HYBRID DELIVERY SYSTEM: DELIVERY SCHEDULE OPTIMIZATION AND COMPARATIVE ANALYSIS

by

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LIST OF ABBREVIATIONS

UAV:	Unmanned Aerial Vehicle
VRP:	Vehicle Routing Problem
MILP:	Mixed-Integer Linear Programming
ICT:	Information and Communications Technology
FSTSP:	Flying Sidekick Traveling Salesman Problem
TSP:	Traveling Salesman Problem
NP-hard:	Non-deterministic Polynomial-time Hardness
AFC:	Airborn fulfillment center
MHF:	Material Handling Facility
CV-TSP:	Carrier-Vehicle Traveling Salesman Problem
TTRP:	Truck and Trailer Routing Problem
TSP-D:	Traveling Salesmen Problem with drone
GRASP:	The Greedy Randomized Adaptive Search Procedure
HDP:	Heterogeneous Delivery Problem
GTSP:	Generalized Traveling Salesman Problem
VRP-D:	Vehicle Routing Problem with Drone
DRP-T:	Drone Routing Problem with Truck
2E-VRP:	Two-Echelon Vehicle Routing Problem
mFSTSP:	multiple Flying Sidekick Traveling Salesman Problem
MACH:	Memetic Algorithm with Constructive Heuristic
MA:	Memetic Algorithm
GA:	Genetic Algorithm
PMX:	Partially Mapped Crossover
HCA:	Hybrid Cargo Airship
FWSP:	Flying Warehouse Scheduling Problem
FAA:	Federal Aviation Administration
SUAV:	Stationary Unmanned Aerial Vehicle

ABSTRACT

Unmanned Aerial vehicles (UAVs) or drones have significant market potential benefiting from inherent flexibility, mobility, and cost savings. However, the mobility of the drone limited its battery capacity, which makes it impractical to perform delivery operations independently. The hybrid delivery system is getting attention to complement such weaknesses by incorporating another vehicle with the drone. Whereas the hybrid delivery system can selectively and synergistically exploit the strengths of these individual vehicles, they are challenging from an operational perspective since they require simultaneous cooperation between multiple components. In this study, we proposed two types of hybrid delivery: truck-drone and airship-drone systems. Each system has a high delivery capacity and timely delivery based on their complementary cooperation. The proposed systems are formulated as mixed-integer linear programming (MILP), which minimizes the delivery completion time and maximizes the revenue of the operator. A set of experiments are conducted to evaluate the performance and the capability of the developed model of the hybrid delivery systems. The results show that the hybrid delivery system has a distinct advantage over the existing delivery systems.

CHAPTER 1 INTRODUCTION

1.1 Introduction

Delivery service is not a modern industry. The first documented delivery service was written in Egypt in 2400 BC, where Pharaohs used enslaved Egyptians to deliver their message between cities. Throughout humans started taming animals, animals were used to deliver packages and messages. Carrier pigeons carried messages for long distances, and horses were the most common animal for delivery services. In the late 1800s, the invention of the railroad system took over most of the mailing and delivery services. After commercializing the personal automobile in 1907, James Casey initiated daily pickup and delivery services named United Parcel Service (UPS). Over the centuries since then, there have been attempts to change, but gasoline vehicles are still the primary delivery service.

The biggest change in the 21st century is the Internet, and the logistics industry is not an exception. E-commerce, for example, is the online purchase or sale of products and services that have become the most common practice for many people around all over the world. This marketplace platform offers convenient online purchases, competitive pricing, and a variety of digital resources such as brand emails and product reviews, resulting in a steep increase in the number of digital buyers. From 1.32 billion global digital buyers in 2014, it is expected to increase to 2.14 billion people worldwide in 2021 (Clement, 2019). In addition to the increase in the number of buyers, sales are expected to increase at a steeper pace. According to a report (Clement, 2020), global e-commerce sales are expected to reach $4.9 trillion by 2021, from 1.3 trillion in 2014, which indicates that online shopping is the most popular online activity worldwide. Figure 1.1

illustrates the prediction of the Global number of digital buyers and e-commerce sales in U.S. dollars (Clement, 2019;2020).

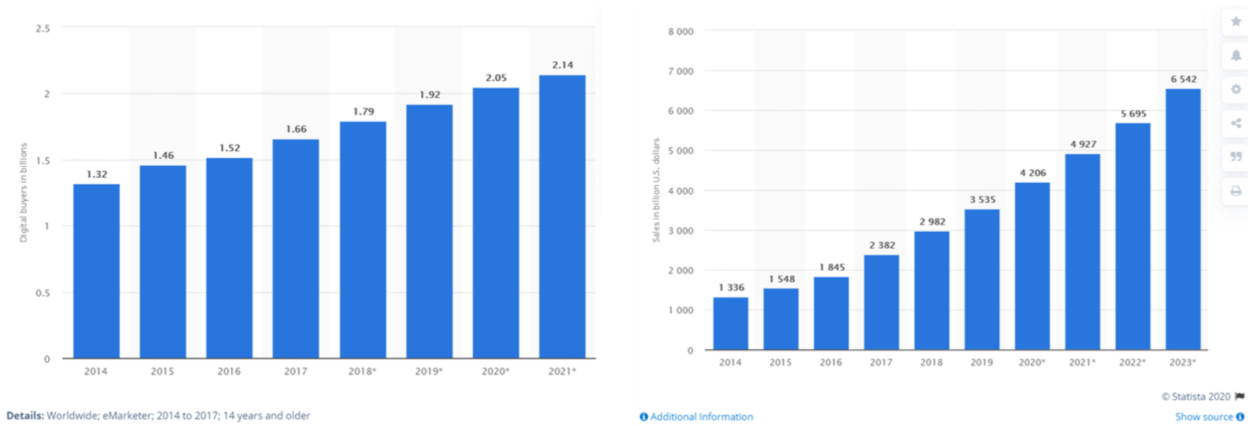


Figure 2.1 Global number of digital buyers and e-commerce sales prediction (Clement, 2019;2020).

Along with the e-commerce market expanded, information and communications technology (ICT), artificial intelligence, and robotics have become the focus of intense development, which has innovated the logistics process. First, the Internet of Things and ICT have automated logistics systems to ensure that all processes, from customer orders to delivery, are performed efficiently while minimizing human error. This also allows customers to check delivery status in real-time and receive goods within one or two days from ordering. Besides the logistics industry's automation, a physical revolution is underway with the development of commercial unmanned aerial vehicles (UAVs). UAV delivery system provides economical and fast service with flexible maneuverability and low cost. It is introduced by various logistics companies such as DHC, Amazon, and Alibaba. For example, in December 2013, Amazon.com founder Jeff Bezos announced plans to rapidly deliver lightweight commercial products using Unmanned aerial vehicles (UAVs), delivery drones, and it began to gain attention as a new technology in logistics (David, 2013). Numerous logistics companies have begun to focus on drone delivery, one of which, Flirtey, has performed the first fully autonomous FAA-approved drone delivery in an urban environment in the United States (Manoj, 2016). Drone delivery technology has been continuously studied, and drones of numerous companies are undergoing testing and are about to be commercialized. Another emerging delivery alternative is autonomous delivery robots. Starship, the first commercially available, provided pilot services in the US and the UK in 2016, with commercial services launched in 2017. Figure 1.2 shows the image of the delivery drone and delivery robot.

(a) (b)

Figure 2.2 (a) Delivery drone (Amazon Prime Air, 2021) and (b) delivery robot (Starship, 2021)

1.2 Problem Description

The emerging technologies of delivery methods have distinct advantages such as mobility, flexibility, and low cost. In the case of drones, they can operate without being affected by traffics or the road network. In addition, the delivery cost per mile is very cheap compared to traditional transportations, since they are powered by an electric battery. Similarly, a delivery robot, a droid, is another battery-powered driverless vehicle that provides low-cost delivery. However, while these emerging transportations are cost-effective, there are fundamental drawbacks in endurance and loadable capacity due to their limited battery, making it difficult to operate in large areas for a long time. For example, commercial drones are often powered by lithium polymer batteries that store limited energy. Therefore, the flight time of commercial drones is limited, so the drone delivery service cannot reach customers located far from the depot. For example, the flight time of the DJI Phantom series, which has the largest share of the commercial drone market, is limited to 25 to 30 minutes (DJI, 2021).

One way to overcome the battery issue is to use a hybrid delivery system consisting of the collaboration of heterogeneous vehicles. Hybrid delivery systems offer significant advantages over conventional delivery because they can selectively and synergistically leverage the strengths of individual vehicles. One example of hybrid delivery systems is truck-drone delivery systems, first reported in 2014 and developed by University of Cincinnati researchers and AMP Electric Vehicles (HorseFly, 2014). This system uses a truck as a station for drones in addition to its delivery function (Figure 1.3 (a)). Another state-of-the-art system is the airborne fulfillment center (AFC) delivery system of Amazon (Figure 1.3 (b)), firstly revealed in April 2016 when Amazon patented a flying warehouse that would deploy UAVs to deliver parcels to customers (Berg et al., 2016). The primary contribution of this dissertation is developing a mathematical model of different hybrid delivery systems and providing the practical usability of the hybrid delivery system with quantitative system analysis.

(a) (b)

Figure 2.3 Hybride delivery system. (a) truck-drone system (HorseFly, 2014), Airship-drone system (Berg et al., 2016).

1.2.1 Hybrid delivery system 1: Truck-drone

The first mathematical model of the truck-drone system was named "Flying Sidekick Traveling Salesman Problem (FSTSP)" proposed by Murray and Chu (2015). In FSTSP, the drone moves with the truck and is launched to provide delivery while the truck continues to serve customers at different locations. When the drone finishes servicing one customer, it must return to the truck. The goal of FSTSP is to develop truck and drone routes that can minimize the time to complete all deliveries. The unique approach of using trucks as drone stations and delivery vehicles has several advantages. Firstly, moving the drone closer to the customer can save the drone energy and allow more customers to use it. Second, the truck can be used for delivery or support delivery. Situations where drone use is restricted due to payload restrictions or flight restrictions. As a result, these two delivery methods complement each other to reduce the overall delivery time compared to regular truck delivery, as shown in Figure 1.4.

The FSTSP model, as the name implies, is based on the traveling salesman problem (TSP) problem but includes the collaborative movement of a drone and truck. The TSP was proven to be NP-hard (Korte and Vygen, 2012), and since the FSTSP is a generalized model, it is obviously NP-hard which is computationally expensive. Thus, a computationally efficient solution approach is often required for the practical use of the model.

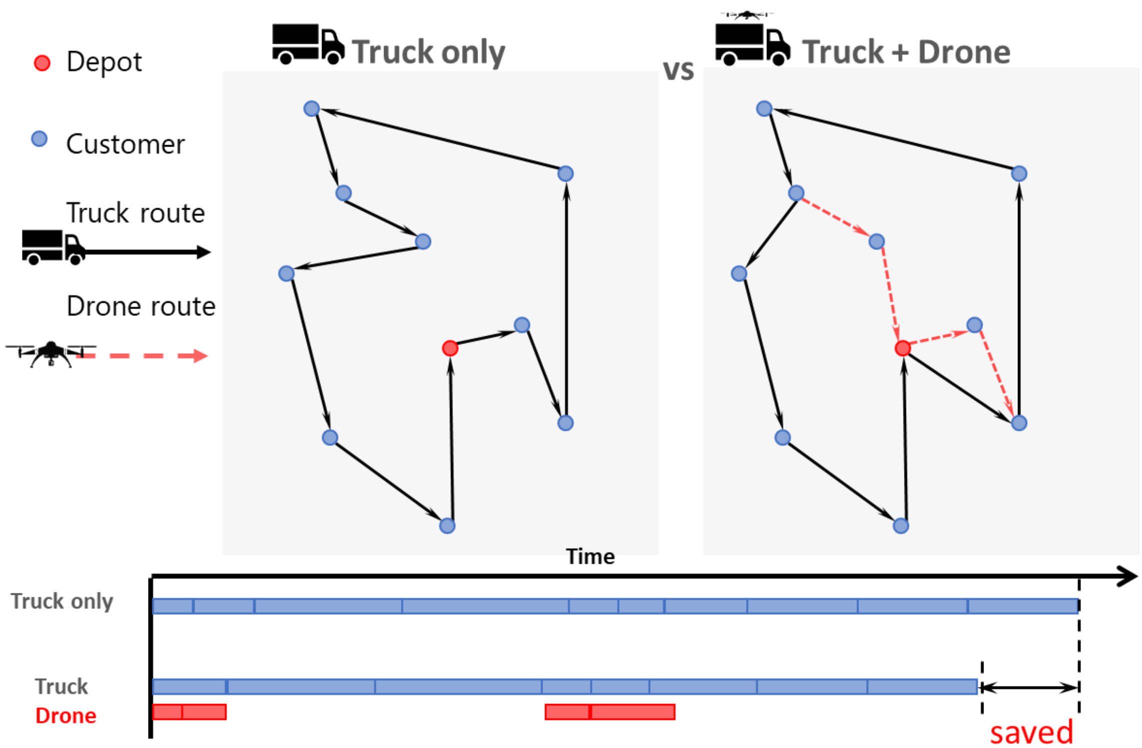


Figure 2.4 Delivery time comparison; truck only system and truck-drone system.

1.2.2 Hybrid delivery system 2: Airship-drone

Amazon firstly suggests the Airship-drone hybrid delivery system as an AFC delivery system. The AFC stands for a large airship that carries inventory and drones remaining in midair at an altitude close to the stratosphere. AFC keeps some orders in stock, and drones process items right after customer orders arrive. UAVs are deployed in the AFC and can quickly descend to customers to deliver items, as shown in Figure 1.5 (a). Then, after performing the delivery, they return to the Amazon Material Handling Facility (MHF). When AFC runs out of resources, the shuttle, a supply ship for AFC, takes off from the MHF and supplies inbound and outbound resources to the AFC, as illustrated in Figure 1.5 (b). With certain replenishment cycles, the AFC will remain in the sky for an extended period of time.

(a) (b)

Figure 2.5 Amazone’s AFC delivery system simulation demonstration. (NBC, 2017)

The AFC Shipping System is an attractive system that fits Amazon's management strategy. One of Amazon's primary goals is to protect and expand its ecosystem by attracting more sellers and customers to its marketplace. Recent studies show that nearly 25% of consumers are willing to pay a significant price premium for same-day or immediate delivery (Joerss et al., 2016). The fast delivery capability of the AFC system can sustain and expand Amazon's ecosystem by increasing the number of Amazon Prime subscribers and sellers (Berg et al., 2016). Shipping cost is also a major concern for Amazon as it incurs a net loss on annual shipments (Bishop, 2017). In this regard, AFC delivery systems can reduce transportation costs and operating energy by staying or moving in the stratosphere with low air density and resistance (Berg et al., 2016). AFC also uses electrical and renewable energy such as solar energy. These factors allow companies to provide sustainable membership services by reducing shipping costs.

