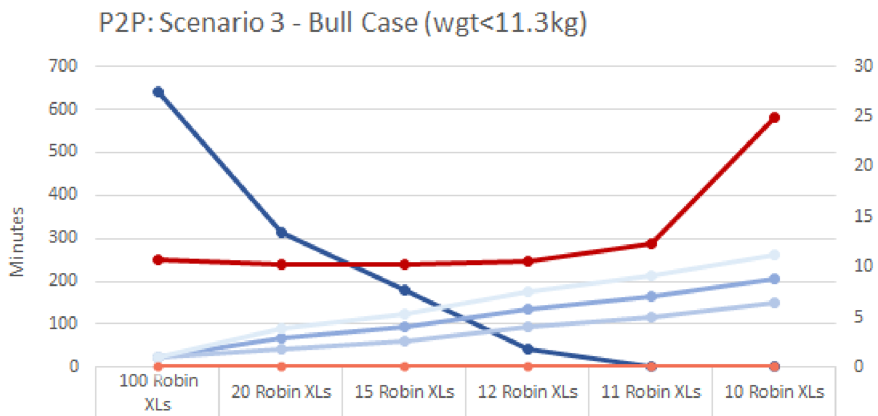
From Figure 5.5, it is observed that the bull case scenario has zero ground time on average if the network has six or less Sparrows in operation. The six drones are able to deliver the Xpress packages within two hours and the Normal packages approximately in three and a half hours. The network is just not able to deliver one package on average, disregarding the package arrivals at 7 pm. Increasing the network's fleet with one more drone gives quicker delivery services, but it increases the ground time to approximately one and a half hour. So, utilizing the network with six Sparrows seems to be the most favorable configuration for the Bull Case scenario. Considering again an insignificant number of packages outside the range of the Sparrow.



	100 Sparrows	20 Sparrows	10 Sparrows	8 Sparrows	7 Sparrows	6 Sparrows	5 Sparrows
Average Ground Time	676.1	500	282	170.1	93.5	0	0
Average Delivery Duration	24.2	40.2	75.5	99.6	121.7	164.5	244.6
Average D.D. Xpress	24.1	27.8	49.1	65.5	83.1	115.7	177.2
Average D.D. Normal	24.3	52.6	102.5	132.9	161.3	214.4	312.7
Not delivered	5.9	5.5	5.9	5.4	5.7	6.6	20.8
Outside range	7.17	7.25	7.32	7.42	7.15	7.09	7.08

Figure 5.5: P2P: Results of Scenario 3.1

Figure 5.6 shows the result of the P2P network for the Bull Case scenario with bigger packages. Observing the figure allows to conclude that the network with 11 Robin XLs has zero ground time while meeting the delivery criteria. It is, however, not able to complete all deliveries by the end of the day and missed two packages. Two packages that were not able to be delivered the same day is considered insignificant and can be taken granted when aiming for cost minimization.



	100 Robin XLs	20 Robin XLs	15 Robin XLs	12 Robin XLs	11 Robin XLs	10 Robin XLs
Average Ground Time	639.2	312.4	180	43.3	0	0
Average Delivery Duration	24.1	67	93.1	135.8	163.6	204.5
Average D.D. Xpress	24.1	43.6	61.3	94.2	115.6	149.2
Average D.D. Normal	24.1	90.1	124.8	176.9	211.5	260.6
Not delivered	10.7	10.3	10.2	10.5	12.3	24.9
Outside range	0	0	0	0	0	0

Figure 5.6: P2P: Results of Scenario 3.2

5.3. H&S Network Design

First, different design configurations of the H&S network will be examined by running MCS (5.3.1). The obtained network design can be used to find the optimal configuration of the network (5.3.2).

5.3.1. H&S network set-up

19 different candidate locations for the satellites were selected in Section (4.7.3). The Facility Assignment algorithm decides the distribution of all orders over the satellites. When running Scenario 1.1 10,000 times, the system distributes the packages to 3 satellites (Satellite 14, Satellite 16, Satellite 17) only. Figure 5.7 shows that the three chosen satellites are the ones closest to the airport. The decision making tool is mainly driven by distance efficiency, which explains the choice of the 3 satellites.

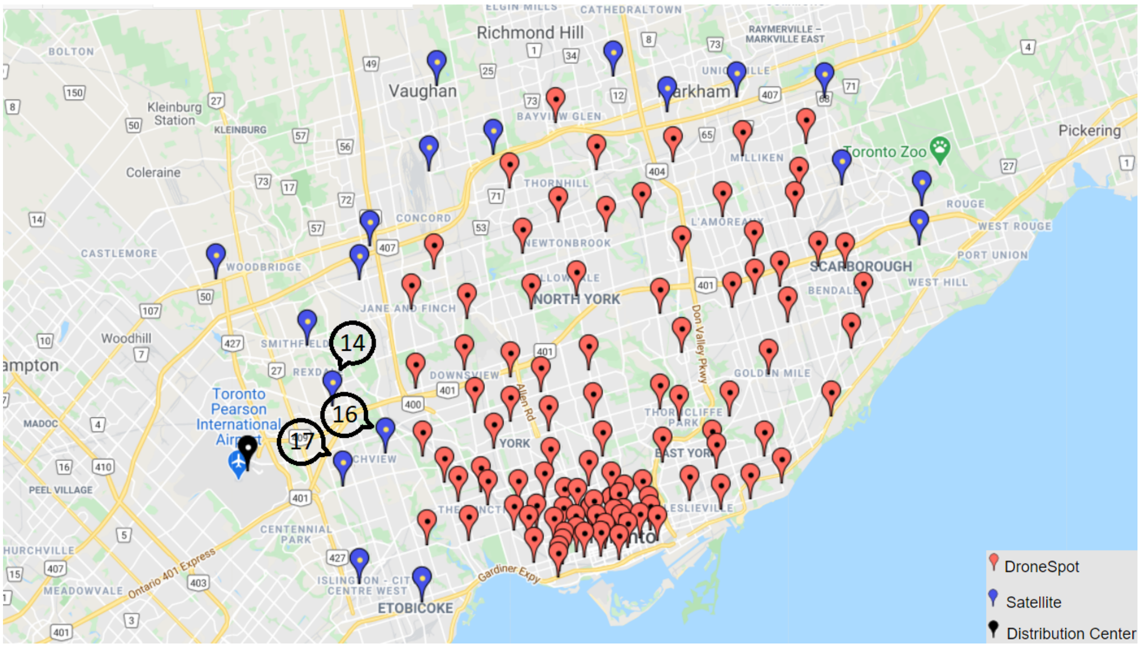


Figure 5.7: Three selected satellites by the model

In reality, however, landing, visual check, and unloading of the Condor at the three satellites will take longer than the flight times. Which takes out the efficiency of the satellite locations. Consequently, the simulation is run again, this time the satellites located close to the airport are taken out. The model distributed the packages to Satellite 1, Satellite 2, Satellite 4, and Satellite 10, see Figure 5.8.

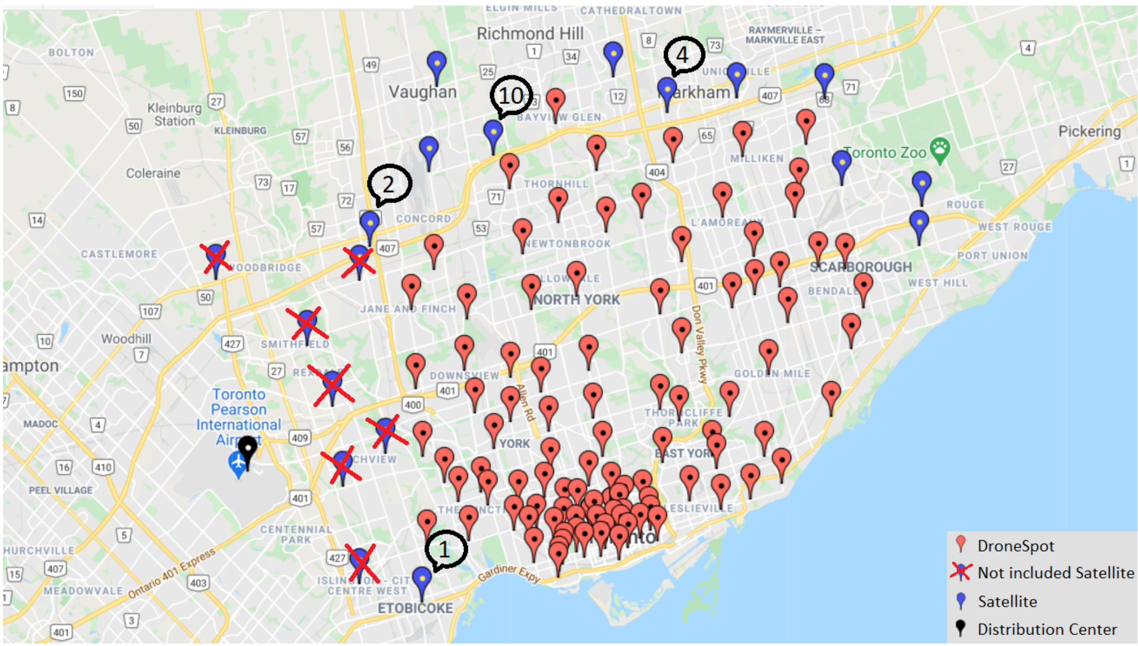


Figure 5.8: Four selected satellites by the model

Combining the four satellites ensures more than just the entire catchment area of the City of Toronto within the 30 kilometer range of the Sparrow. Taking a closer look to the package distribution of each satellite allows to observe the number of packages distributed by each satellite. Which will be an indicator to understand the importance and potential size of the satellites. The MCS calculates the average number of packages distributed per one simulation run. By doing that 10,000 times, the system is able to count how many times the average number occurs. Figure 5.9 shows the package distribution of Satellite 1 - Scenario 1 Base Case for small packages. The x-axis shows the number of packages distributed and the y-axis indicates the number of occurrences. The figure indicates a normal distribution with an average of 39 packages. Law of Large Numbers (LLN) implies that the mean of the simulation goes to the average value as the number of simulation runs goes to infinity when it is assumed that the random variables are independent identically distributed (i.i.d.), by definition [81]. For a normally distributed random variable Y, the Confidence Interval (CI) can be defined as follows:

$$P(\mu - 1.96\sigma \leq Y \leq \mu + 1.96\sigma) = 0.95 \tag{5.1}$$

with μ the mean and σ the standard deviation. 1.96 is derived from the standard normal z distribution for a 95% confidence interval. In other words, it can be said with 95% confidence that Satellite 1 will distribute between 32 and 45 packages a day for this specific scenario. The 95% CI interval is indicated with the grey area and the two red zones indicate the area outside the CI interval. Performing the same calculations show a mean of 9 packages with a 95% CI of 4 to 15 packages a day for Satellite 2, see Figure 5.10. The other two satellites have an insignificant number of packages it distributed a day, see Figure 5.11 and Figure 5.12. Satellite 4 and Satellite 10 distribute approximately more than three quarter of the times less than 5% of the total packages. It can be concluded that these two satellites will not be relevant for the H&S network. Satellite 1 and Satellite 2 are summarized in Table 5.1. The reader can visit Appendix (G) to observe the same analysis for the other scenarios.

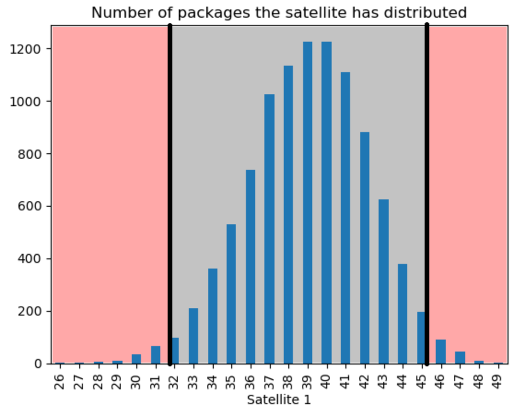


Figure 5.9: Simulation Satellite 1 - 10.000 runs

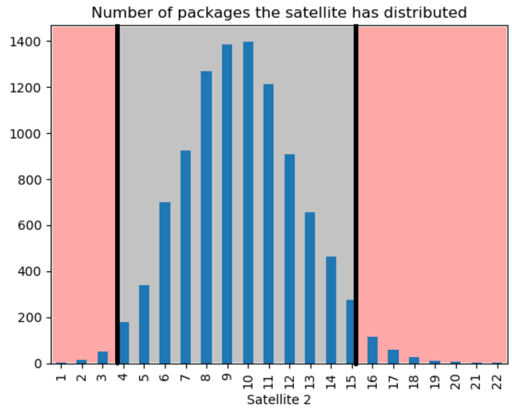


Figure 5.10: Simulation Satellite 2 - 10.000 runs

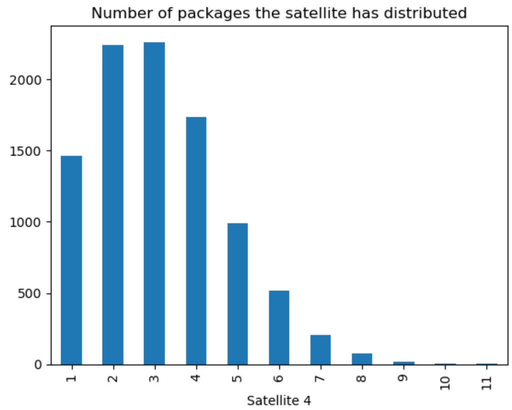


Figure 5.11: Simulation Satellite 4 - 10.000 runs

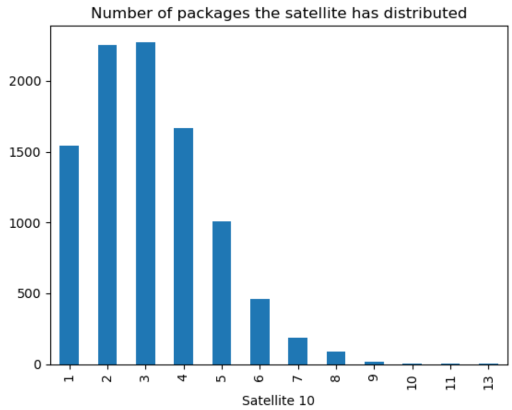


Figure 5.12: Simulation Satellite 10 - 10.000 runs

Satellite	Average #packages	Variance	Standard deviation	C.I. lower limit	C.I. upper limit
Satellite 1	39	9.9	3.2	32	45
Satellite 2	9.7	7.9	2.8	4	15

Table 5.1: CI of Satellites 1 and 2 - Scenario 1.1

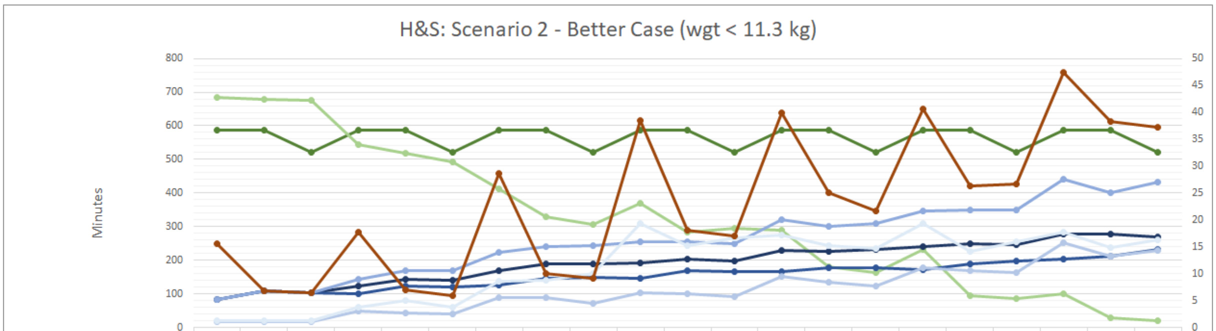
This will give a better understanding of the size and the number of drones required at each satellite. Assuming the expected packages to be distributed by each satellite equals the mean. The ratio of packages that is expected to be distributed per satellite can be determined. The average number of packages that are not distributed by Satellite 1 and Satellite 2, due to the inclusion of Satellite 4 and Satellite 10 in the simulation, are subtracted from the total number of packages. In other words, the packages distributed by Satellite 1 and Satellite 2 are assumed to be the full 100%. Satellite 1 is, therefore, expected to distribute 80% of all packages and Satellite 2 is expected to distribute 20% of all packages. The calculation allows for a better approximation to distribute the drones over the satellites. Because of the nature of i.i.d., it can be concluded that the ratio of packages distributed per satellite is constant and independent of the size of orders. For example, the network would assign eight outbound vehicles to Satellite 1 and two outbound vehicles to Satellite 2, in the case of ten outbound vehicles.