1.3 Organization of the Dissertation

The remainder of this proposal is organized as follows. In the next section, the previous literature on drone delivery and hybrid delivery system is reviewed. Chapter 3 presents the hybrid delivery system of truck and drone with a mathematical model, heuristic algorithm, and sensitivity analysis result. Chapters 4 and 5 propose an airship-drone delivery system and its mathematical formulation followed by quantitative analysis and potential complementary operation with a drone-only system. In Chapter 6, a comparative analysis of the proposed hybrid delivery system has been presented with a quantitative approach. Lastly, Chapter 7 presents the potential direction of further work for the hybrid delivery system.

CHAPTER 2 . BACKGROUND AND LITERATURE REVIEW

2.1 Drone delivery system

In recent years, drones have been intensively studied as new delivery transportation. However, few studies have been done related to the operational efficiency of drone delivery. Drones have a limited delivery range, so efficient operation and management are more important than ground delivery systems. For generic drone operation systems in which drones provide services from a fixed depot, Dorling et al. (2017) explored d the relationship between energy consumption, payload, and battery weight of the drones. They proposed a cost minimization model for drone utilization on last-mile delivery. Similarly, Song et al. (2018) present drone application on delivery considering limited flight time, loadable capacity, and the effect of cargo weight on flight ability. Coutinho et al. (2018) reviewed different models of drone routing and trajectory optimization problems.

The operation of a commercial UAV is limited by its inherent weaknesses, such as short flight time due to the limited amount of energy stored in a battery and the capacity to deliver only small-sized products. Such weaknesses restrict the serviceable range and coverage of UAVs. Therefore, recent studies using drones for delivery services considered the cooperation between movable system components to overcome the limitations of UAVs. This cooperation use of heterogeneous vehicles that exploit individual vehicles' strengths is defined as a hybrid-delivery system.

2.2 Hybrid-delivery system

Although intensive development in drone delivery technology, there are fundamental drawbacks to the drone's flight range due to the battery capacity that greatly limits the drone's service range and coverage. A recent trend towards mitigating these weaknesses in drones is using hybrid delivery systems that use different types of vehicles as drone stations. This hybrid delivery system can selectively and synergistically utilize the strength of individual vehicles, enabling an efficient and wide range of delivery tasks. Specifically, a carrier vehicle, truck, or airship, is carrying drones near its destination, and the drones act as a swarm of delivery vehicles.

2.2.1 Truck-drone system

The The truck drone delivery problem can be considered as Carrier-Vehicle TSP (CV-TSP), which has been extensively studied by Garone et al., (2008, 2010, 2011, 2014), in which marine carriers and aircraft work as a team performing rescue missions by visiting a series of locations. In such a system, the marine carrier does not visit the rescue team but instead carries the aircraft near the area, and the aircraft itself works as a rescuer. The truck and trailer routing problem (TTRP) also considers the simultaneous use of two means of delivery, and in TTRP, customers are defined as two groups that a truck or trailer can visit (Chao, 2002; Scheuerer, 2006; Lin et al., 2009; Derigs et al., 2013; Drexl, 2011, 2014). The biggest difference with TTRP is that a trailer cannot serve customers without a truck.

The collaborative truck and drone delivery team has received a lot of attention recently, and there are several studies covering this cooperation system (Murray & Chu, 2015; Ferrandez et al., 2016; Ponza, 2016; Agatz et al., 2018; Ha et al., 2018); Mathew et al., 2015). The concept of this system was first described by Murray and Chu (2015), and the authors named it the FSTSP, which optimizes the delivery schedule for a single truck single drone scenario. Ferrandez et al. (2016) expanded the FSTSP to include multiple drones and investigated the efficiency of truck drone delivery. They proposed an algorithmic design that uses K-means clustering to find the launch location and GA to find the truck path. Another literature (Ponza, 2016) proposed a heuristic method based on Simulated Annealing to provide a solution for FSTSP using different types of drones. Another heuristic based on RVND (Randomized Variable Neighborhood Descent) is proposed and evaluated (de Freitas & Penna, 2018). More recently, Murray and Raj (2020) extended the previous model FSTSP with multiple drones called multiple FSTSP (mFSTSP), which ensure even more time savings.

Agatz et al. (2018) proposed Drone's Traveling Salesmen Problem with Drone (TSP-D), which shares the same structure as the FSTSP, but assumes that the drone moves on the same road network as the truck. The authors gave a lower bound on the optimal solution for truck-only systems, giving up the advantage of using shortcuts through Euclidean Street. A path primary-cluster secondary heuristic has been proposed, utilizing the strength of the lower bound of the truck-specific solution provided prior to clustering. In Ha et al. (2018), two heuristic algorithms have been proposed to solve TSP-D: The Greedy Randomized Adaptive Search Procedure (GRASP) and the heuristic adopted in the work of Murray and Chu (2015) called TSP-LS.

Another related problem, the Heterogeneous Delivery Problem (HDP), was designed on a physical distance network and allowed trucks to launch drones at all endpoints of the arc (Mathew et al., 2015). The difference between FSTSP and HDP is that trucks cannot deliver directly to customers. Instead, they only launch drones to serve customers. For a solution approach, the author converts the problem to a Generalized Traveling Salesman Problem (GTSP) and reduces GTSP to TSP using the Nood-Bean transformation available in Matlab, then heuristically solves it. Table 2.1 provides an overview of the above study and briefly summarizes the problem nature and solution approach.

Table 2.1.Overview of the cooperative team delivery problem.

Problem type	**Literature**	**Number of**		**Solution approach**
		trucks	**drones**	
FSTSP	(Murray & Chu, 2015)	Single	Single	MILP formulation Heuristic
	(Ferrandez et al., 2016)	Single	Multiple	GA and K-means
	(Ponza, 2016)	Single	Single	SA
	(de Freitas & Penna, 2018)	Single	Single	Heuristic
	(Murray & Raj, 2020)	Single	Multiple	MILP formulation Heuristic
TSP-D	(Agatz et al., 2018)	Single	Single	MILP formulation Heuristics
	(Ha et al., 2019)	Single	Single	MILP formulation Heuristics
HDP	(Mathew et al., 2015)	Single	Single	Reduction to GTSP Reduction to TSP Heuristic

In terms of analysis of this hybrid system, Carlsson et al. (2017) demonstrated terms of analysis of this hybrid system using theoretical analysis. They used a theoretical analysis to demonstrate that the potential benefit of using a hybrid system is proportional to the square root of the speed ratio between the vehicle and the drone. Wang et al. (2017) proposed the Vehicle Routing Problem with Drone (VRP-D), which includes multiple trucks and drones, and conducted a worst-case scenario analysis to understand the benefits of using drones. Poikonen et al. (2017) described that the use of this hybrid system is required not only explicitly consider limits on battery life and cost targets, but in the worst case, to extend the boundary to distance/cost metrics.

Most previous research on truck-drone cooperative delivery uses both truck and drone as the subject of delivery. However, some models take the truck out of shipping, forcing the truck to only serve as a hub for transporting drones. Savuran and Karakaya (2016) proposed a single truck, single drone system in which the truck only serves as the take-off and land-on location for the drone, Luo et al. (2017) also considered cooperative one ground vehicle, one drone model in which truck only serves as moving hub and all the tasks are assigned to a drone. Liu et al. (2019) investigated a team of ground vehicles and aerial vehicles, which explicitly divided their job to carry aerial vehicles closer to the target, make direct contact with the target, and perform their mission. Peng et al. (2019) extended the model even further with multiple drones with multi-travels which have truck parking in parking space and launch drones for package delivery. Poikonen and Golden (2019) propose Mothership and Drone Routing Problem (MDRP), which the mothership only serves as a moving hub for drones. In MDRP, there is no designated parking place, but the mothership can launch and retrieve the drone at any point along its en-route.

In this study, we propose a new variant of the cooperative delivery system called DRP-T to take full advantage of drones in the delivery process. To achieve the purpose, in order to achieve this, it is necessary to remove restrictions on drone activity as much as possible and secure their flexible operation. In this regard, the model has the following features: 1) multiple drones can be assigned to a truck, 2) drones can serve multiple customers per flight, 3) trucks are not serving customers but carrying drones to parking locations, and 4) visits all parking locations are not compulsory but according to their objectives. These features are linearly formulated and included in the proposed mathematical model. To mitigate the high complexity of the model, a computationally efficient heuristic algorithm is developed. The model evaluation has been conducted with a comparative analysis between mFSTSP. The sensitivity analysis provides further insight and guidelines for efficient application of the system.

2.2.2 Airship-drone system

Airships are a recent technological development attracting significant attention as a new solution to transportation (Tatham et al., 2017). They are aircraft filled with inert helium that provides much of the lift that enables long operational persistence with a massive payload. The airship engine also enables vertical take-off and landing, which eliminates the need for a wide range of ground handling equipment on the ground. Aeros Corp, the world's largest producer of cargo airships, has a model named ML86X that is capable of moving 9,445.2 km with a maximum speed of 222 km per hour and a maximum load of 500 tons (Aeroscraft, 2016a), which is far greater than a general fixed-wing aircraft (Figure 2.1).

Figure 2.1 The half-size prototype of ML868 (Aeroscraft, 2016b).

The primary advantages of airship compared to ground transport or fixed-wing aircraft include greater cargo volume and persistence with avoidance of the disrupted road network. Knotts (2012) provides an extensive discussion of the potential uses of airships. This observation was supported by research on emergency supply chain management (Lynch, 2018), pointing out the inherent importance of effective responses by using hybrid airships in the logistics industry. Tatham et al. (2017) also demonstrate that airships would have offered considerable benefits to the logistician by investigating airship applications for supply chain management in the United States. In addition to the airship's outstanding utility as effective transporter, there is also the opportunity for significant reductions in greenhouse gas emissions compared to other modes of transport (Prentice et al., 2009). With these advantages in mind, these airships clearly have significant potential to improve the efficiency, efficiency, and flexibility of logistics operations.

The development of hybrid airship technology has been going on continuously for the last decades. Several prototypes of airships have already been tested, but advanced models are still under development within commercial use dates over the next few years. Table 2.2 demonstrates the summary of emerging capabilities provided on the websites of the relevant companies. Please refer to the detailed description of Lockheed (2015), Hybrid Air Vehicles (2016a, 2016b), and Aeroscraft (2016a) for more details.

Table 2.2. Capabilities of hybrid airships.

Company	Lockheed Martin	Hybrid Air Vehicles		Aeroscraft		
Model	LMH-1	AL10	AL50	ML866	ML868	ML86X
Payload (kg)	21,000	10,000	60,000	60,000	225,000	450,000
Range (n.miles)	1400	Not available	2,000	3,100	5,100	5,100
Speed (knots)	60	80	105	120	120	120
Cargo Bay (m)	3x3x18	7.2x3.2x1.7.	30x5.6x4.0	60x12x9	115x18x13	138x22x16

The cooperative use of airships and drones to increase the efficiency of logistics operations has drawn the attention of the world's largest retailers: Amazon and Wal-Mart. In April 2016, Amazon obtained a patent for a small airship-style airship-shaped warehouse containing unmanned aerial vehicles (UAVs) to deliver parcels to end customers (Berg et al., 2016). The following year, Wal-Mart applied for a US patent for a very similar system (High et al., 2017). In these systems, gas-filled air transport moves horizontally while maintaining a high altitude and carrying stock of goods and drones. The drone is deployed on the airship and sent along with the delivery item to the designated final recipient. Since the flight depot carries the UAV near the delivery point, it partially solves the limited battery problem, a major drawback of the UAV. In addition, the mobility and dynamic operation of the UAV alleviates the shortcomings of the long take-off and landing times of huge airships.

CHAPTER 3 . TRUCK-DRONE HYBRID DELIVERY SYSTEM

This section proposes the drone routing problem with truck (DRP-T) that uses only drones as the final delivery method and trucks as supportive means to help deliver drones. In DRP-T, trucks are not delivering packages to customers but carrying drones to parking locations, and drones are serving customers directly and returning to trucks. Compared to the TSP-D, the DRP-T limits the truck's use and maximizes drones' use, thoroughly enjoying the wealth of drones' mobility and costlessness. This paper proposes a new delivery model DRP-T with a new mixed-integer linear programming (MILP) formulation. The new delivery model's performance was verified with comparative analysis with TSP and mFSTSP.

3.1 Problem description

The DRP-T can be considered an extension of the TSP. The FSTSP, or TSP-D, is also an extension of TSP that first appeared that adds a subsidiary delivery vehicle, a drone, to help serve a part of customers in the existing route of TSP. As an extension of the FSTSP, Murray et al. recently proposed m-FSTSP, expanding the single drone availability to multi-drones that achieved further improvement in delivery time while increasing the problem's complexity (Murray and Ritwik, 2019).

The DRP-T, however, is not an extension of the mFSTSP since it has different roles for the two delivery vehicles. In contrast to m-FSTSP, which uses drones as a supportive delivery for the truck, DRP-T uses drones as the primary delivery method, and the truck does not directly serve the customers but only carries drones to a parking location. This routing strategy constitutes an entirely different delivery network from m-FSTSP. Therefore, the DRP-T can be defined as an extended model of the Two-Echelon Vehicle Routing Problem (2E-VRP) when replacing the parking location with a satellite that has flexible routing for delivery vehicles (drones) not restricted to the assigned satellite (parking location) and having flight endurance limit due to drone battery capacity. Figure 3.1 illustrates the routes of 4 different problems TSP, FSTSP, mFSTSP, and DRP-T.

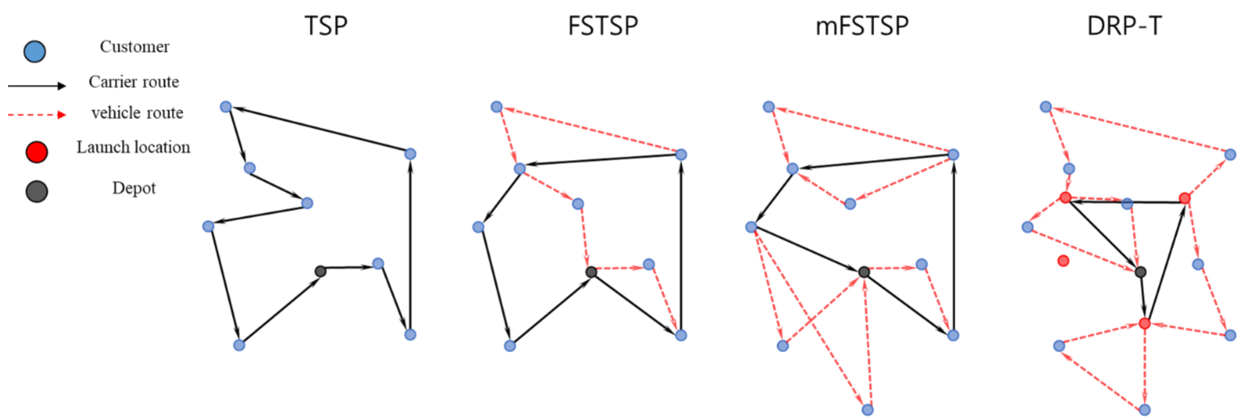


Figure 3.1. Example of solutions for TSP, FSTSP, mFSTSP, and DRP-T.