5.3.2. H&S Network Configuration

The H&S network uses the same previously discussed 100 DroneSpot locations, Satellite 1 and Satellite 2 as the only intermediate facilities, and one Condor for the following simulations. The Condor is able to fit at least 77 Sparrow packages and 59 Robin XL packages considering the volume capacity of the Condor and the max dimensions of the packages that Robin XL and Sparrow can carry, assuming perfect fit of the packages. However, it implies that the Condor is able to carry the entire demand for Scenario 1.1 and Scenario 2.1. Without running the simulations, it can already be concluded that the Condor would either have a high ground time or it would fly with low load factors. The H&S network would be poorly utilized and thus this network strategy is not efficient for these specific scenarios. The Condor would carry maximum three times a day packages considering the distribution for Scenario 1.2 and Scenario 3.1. with approximately a 30% load factor. So, the H&S network is also considered inefficient for these two scenarios. Therefore, only Scenario 2.2 and 3.2 will be discussed for the H&S network.

The results of Scenario 2.2 are presented in Figure 5.13. The ground time is distinguished by the inbound vehicle and the outbound vehicles, represented by the green lines. The average delivery duration is distinguished by Xpress service and Normal service and per satellite, indicated by the blue lines. Each simulation is run 50 times. The x-axis indicates the configuration of the H&S network for each simulation. The configuration changes in the number of outbound vehicles, or in the minimum required load factor of the Condor. The network contains a fixed constraint that the Condor will transport the packages only if its capacity is at least 50%, 70%, or 100%. For all three set-ups, the number of outbound vehicles are decreasing from left to right with a starting point of 100 Robin XLs. The y-axis indicates the minutes on the left side for the previously discussed KPIs. The right side of the y-axis indicates quantities measured in number of non-delivered packages. This KPI is displayed with the red line.
Observing the figure shows that the ground time of the outbound vehicles is decreasing with decreasing number of Robin XLs and with lower load factors of the Condor. It is self-explanatory that less outbound vehicles implies less ground time. A lower load factor could indicate a more frequent package delivery to the satellites, which could explain the lower ground time with lower load factors. The average number of not delivered packages has a strong peak whenever the Condor has a minimum load factor of 100%. It takes longer until the Condor meets the minimum load factor criteria which could explain this peak.
The overall quickest delivery of the network is reached with 100 outbound vehicles at a 100% load factor. The average delivery duration is approximately 80 minutes for both services with an average delivery duration of less than 20 minutes from the satellites. However, regarding the high ground times of the vehicles it is not considered the best configuration set-up.

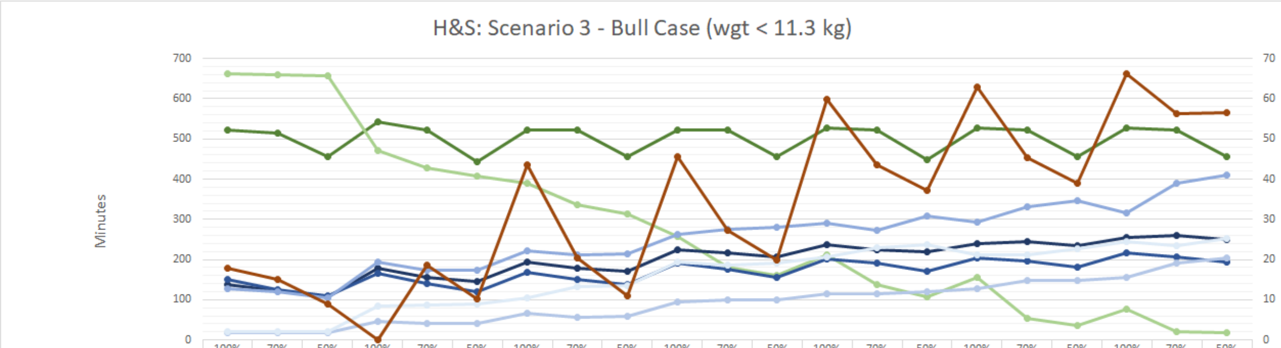
Instead, a minimum of 50% load factor for the Condor together with a total of five outbound vehicles is considered the best configuration of the H&S network for Scenario 2.2. The delivery criteria of Xpress and Normal are met. The ground time of the outbound vehicles are approximately half of the ground time with six outbound vehicles while the average delivery duration increases by only 15 minutes. Just five more packages, a total of 26.6, are not delivered by the end of the day with five outbound vehicles compared to six outbound vehicles. Which is increased to 37.2 packages when the network is utilized with 4 outbound vehicles. 37.2 not-delivered packages by the end of the day plus the expected 60 packages at opening time of the next day, together with the higher delivery duration implicate that four outbound vehicles is too low. Especially considering the low ground time of the outbound vehicles when it is utilized with four Robin XLs. Indicating that there is not much safety margin left for this configuration to cope with backlogged packages. It is, therefore, concluded that the optimal H&S network configuration for Scenario 2.2 contains five Robin XLs with a minimum inbound vehicle load factor of 50%.



	100% Capacity 100 Robin XL	70% Capacity 100 Robin XL	50% Capacity 100 Robin XL	100% Capacity 20 Robin XL	70% Capacity 20 Robin XL	50% Capacity 20 Robin XL	100% Capacity 10 Robin XL	70% Capacity 10 Robin XL	50% Capacity 10 Robin XL	100% Capacity 8 Robin XL	70% Capacity 8 Robin XL	50% Capacity 8 Robin XL	100% Capacity 6 Robin XL	70% Capacity 6 Robin XL	50% Capacity 6 Robin XL	100% Capacity 5 Robin XL	70% Capacity 5 Robin XL	50% Capacity 5 Robin XL	100% Capacity 4 Robin XL	70% Capacity 4 Robin XL	50% Capacity 4 Robin XL
Ave G.T.inbound	588	588	522	588	588	522	588	588	522	588	588	522	588	588	522	588	588	522	588	588	522
Ave G.T. outbound	683.1	679.3	675.8	544.5	517.3	491.8	413	329.5	306	369.9	284.8	295.8	288.3	181.7	162.8	232.6	93.5	85.7	99.1	29.8	19.1
Ave D.D.	82.3	109.2	102.3	122.2	143.6	141.7	170	189.3	188.6	191.4	204.4	198.6	229	225.9	231.8	241.4	250.2	247.4	277.6	276.8	269.6
Ave D.D. Xpress	82.6	109.8	102.2	101.4	122.2	119.8	125.4	146.1	150.2	146.8	170.6	165.4	165.2	177.9	177.7	172.5	189.9	197.3	203.5	212.2	231.7
Ave D.D. Normal	82.1	109.3	103	144.6	168	168.1	222.5	241.2	242.6	254.9	254.9	250	321.5	299.7	308.6	345.5	348.9	348.5	441.4	402	433.7
Ave D.D. sat 1	18	18.1	17.8	48.8	44	40.1	88.5	89.7	72.8	104.1	100.9	91.2	153	133.9	124.1	178.7	168.1	163.4	251.9	213.4	228.8
Ave D.D. sat 2	19.9	20.4	20.2	60.4	79.7	61.2	137.4	141.2	160.4	308.3	244.3	267.8	276.4	243.8	233.8	310.3	225.4	255.9	284.3	236.9	260.1
Ave #packages not delivered	15.5	6.9	6.4	17.8	7	5.9	28.6	10.1	9.2	38.4	18	17.1	39.9	25.1	21.6	40.6	26.3	26.6	47.5	38.3	37.2

Figure 5.13: H&S: Results Scenario 2.2

The results of Scenario 3.2 are shown in Figure 5.14. The patterns are relatively similar to the patterns found in Figure 5.13. However, the ground time of the outbound vehicles are decreasing more rapidly, which can be explained by the higher number of packages distributed by the Bull Case. The quickest delivery duration differs as well. It has an average delivery duration of 108 minutes with 100 outbound vehicles and a minimum of 50% load factor for the Condor. Which is almost 30 minutes longer than for the previous scenario that achieved its quickest delivery with a load factor of 100%. Which can be explained by the higher demand for each time frame for this scenario that will activate the minimum of 50% capacity of the Condor. The best configuration for this scenario is with seven outbound vehicles with a 50% minimum load factor. The ground time of the outbound vehicles is 100 minutes less when comparing this configuration with eight outbound vehicles while the delivery duration increases with less than 15 minutes. The delivery criteria are still met, and the number of packages not delivered of one day increases only by two packages to a total of 39 packages. Whereas the number of packages not delivered with six outbound vehicles increases to more than 56 packages in total which could cause problems the following day.



	100% Capacity - 100 Robin XL	70% Capacity 100 Robin XL	50% Capacity 100 Robin XL	100% Capacity 20 Robin XL	70% Capacity 20 Robin XL	50% Capacity 20 Robin XL	100% Capacity 15 Robin XL	70% Capacity 15 Robin XL	50% Capacity 15 Robin XL
Ave G.T. inbound	522	514.4	456	541.8	522	442.8	522	522	456
Ave G.T. outbound	661.2	659.9	657.1	470.8	426.9	407	391.1	336.7	312.7
Ave D.D.	138.8	121.3	107.8	179.1	156.7	144.5	193.3	178.8	172.1
Ave D.D. Xpress	151.7	124.1	111	165.4	140.2	118.8	168.5	150.8	136.7
Ave D.D. Normal	127.1	119	105	194.8	173.5	172.7	221	211.7	213
Ave D.D. sat 1	18	18	18	46.9	42	40.3	65.7	56.8	59.3
Ave D.D. sat 2	20.4	20.3	20.1	84.5	87	90.4	103.7	132.5	134.1
Ave #packages not delivered	17.8	15.1	9	0	18.6	10.3	43.6	20.5	11.1

	100% Capacity 10 Robin XL	70% Capacity 10 Robin XL	50% Capacity 10 Robin XL	100% Capacity 8 Robin XL	70% Capacity 8 Robin XL	50% Capacity 8 Robin XL	100% Capacity 7 Robin XL	70% Capacity 7 Robin XL	50% Capacity 7 Robin XL	100% Capacity 6 Robin XL	70% Capacity 6 Robin XL	50% Capacity 6 Robin XL
Ave G.T. inbound	522	522	456	528.6	522	449.4	528.6	522	456	528.6	522	456
Ave G.T. outbound	257.1	180.5	160.2	211.4	136.8	108.3	155.7	52.8	36.6	76.4	19.8	18.2
Ave D.D.	225.2	216.8	205.5	236.2	224.4	220.4	239.8	244.5	233.8	254.8	259.3	249.9
Ave D.D. Xpress	191.8	175	155.6	201	190.6	171.7	204.6	196.9	181.8	217.4	207.7	193.9
Ave D.D. Normal	263.4	275.9	279.8	291.1	274	307.6	293.7	331.7	347.7	315.4	390.1	411.4
Ave D.D. sat 1	95.7	100.4	99.6	113.8	115.2	120.7	128	147.5	148.3	155	192	203.2
Ave D.D. sat 2	192.9	186.2	191	205.7	228.2	236.4	212.5	211	227.1	245.2	233.3	252.8
Ave #packages not delivered	45.6	27.4	20	59.8	43.6	37.1	63	45.4	39	66.3	56.3	56.5

Figure 5.14: H&S: Results Scenario 3.2

5.4. P2P versus H&S

Comparing the results of the P2P network and the H&S network for Scenario 2.2. Shows that the P2P network is able to achieve package deliveries in 24 minutes with its quickest performing configuration while it takes the H&S network up to 80 minutes. It could be a good initial approximation of the overall delivery speed of each network. Potentially indicating that the P2P network is three times quicker. It was concluded that the optimal network set-up of the P2P network should have eight outbound vehicles for Scenario 2.2. The H&S network requires five outbound vehicles. Even though, the H&S network needs less outbound vehicles, it requires more resources such as an inbound vehicle and two satellites. In addition, the P2P network delivers on average almost 100 minutes quicker, with a much lower ground time, and delivers also more packages the same day than the H&S network. From these conclusions the best network strategy for Air Canada tends to be the P2P network.

The benefit of a H&S network is, however, its ability to scale. It is perhaps possible to observe a cross-over point at which the H&S network becomes more efficient by analyzing the required resources with increasing demand for both networks, see Figure 5.15.

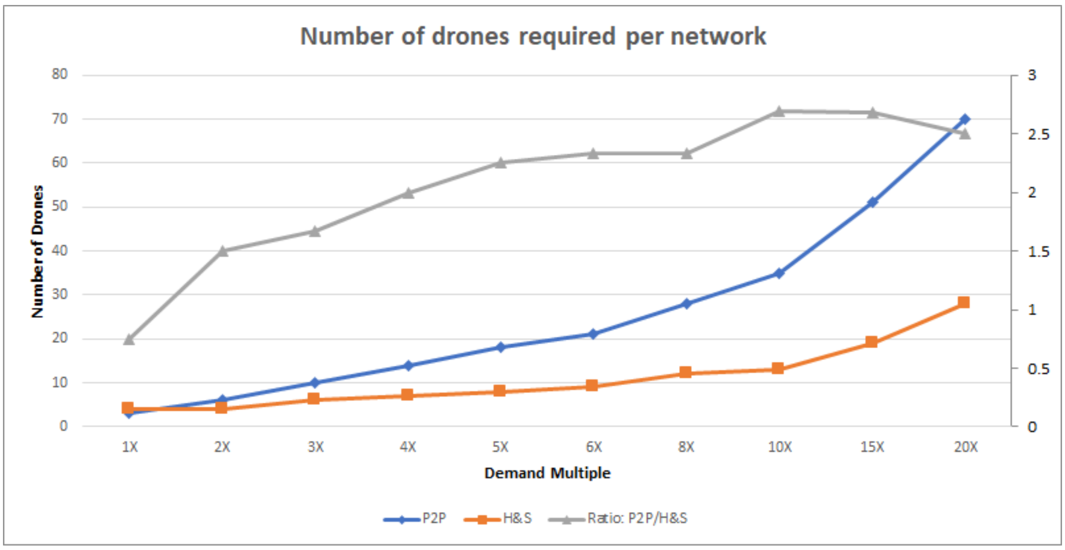


Figure 5.15: P2P versus H&S

The x-axis indicates the multiple of Scenario 1.1 and the left side of the y-axis indicates the optimal number of outbound vehicles required per network strategy. The graph shows that the number of drones required by the P2P network, indicated by the blue line, increases quicker than the H&S network, indicated by the orange line. The grey line is a ratio of the blue line over the orange line to get a better grasp of the relation between them, which is quantified on the ride side of the y-axis. The ratio reaches a peak at a 10X multiple. So, the graph is indicating what was expected and could confirm that the H&S network becomes more interesting when there is a demand for network scalability. Observing the performance of both networks at this configuration for a 10X multiple is essential to make any conclusions. Both performances are summed in Table 5.2, Outbound Vehicle (O.V.), Xpress Service (X), and Normal Service (N).

	P2P 35 O.V.	H&S 13 O.V.
Average G.T. I.V.	N/A	86.4
Average G.T. O.V.	27.8	20
Average D.D.	143.4	219.5
Average D.D.X	99.4	202.3
Average D.D.N	189.4	301.3
Not delivered	30.4	98.6

Table 5.2: Performance of P2P and H&S network for 10X multiple

The ground time of the outbound vehicle for the H&S network is lower than the average ground time of the outbound vehicle of the P2P network. The delivery duration is on average about 70 minutes slower for the H&S network and it delivers approximately 60 packages less per day. It uses, however, 22 outbound vehicles less than the P2P network. The costs are, unfortunately, unknown which makes the trade-off of costs versus quality of service difficult between the two network strategies. It could be concluded that the P2P network has a better performance, purely looking at the shorter lead times of the network strategies. Whether this is desired, depends entirely on the desired quality of service that Air Canada wants to provide its customers with.

Note, the framework is not able to apply consolidation of packages at satellites, nor did it include the possibilities of having other inbound vehicles serving the satellites from different locations, nor did it include the increased catchment area from each satellite for the H&S network. Data of small packages that could be consolidated at the satellites, data of incoming trucks to Toronto from different cities, and potential demand from different regions was either unknown or out of the scope of the project. Having such abilities could substantially increase the efficiency of the H&S network.
In addition, the strategy discussed so far is mainly based on the initial goal of finding a competitive Drone Delivery Network for Air Canada in Toronto. A different approach, however, would be by considering the available products, technology, and resources. The Condor might be more efficient for long haul distances considering its max payload and its max range of 200 kilometers. Therefore, the second strategy could focus on increasing the catchment area of the network by finding candidate locations for the satellites in different cities, see Figure 5.16. The blue balloons represent the candidate locations for the satellites, with an additional indication of a 30 kilometer vicinity by the purple circles. The red balloons indicate the 100 DroneSpot locations discussed for the City of Toronto. Similar candidate locations for the DroneSpots should be looked for in the other purple circles. The network increases its catchment area by 2.3 million people by adding a satellite in London (404,699), Hamilton (924,078), Niagara (447,888), and Whitby (519,178) to the network. Which potentially almost doubles the catchment area compared to the City of Toronto only.
A potential solution would be a H&S network on provincial level. The City of Toronto would still be serviced by a P2P network, and the Condor would transport packages from the distribution center at the Pearson Airport to the satellites located at the edge of different cities. Numerous outbound vehicles transport the packages individually from each of these satellites to the end-consumer.

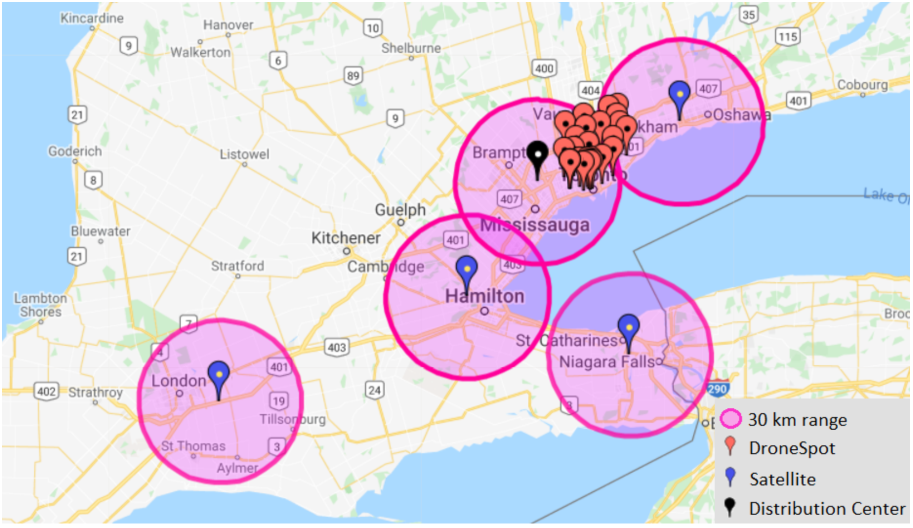


Figure 5.16: H&S Network: Ontario

5.5. Conclusion

The final design of the P2P network and the H&S network is discussed by conducting a sensitivity analysis. The impact the size of the outbound vehicle fleet and the minimum load factor of the inbound vehicle have on each network is measured in ground time, delivery duration, and the daily not delivered packages. The H&S network is considered to be inefficient for the scenarios with a lower demand. The P2P network requires three, four, or seven Sparrows for Scenario 1.1, Scenario 2.1, or Scenario 3.1, respectively, and six Robin XLs for Scenario 1.2. With these configurations it is able to deliver Xpress packages approximately in 1.5 hours and the Normal packages in less than four hours. The ground time is relatively low and the backlogged packages per day is minimal. Comparing Scenario 2.2 and Scenario 3.2 for the P2P network and the H&S network shows that the P2P network delivers on average almost 100 minutes quicker, with a lower ground time, and delivers more packages the same day than the H&S network. It requires six and 11 outbound vehicles, which is respectively 1 and 2 outbound vehicles more than the H&S network requires for Scenario 2.2 and Scenario 3.2, respectively. Even though, the H&S network requires less outbound vehicles, it needs additionally one inbound vehicle and two satellites. So, the H&S network requires in total more resources with higher operational costs. It can, therefore, be concluded that the P2P network is a more efficient approach for the Drone Delivery Network in the City of Toronto for these specific scenarios.

Facilitating the network with intermediate facilities takes away congestion at the main hub, decreases distances from intermediate facilities to end-consumers, and decreases the fleet sizes. The H&S network has, therefore, naturally good scalability performances. When significantly increasing the demand, it is observed that the H&S network becomes competitive at a 10X multiple relative to Scenario 1.1. Although, the P2P network scores better at all KPIs, the H&S network has more potentials with growing demand which have not all been covered in this research. Consolidation of packages at the satellites, increased catchment area from the satellites, and inbound vehicles serving the satellites from different cities could, for example, substantially increase the efficiency of the H&S network. It is, therefore, up to the desires of Air Canada. If quick deliveries are desired with minimum costs, it is recommended to move forward with the P2P network. If Air Canada desires a scalable network and accepts a longer delivery duration, it is recommended to move forward with the H&S network. It is, however, suggested to start utilizing the Drone Delivery Network according to the principal of a P2P network. It allows Air Canada to minimize costs and to be more flexible to anticipate uncertainties in demand. Subsequently based on real-life data, Air Canada can decide at a later stage to include an inbound vehicle and (an) intermediate facilit(y)(ies) to scale the network.

The research is solely focused on servicing the City of Toronto. The range of the Condor could include multiple cities to its network, potentially doubling the catchment area. A H&S network could be realized on a provincial level rather than on a city level. However, doubling the catchment area does not necessarily imply doubling the demand. It is suggested to conduct an elaborate market research in the demand of package deliveries to homes in other cities in Ontario. Before moving forward with this approach.

In Subsection (4.3.2) it was concluded that the demand for package arrivals and departures follow approximately the same distribution per day, except during the early afternoon. Therefore, it can be assumed that with a small increase in fleet sizes the Drone Delivery Network could potentially double the number of packages it transports when considering two mission fleets - home deliveries and home-pick ups.

6 Conclusion

This research aimed to identify the optimal network design of a Drone Delivery Network for logistic operators. It focuses on the last part of the supply chain servicing the final mile to the end-consumers. Given the uncertainty in demand and network performance of different strategies, this research described a framework to design different network strategies and to find the optimal configuration of each network strategy. Resulting in the following research question:

What is the design of a Drone Delivery Network and how should it be configured to ensure delivery to the end-consumer in metropolitan areas under cost minimization such that a profitable Drone Delivery Network can be adopted to the network of logistic operators?

The initiative was risen from the found opportunities in home delivery services due to globalization and the rapid growth in e-commerce, which underwent an even bigger growth during the pandemic in 2020. The challenges city logistics faces resulting from urbanization, policy restrictions, and the demand for sustainable solutions, showed the potentials for utilizing drones as the last-mile vehicle. There is not one Drone Delivery Network, currently as of writing, commercially operative, but the technology is ready for utilization. Consequently, the researcher focused on finding the optimal way to utilize drones by the aid of a P2P network strategy and a H&S network strategy.

The first step of the research was to formulate a sequential framework and a Monte Carlo Simulation with a focus on designing a last mile delivery network. It allows to design a P2P and a H&S network under cost minimization. Research clearly illustrated, when utilizing drones as delivery vehicles, that the P2P network was more cost efficient compared to the H&S network measured in ground time, quality of service, and number of required resources. But, it also raised questions towards its ability to scale at which the H&S network was able to show its competitiveness to the P2P network. The H&S network is, however, limited in assigning optimal intermediate facilities based on minimum distance, a fixed minimum load factor constraint, and no consolidation at intermediate facilities. Implementing these factors in the model could substantially increase the efficiency of the H&S network, which could result in preferences for the H&S network with lower demands.

Future research could consider a two-mission fleet with operation between any two sets of facilities to better understand the implications of the results. A two-mission fleet would allow a drone to make profit on any route instead of making purely costs going back to its origin and operation between any two sets of facilities would greatly benefit the potential utilization of the network, which would have a direct impact on fleet sizing. Considering a weekly demand rather than a daily demand would allow the experimenter to assess the impact of backlogged packages from the previous day to the performance of the network as a whole. Better fleet sizing estimates would result by considering such uncertainties on the network. Formulating a MCS allowing to simulate the average delivery duration of a service type for a specific network strategy and configuration. Having this analysis allows the operator to define the quality of service within a confidence interval it is able to provide to its customers. It would help the operator to create its product. Finally, clustering destination locations and assigning orders of one cluster to the inbound vehicle could decrease distance travelled and delivery duration. These matters could implicate better how network strategies and configurations impact the performance of the Drone Delivery Network allowing the operator to find a more optimized network design.

The main contribution of the research follows from the fact that the framework allows the operator to find the optimal network design of a Drone Delivery Network for two network strategies. The framework finds the optimal locations of intermediate facilities and how frequently each facility will be used per scenario with certainty. Which allows the operator to find the ideal distribution of drones over the intermediate facilities. The flexibility of the framework allows the operator to enter the fleet sizes, destination locations, number of destinations, desired quality of service, and the size of daily orders. The quality of service can be divided into an Xpress service and a Normal service. The operator has the flexibility to define the pdf of the two service types and their ultimate delivery time. The framework is formulated with a package valuation allowing the model to prioritize packages based on the service type and due delivery. Different scenarios and repeated random sampling used by the Monte Carlo Simulation allow to consider the impact of risks and uncertainties in demand. The given input to the model will be used to simulate the performance of the chosen network strategy that is aimed to minimize costs. The costs are measured in ground time, delivery duration, and not delivered packages. Changing a parameter would result in a change in any of the operational costs, which can be used by the operator to find the optimal configuration of the network.

7 Recommendation

This research has helped to set a start in finding an optimal Last-Mile Delivery Network design serviced by drones. The research is at its very early stage and it is important for scientific research to continue moving forward with this study. The following suggestions are recommended to consider:

1. Implementing a two-mission fleet would allow a drone to make profit on any route instead of making purely costs going back to its origin. Moreover, allowing the drones to operate between any two sets of facilities would greatly benefit the potential utilization of the network. Rather than providing long-haul B2C services only, it would allow the logistic provider to provide short-haul C2C services as well. This addition could increase the demand which would have a direct impact on fleet sizing of the network.

2. Considering a weekly demand rather than a daily demand would allow the experimenter to assess the impact of backlogged packages from the previous day to the performance of the network as a whole. Better fleet sizing estimates would result by considering such uncertainties on the network.

3. Formulating a MCS allowing to simulate the performance of a service type for a specific network strategy and configuration. Assessing the result would allow the operator to find a confidence interval of the average delivery duration per service type. Having this analysis allows the operator to define the quality of service it is able to provide to its customers. It would help the operator to create its product.

4. Implementing an optimization tool that decides the optimal load factor of an inbound vehicle by machine learning can improve the efficiency of the H&S network. Rather than a fixed static constraint, the tool could learn under which circumstances it is worthwhile waiting for the upcoming packages, or when it is more efficient to transport packages with a lower load factor. It could decrease the distance travelled and potentially the delivery duration.

5. Considering destination locations when assigning orders to the inbound vehicle could decrease distance travelled and delivery duration. It can be incorporated in the Knapsack Problem by clustering destination locations such that the model assigns only orders of one cluster to an inbound vehicle.

6. Assigning intermediate facilities to inbound vehicles based on drone availability and package capacity at the facility would allow for more realistic results. It would also allow to take away congestion at an intermediate facility that could improve lead times.

7. Considering package valuation when defining the order at which the inbound vehicle should visit the intermediate facilities could improve the quality of service. For example, packages that are assigned to a facility can be clustered to find the intermediate facility with the highest valuation. Following, the model can take such valuations into consideration while still aiming to minimize the distance travelled.

8. Consolidating packages at intermediate facilities could increase the efficiency of the network in terms of distance travelled. It would result in higher ground times, which could imply lower required fleet sizes.

To conclude, continuing the study with the suggested recommendations could allow to improve the accuracy of the proposed design aspects for the P2P network and the H&S network. Moreover, there is more space for optimization for the H&S network by integrating point 4 to point 8 which could potentially result in better performances, such that the H&S network would be preferred over the P2P network.