3.2 Mathematical model

The DRP-T aims to minimize the truck's arrival time at the depot after serving all the customers. The truck selectively visits parking location j $(j \in J)$ that is close enough for drones to make delivery to customers. After the truck arrives at a particular location, drones are launched to serve the customer i $(i \in I)$. While drones are delivering items to customers, the vehicle moves to another location and collects returning drones. The following represent notations and the mathematical model of DRP-T.

Notations

Variables		
I	:	Set of customer locations.
J	:	Set of parking locations and depot locations.
$0, \lvert J \rvert$	:	Starting and ending depot location ($0,\ \lvert J \rvert \in J$).
N	:	Set of all locations. ($I, J \subset N$).
K	:	Set of vehicles flights
$\tau_{ij'}$	:	Traveling time (sec) between location j and j' by truck
$\tau_{nn'}^{d}$	:	Traveling time (sec) between location n and n' by drone
E	:	Maximum flight time (sec) of drones
M	:	Positive and large number
Decision variables		
$x_{jj'}$	:	Binary decision variable, 1 if carrier travels from location j to j'
$y_{nn'}^{k}$	:	Binary decision variable, 1 if vehicles travel from location n to n' in k-th flight.
$z_{jj'}$	:	Integer decision variable, equal to available vehicles when carrier travel from location j *to* j'.
b_n^k	:	Real number decision variable, equal to available endurance of vehicle k when vehicle visit location n.
T^t_j	:	Real number decision variable, time when the truck arrives at location j.
Td_n^k	:	Real number decision variable, time when the vehicle k arrives at location n.

Mixed integer linear programming

Minimize

$$T_{|J|} \tag{3.1}$$

Subject to

$$\sum_{\substack{j \in J \\ j \neq 0}} x_{0j} = 1 \tag{3.2}$$

$$\sum_{\substack{j \in J \\ j \neq |J|}} x_{j|J|} = 1 \tag{3.3}$$

$$\sum_{j \in J} x_{jj'} = \sum_{j \in J} x_{j'j} \qquad \forall j \in J^{+} \tag{3.4}$$

$$\sum_{n \in N} y_{jn}^{k} \leq M \cdot \sum_{j' \in J} x_{j'j} \qquad \forall k \in K, j \in J \tag{3.5}$$

$$\sum_{\substack{n \in N \\ n \neq j}} y_{nj}^{k} \leq M \cdot \sum_{\substack{j' \in J \\ j \neq j'}} x_{j'j} \qquad \forall k \in K, j \in J \tag{3.6}$$

$$\sum_{\substack{n \in N \\ n \neq i}} \sum_{k \in K} y_{ni}^{k} = 1 \qquad \forall i \in I \tag{3.7}$$

$$\sum_{\substack{n \in N \\ n \neq i}} y_{nik} = \sum_{\substack{n' \in N \\ n' \neq i}} y_{in'k} \qquad \forall k \in K, i \in I \tag{3.8}$$

$$T_{j'} \geq T_{j'} + \tau_{jj'} - M \cdot (1 - x_{jj'}) \qquad \forall j \in J, j' \in J \tag{3.9}$$

$$Td_{j'}^{k} \geq T_{j'} - M \cdot (2 - \sum_{j \in J} x_{jj'}^{t} - \sum_{i \in I} y_{j'i}^{k}) \qquad \forall k \in K, j \in J \tag{3.10}$$

$$Td_{n'}^{k} \geq Td_{n}^{k} + \tau_{nn'}^{d} - M \cdot (1 - y_{nn'}^{k}) \qquad \forall k \in K, n \in N, n' \in N \tag{3.11}$$

$$T_{j'}^{k} \geq Td_{j'} - M \cdot (2 - \sum_{j \in J} x_{jj'} - \sum_{i \in I} y_{ij'}^{k}) \qquad \forall k \in K, j \in J \tag{3.12}$$

$$z_{0j}^{t} = |K| \qquad \forall t \in T, j \in J, j \neq 0 \tag{3.13}$$

$$\sum_{\substack{j'' \in J \\ j'' \neq j'}} z_{j'j''} = \sum_{\substack{j \in J \\ j \neq j}} z_{jj'} - \sum_{k \in K} \sum_{i \in I} y_{j'i}^{k} + \sum_{k \in K} \sum_{i \in I} y_{ij'}^{k} \qquad \forall j' \in \{J : j' \neq 0\} \tag{3.14}$$

$$\sum_{k \in K} \sum_{\substack{i \in I \\ i \neq j'}} y_{j'i}^{k} \leq z_{jj'} \qquad \forall j, j' \in \{J : j \neq j\} \tag{3.15}$$

$$0 \leq z_{jj'} \leq |\mathrm{K}| \qquad \forall j, j' \in \{J : j \neq j\} \tag{3.16}$$

$$b_{i}^{k} \geq \tau_{ij}^{d} - M \cdot (1 - y_{ji}^{k}) \qquad \forall k \in K, i \in I, j \in \{J : j \neq 0\} \tag{3.17}$$

$$b_{n}^{k} \geq b_{i}^{k} + \tau_{in}^{d} - M \cdot (1 - y_{in}^{k}) \qquad \forall k \in K, i \in I, n \in N, n \neq 0 \tag{3.18}$$

$$0 \leq b_{n}^{k} \leq \mathrm{E} \qquad \forall k \in K, n \in N \tag{3.19}$$

The objective function (1) seeks to minimize the truck's returning time to the depot after completing the delivery job. Constraints (2) and (3) describe the truck’s fixed start and end location to the depot. Constraint (4) preserves the truck routing by forcing it to depart from node j' when visiting node j'. Constraints (5) and (6) allow all drones to depart/return only to the parking location that has been visited by the truck. In constraint (7), drones should serve each customer precisely once. Constraint (8) works the same way as constraint (4), providing flow balance for the drones. Constraint (9) cumulatively calculates the arrival time at each parking location j that has been visited by the truck. Constraint (10) calculates the arrival time of drones at customer i that has been visited just after being launched from the carrier. The constraint (11) works under the same logic as a constraint (9), which calculates the arrival time at each node n that drones have visited. Constraint (12) allows both truck and drone to wait for each other at rendezvous points.

The constraints (13) to (16) ensure that the available number of drones exceeds when the truck launch drones. First, constraint (13) states that the initial number of drones when the truck departs from the depot should be equal to the drone's maximum index. The constraint (14) updates the number of available drones whenever the drones are launched or returned to the truck. In constraint (15), the number of drones launched from trucks should not exceed the number of drones available on the truck at that moment. Lastly, constraint (16) ensures that the number of available drones should not exceed the maximum index of drones, which equals the maximum number of drones. Figure 3.2 illustrates the way how the decision variable "z" works as an example.

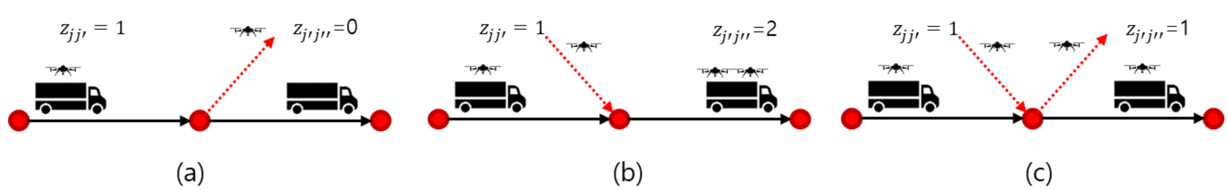


Figure 3.2. Tracking the number of available drones at each location.

The fundamental difference between truck and drone is the available traveling distance owing to the battery limit. Constraints (17) and (19) precisely track the flight time of drones to ensure they operate in a feasible range. Constraint (17) accounts for the drone's flight time from launching location j to customer node i where it is the first visit. After the drone's first visit until it returns to the truck, its flight time is updated in the constraint (18). The flight time b_i^k is updated by cumulatively adding up the travel time of the drone k at each visited location i. Since the drones' available flight time is limited to its endurance in constraint (19), the flight time from launch to return will not exceed the drone's endurance—the flight time limit mechanism in detail through an example in Figure 3.3.

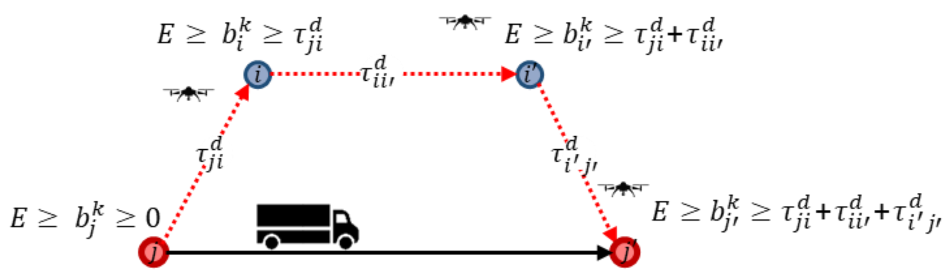


Figure 3.3. Flight time monitoring formulation

3.3 Solution approach

Vehicle Routing Problem (VRP) is a well-known NP-hard problem where the aim is to serve a set of customers with a fleet of vehicles under certain constraints. The VRP is a special case that occurs when the single satellite is considered in 2E-VRP so that 2E-VRP is also NP-hard. Thus, it is obvious that the proposed DRP-T also belongs to the NP-hard class since it is a generalized model of 2E-VRP. The proposed mathematical model allows solving small instances, but solving large instances requires a computationally inexpensive solution approach. Therefore, we propose a new heuristic called Memetic Algorithm with Constructive Heuristic (MACH), which consists of an evolutionary-based structure with a constructive phase.

The MACH adapts the framework of the memetic algorithm (MA). The MA is an extension of the traditional genetic algorithm (GA), which uses local search technology to reduce the likelihood of premature convergence (Garg, 2010). It has been proven that MA overperformed GA with better solution quality with broader search space in TSP problems (Krasnogor and Smith, 2000). Additionally, MACH has added a constructive phase to the search structure of the MA. This combined approach has proven to dramatically reduce computation time and improve solution quality in scheduling problems (Liu and Reeves, 2001). In this section, we present the detail procedure of the proposed heuristic algorithm, MACH. The overall procedure of MACH can be summarized as follows (Figure 3.4).

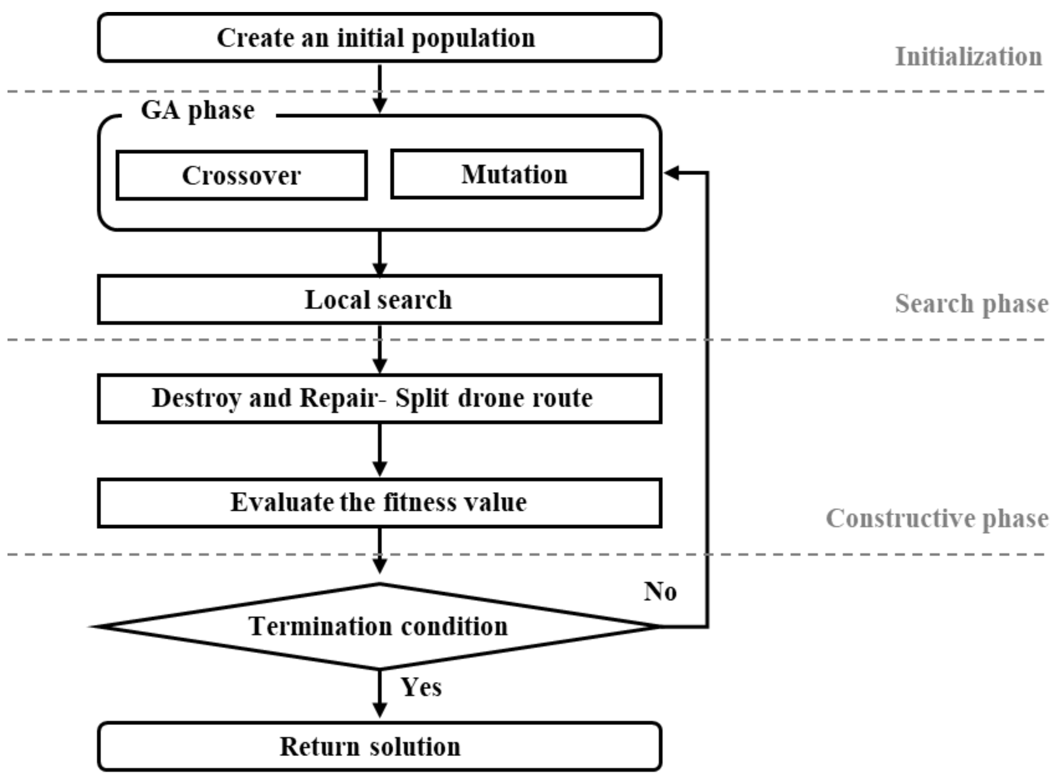


Figure 3.4. Flowchart of MACH.

3.3.1 Solution representative

The DRP-T problem has two heterogeneous vehicles, truck and drones. Therefore, the solution should include the route information of those two. The solution for the truck route is represented by a string of numbers consisting of an index in the set of parking location *J*. Each parking location visited by the truck is followed by the drone route, which contains a permutation of customers denoted by the set of customers I. Figure 3.5 illustrates an example of solution representation. Each parking point might have a set of customers served by drones that launch from the parking point. By collecting the customers' sequence, and their assignment on parking points, the solution will have two lists, customer sequence and parking points, as seen on the right side of Figure 3.5.

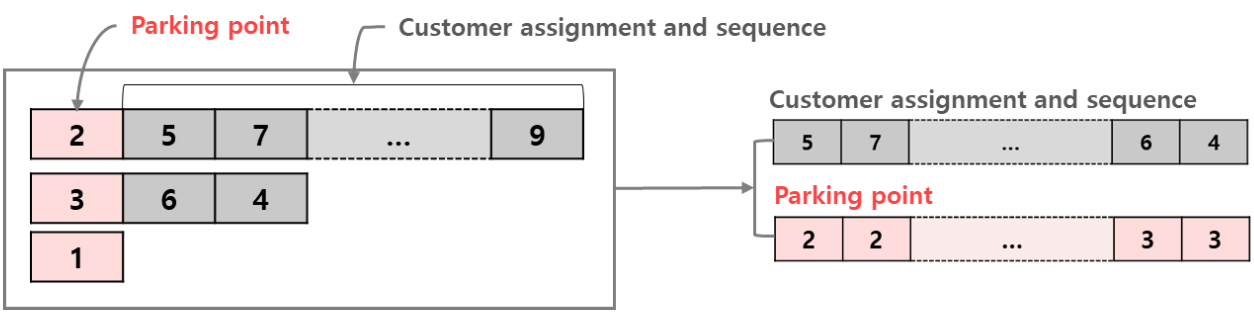


Figure 3.5. Solution representative.

3.3.2 Initial feasible solution generation

The proposed algorithm begins by generating an initial solution of a full route that utilizes the truck and drones. First, the truck route R^T is generated by randomly shuffling the index of parking location J. Then, for each parking location, a set customer is sequentially assigned based on its distance until it reaches the max capacity with the flight endurance and the number of drones. After assigning all customers, the parking locations with any assigned customers are removed from the truck route. The algorithm repeats the above process until the number of solutions produced reaches the population size. Algorithm 1 provides the pseudo-code of the initial feasible solution generation.