A

Market Research

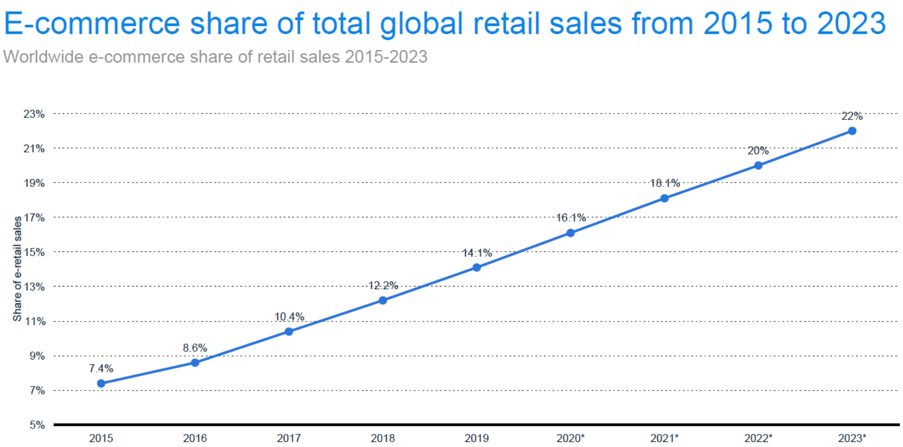


Figure A.1: Worldwide e-commerce share of retail sales, [33]

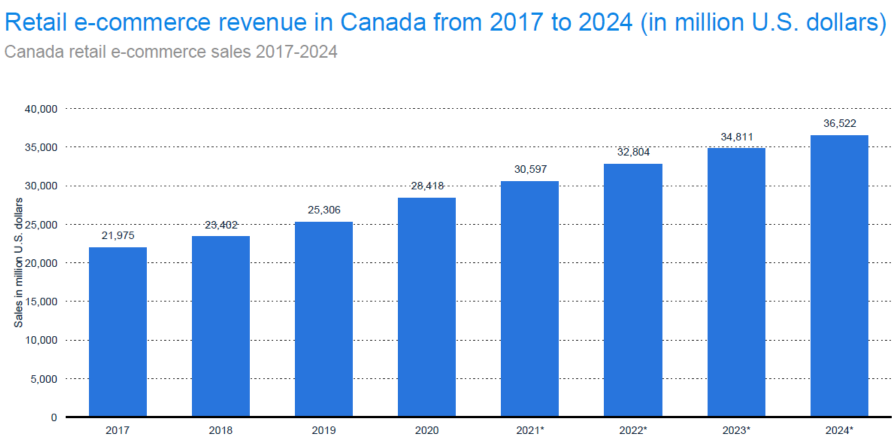


Figure A.2: Canada retail e-commerce sales [82]

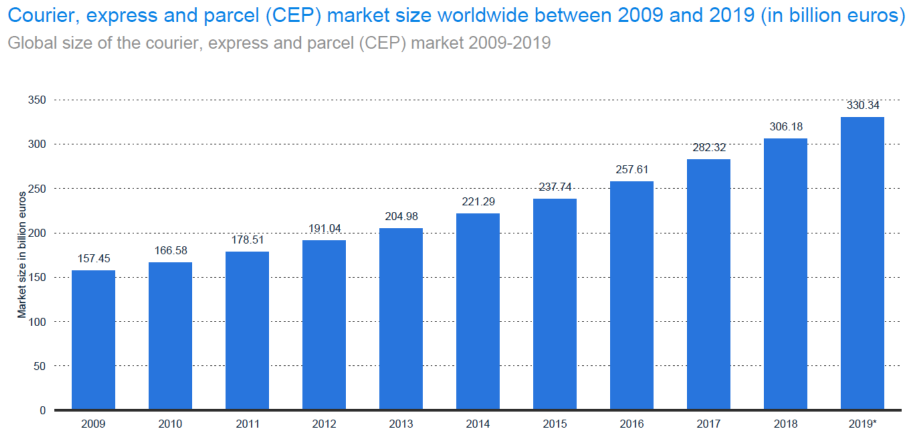


Figure A.3: Global size of the CEP market [83]

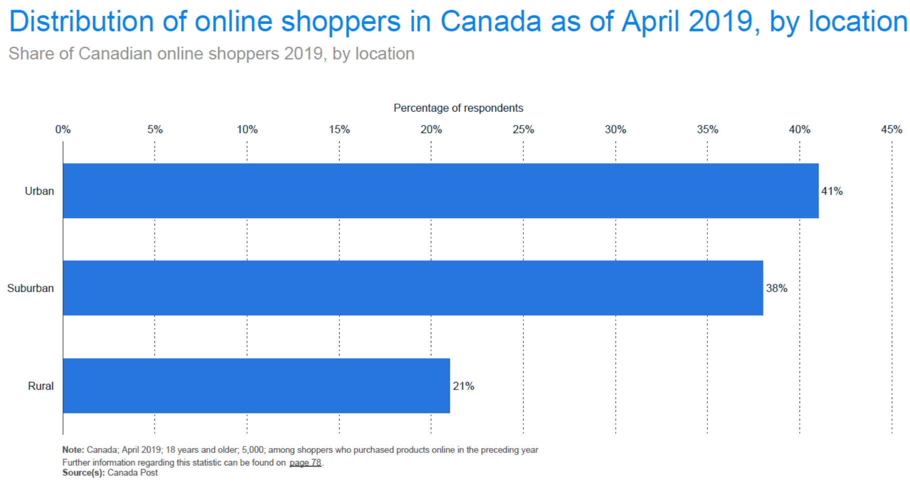


Figure A.4: Distribution of online shoppers in Canada by location [75]

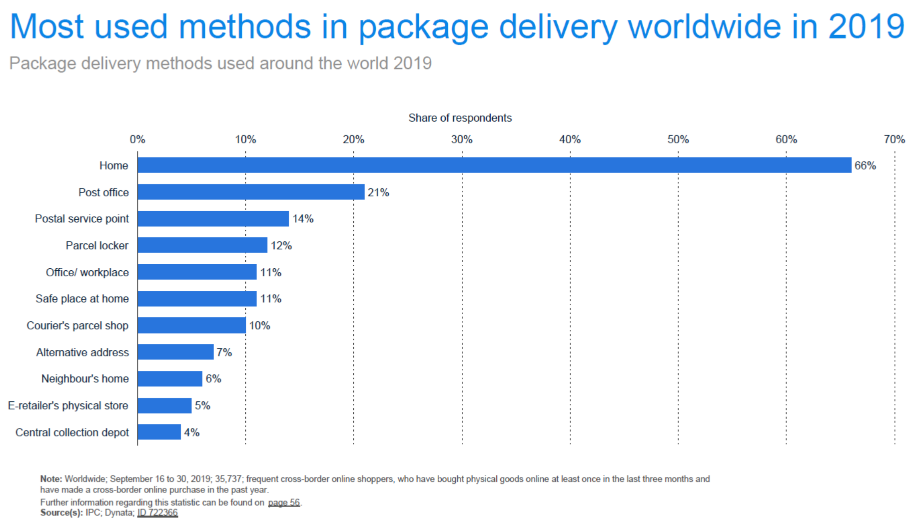


Figure A.5: Home delivery versus other location deliveries globally 2019 [84]

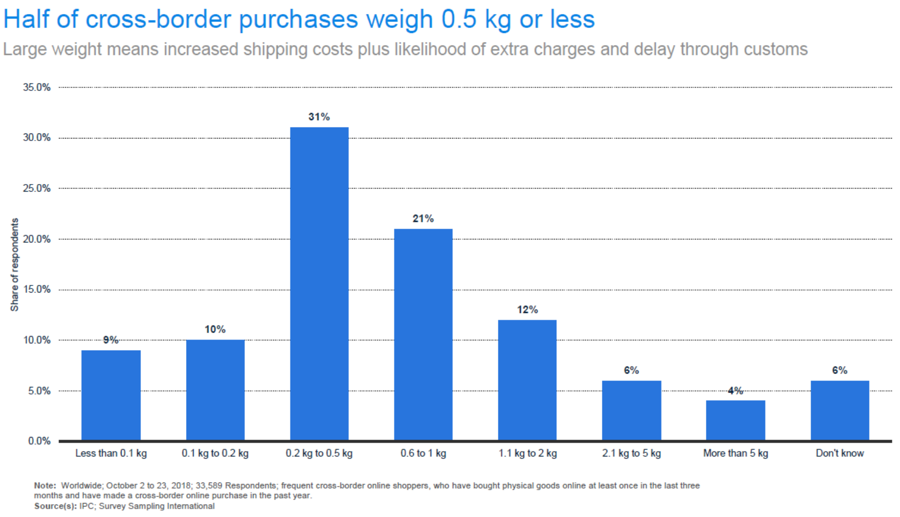


Figure A.6: Cross-border purchases weight [76]

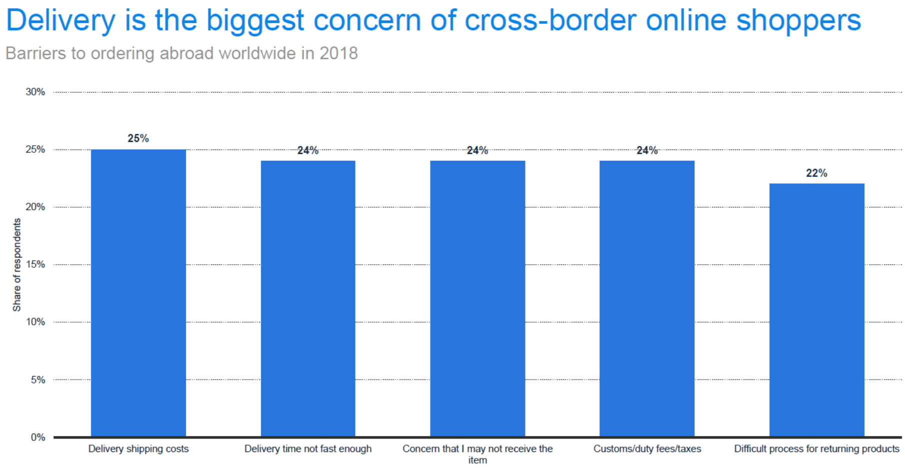


Figure A.7: Barriers for online shoppers to not purchase products cross-border [85]

B

Toronto Demographics

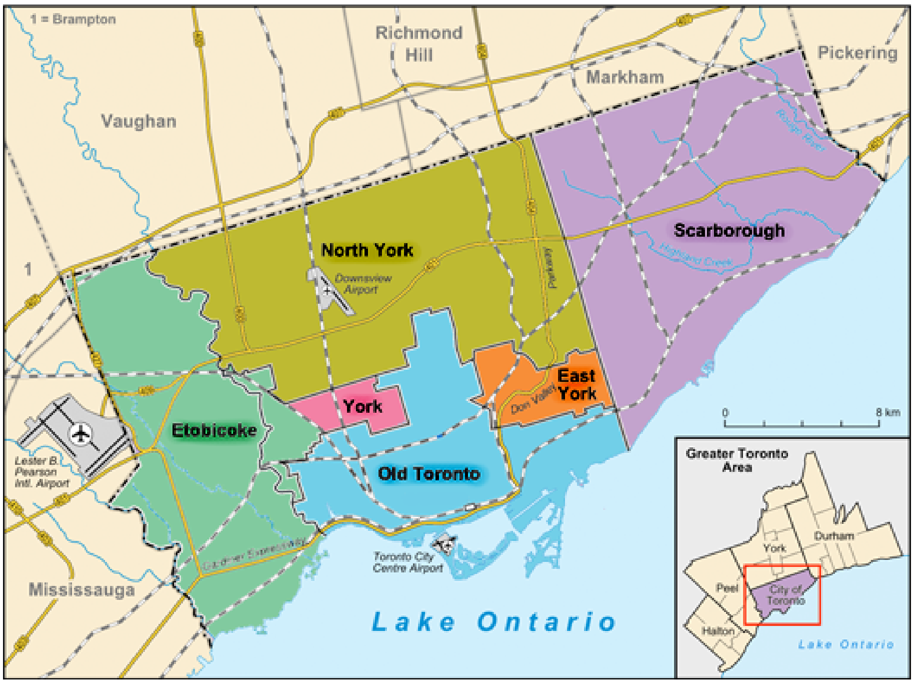


Figure B.1: City of Toronto with regions

C

Demand for Toronto Departures

The data set with packages smaller than 4.5 kilograms is addressed in Subsection (C.1). It shows the full analysis and highlights the differences with the data set of the bigger packages. If there is no difference mentioned, it can be assumed that both data sets follow a similar distribution. All graphs of the demand of bigger packages for Toronto departures are displayed in Subsection (C.2). The appendix is concluded with scenarios for both data sets (C.3).

C.1. Small Packages

Observing the average packages departed from Toronto for each DoW over the past four years shows an average of 44 packages, see Figure C.1. The graph shows again a higher demand during the weekdays just as explained in Subsection (4.3.1). The highest average of 53 package departures is seen on Fridays, whereas the packages smaller than 11.3 kilograms see the highest average of 92 on Wednesdays, see Figure C.7. For both data sets, the differences between the weekdays and weekends are less significant compared to the arrivals in YYZ. There is also no clear growing or shrinking pattern from 2016 to 2019.

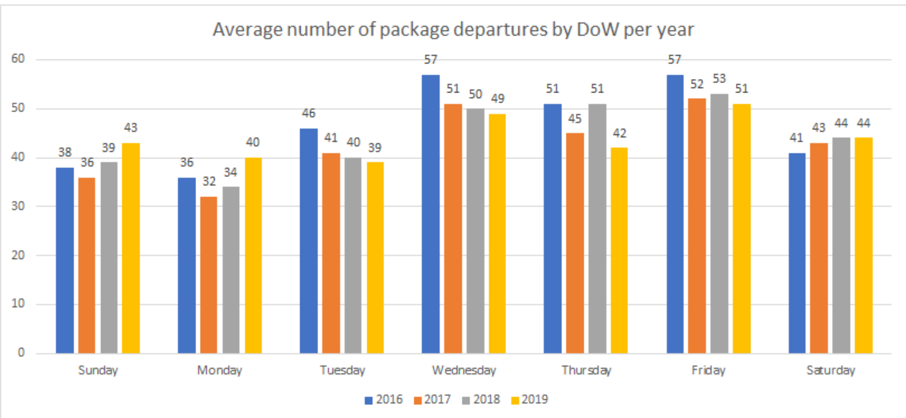


Figure C.1: Average number of package departures by DoW per year

The distribution of package departures per day does not correlate with the arrivals, see Figure C.2. It has an average of 6 departures per time frame, but with strong varieties between each time frame. Late night has zero departures and peaks during the end of the morning with an average of 10 packages. At opening time, an average of 18 packages is expected to be picked-up when considering the early night, late night, early evening, and late evening time frames.

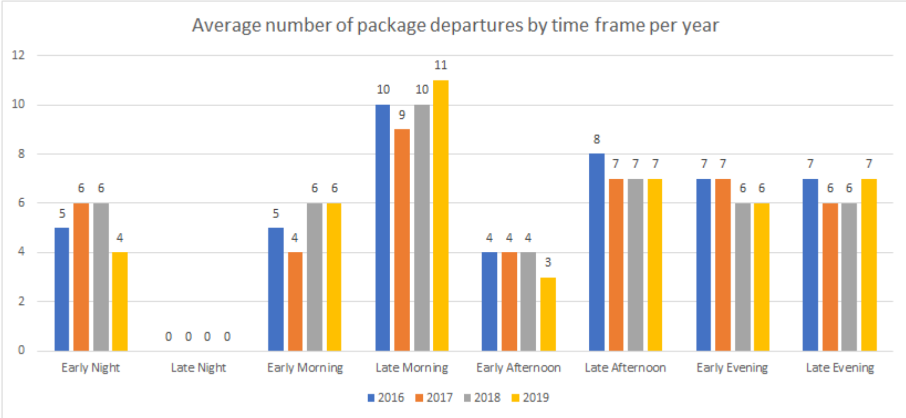


Figure C.2: Average number of package departures by time frame per year

The distribution of package departures per Fridays per year is shown in Figure C.3. According to data it has an average of 7 packages per time frame, which is one package on average more than seen in Figure C.2. They also share a similar distribution over the day, but the number of package departures on Fridays seem to occur more during the late afternoon and evening rather than in the late morning. Which has a considerable impact on the demand of package departures at opening time of the Drone Delivery Network as it rises the average demand on Fridays to 24 packages compared to the average demand of 18 packages for all days discussed previously. The data set of 11.3 kg sees, however, a small increase of 4 packages from 33 to 37 packages outside opening hours of the Drone Delivery Network on Wednesdays, see Figure C.9.