Algorithm 1: Initial feasible solution generation.

For *p=0* to *PopulationSize* **do**
    R_p^T=shuffle(*J*)
While *customer≠ø* **do**
    $j=R_p^T[idx]$
    Forall *k* in *K* **do**
        While *FlightDistance*+$\tau_{i,RpT[idx+1]}^d$ <Endurance **do**
            Find *customer i* nearest to *j*
            Add *i* to drone route $R_p^D[j]$
            FlightDistance++ $\tau_{i,i'}^d$
    idx++
return R^T, R^D

3.3.3 Search phase-GA phase and local search

The search phase begins with search operators generally used in genetic algorithms, crossover, and mutation to diversify the search area by perturbing the current solutions. These operators target the truck route R^T only, but as the truck route changes, the customer assignment also changes, making a change in the drone route. Next, the local search is applied to the customer sequence, which decides the drone route R^D. Before all operators start, two pairs of solutions are randomly selected from the existing solutions, and after the operator, record only when the fitness value is better than the previous solution.

In the case of crossover, a two-point crossover is applied which maintains relative order and absolute position within the parent permutation. In the crossover. the two selected parents exchange their solutions between two randomly generated points. For the other way to change the customer assignment on parking location, a mutation operator, reverse, has been adapted that reverse the assignment order between two points selected randomly. These two operators each have a probability that the selected parent will pass through the operators, and parents outside the probability will pass through without going through the operator. This allows keeping solutions that have not changed over iterations.

The partially mapped crossover (PMX) is adapted, which chooses two random points on parents and passes on ordering information between points from the parent tours to the offspring. Part of one parent string is mapped to part of another string, and the rest of the information is exchanged to remove the duplicated visit. An example of the implementation of the operators is shown in Figure 3.6.

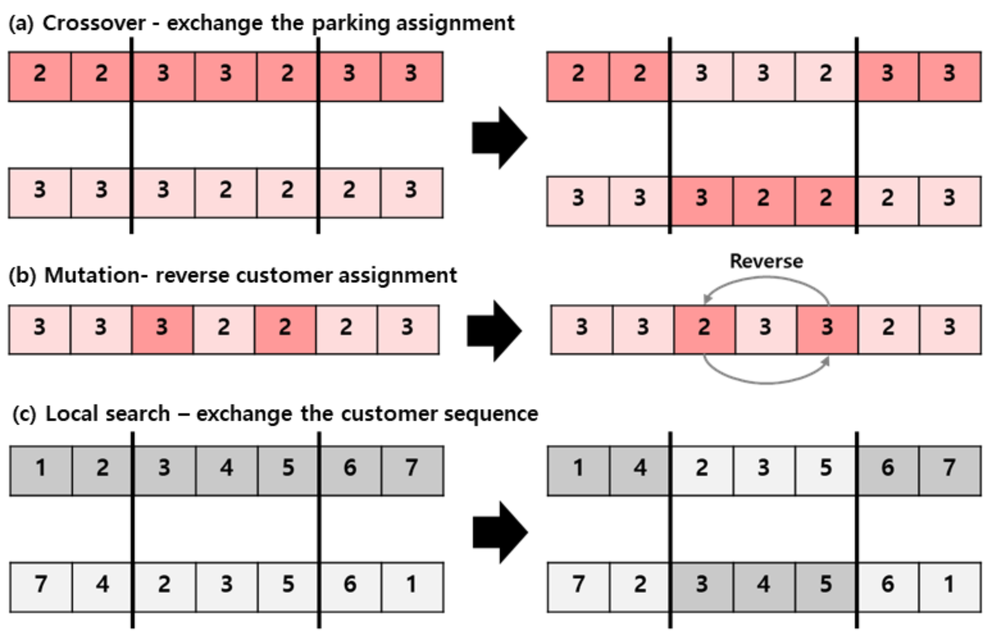


Figure 3.6. Search operators (a) crossover, (b) mutatoin, (c) local search.

3.3.4 Constructive phase- destroy and repair drone route.

After the search phase, returning routes for drones are constructively built with destroy/repair procedures. In each subroute, the case with the highest saving value is selected after it destroyed and repaired all possible pairs of paths. First, in the destroy operator, the drones' subroutes in the given solution are broken down. The number of destroying points is equal to the number of available drones. Then, the repair operator replaces the broken route with the returning route to the following parking location. It then adds the departing route from the current parking location to the customer that got destroyed. In this constructive phase, the destroy/repair procedure is applied to all possible pairs of routes, and the best repair solution in terms of time will be selected and recorded. All subroutes in the solution are going through the destroy-repair operation. Figure 3.7 illustrates the example of destroying and repair procedure.

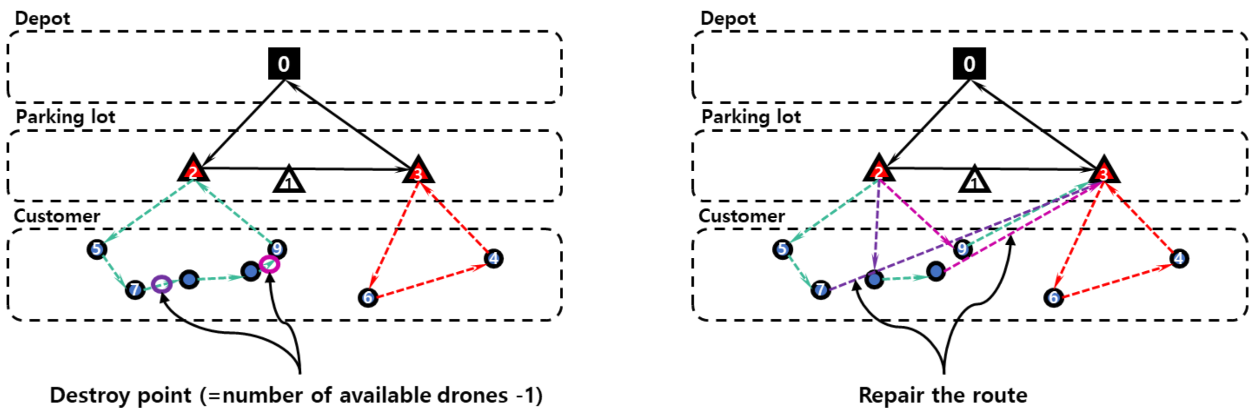


Figure 3.7. Construction of drone route with destroy and repair operation.

3.3.5 Termination condition

The algorithm terminates when there is no improvement for a given number of iterations or the maximum number of iterations is reached.

3.4 Computational result

This section presents the comparative analysis result of the mFSTSP and DRP-T with a case study. The case study uses problem instances generated by GPS data of two cities, Seattle and Buffalo, online-available at https://github.com/optimatorlab/mFSTSP (Github, 2021). The instance set 1 (Seattle) has a broader operation area with a longer average distance than set 2 (Buffalo). The detailed specification of each instance is provided in Table 3.1. The truck speed is set to 13 m/s. The drone of 23 m/s with a 55minute flight time is assumed according to DJI's MATRICE 300 RTK (DJI, 2021). All the experiments were run on an Intel i7-8750H 2.20GHz processor with 32 GB of RAM.

Table 3.1. Case study map specification.

Set 1 (Seattle)			**Set 2 (Buffalo)**		
Avg. Distance [m]	Width [m]	Length [m]	Avg. Distance [m]	Width [m]	Length [m]
18059.7	27277.01	22713.15	10331.26	17024.88	15068.17

3.4.1 Performance comparison with small size instances.

In this section, we compared the performance of the model mFSTSP and DRP-T with 1 to 3 drones. Each instance set has 10 problems with 8 customers and 1 depot. In DRP-T, 3 parking locations are generated based on the centroid of customers found by k-mean clustering. For the mFSTSP, the recent model presented by Murray and Raj (2019) is used. Both models were solved using the commercial solver, Gurobi 8.1.1.

As shown in Figure 3.8, the TSP, mFSTSP, and DRP-T have a distinct differences in their route. The TSP displays only truck routes because TSP is truck-only delivery. In mFSTSP, parts of the TSP route are removed and replaced by drones, and more routes are replaced as drones are added. In the case of DRP-T, compared to the other two cases, the use of trucks decreased significantly, and drones were actively used.

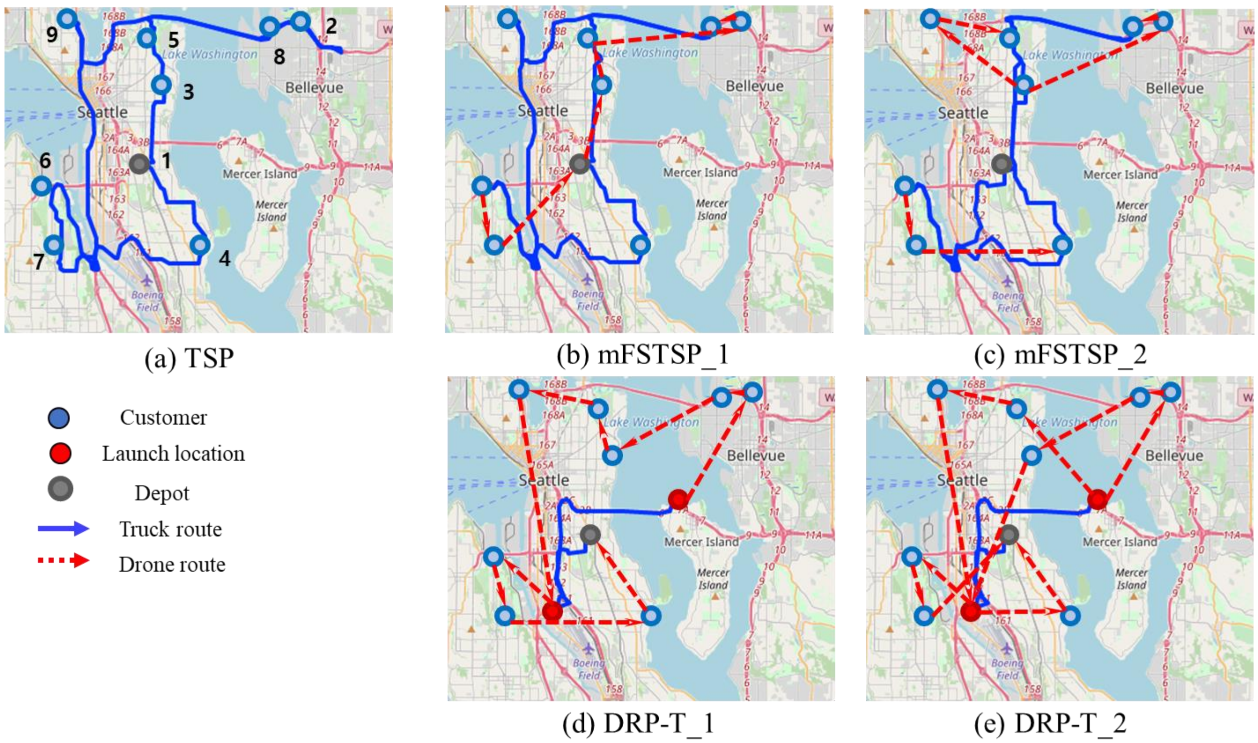


Figure 3.8. Solution examples of (a) TSP, (b) mFSTSP with 1 drone, (c) mFSTSP with 2 drones, (d) DRP-T with 1 drone, (e) DRP-T with 2 drones.

Table 3.2 shows the computational results of mFSTSP and DRP-T obtained by MILP. The "% saving" captures the percentage difference of completion time compared with the TSP, truck-only delivery. The result shows that the completion time decreases consistently with a rise in the number of drones. Specifically, when there was only one drone, the DRP-T showed a slightly shorter makespan, but the difference expanded as more drones were used. The mFSTSP and DRP-T have a maximum of 44.5% and 55.8% savings, respectively, compared to truck-only delivery.

Table 3.2. Computational result of mFSTSP and DRPT-T.

		Set 1 (Seattle)			Set 2 (Buffalo)		
	Num. Drones	Obj value	% Savings	CPU time	Obj value	% Savings	CPU time
mFSTSP	1	2288.23	26.2317	15.8650	587.67	26.6612	14.6771
	2	1914.69	38.0834	37.3093	519.15	35.2892	33.8145
	3	1714.68	44.5361	49.5717	479.58	40.2486	21.0144
DRPT-T	1	2211.25	29.2235	71.4610	550.49	31.3512	61.6904
	2	1646.75	47.1858	111.8248	400.26	50.0400	69.0164
	3	1531.63	50.8134	102.5860	353.25	55.8329	50.0477

In problem instance set 1 with a broader operation area, the completion time tends to be longer than 2 sets. Besides, the time reduction effect of the additional use of drones seemed stronger in a large area. Interestingly, however, savings showed alike in the two regions. It can be seen that the use of drone trucks in a large area can save more delivery time, but the saving ratio is constant regardless of the size of the area. In most cases, mFSTSP takes less computation time than DRP-T, and both models consume more computation time in set1. The calculation time seems to increase as the number of drones increases, but some discrepancy has been observed. Figure 3.9 illustrates the computational result of two models in a bar graph.

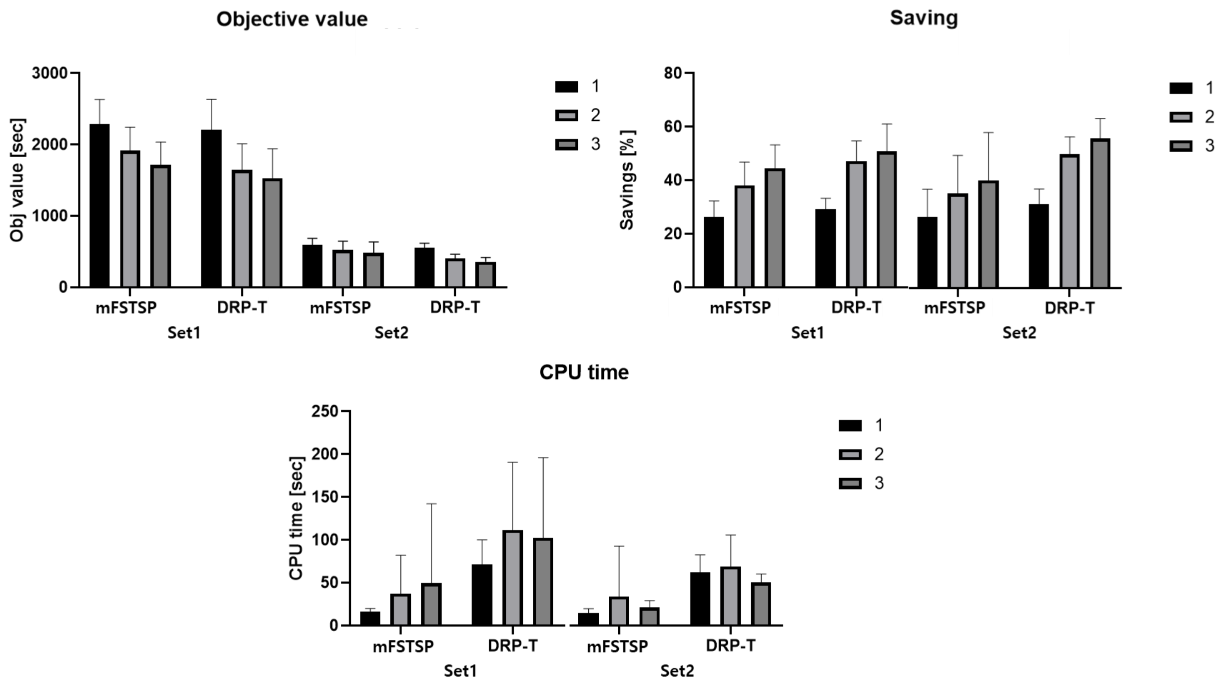


Figure 3.9. Computational result of mFSTSP and DRP-T in small instances.

3.4.2 Verification of proposed solution approaches

The computational result of the proposed solution approach MACH was compared with the optimal solution obtained using a mathematical model. This experiment used the same problem with 8 customers, 1 depot, and 3 parking locations as used in the session above. In the case of a single drone, the gap between optimal value and are relatively large, but the gap decreases sharply as multiple drones are used, to less than 1 percent. As a result, it shows the optimal solution and a gap of 4% on average, and we accurately found 16 optimal values out of 60 instances. On the other hand, the calculation time showed a tremendous saving of about 98% in all instances. This mighty computational power supports the practical contribution of this MACH heuristic.

Table 3.3. Computational result from MILP and MACH.

		MILP		MACH		
	Num. Drones	Obj value [sec]	CPU time [sec]	Obj Value [sec]	CPU time [sec]	Obj gap [%]
Set 1	1	2211.245	71.46103	2330.341	1.626853	6.722405
	2	1646.752	111.8248	1704.177	2.010685	3.587734
	3	1531.634	102.586	1544.676	2.496277	0.966903
Set 2	1	550.4889	61.69039	600.5187	1.506379	9.510406
	2	400.2648	69.0164	409.532	1.781361	2.570262
	3	353.2503	50.04773	356.4272	2.726085	0.85272
				Average gap [%]		4.035072
				Optimal values found		16/60

3.4.3 Performance comparison with large size instances.

As shown in the above experimental results, both mFSTSP and DRP-T are computationally expensive problems. Therefore, Murray and Raj (2019) propose a three-phase heuristic approach. In this section, through heuristics, mFSTSP and DRP-T are solved, and a comparative analysis of the two is performed in various sizes of problem instances. The size of the problem has 5 levels of the customer numbers 8, 10, 25, 50, 100. Each size levels have 10 instances for each problem set. The generated number of parking locations is equal to an integer value obtained by dividing the number of customers by 2.5 and is determined as the centroid of the customer location obtained using k-mean clustering. The average computational result for each size level is illustrated in Table. 3.4 and Figure 3.10.

Table 3.4. Computational result of MACH with various problem sizes.

			Set 1 (Seattle)			Set 2 (Buffalo)		
		Num. Drones	Obj value	% Savings	CPU time	Obj value	% Savings	CPU time
8	mFSTSP	1	2544.46	18.2475	0.1069	645.03	19.4917	0.0942
		2	2227.35	28.1247	0.1539	575.07	28.2937	0.1160
		3	1933.30	37.6105	0.1802	510.27	36.3746	0.1144
	DRPT-T	1	2330.34	25.1896	1.6269	600.52	25.0509	1.5064
		2	1704.18	45.3377	2.0107	409.53	48.8675	1.7814
		3	1544.68	50.4679	2.4963	356.43	55.4257	2.7261
10	mFSTSP	1	2648.69	20.0810	0.1490	700.49	18.8952	0.1462
		2	2373.58	28.3890	0.2182	608.32	30.0612	0.2231
		3	2181.51	34.3198	0.2489	544.48	37.1919	0.2292
	DRPT-T	1	2425.44	27.2180	2.8318	606.77	29.7423	2.8757
		2	1673.83	49.8805	3.6115	411.95	52.6036	3.4854
		3	1471.28	55.7611	5.5220	361.61	58.3467	5.9876
25	mFSTSP	1	5808.33	12.0045	2.0080	3715.54	16.0762	2.0024
		2	5209.28	20.8810	3.6238	3293.45	25.6090	3.6325
		3	4698.31	28.5145	4.5335	3008.18	32.1064	4.5257
	DRPT-T	1	4757.78	27.9567	14.3174	3192.40	27.9356	14.8154
		2	3099.07	53.0748	11.0976	1955.62	55.9592	15.1041
		3	2466.48	62.5739	63.3614	1598.98	64.0062	53.2643
50	mFSTSP	1	7613.78	13.4700	23.5487	5011.84	15.6047	25.0530
		2	6650.58	24.2989	39.3612	4510.90	23.9841	41.4086
		3	6180.45	29.7030	51.8476	3976.75	32.9026	53.9837
	DRPT-T	1	6647.69	24.2571	35.1320	4554.49	23.3793	28.5984
		2	4346.51	50.5404	45.6254	2604.58	56.1104	28.4083
		3	3025.80	65.5387	126.2259	2017.04	65.9475	101.8185
100	mFSTSP	1	10549.69	15.2653	618.8145	7196.73	13.1689	655.2133
		2	9562.32	23.2395	782.5988	6415.75	22.5522	800.3503
		3	8419.99	32.4008	947.5138	5659.16	31.6758	923.7381
	DRPT-T	1	10089.71	18.9937	108.0732	6397.77	22.9285	96.0494
		2	6331.24	49.2043	107.5848	3727.94	55.0896	167.7592
		3	4794.60	61.5073	628.6786	2661.99	67.9175	505.1441

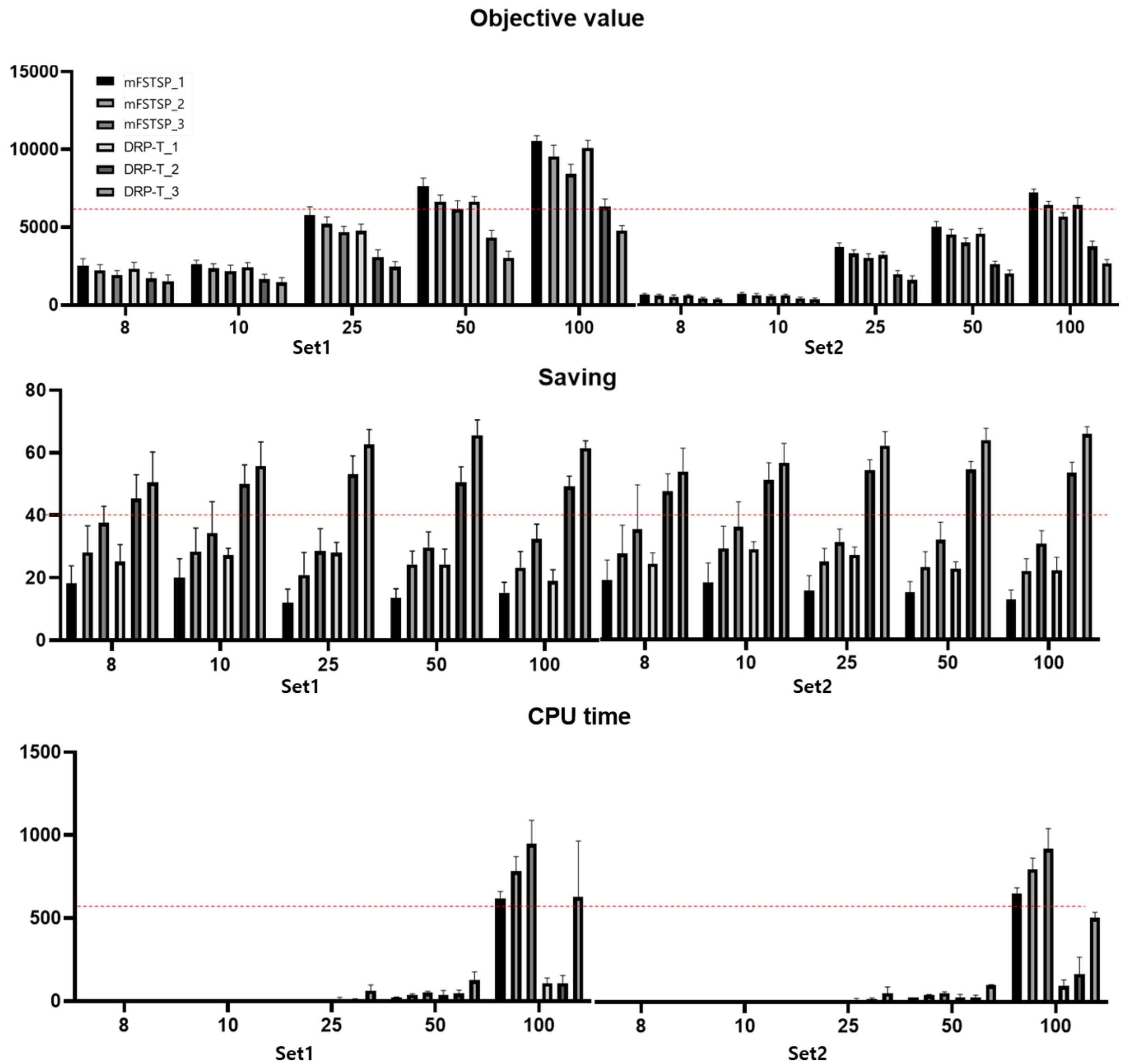


Figure 3.10. Result from MACH with the different problem sizes.

The objective value and computational time rise as the size of the problem increases. In particular, the objective value completion time decrease as drones are added, and as the problem size grows, the reduction increases. Overall, mFSTSP had a longer delivery time than DRP-T, and the difference increased as the number of drones increased. Relatively, compared to mFSTSP, the decrease in DRP-T was more noticeable. Besides, compared to set 2, which has a narrow operation area, set 1 showed a more significant reduction.

In particular, there is no noticeable difference in savings according to the size of the problem. At any size of both set1 and set2, each model showed a similar savings percentage. Therefore, even though there is a significant variation in delivery time, the time-saving proportion compared to the traditional truck-only system always gives a constant value. However, the change in the number of drones was evident. More drones always showed shorter delivery times with higher savings. The difference between the two models was also noticeable. As the number of drones increased, the difference between the two also increased. In other words, the more drones used, the more overwhelmingly the DRP-T's performance increased. The comparison of savings is shown in Figure 3.11.

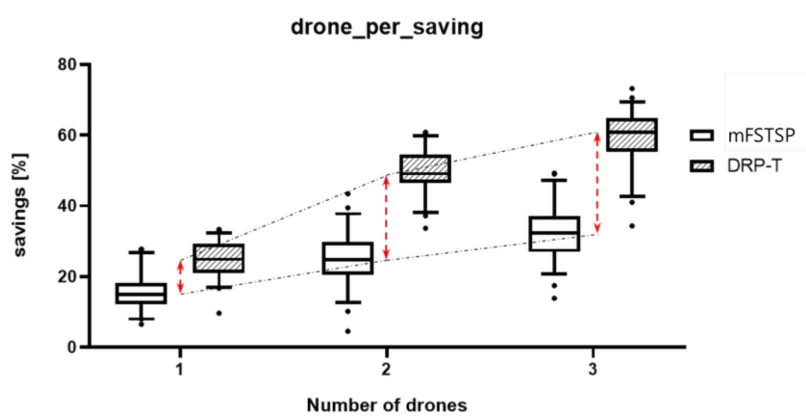


Figure 3.11. Comparison of savings with different number of drones.

The computational time was the result that responded most to the increase in the size of the problem. With the increasing number of customers, the process times got exponentially exploded.

Fortunately, 25 or fewer customers were solved in almost less than a minute. However, the problem of 50 and 100 customers required a significantly long calculation time. The increase in the number of drones has largely affected computation time. The singularity was that the calculation time of mFSTSP was short in the small size problem, whereas the calculation time of DRP-T tended to be relatively small as the size increased. According to the number of customers, the calculation time can be checked in detail in Figure 3.12.

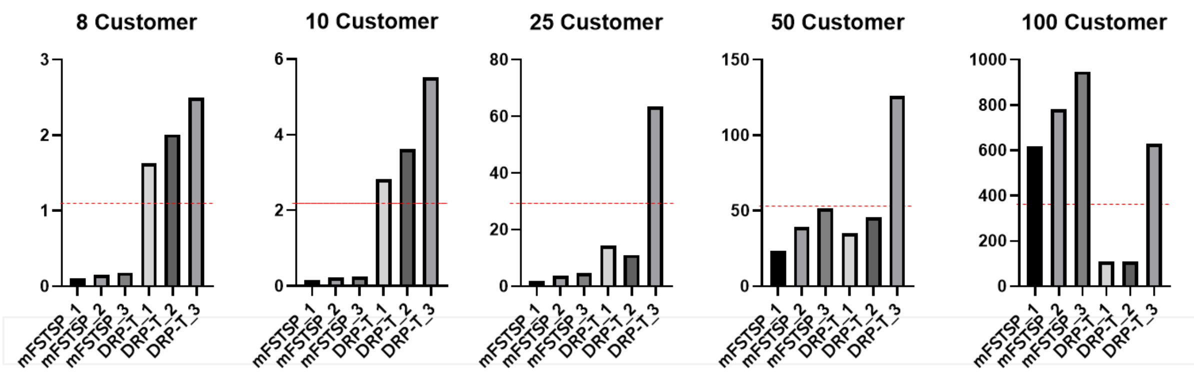


Figure 3.12. Computational time for each model with the different problem sizes.

3.5 Conclusion

In this chapter, we study a new type of collaborative delivery with drones and trucks. The empirical study shows that substantial saving is possible compared to truck-only and previous truck-drone systems. Since this study proposed a new delivery system, there are many potential future research topics. One promising area is to develop a solution approach that provides a near-optimal solution with reasonable computational time. In addition, an extension of the DRP-T problem with multiple trucks and consideration of drone recharging can be another interesting study. Since the model includes battery monitoring, a flexible recharging policy can be another extension.

CHAPTER 4 . AIRSHIP-DRONE HYBRID DELIVERY SYSTEM

4.1 Problem Description

The AFC delivery system is an airship-drone hybrid delivery system suggested by Amazon. In this chapter, we address the operational optimization issue of the AFC delivery system, which is a newly emerging concept using UAVs for the delivery context. A new mathematical model is developed that quantitatively supports the simultaneous operation of the airborne, UAVs, and supplementary shuttles. Operational and managerial issues of the AFC delivery system are analyzed through the system analysis. Moreover, the complementary cooperation of the AFC delivery system and existing UAV delivery service is investigated to efficiently serve the customer by taking advantage of each system.

The AFC delivery system is fundamentally a complex system that requires simultaneous cooperation of multiple components, including AFC, shuttle, and drone. This section elaborates on the technical status of each component and the overall operation of the AFC system.