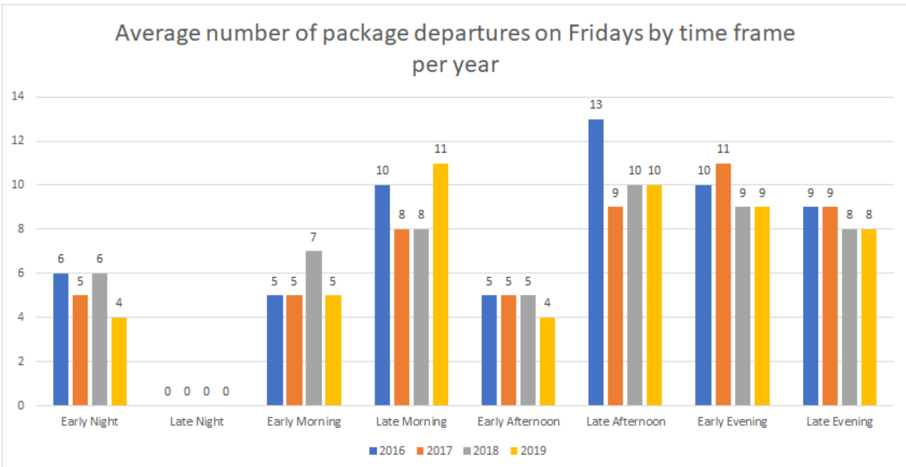
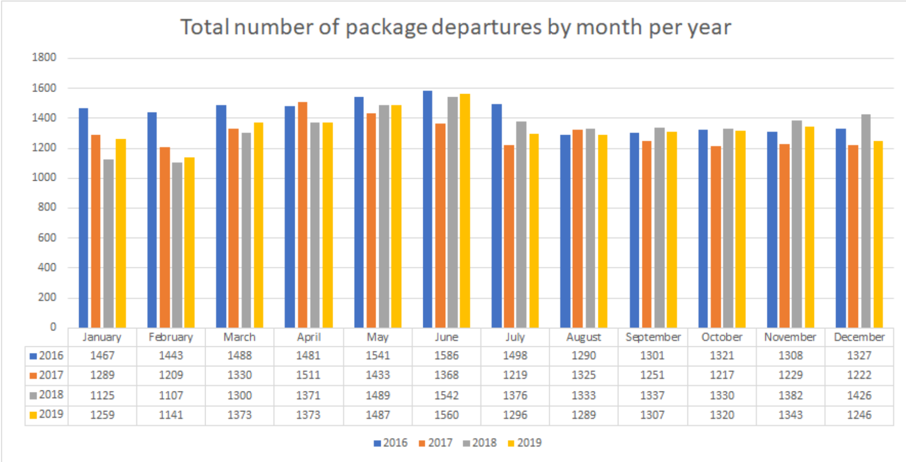


Figure C.3: Average number of package departures by time frame on Fridays per year

The trend of package demand is observed per month to consider any potential seasonality in Figure C.4. Observing the graph shows the highest demand of package departures during the month June, which has an average of 2422 package departures over the four years. The first four months of the year have a downtrend of demand and the last five moths show a relative constant demand over the years.



	January	February	March	April	May	June	July	August	September	October	November	December
2016	1467	1443	1488	1481	1541	1586	1498	1290	1301	1321	1308	1327
2017	1289	1209	1330	1511	1433	1368	1219	1325	1251	1217	1229	1222
2018	1125	1107	1300	1371	1489	1542	1376	1333	1337	1330	1382	1426
2019	1259	1141	1373	1373	1487	1560	1296	1289	1307	1320	1343	1246

Figure C.4: Total number of package departures per month

When looking at the demand for package departures in June, the average of 50 packages can be observed in Figure C.5. The pattern is rather similar as seen previously with the average number of package departures by DoW per year in Figure C.1. Both have a peak on Friday, however, Fridays in June have a higher average of 10 packages. Packages smaller than 11.3 kg see also no significant change in the distribution with also an increase of 10 packages on average, which is a relative weak seasonal impact, see Figure C.11. The pattern from 2016 to 2019 is also for both data sets rather scattered.

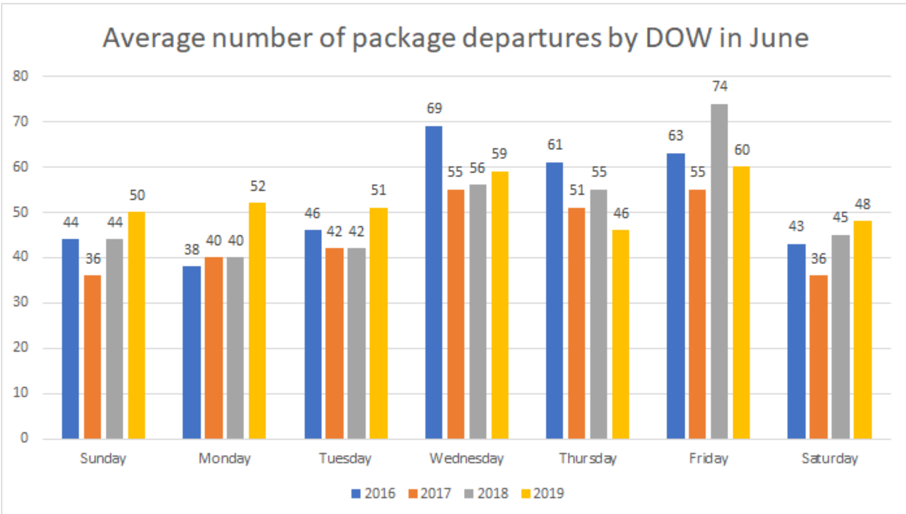


Figure C.5: Average number of package departures per DoW in June

The next drill down is focused on Fridays in the month June over the four years, see Figure C.6. It clearly shows that there is a higher demand of package departures in the late afternoon and evening compared to the other day times. Early evening has the highest demand with an average of 15 packages. Which is a shift from a peak in the late morning that was observed in the graph average number of package departures by time frame per year C.2. In addition, the demand tends to be constant over the four years during the night and in the early morning. Whereas the late morning sees relatively a steady growth pattern over the years with the other time frames a rather scattered pattern over the years. Packages smaller than 11.3 kg see a constant peak in the late morning for the different days and months discussed, see Figure C.12.

Considering the opening times of the Drone Delivery Network, one can expect on average a demand of 31 or 43 packages to depart from the City of Toronto in the morning at opening in June on Fridays for packages smaller than 4.5 kg and smaller than 11.3 kg respectively. Which is almost a double relative to the average of package departures over a year that was observed from Figure C.2 for the small packages. Whereas packages smaller than 11.3 kg see an increase of 30%.

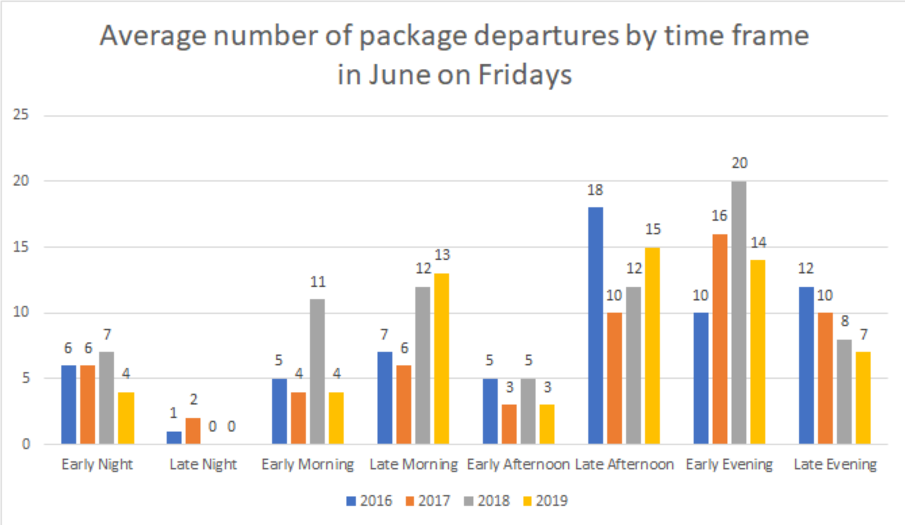


Figure C.6: Average number of package departures by time frame in June on Fridays

C.2. Big Packages

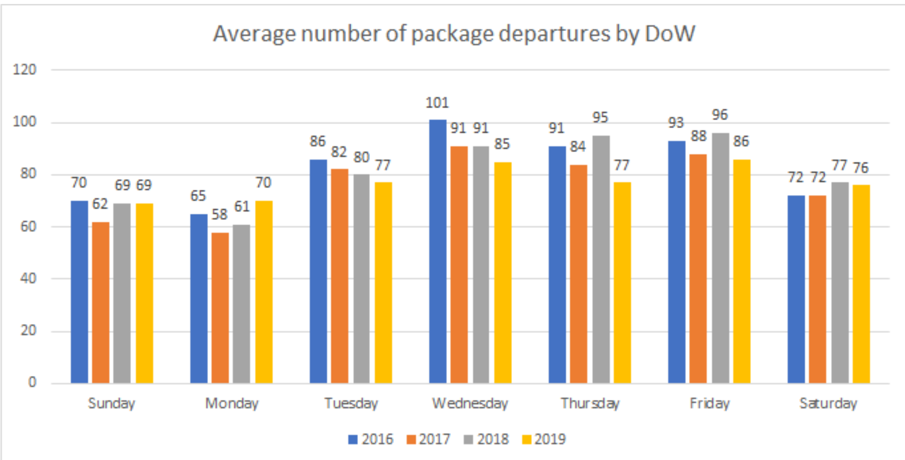


Figure C.7: Average number of package departures by DoW per year

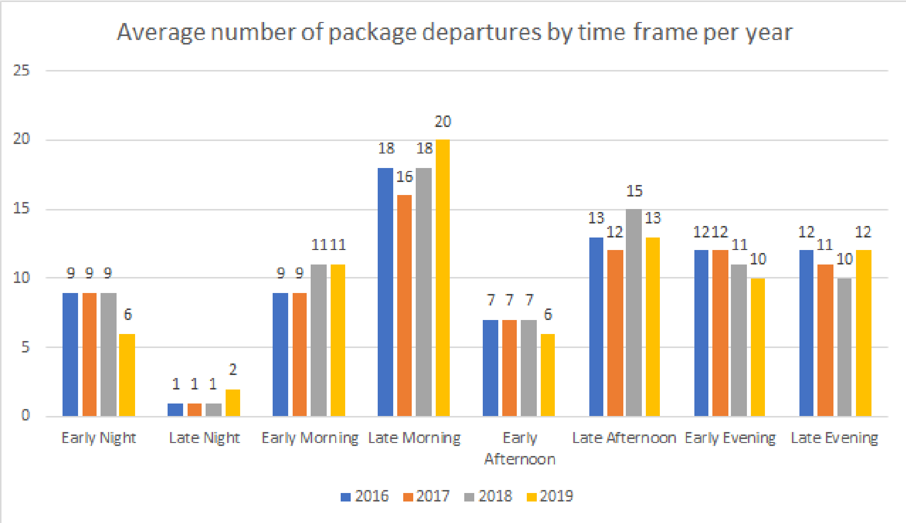


Figure C.8: Average number of package departures by time frames per year

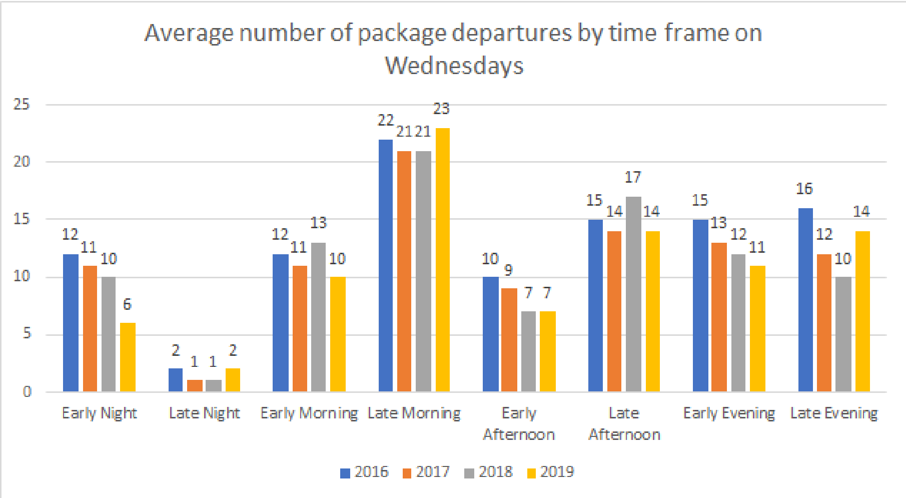
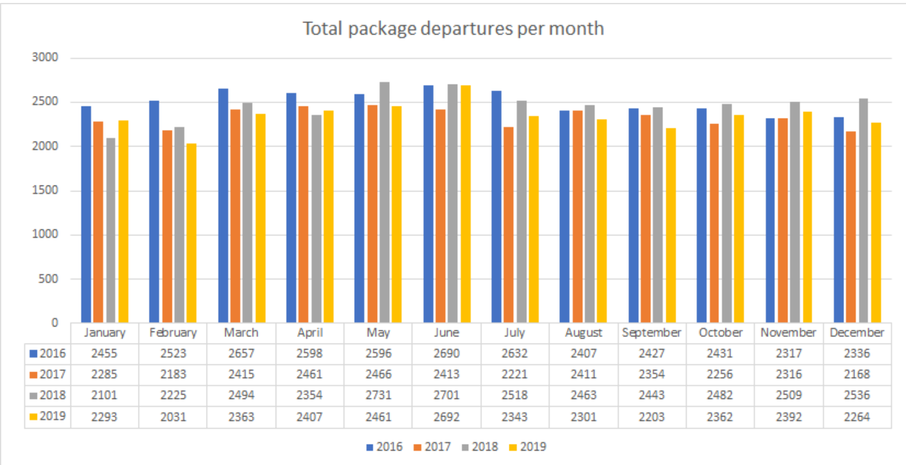


Figure C.9: Average number of package departures by time frames on Wednesday per year



	January	February	March	April	May	June	July	August	September	October	November	December
2016	2455	2523	2657	2598	2596	2690	2632	2407	2427	2431	2317	2336
2017	2285	2183	2415	2461	2466	2413	2221	2411	2354	2256	2316	2168
2018	2101	2225	2494	2354	2731	2701	2518	2463	2443	2482	2509	2536
2019	2293	2031	2363	2407	2461	2692	2343	2301	2203	2362	2392	2264