4.1.1 System component

The AFC is a giant flying warehouse that carries delivery resources such as drones, inventory, and staff. To make this viable, advanced aircraft technique is required, which can maintain massive weight over a long period in high altitude at a low cost. In this regard, the hybrid cargo airship (HCA), a recent airship technology, seems to be the closest technology to this concept. The HCA is an aircraft with inert helium-filled that provides lasting lifts with a large payload and cargo capacity. The world's largest producer of hybrid cargo ships, Aeros Corp, already has a model ML86X that has 450 tons of payload with a 138x22x16 m3 cargo bay (Aeroscraft, 2021). In addition, the development of other HCA models has been ongoing by several companies in recent years (Airship Association, 2021; Hybrid Airship, 2021; Hybrid Air Vehicles, 2021), and many prototypes of the airship have already been tested and waiting for commercial use in the next few years (Govers, 2013; Liptak, 2019; Lockheed Martin, 2019). About these technological advances of HCA, Prentice & Knotts have positively evaluated the practicality of cargo management using airships by comparing it with jet engines (Prentice, 2016). The HCA technology also excels when applied to shuttles. The engine of the airship enables for vertical take-off and landing, which provides flexible operation without the need for a wide range of ground handling equipment. This advantage comes to a large extent due to the nature of the shuttle, which must move continuously between the high-altitude AFC and the ground MHF.

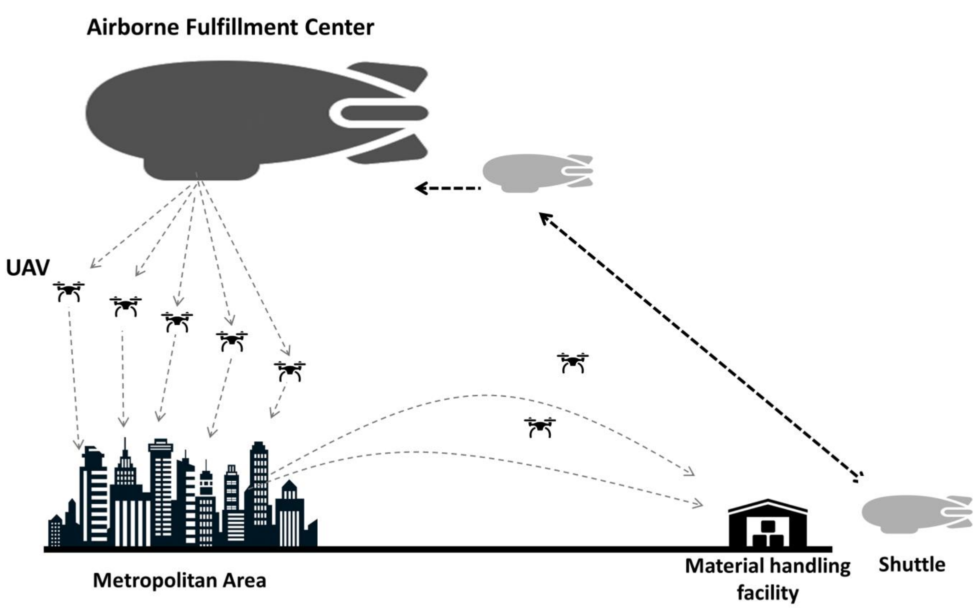


Figure 4.1. Operations of Amazon AFC delivery system (Berg, 2016).

Advances in technology have made the commercialization of drone delivery closer than ever before. Lately, The Federal Aviation Administration (FAA) has certified the first U.S. drone delivery operation to Alphabet's Wing Aviation in southwest Virginia (Chappell, 2019). This certification indicates that commercial drone delivery service is allowed in the United States. More recently, the FAA also issued a special certificate to test the latest delivery drone of Amazon Prime Air, and Amazon executive Jeff Wilke said that the package delivery by drone would be ready "within months." (Webb, 20109). Despite this progress to commercialization, there is still a simple technical barrier to widespread use regarding limited battery life (Koenig and Pisani, 2018). The drones to date have a limited flight time and require repeated charging. In this regard, the AFC system is an appealing approach for using drones as a delivery method since AFC carrying drones closer to customers mitigates the drone's battery problem while taking advantage of drones' fast delivery.

4.1.2 AFC System

In the AFC delivery system, the AFC is positioned at a high altitude, around 45,000 feet above a metropolitan area with an inventory. This inventory consists of items with higher chances to be purchased and with less than 5 lb, which can be carried by a drone. When an order is placed for an item in the inventory of the AFC, a UAV will engage the package and depart from the AFC to deliver it to the customer. After performing a delivery service, the UAV probably will not have enough battery to return to the AFC, proceeding to the ground MHF.

At the MHF, a shuttle is waiting for a departure to the AFC. The awaiting airship is a smaller airborne that is used to transport items to and from the AFC and has two important roles; 1) transport inbound items such as UAVs, inventory, staff, and fuel, 2) retrieve outbound overstock inventory, waste, and staff from the AFC. After successfully replenishing inbound and outbound items, the AFC can remain in the sky for extended periods of time. In addition, since the location of the AFC is not limited to a fixed location like a traditional ground-based material handling facility, the AFC can move to different areas depending on a variety of factors such as demand intensity and weather. As a result, the AFC delivery system can provide a flexible and faster delivery service compared to current practices. Figure 4.1 depicts the aforementioned AFC delivery system. Please refer to the description in Berg et al. (2016) for more details.

4.2 Mathematical Model

With the concepts developed above, the proposed model is formulated to derive the operation schedules of the AFC system. In this model, I is the number of customers distributed throughout the operating area. Each customer is defined as having their revenue value, and it may vary by time period t. In the operating area, there may be single or multiple shuttle ports (MHFs), and the shuttle departs from one of the shuttle ports to supply AFC consumables, fuel, and staff. The movement of AFC is limited to the J number of candidate locations in the sky, and AFC deploys UAVs from one of the locations to serve customers. After UAVs serve customers, they are navigated to the scheduled shuttle port and returned to the AFC by the shuttle. The shuttle will meet with AFC at one of the J candidate locations. The number of candidate locations can be unlimited and dynamic theoretically, but we used fixed points due to the computational issue. After the supplement, AFC will conduct delivery service continuously, and the shuttle will return to its depot. The followings represent the notations and the mathematical model to optimally support the simultaneous operations of the AFC, shuttles, and UAVs. The proposed mathematical model possesses real-time capability by using the data considering current location, schedules, and available UAVs.

Notations

System variables		
I	:	Set of customer locations
J	:	Set of candidate locations for AFC
S	:	Set of shuttle ports (MHFs)
O	:	Set of shuttle operation times. It is predetermined by the operation policy of the system
T	:	Set of time period under consideration
t_{max}	:	The last time period under consideration
d_{ij}	:	Distance between locations i and location j ($i, j \in ini_{afc} \cup I \cup J \cup S$)
r_i^t	:	Revenue for serving customer i in time t ($i \in I, t \in T$)
SR_{AFC}	:	Serviceable range of AFC
SR_{SP}	:	Serviceable range of shuttle port
o_e	:	The value of e^{th} element of set O
ini_afc	:	Initial location of AFC
ini_s	:	Initial shuttle port that scheduled to next operation
uav_{ini}	:	Number of initially available UAVs
uav_{max}	:	Maximum number of available UAVs
M	:	Positive large number
Decision variables		
X_{jis}^t	:	Binary decision variable, it is equal to 1 if a UAV departs from AFC location $j \in J$ and moves to shuttle port $s \in S$ after serving customer $i \in I$ in time period $t \in T$.
Y_j^t	:	Binary decision variable, it is equal to 1 if the AFC is located at $j \in J$ in period $t \in T$
Z_s^t	:	Binary decision variable, it is equal to 1 if the shuttle port $s \in S$ operates a shuttle at time $t \in T$
$U_{jj'}^t$	:	Binary decision variable, it is equal to 1 if the AFC is located at $j \in J$ in $t \in T$:$t \neq t_{max}$ and moved to $j' \in J$ in t+1.

Mixed integer linear programming (P1)

Maximize
$$\sum_{j\in J}\sum_{i\in I}\sum_{s\in S}\sum_{t\in T} r_i^t \cdot X_{jis}^t \quad (4.1)$$

Subject to
$$\sum_{s\in S} Z_s^t = 1 \qquad (\forall t \in T \cup O) \quad (4.2)$$

$$Z_{ini\_s}^{o_1} = 1 \quad (4.3)$$

$$\sum_{s\in S}\sum_{j\in J} X_{jis}^t \leq 1 \qquad (\forall i \in I, \forall t \in T) \quad (4.4)$$

$$\sum_{s\in S}\sum_{i\in I} X_{jis}^t \leq M \cdot Y_j^t \qquad (\forall j \in J,\ \forall t \in T) \quad (4.5)$$

$$\sum_{s\in S} X_{jis}{}^{t} \le 1 \qquad (\forall j \in J, \forall i \in I, \forall t \in T) \tag{4.6}$$

$$d_{ji} \cdot X_{jis}{}^{t} \le SR_{AFC} \cdot Y_j^t \qquad (\forall i \in I, \forall j \in J,\ \forall t \in T,\ \forall s \in S) \tag{4.7}$$

$$d_{is}{}^{d} \cdot X_{jis}{}^{t} \le SR_{SP} \quad (\forall i \in I, \forall j \in J, \forall s \in S, \forall t \in T) \tag{4.8}$$

$$\sum_{j\in J} Y_j^t = 1 \qquad (\forall t \in T) \tag{4.9}$$

$$U_{jj'}{}^{t} \ge Y_j^t - (1 - Y_{j'}{}^{t+1}) \qquad (\forall j \in J,\ \forall j \in J, \forall t \in T : t \ne t_{\max}) \tag{4.10}$$

$$\sum_{j\in J}\sum_{j'\in J} U_{jj'}{}^{t} \le 1 \qquad (\forall t \in T : t \ne t_{\max}) \tag{4.11}$$

$$\sum_{s\in S}\sum_{j\in J}\sum_{i\in I}\sum_{t=1}^{o_e} X_{jis}{}^{t} \le uav_{ini} \qquad (e=1) \tag{4.12}$$

$$\sum_{s\in S}\sum_{j\in J}\sum_{i\in I}\sum_{t=o_{e-1}+1}^{o_e} X_{jis}{}^{t} \le uav_{\max} \qquad (\forall e \ne 1) \tag{4.13}$$

$$\sum_{j\in J}\sum_{i\in I}\sum_{t=1}^{o_e} X_{jis}{}^{t} \le M \cdot Z_s^{o_e} \qquad (\forall s \in S, e=1) \tag{4.14}$$

$$\sum_{j\in J}\sum_{i\in I}\sum_{t=o_{e-1}+1}^{o_e} X_{jis}{}^{t} \le M \cdot Z_s^{o_e} \qquad (\forall s \in S, \forall e : e \ne 1) \tag{4.15}$$

$$X_{jis}{}^{t}, U_{jj'}{}^{t}, Y_j{}^{t}, Z_s{}^{t} \in \{0,1\} \qquad (\forall i \in I, \forall j, j' \in J, \forall s \in S, \forall t \in T) \tag{4.16}$$

The goal of the proposed MILP is to maximize the total revenue of the AFC delivery system, as shown in (1). Equation (2) indicates that the shuttle should depart from a shuttle port (MHF) in a shuttle operation time. Considering the proposed MILP is addressing the rolling horizon approach, (3) is necessary to return UAVs correctly. Suppose a new schedule is needed due to some system changes. During the previous periods, UAVs were moved to the shuttle port, which is scheduled for the next shuttle operation. Therefore, without (3), the shuttle may depart from another shuttle port and may not be able to fully supply UAVs. Via (4), the proposed model can serve customers selectively in a way to maximize the objective function. Equations (5) and (6) are developed to link AFC movements, shuttle operations, and UAV operations. UAVs should depart from an AFC and return to a shuttle port. Customer services are limited by the serviceable range of AFC using (7). Moreover, the serviceable range of the shuttle port is necessary to prevent the loss of UAVs. Without (8), the UAV may not successfully move to the scheduled shuttle port due to a lack of battery. Equation (9) guarantees the movement of AFC. The AFC must be located at one of the candidate locations for each time period. Equation (10) is developed to trace the movement of the AFC with the decision variable $U_{jj'}^{t}$, which is a product of, Y_j^t and $Y_{j'}^{t+1}$. Equation (10) linearizes the multiplication relationship and guarantees the linearity of the proposed MILP. Equation (11) limits the movement of AFC to moves only once per period. The availabilities of UAVs are limited by uav_{ini} and uav_{max} during the service via (12) and (13). Equations (14) and (15) ensure that the UAVs return to a shuttle port where the next shuttle operation is scheduled. Finally, (16) describes the decision variable of the proposed model. To derive initial operation schedules rather than the rolling horizon approach, (3), (12), and (14) are not necessary, and (13) and (15) should be extended to include a case of e=1.

4.3 Model Verification and System Analysis

The proposed MILP is tested and analyzed with a realistic case study. The target area for the case study is in San Francisco, San Hose, and Stockton areas of California, as shown in Figure 4.2. The problem instance includes 500 customer locations, 24 candidate AFC locations, and 2 MHFs. The time scope of system analysis was set to 24 hours. The revenue from the delivery service was estimated using the managerial data the Amazon, on which customers of the AFC delivery system are mainly Amazon Prime Members. During the first quarter of 2017, Amazon Prime achieved \$1.9 billion in revenue (Rao, 2017), with over 5 billion items shipped in 2017 (Perez, 2018). Assuming that the number of shipping follows the same for each quarter, the average revenue of each demand is estimated at \$1.52 (\$1.9 billion / 1.25 billion). Therefore, the revenue of each demand node is assumed to follow a normal distribution with a mean of \$1.52 and a standard deviation of $1.0. Two Amazon ground warehouses near San Jose and Stockton were selected as the shuttle ports. The 24 candidate AFC locations are randomly selected near MHFs locations. The serviceable range of the shuttle port was estimated based on the UAV capability. The Phantom 4 Advanced model of DJI can fly 72 km per hour, and the flight time is 30 minutes. Therefore, the serviceable range of the shuttle port (MHF) was set to 36 km. The serviceable range of AFC is set to 10 miles. The maximum number of UAVs in the AFC was set to 300. Data settings such as revenue, serviceable range, and number of UAVs may contain discrepancies from the actual data. Still, the proposed data structure and model can accommodate the real data to derive the schedule of AFC components. The proposed MILP and case study were tested via a commercial optimization software CPLEX 12.9 using a computer with a 3.1-GHz processor and 4GB RAM.

4.3.1 Analysis of the shuttle supplement periods.

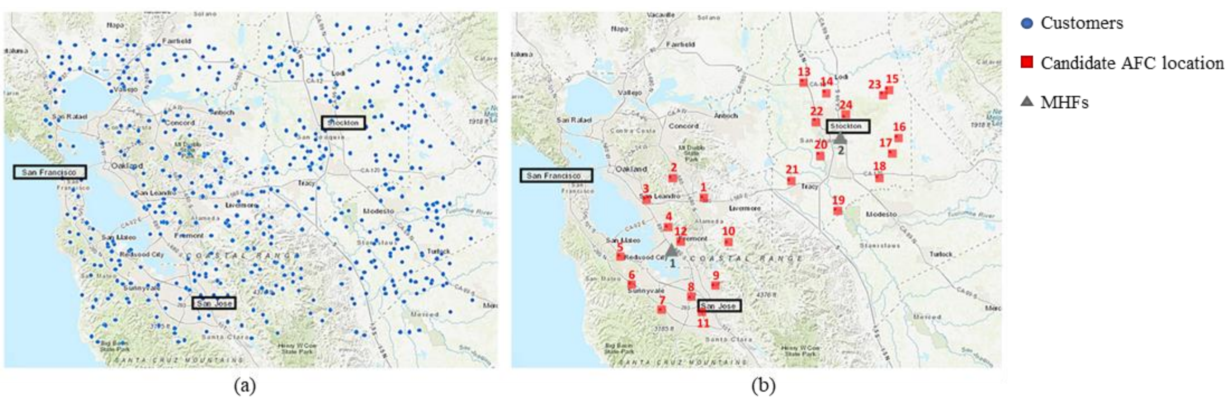


Figure 4.2. 500 Demand locations (a), 24 AFC candidates and 2 shuttle ports locations (b).

In the AFC delivery system, the role of the shuttle is to provide products, fuels, and UAVs as well as supporting the commute of pilots and staff who work inside an AFC. The cycle of the consumable supplement may depend on the size of AFC, shuttle, and demand forecasting.

However, for the flight time of pilots and employees, FAA strictly limits the consecutive flight time of flight crew members. According to the 14 CFR 91.1057 (FAA, 2018) and 14 CFR 91.1059 (FAA, 2012) of FAA, the flight time of pilots and flight attendants are restricted as follows:

- For flight attendants: Each flight assignment must provide for at least 10 consecutive hours of rest during the 24-hour period that precedes the completion time of the assignment (14 CFR 91.1057)
- For pilots: During any 24 consecutive hours, the total flight time may not exceed 8 hours for a flight crew consisting of one pilot; or 10 hours for a flight crew consisting of two pilots (14 CFR 91.1059).

Such regulations should be obeyed to manage the fatigue of flight crews and prevent any accidents. Therefore, in this case study, it is assumed that a shuttle is deployed every 8 hours. The AFC, shuttle, and UAV operation schedules are derived using the proposed MILP. Table 4.1 summarizes results, and yellow cells highlight the replenishment between AFC and shuttle. The schedule shows that AFC moves the operation area and stays in a certain area according to customer demand. There are three times of regular shuttle supplements when t = 8, 16, and 24. As the AFC moves, the shuttle also departs from a different shuttle port. The AFC and shuttle meet at locations 8, 17, and 6 to replenish inbound and outbound items for t = 8, 16, and 24, respectively. The result also shows that even there are uncovered demands and available UAVs, UAVs are not fully operational due to their limited serviceable range. If the customer's demand has been more intensively dispersed, AFC would have used more UAVs to fulfill the demand. The calculation time to derive the optimal operating schedule was 5.72 seconds, with a profit of $ 1100.36.

Table 4.1. Operation schedules of AFC, shuttle, and UAVs with the periodicity of 8 hours.

Period	1								2								3							
hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
AFC location	6	8	6	8	8	8	6	8	20	20	17	14	17	14	17	17	8	8	8	8	8	8	8	6
Available UAVs	274	246	220	192	164	136	110	82	274	248	222	199	173	150	124	98	272	244	216	188	160	132	104	78
Shuttle port	1								2								1							
#Serve tasks	218								202								222							

4.3.2 Use of the rolling horizon approach

In this section, the use of the proposed model for a rolling horizon approach is verified. During the service, many events may occur: new customer delivery requests may arrive, the customer may cancel their order, UAVs may fail, the weather restricts the service for a certain area, etc. In a rolling horizon approach, such changes can be addressed by deriving new operation schedules of system components. The changed information is collected and used as input data, and a new schedule can be derived together with the current location of the AFC, the number of UAVs available, and the next shuttle supplement schedule.

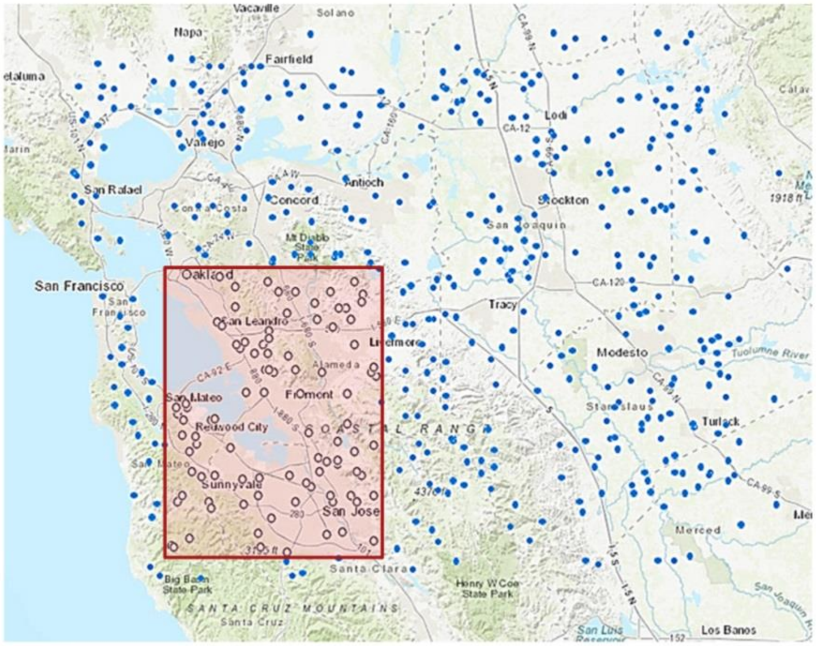


Figure 4.3. Graphical description of the undeliverable area from t = 20 to 30.

Suppose that from t = 20 to 30, heavy rainfall is expected to make some areas undeliverable by UAVs, as shown in Figure 4.3. If AFC visits the area and provides delivery service, it will cause a loss of UAVs, and customers may not be satisfied due to wet products. Moreover, it is assumed that new customer service requests are newly arrived until t = 40 as well as the weather change. In this situation, the derivation of the new schedule is highly recommended to reduce the loss of UAVs, prevent the decrease in customer satisfaction, and achieve more revenue. Due to the real-time perspective of the proposed MILP, AFC, shuttles, and UAVs can change their schedule and provide persistent AFC delivery services. Table 4.2 in Appendix C compares the original and changed schedules of AFC, shuttles, and UAVs. Blue and green cells in Table 4.2 show the changes and new schedules until t = 40. During a rainfall, AFC avoids the undeliverable area and provides delivery service persistently. New operation schedules of shuttles and UAVs are successfully derived and support the AFC delivery system. A rolling horizon MILP only consumes 22.53 seconds to derive new schedules. As a consequence, the proposed MILP is expected to be capable of real-time use and be a powerful tool for a persistent AFC delivery system by handling dynamic system changes.

Table 4.2. The result of rolling horizon approach.

<table>
<tr><td rowspan="6">Original schedule</td><td>Period</td><td colspan="8">1</td><td colspan="8">2</td><td colspan="8">3</td><td rowspan="6" colspan="16">Out of time scope in original schedule</td></tr>
<tr><td>hour</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>11</td><td>12</td><td>13</td><td>14</td><td>15</td><td>16</td><td>17</td><td>18</td><td>19</td><td>20</td><td>21</td><td>22</td><td>23</td><td>24</td></tr>
<tr><td>AFC location</td><td>6</td><td>8</td><td>6</td><td>8</td><td>8</td><td>8</td><td>6</td><td>8</td><td>20</td><td>20</td><td>17</td><td>14</td><td>17</td><td>14</td><td>17</td><td>17</td><td>8</td><td>8</td><td>8</td><td>8</td><td>8</td><td>8</td><td>8</td><td>6</td></tr>
<tr><td>Available UAVs</td><td>274</td><td>246</td><td>220</td><td>192</td><td>164</td><td>136</td><td>110</td><td>82</td><td>274</td><td>248</td><td>222</td><td>199</td><td>173</td><td>150</td><td>124</td><td>98</td><td>272</td><td>244</td><td>216</td><td>188</td><td>160</td><td>132</td><td>104</td><td>78</td></tr>
<tr><td>Shuttle port</td><td colspan="8">1</td><td colspan="8">2</td><td colspan="8">1</td></tr>
<tr><td>#Serve Tasks</td><td colspan="8">218</td><td colspan="8">202</td><td colspan="8">222</td></tr>
<tr><td rowspan="6">New schedule</td><td>Period</td><td rowspan="6" colspan="19"></td><td colspan="5">1’</td><td colspan="8">2’</td><td colspan="8">3’</td></tr>
<tr><td>Hour</td><td>20</td><td>21</td><td>22</td><td>23</td><td>24</td><td>25</td><td>26</td><td>27</td><td>28</td><td>29</td><td>30</td><td>31</td><td>32</td><td>33</td><td>34</td><td>35</td><td>36</td><td>37</td><td>38</td><td>39</td><td>40</td></tr>
<tr><td>AFC location</td><td>5</td><td>10</td><td>5</td><td>5</td><td>5</td><td>16</td><td>24</td><td>17</td><td>17</td><td>17</td><td>20</td><td>16</td><td>24</td><td>5</td><td>6</td><td>6</td><td>8</td><td>8</td><td>8</td><td>5</td><td>6</td></tr>
<tr><td>Available UAVs</td><td>209</td><td>203</td><td>196</td><td>189</td><td>182</td><td>276</td><td>253</td><td>227</td><td>201</td><td>175</td><td>149</td><td>125</td><td>102</td><td>277</td><td>251</td><td>225</td><td>197</td><td>169</td><td>141</td><td>118</td><td>92</td></tr>
<tr><td>Shuttle port</td><td colspan="5">1</td><td colspan="8">2</td><td colspan="8">1</td></tr>
<tr><td>#Serve tasks</td><td colspan="5">118</td><td colspan="8">198</td><td colspan="8">208</td></tr>
</table>

4.3.3 Bi-objective approach for UAV investment decision

In the AFC delivery system, the number of possible delivery services is limited by the number of UAVs in the AFC. The more UAVs in the AFC, the more delivery services it can provide. However, it requires a higher cost of purchasing more UAVs. Investigating trade-offs can provide an opportunity to economically operate the AFC delivery system. A bi-objective mathematical model (P2) is applied to investigate such relationships. In P2, uav_{max} becomes a nonnegative and integer decision variable. The P2 has bi-objective functions consisting of the maximization of $F1$ and the minimization of $F2$ (uav_{max}). Due to the inverse relationship between $F1$ and $F2$, solutions of P2 will have a Pareto relationship. Exact Pareto solutions can be obtained by applying the epsilon-constraint algorithm to P2. The use of the epsilon-constraint algorithm transforms P2 to P3. In

P3, *F2* moves to the constraint, and it is restricted by ε. Initially, the value of ε can be set to the upper bound value of *uavmax* or any large positive numbers. The epsilon constraint algorithm replaces the value of ε with the optimal *uavmax* value of the previous run and iteratively solves P3. In this manner, the algorithm iteratively solves the bi-objective problem and derives every exact Pareto solution without the loss of solution space (Chankong and Haines, 2008). Please refer to Abounacer et al. (2014) and Jin et al. (2018) for the recent use of the epsilon constraint algorithm for the multi-objective optimization problem.

Iteratively solving P3 may require a long computation time to derive every exact Pareto solution. Moreover, too many Pareto solutions may confuse the decision-maker. Therefore, a temporary gap can be subtracted from the epsilon value to derive a smaller number of Pareto solutions within a relatively short time compared with the original approach. Figure 4.4 shows the result of the UAV investment analysis by showing the Pareto relationship between the two objectives. In the analysis, the temporary gap was set to 10 to reduce both computation time and confusion coming from the overflow of decision options. Obviously, as the number of UAVs increases, total revenue increases if there are sufficient service requests within serviceable ranges. However, the increase in the number of UAVs requires higher UAV purchasing costs, and it may put an economic burden on the company's investment. In such a situation, the proposed P2 and P3 can provide business guidelines for investment and revenue by analyzing the relationship between the level of UAV purchase and total revenue based on the expected customer location and demand data.

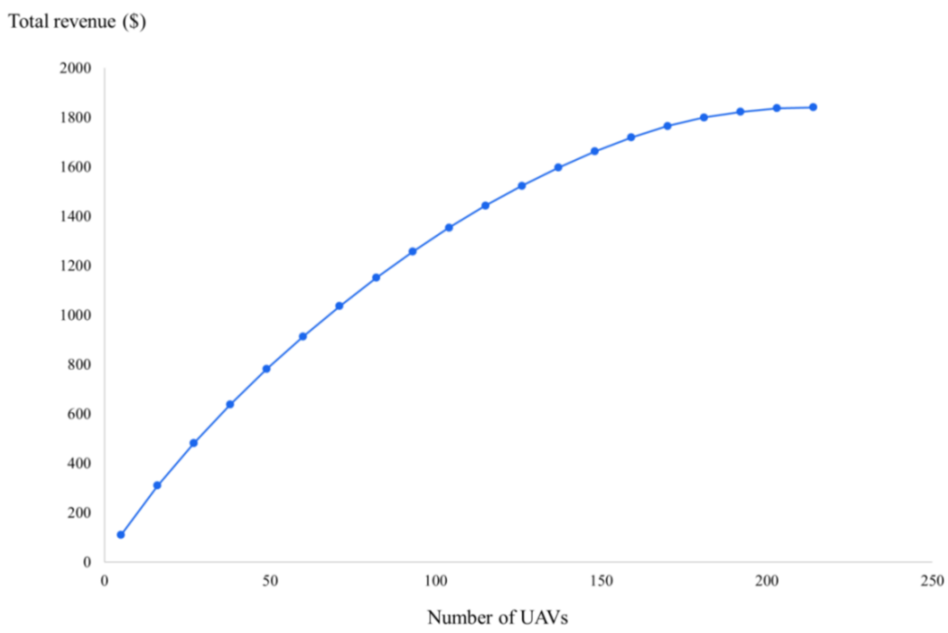


Figure 4.4. Pareto relationship between total revenue and UAV investment.

(P2)

$$\begin{aligned} &Max && F_1 && \\ &Min && uav_{max}\ (F_2) && (17) \\ &Subject\ to && && \\ &(2)-(16) && && \\ &uav_{max} \geq 0 && && (18) \end{aligned}$$

(P3)

$$\begin{aligned} &Max && F_1 && \\ &Subject\ to && && \\ &uav_{max} < \varepsilon && && (19) \\ &(2)-(16), (18) && && \end{aligned}$$

4.3.4 Model verification for large size problem

In this section, the proposed mathematical model is verified with the large size problems that are randomly generated. For the verification test, systemic parameters are proportionally increased, and the objective value and computation time are checked to verify the consistency of the proposed model. Table 4.3 summarizes the results. Obviously, more customer locations ensure higher revenue, and this can be observed in all cases. Similarly, as the number of AFC locations increases, the objective value and computation time changes in a way to a non-decrease manner. This is because more AFC locations provide more decision options for AFC locations. The extended decision options increase system performance and problem complexity. In our model, the shuttle port has a limited serviceable range that comes from the limited flight time of UAVs. Therefore, an increase in the number of shuttle ports means an increase in both the number of serviceable customers and total revenue. For example, in the case of 1000 customer locations and 100 AFC locations, the objective value continuously increases from 1208.4752 to 2306.7234 (90.88 %) as the number of shuttle ports increases. As a consequence, in the operational aspect of the AFC system, a sufficient number of shuttle ports will increase the number of serviceable customers, thereby maximizing revenue through the efficient utilization of limited AFC and UAV.