Figure C.10: Total number of package departures by month

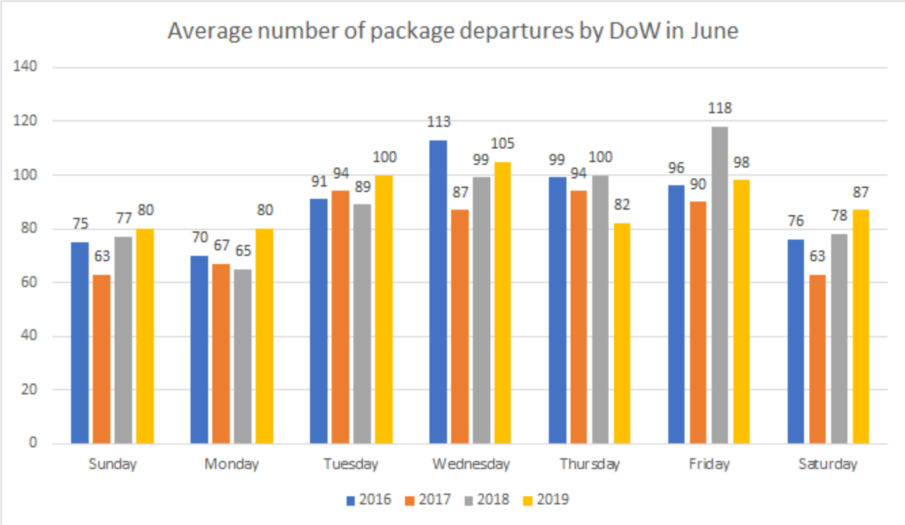


Figure C.11: Average number of package departures by DoW in June

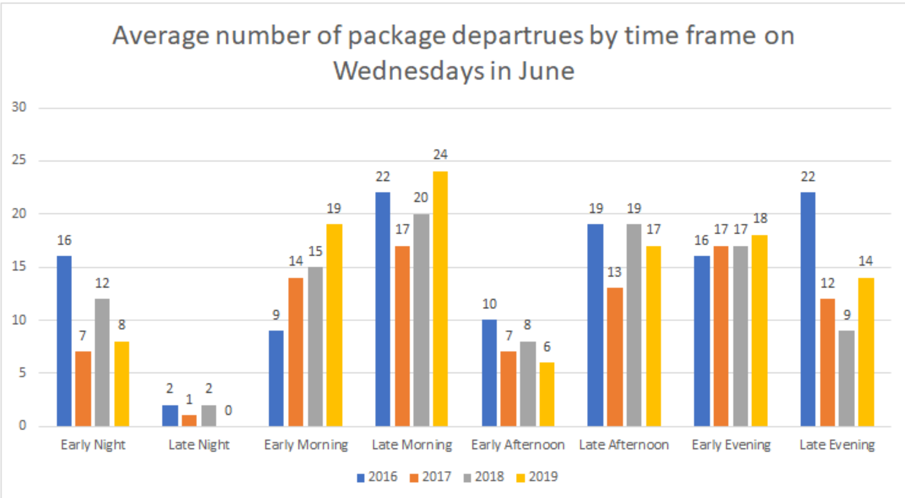


Figure C.12: Average number of package departures by time frames on Wednesdays in June

C.3. Scenarios

The scenarios are displayed in Table C.1 and set-up similarly as explained in Subsection (4.3.2).

Table	Scenario 1: Base Case		Scenario 2: Better Case		Scenario 3: Bull Case	
Time Frame	1.1) Small Packages	1.2) Big Packages	2.1) Small Packages	2.2) Big Packages	3.1) Small Packages	3.2) Big Packages
Opening	31	43	45	60	64	86
Morning 1	6	14	8	20	12	28
Morning 2	10	21	14	28	20	40
Afternoon 1	4	8	6	11	8	16
Afternoon 2	14	17	20	24	28	34
Total	65	103	93	143	132	206

Table C.1: Scenarios

D

Demand for Package Arrivals in Toronto

Data set with packages smaller than 11.3 kilograms is addressed here:

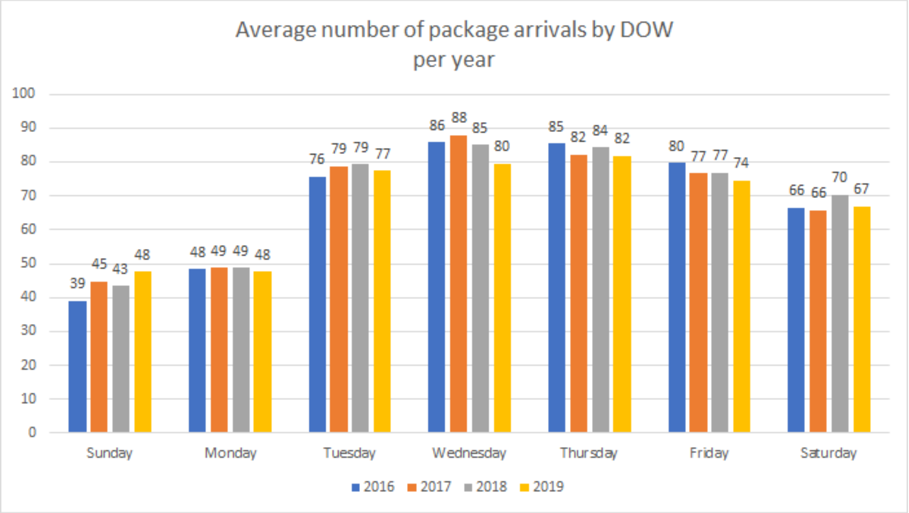


Figure D.1: Average number of package arrivals by DoW per year

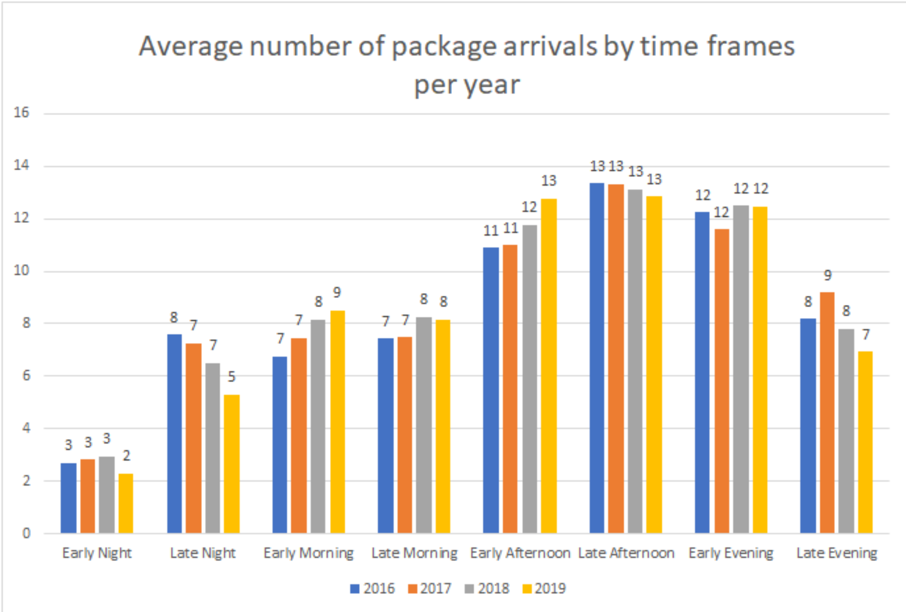


Figure D.2: Average number of package arrivals by time frames per year

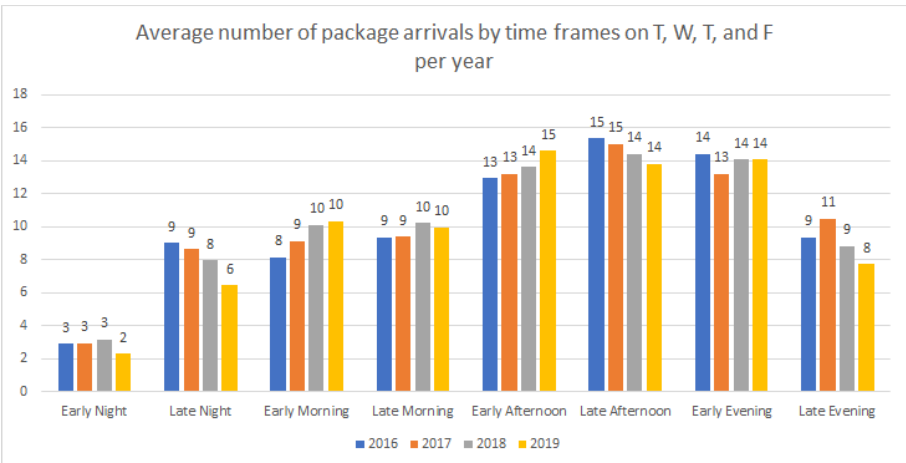


Figure D.3: Average number of package arrivals by time frames on Tuesday, Wednesday, Thursday and Friday per year

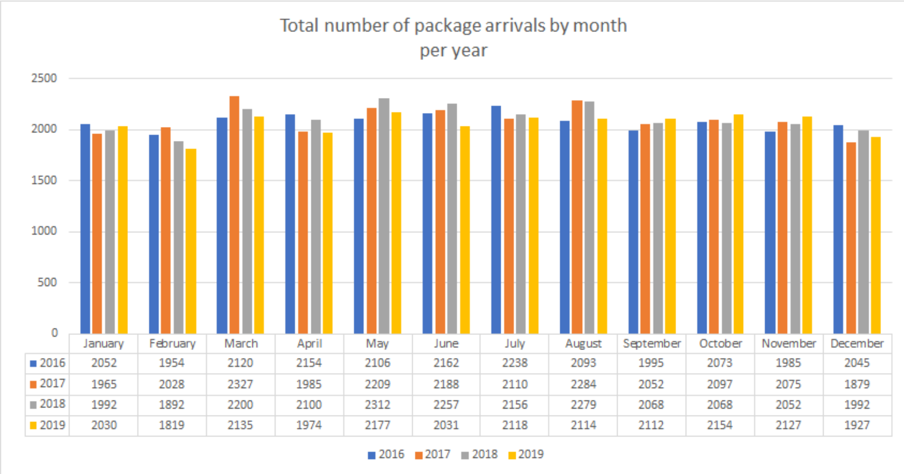


Figure D.4: Total number of package arrivals by month

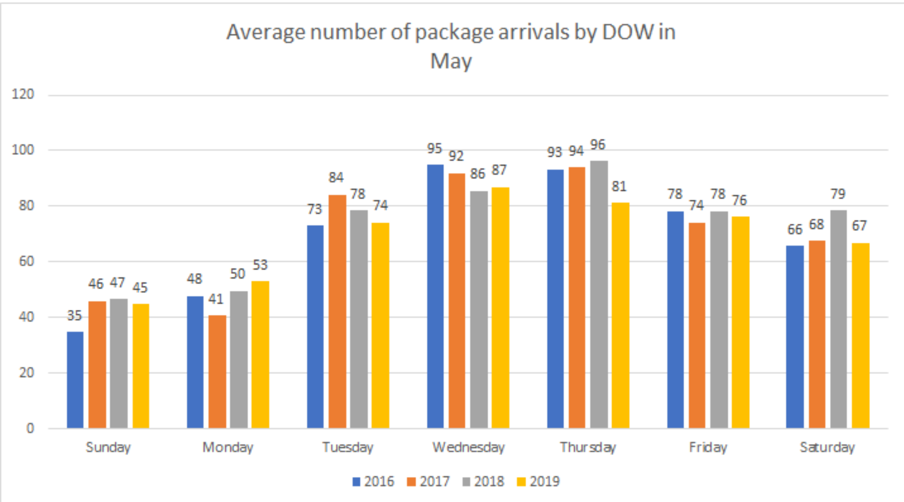


Figure D.5: Average number of package arrivals by DoW in May

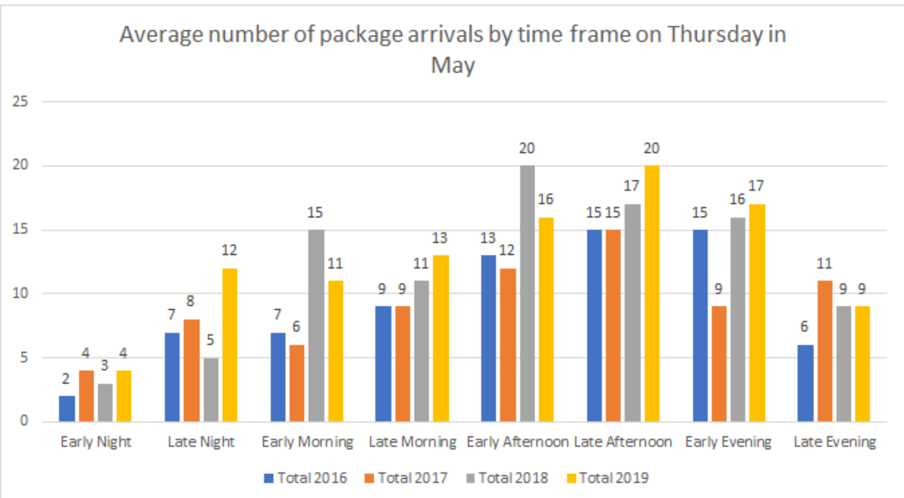


Figure D.6: Average number of package arrivals by time frames on Thursdays in May

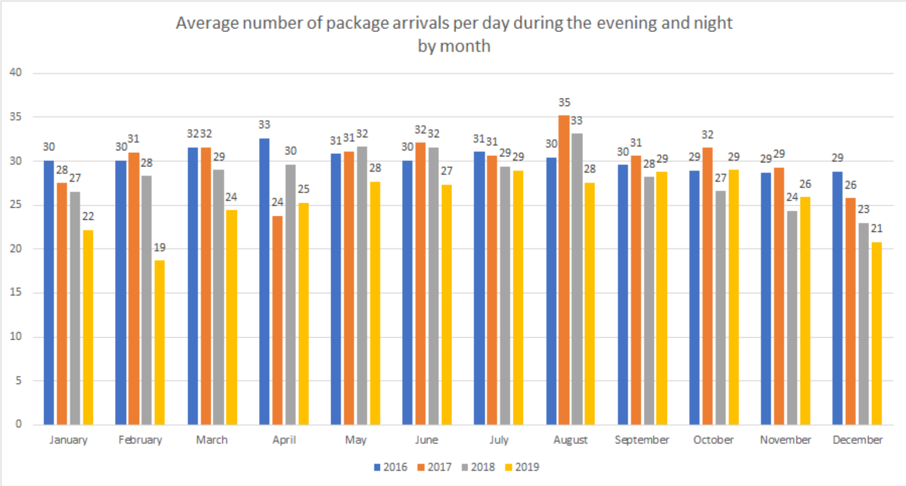


Figure D.7: Average number of package arrivals by month during the evening and night

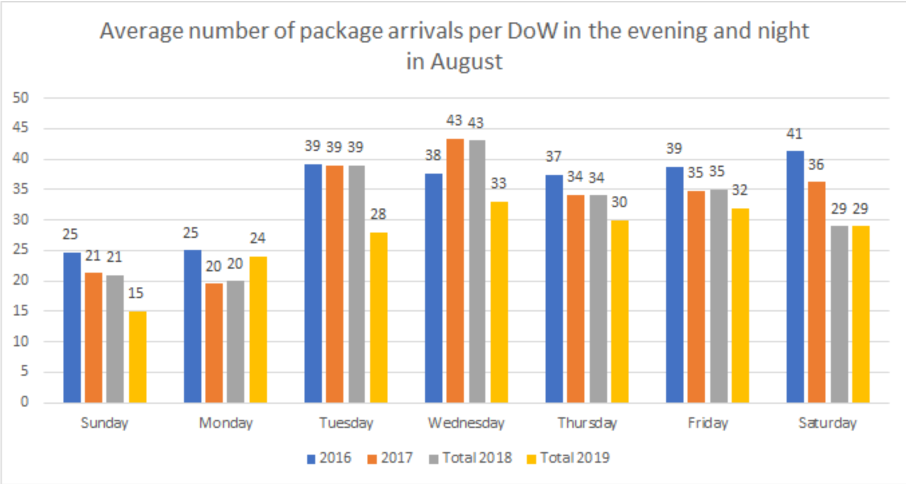


Figure D.8: Average number of package arrivals by DoW during the evening and night in August

E

Retrieval Times

Flights from 2016 to 2019 are considered to assess the average time it takes for a package to be received in the warehouse after aircraft landing, see figure E.1. The average retrieval time is shown by product group per year. Most product groups have on average inconsistent retrieval times. AC Expedair is the only product group with a relative constant retrieval time, with an average of 49 minutes. It is one of the most expensive services that Air Canada provides explaining also the quick retrieval time compared to the other product groups. The Drone Delivery Network aims to provide quick home delivery services. It is, therefore, assumed that Air Canada will implement the AC Expedair service for packages dedicated for the Drone Delivery Network.

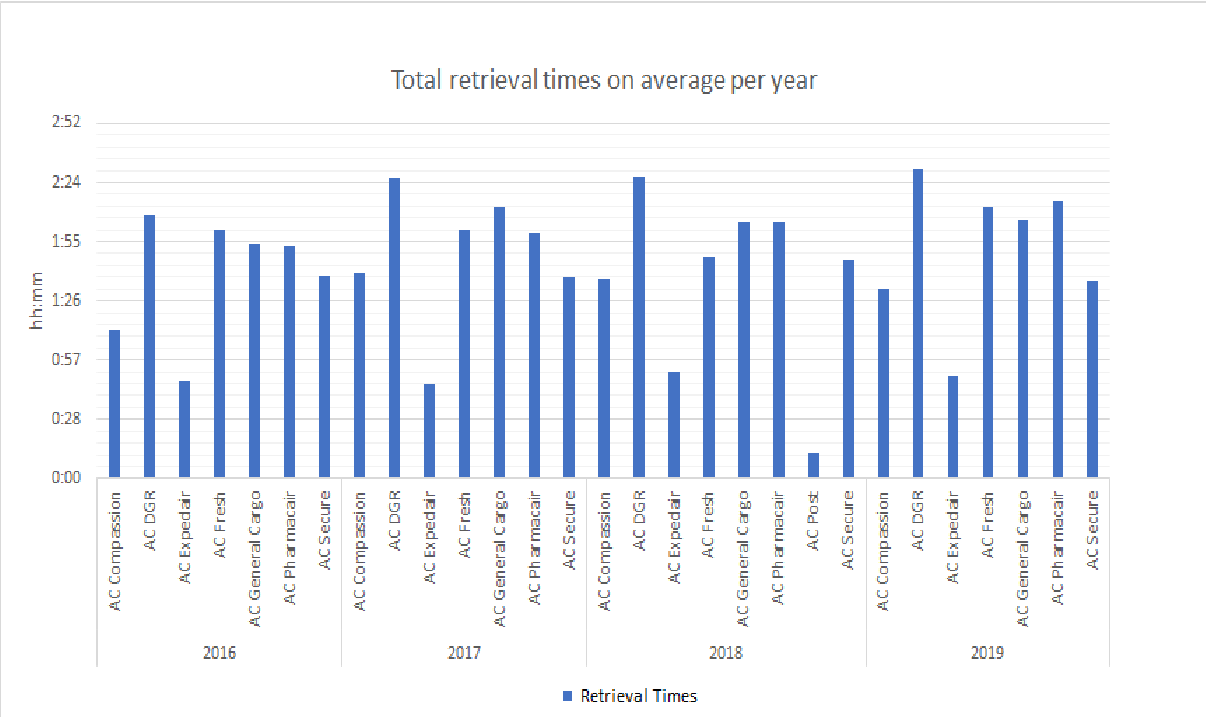


Figure E.1: Average retrieval times per cargo type

F

Air Canada Cargo Trend

From Subsection (1.1.3) it is expected to see a strong rise in demand for small parcels globally. But surprisingly, from Section (4.3) Air Canada did not see a clear increase in demand for small parcels from 2016 to 2019. For a better overview of the demand, a trend line for both package arrivals at Toronto and departures from Toronto per month for both package data sets, are shown in Figure F.1, and Figure F.2 respectively. The trend lines between packages smaller than 4.5 kilograms and smaller than 11.3 are approximately the same. The only minor difference can be observed from the arrivals where packages of up to 11.3 kilograms have a smaller decreasing trend line over the years. The more outsanding observation comes from the fact that all trend lines are trending downwards. However, when looking purely at the total weight transported to Toronto, Air Canada observes an increase in demand over the four years as shown in Figure F.3, but still a decrease in the demand from Toronto, see Figure F.4.

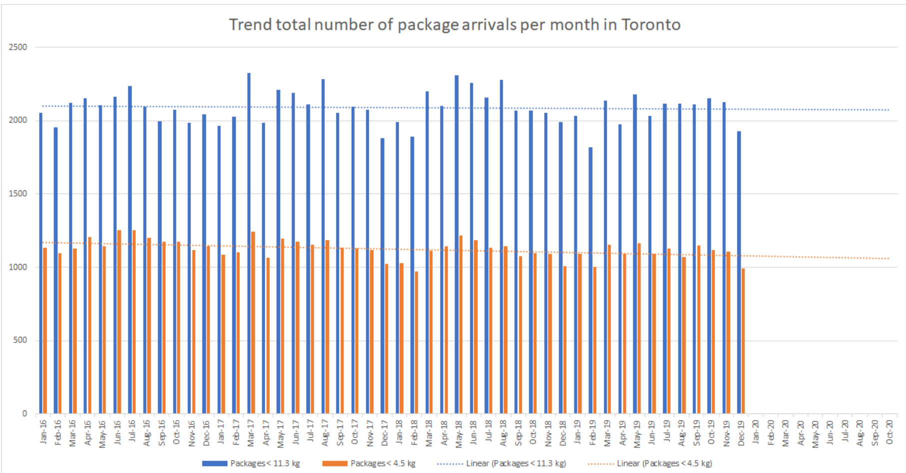


Figure F.1: Trend total package arrivals per month Toronto

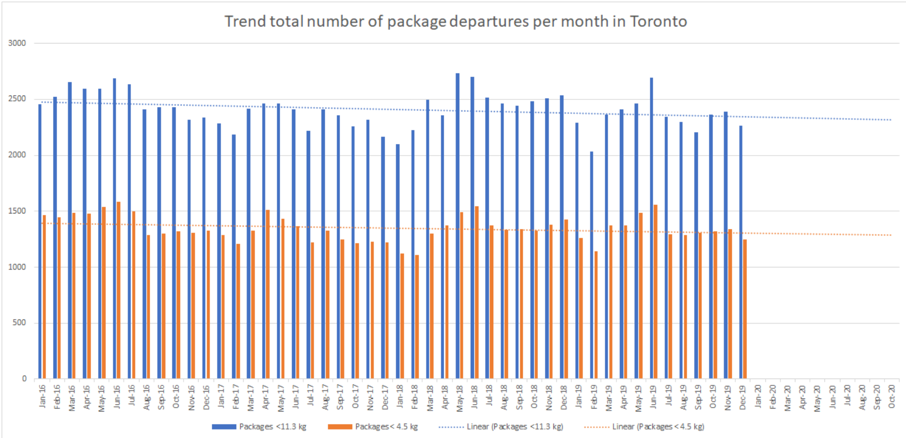


Figure F.2: Trend total package departures per month Toronto

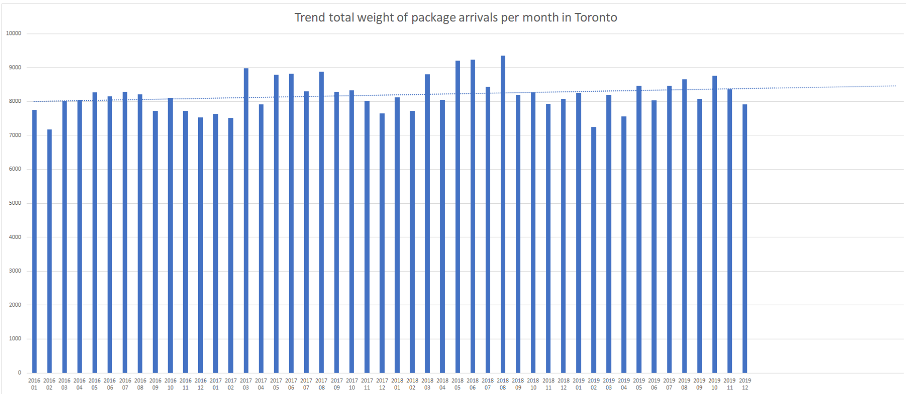


Figure F.3: Trend total package weight arrivals per month Toronto

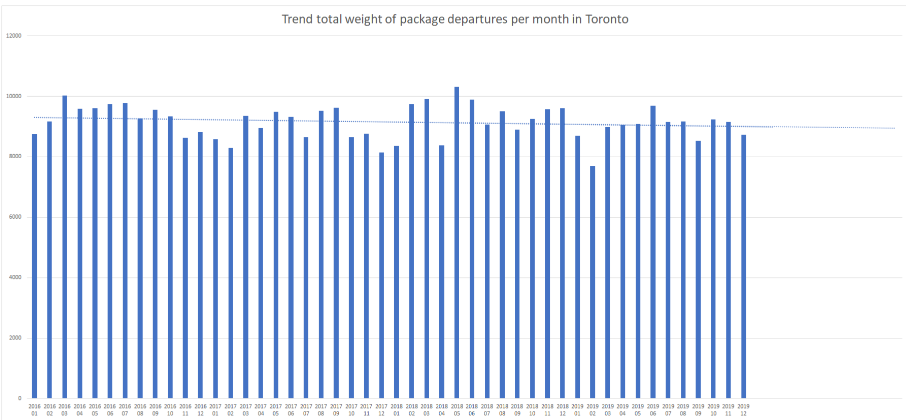


Figure F.4: Trend total package weight departures per month Toronto

The inverse correlation between the number of packages and the total weight arriving at Toronto can be explained by consolidation. Freight forwarders consolidate pieces onto one skid that is registered as one piece with Air Canada causing an increase in weight but not in pieces. The inverse correlation as shown by the two graphs F.1, and F.3 is bigger than with packages of up to 11.3 kg. Allocation of small packages into a big cargo belly of an airplane, or even in trucks, gets much more efficient when they are consolidated onto one skid. Which explains the bigger inverse correlation for the smaller packages. The demand for the number of packages and the total weight arriving at Toronto are, however, both in a decreasing trend. Many different factors can influence this matter, but there is no direct evident explanation. Changes in the flight schedule, extra truck routes taking cargo weight from the planes, but also network changes and market share from Chicago, Montreal, Boston, and New York can take cargo weight away from Toronto. In other words, this explanation is most likely due to network changes which is not the focus and, therefore, outside the scope of this project.

Due to the pandemic, Air Canada was forced to switch its business core temporarily from transporting passengers to transporting cargo. It has done so successfully by being the first airline to convert passenger aircraft into freighters. The results payed off in Air Canada's benefit as they were pleased to see that they were able to gain market share. Considering its freighter success and its strong believe in a rapid increasing e-commerce growth, Air Canada decided in 2021 to pursue operation with freighters. Moreover, customer behaviour was changing, it has changed during the pandemic, and according to Air Canada will continue the same trend with more demanding customers. As customers were pleased with the adapted solutions, they will continue to expect adapted solutions to the benefit of the customers. As such, maintaining operation of the freighters, Air Canada is expecting to see a continuous growth in its cargo operation including e-commerce demand. Moreover, adding a home delivery service by drones will enable Air Canada to reach new customers, gain e-commerce market share, and an expected growth in satisfied customers by meeting their higher expectations.

G
Satellite useage

Scenario 1 - Base Case (wgt<11.3kg)

Satellite 1, Satellite 2, Satellite 4, and Satellite 10 are displayed in figure G.1, figure G.2, figure G.3, and in figure G.4 respectively. See table G.1 for a summary of Satellite 1 and Satellite 2. Satellite 4 and Satellite 10 are left out due to its insignificant impact on the network. They are also not normally distributed which would skew the variables in the table.

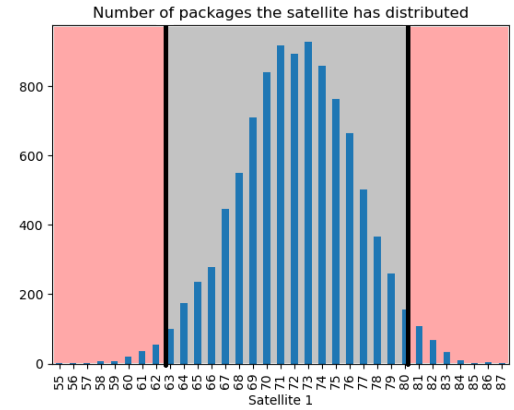


Figure G.1: Satellite 1, 10.000 runs - Base Case (wgt<11.3kg)

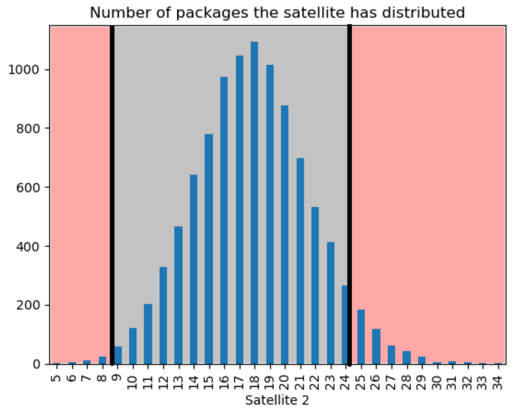


Figure G.2: Satellite 2, 10.000 runs - Base Case (wgt<11.3kg)

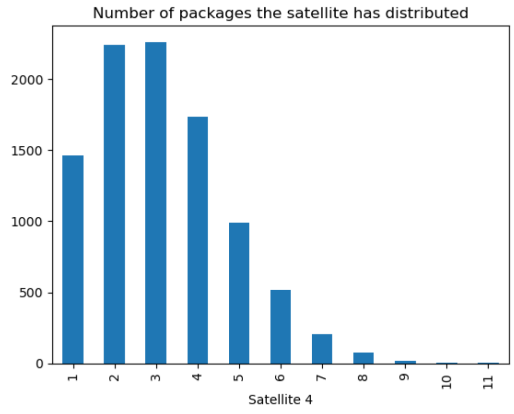


Figure G.3: Satellite 4, 10.000 runs - Base Case (wgt<11.3kg)

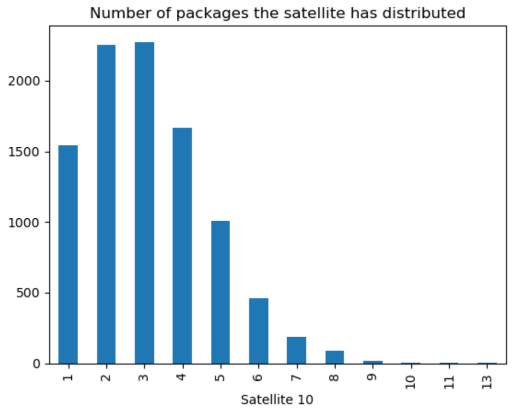


Figure G.4: Satellite 10, 10.000 runs - Base Case (wgt<11.3kg)

Satellite	Average #pack-ages	Variance	Standard devia-tion	C.I. lower limit	C.I. upper limit
Satellite 1	72	18	4.2	63	80
Satellite 2	17	14.4	3.8	9	24

Table G.1: CI of Satellites 1 and 2 - Base Case (wgt<11.3kg)

Scenario 2 - Better Case (wgt<4.5kg)

Satellite 1, Satellite 2, Satellite 4, and Satellite 10 are displayed in figure G.5, figure G.6, figure G.7, and in figure G.8 respectively. See table G.2 for a summary of Satellite 1 and Satellite 2. Satellite 4 and Satellite 10 are left out due to its insignificant impact on the network. They are also not normally distributed which would skew the variables in the table.

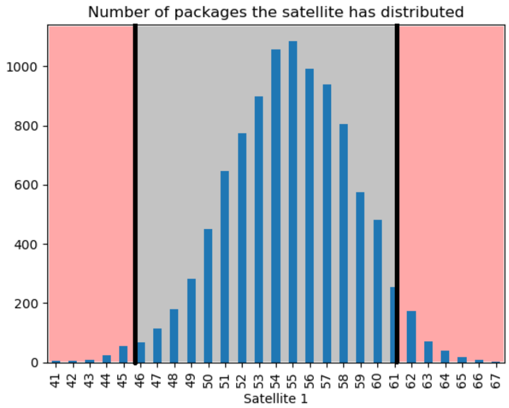


Figure G.5: Satellite 1, 10.000 runs - Better Case (wgt<4.5kg)

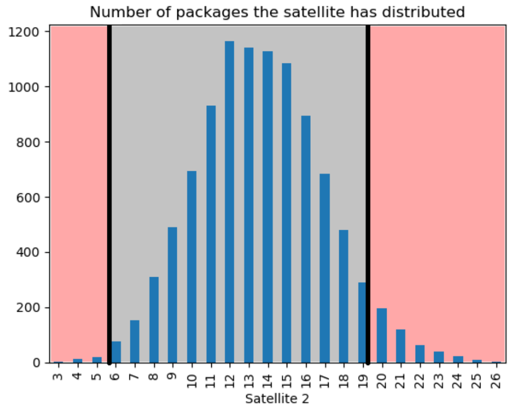


Figure G.6: Satellite 2, 10.000 runs - Better Case (wgt<4.5kg)

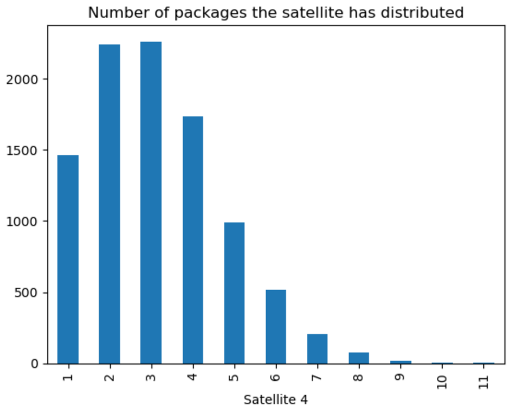


Figure G.7: Satellite 4, 10.000 runs Better Case (wgt<4.5kg)

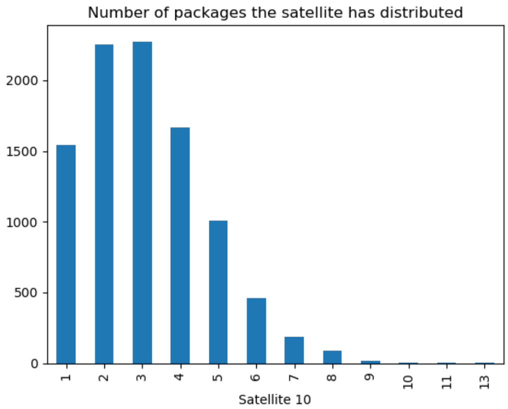


Figure G.8: Satellite 10, 10.000 runs - Better Case (wgt<4.5kg)

Satellite	Average #packages	Variance	Standard deviation	C.I. lower limit	C.I. upper limit
Satellite 1	54	13.7	3.7	46	61
Satellite 2	13	11.2	3.3	6	19

Table G.2: CI of Satelltes 1 and 2 - Better Case (wgt<4.5kg)

Scenario 2 - Better Case (wgt<11.3kg)

Satellite 1, Satellite 2, Satellite 4, and Satellite 10 are displayed in figure G.9, figure G.10, figure G.11, and in figure G.12 respectively. See table **??** for a summary of Satellite 1 and Satellite 2. Satellite 4 and Satellite 10 are left out due to its insignificant impact on the network. They are also not normally distributed which would skew the variables in the table.

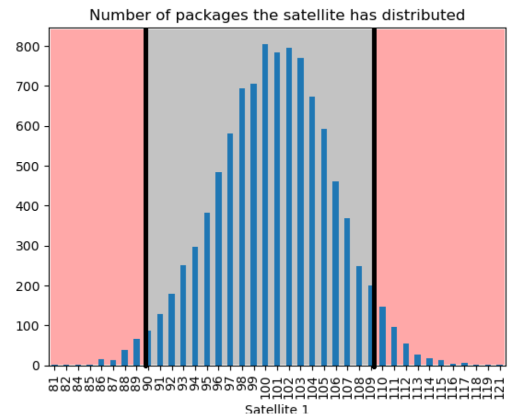


Figure G.9: Satellite 1, 10.000 runs - Better Case (wgt<11.3kg)

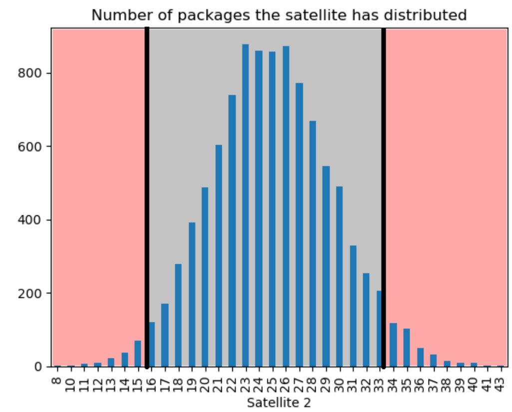


Figure G.10: Satellite 2, 10.000 runs - Better Case (wgt<11.3kg)

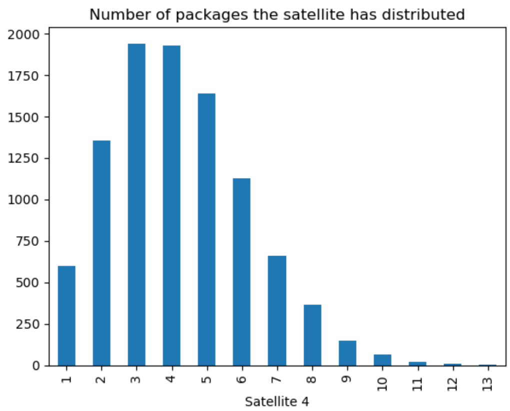


Figure G.11: Satellite 4, 10.000 runs - Better Case (wgt<11.3kg)

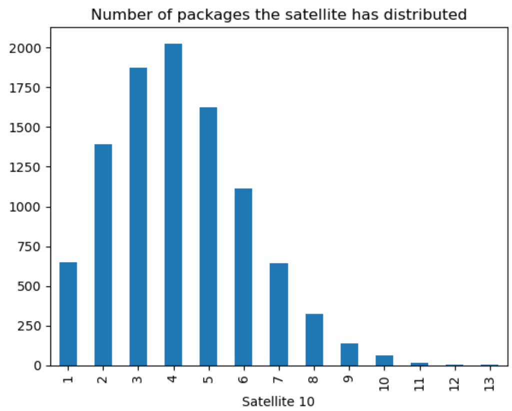


Figure G.12: Satellite 10, 10.000 runs - Better Case (wgt<11.3kg)

Satellite	Average #packages	Variance	Standard deviation	C.I. lower limit	C.I. upper limit
Satellite 1	100	24.7	5	90	109
Satellite 2	25	20.5	4.5	16	33

Table G.3: CI of Satellites 1 and 2 - Better Case (wgt<11.3kg)

Scenario 3 - Bull Case (wgt<4.5kg)

Satellite 1, Satellite 2, Satellite 4, and Satellite 10 are displayed in figure G.13, figure G.14, figure G.15, and in figure G.16 respectively. See table G.4 for a summary of Satellite 1 and Satellite 2. Satellite 4 and Satellite 10 are left out due to its insignificant impact on the network. They are also not normally distributed which would skew the variables in the table.

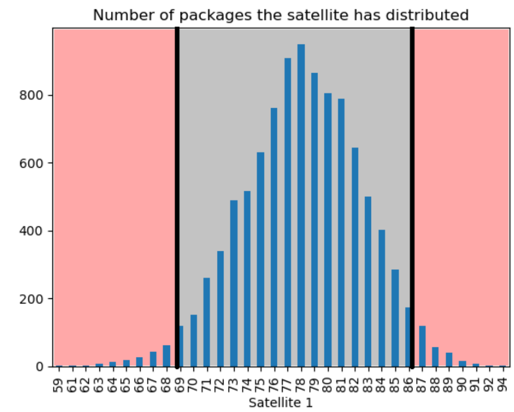


Figure G.13: Satellite 1, 10.000 runs - Bull Case (wgt<4.5kg)

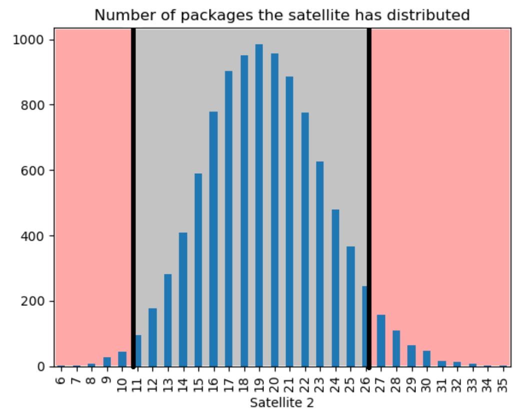


Figure G.14: Satellite 2, 10.000 runs - Bull Case (wgt<4.5kg)

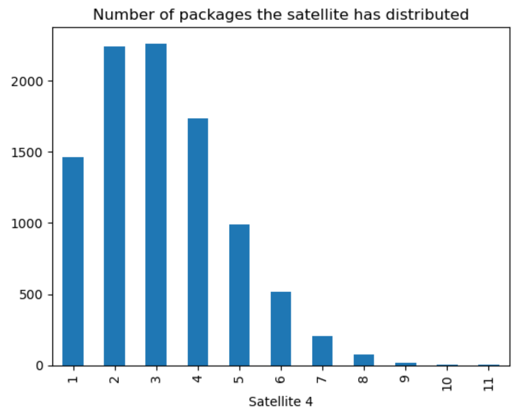


Figure G.15: Satellite 4, 10.000 runs - Bull Case (wgt<4.5kg)

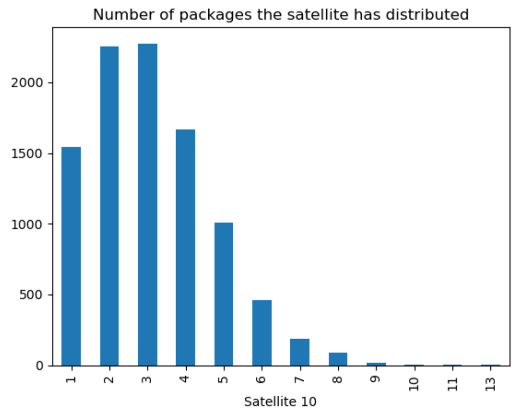


Figure G.16: Satellite 10, 10.000 runs - Bull Case (wgt<4.5kg)

Satellite	Average #packages	Variance	Standard deviation	C.I. lower limit	C.I. upper limit
Satellite 1	78	19.6	4.4	69	86
Satellite 2	19	15.9	4	11	26

Table G.4: CI of Satellites 1 and 2 - Bull Case (wgt<4.5kg)

Scenario 3 - Bull Case (wgt<11.3kg)

Satellite 1, Satellite 2, Satellite 4, and Satellite 10 are displayed in figure G.17, figure G.18, figure G.19, and in figure G.20 respectively. See table G.5 for a summary of Satellite 1 and Satellite 2. Satellite 4 and Satellite 10 are left out due to its insignificant impact on the network. They are also not normally distributed which would skew the variables in the table.

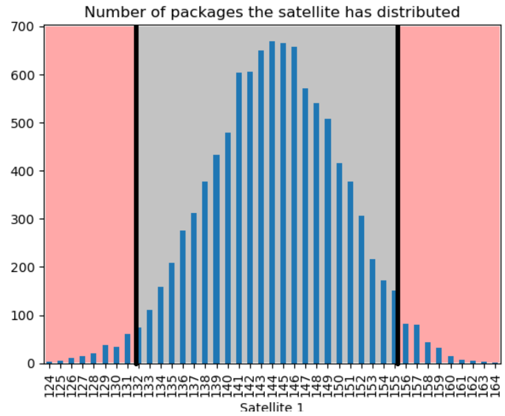


Figure G.17: Satellite 1, 10.000 runs - Bull Case (wgt<11.3kg)

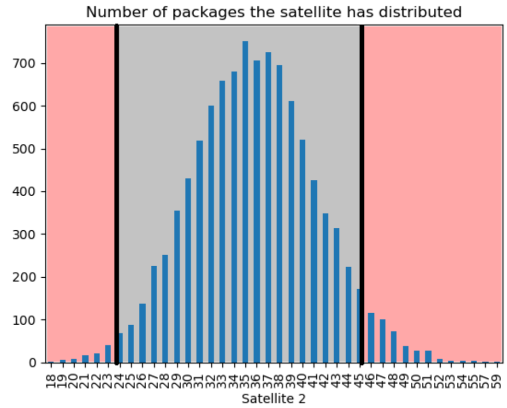


Figure G.18: Satellite 2, 10.000 runs - Bull Case (wgt<11.3kg)

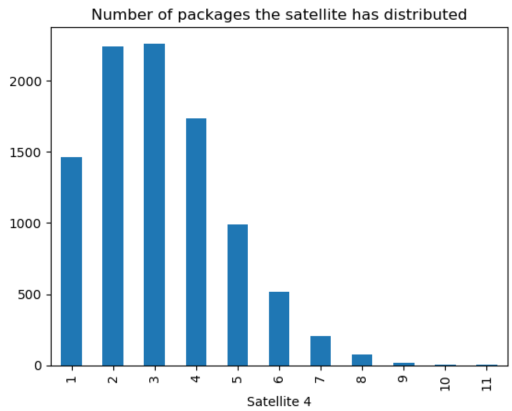


Figure G.19: Satellite 4, 10.000 runs - Bull Case (wgt<11.3kg)

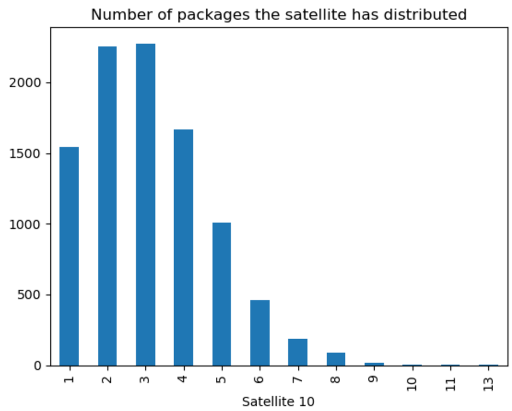


Figure G.20: Satellite 10, 10.000 runs - Bull Case (wgt<11.3kg)

Satellite	Average #packages	Variance	Standard deviation	C.I. lower limit	C.I. upper limit
Satellite 1	144	35.8	6	132	155
Satellite 2	35	29.5	5.4	24	45

Table G.5: CI of Satellites 1 and 2 - Bull Case (wgt<11.3kg)

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