Table 4.3. Model verification with large size problems

Num. of Shuttle ports	Num. of AFC locations	**Number of customer locations** (Available number of the UAV)							
		250 (150)		**500** (300)		**750** (450)		**1000** (600)	
		Obj value	CPU time (sec)	Obj value	CPU time (sec)	Obj value	CPU time (sec)	Obj value	CPU time (sec)
1	25	500.9489	1.42	704.3042	2.58	869.4395	2.89	1164.7588	3.55
	50	508.6026	10.02	723.471	13.17	947.6552	13.67	1208.4752	14.34
	75	508.6026	73.58	723.471	74.61	947.6552	88.89	1208.4752	77.45
	100	508.6026	227.89	723.471	247.47	947.6552	242.22	1208.4752	237.94
2	25	500.9489	2.45	704.3042	4.16	966.3855	5.27	1290.2782	15.75
	50	514.3562	7.38	723.471	11.80	1068.722	13.52	1375.9264	17.97
	75	514.3562	33.39	723.471	39.69	1068.722	39.39	1375.9264	52.22
	100	514.3562	139.47	723.471	137.39	1068.722	120.88	1375.9264	173.27
3	25	500.9489	3.16	704.3042	4.48	966.3855	6.58	1290.2782	18.02
	50	514.3562	7.20	723.471	16.44	1068.722	17.47	1375.9264	21.88
	75	619.7323	32.20	941.5424	33.69	1326.9059	41.08	1703.815	52.98
	100	694.0942	47.88	1209.5883	44.41	1756.8803	55.06	2122.0344	65.16
4	25	500.9489	3.33	704.3042	5.69	966.3855	12.47	1290.2782	15.86
	50	514.3562	8.48	723.471	16.31	1185.2449	20.84	1794.0094	27.14
	75	731.5238	20.45	1376.8289	28.78	1834.1409	41.58	2306.7234	59.20
	100	731.5238	34.31	1376.9288	30.88	1834.2577	48.03	2306.7234	73.81

4.3.5 The comparison between new and existing systems

The introduction of the AFC system can conflict with the existing delivery system, and it may not always guarantee a superior delivery service. This section investigates the advantages and disadvantages of the AFC system and existing stationary UAV delivery service. The stationary UAV delivery service indicates Amazon Air, a trial service of the UAVs delivery service in December 2016 United Kingdom (CNN tech, 2016). In the system, UAVs launch from a ground warehouse (MHF), serves nearby customers, and return to the depot. On the other hand, the stationary UAV delivery service is limited to customers near the MHF. However, it is possible to provide intensive service since the shuttle is not required for periodic replenishment. This section quantitatively analyzes the characteristics of the two systems through mathematical optimization approach and explores the possibility of the complementary cooperation of the two systems.

To derive schedules for the stationary UAV delivery service, a mathematical model is developed. Please refer to Appendix A and B for the notations and optimization model of the stationary UAV delivery system. With the case study data in section 4, two models are implemented, and the solutions are compared. For the stationary UAV delivery service, NR was set to 2 per each time period (hour) t because the maximum flight time of the DJI Phantom series is 30 minutes or less. In addition, the serviceable range, SR_{MHF}, was set to 15 km considering the specification of the DJI Phantom series. Table 4.4 summarizes the results of two systems and a combined system, while Figure 4.5 graphically compares the results.

Table 4.4. Comparison results of two UAV delivery systems.

System	Serviceable range from MHF	Number of served customers	Number of served demand	Total revenue	CPU time (sec)
AFC delivery system	36km	122	642	1100.362	5.72
Stationary UAV delivery system	15km	36	864	1355.125	16.94
Complementary delivery system	36km	135	1,420	2309.660	199.42

The serviceable customer range of the AFC delivery system is broader than that of the stationary UAV delivery system. Therefore, the AFC system can serve a greater number of customers in a wide area. On the other hand, with the same number of UAVs, the stationary UAV delivery service can intensively serve customers within a short serviceable range for 24 hours. Therefore, it can serve more customer demands and achieve more revenue. However, the stationary UAV delivery system has also been shown to be a drawback. In general, the ground warehouse is located in the suburbs of the metropolitan area because of the expensive land price of the metropolitan area. Therefore, the stationary UAV delivery system may not serve customers in the metropolitan area due to the short serviceable range and MHF location, while the delivery service of the AFC system is not limited to the suburban area.

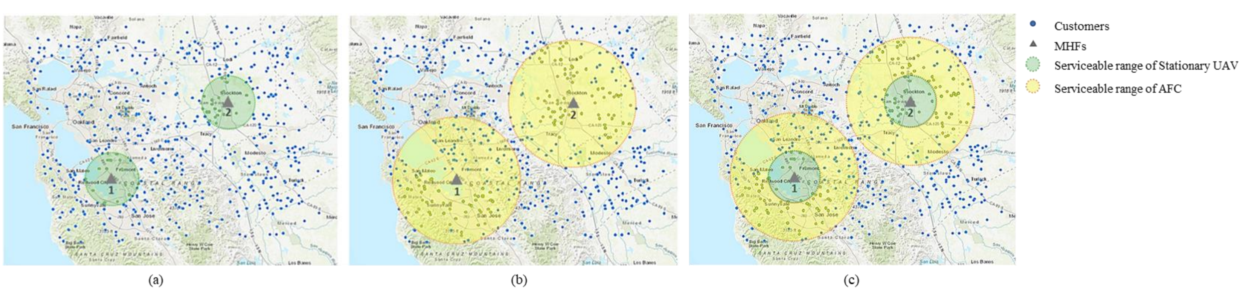


Figure 4.5. Graphical comparison of two UAV delivery systems.

These comparisons results show a clear distinction between the two UAV delivery systems' advantages and disadvantages. Moreover, this implies some insight into the advantages and disadvantages of the two UAV delivery systems. As a consequence, two delivery systems can be simultaneously used to complement their weaknesses and maximize benefits. For example, customer service requests near MHFs can be preferentially served by the stationary UAV delivery service. The remaining service requests may be served by the AFC delivery system. Figure 4.5 (c) shows the complementary cooperation of two UAV delivery systems. For the complementary system, the mathematical model in Appendix B is preferentially applied, and the MILP for the AFC delivery service is used for the remaining customer requests.

The total revenue of the complementary cooperation was $ 2309.660, which is a 109.90% increase compared to the AFC system and a 70.44% increase compared to the fixed UAV delivery system. However, compared to the sum of the independent operation of the two systems, the revenue of the complementary system was reduced by around 6%. This is an obvious result because, in the independent case, some demands may be served multiple times. In the complementary cooperation case, two systems divide their roles and efficiently serve customer orders. The total number of served customers and demand increased by 10.65%, 121.18% compared to the AFC system, respectively, and 275.0%, 64.35% compared to the stationary system, respectively. These results show that the cooperation system can possibly expand not only the total revenue but also the service coverage and capacity.

4.4 Concluding remarks

The development of UAV technology is expected to open a new generation of last-mile delivery of products. However, the limited serviceable range that comes from its finite battery capacity is the first challenge to be addressed before commercialization. Amazon's AFC delivery service is a novel approach that can mitigate this limited capacity and reduce shipping time. The efficient operation of the service gives the opportunity to offer more benefits to more people. However, it is challenging from the operational perspective. Therefore, the operational issue of the AFC delivery system is quantitatively investigated in this chapter. A mathematical model was developed to simultaneously derive the operation schedules of AFC system components. The proposed model is capable of real-time uses by supporting the rolling horizon approach. For the managerial decisions on the UAV investment, the bi-objective mathematical model is suggested, and the epsilon constraint method is applied to derive Pareto managerial options. Moreover, the AFC delivery system was compared with the existing Amazon UAV delivery service. The advantages and disadvantages of two UAV delivery systems are investigated, and the insights for the complementary cooperation of systems are suggested through a case study. As such, the proposed model not only optimizes the operation of the AFC delivery system but also analyzes the system from various perspectives and explores ways to coexist with traditional UAV delivery systems to provide better service to a larger number of customers.

This is the quantitative approach that investigates and analyzes the operation of the AFC delivery system. Therefore, many subsequent research topics can be carried out based on the analysis. First, there is an opportunity to globally optimize the complementary cooperation of the two systems simultaneously. A mathematical model dealing with the simultaneous optimization of the two systems can be developed, and alternative solution approaches may be required to find the optimal or near-optimal schedules. Also, the proposed mathematical model can be advanced by allowing multiple deliveries in a single journey. The inventory control of AFC will be an interesting topic along with the stochastic contexts.

CHAPTER 5 . MULTIPLE AIRSHIP-DRONE HYBRID DELIVERY SYSTEM

5.1 Problem Description

AFCs are cruising at a high altitude of around 45,000 feet over a metropolitan region carrying ready-to-ship stocks and delivery drones. A customer in the metropolitan area may place an order for an item in the inventory of the AFCs. In this case, an AFC engages a UAV with the ordered item and deploys it to the customer. After the UAV completes its delivery mission, it is unlikely to fly back to the AFC due to the high altitude of the AFC. Therefore, the UAV should navigate to a contiguous MHF.

The MHF is collecting used UAVs and preparing shuttles for a journey to the AFCs. The shuttle is a smaller size airship that transports inbound and outbound items between the AFCs and MHF. Shuttles replenish inbound products such as UAVs, inventory, staff, and fuels, all of which are needed for the AFC to maintain continuous operations. In addition, the shuttle retrieves surplus stock, waste, and staff from AFC operations and transports them to the MHF. The successful replenishment of inbound and outbound with the shuttle allows AFC to stay in the sky for prolonged periods and serve customers without landing on the ground. The AFC's location is not limited to a specific point, as is the case with conventional ground stations, so it can move around depending on various factors such as demand and weather changes. As a result, AFC can provide consumers with fast and flexible real-time delivery services. Figure 5.1 depicts the aforementioned AFC delivery system with a single AFC and a single MHF case. Please refer DETAILED DESCRIPTION of Berg et al. (2016) for more details.

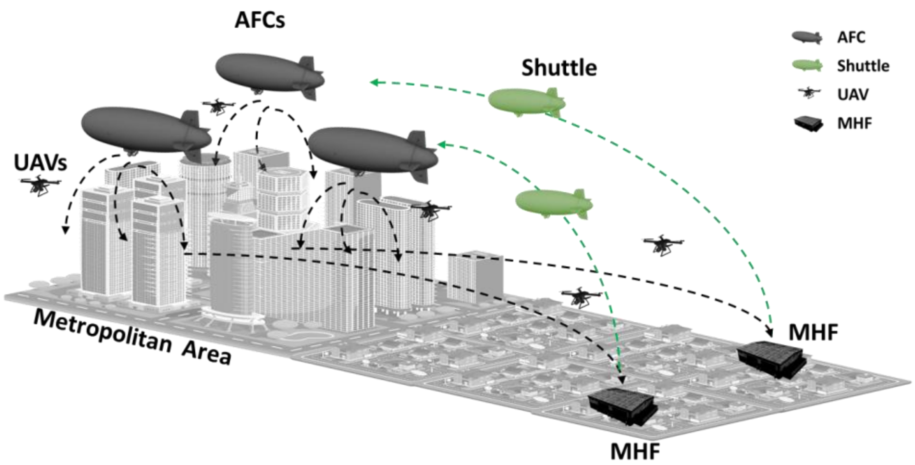


Figure 5.1. Multi-AFCs delivery system (Berg et al., 2016).

The AFC delivery system targets the metropolitan area where the demand is concentrated. In this study, the $|I|$ customers are scattered in the operating area, and each customer request AFC delivery service at certain time periods in $t \in Ti$. There are $|A|$ AFCs in the system, and their movement is restricted to the $|J|$ applicant positions. AFCs use UAVs to provide delivery services until the UAVs in the aircraft run out or get replenishment from the shuttle. The UAVs that have completed their delivery mission will move to and be collected in the MHFs. The MHF is a ground warehouse and a shuttle port where the shuttle launches from. The shuttle loads the inbound item, including the collected UAV, and schedules the location and time to rendezvous with the AFC. Shuttle and AFC meet at the promised location and time to exchange inbound and outbound inventory. After the supplement, AFC will conduct delivery service continuously, and the shuttle will return to its depot. In such situations, the goal of this study is to simultaneously optimize the operations of AFC system components based on the development of a mathematical optimization model. Specifically, operation schedules of multiple AFCs, shuttles, and UAVs will be optimally derived with given service duration in a way to minimize total system operation cost. Moreover, the proposed model has real-time capabilities with the rolling horizon technique. It provides the flexibility to handle unexpected events such as weather changes, inventory issues, etc. The followings represent the notations and the mathematical model to optimally support the AFC delivery system.

5.2 Mathematical Model

Notations

System variables		
A	:	Set of AFCs
I	:	Set of customers
J	:	Set of candidate locations for AFCs
S	:	Set of material handling facilities (MHFs)
O_a	:	Set of shuttle operation times for AFC $a\in A$. It is predetermined by the operation policy of the system (please refer to section 4.1) but changeable by the service situation ($a\in A$)
T	:	Set of time periods
T_i	:	Index of a time period that customer i requests AFC delivery service ($i\in I$)
t_{max}	:	The last time period under consideration
α_{ji}	:	Influence factor for the UAV descent travel from AFC to customer
d_{ij}	:	Distance between locations i and location j ($i, j \in I \cup J \cup S$)
SR_{UAV}	:	Serviceable range of UAVs
SR_{SP}	:	Serviceable range of MHFs
NS_s	:	Number of available shuttles at shuttle port s ($s\in S$)
$o_{a,e}$	:	The value of e^{th} element of set O_a
ini_AFC_a	:	Initial location of AFC a ($a\in A$)
$ini\_Shuttle_a$	:	Initial shuttle port that scheduled to replenish operation for AFC a ($a\in A$)
$UAV_{ini,a}$	:	Number of initially available UAVs at AFC a ($a\in A$)
$UAV_{max,a}$	:	Maximum number of available UAVs at AFC a ($a\in A$)
c_{AFC}		Unit operation cost of AFC
$c_{Shuttle}$		Unit operation cost of shuttle
c_{UAV}		Unit operation cost of UAV
M	:	Positive large number
Decision variables		
$X_{ajis}{}^t$	:	Binary decision variable, equal to 1 if a UAV departs from AFC a at location j serving customer i and moves to shuttle port s in time period t ($a\in A$, $j \in J$, $i \in I$, $s \in S$, $t\in T$)
$Y_{aj}{}^t$	:	Binary decision variable, equal to 1 if the AFC $a\in A$ is located at $j \in J$ in period $t \in T$
$Z_{asj}{}^t$	:	Binary decision variable, equal to 1 if the shuttle port s operates a shuttle at time t for AFC a located at j ($a\in A$, $j \in J$, $s \in S$, $t\in T$)

$U_{ajj'}{}^{t}$: Binary decision variable, equal to 1 if the AFC a is located at j in $t \in T$:$t \neq t_{max}$ and moved to j' in t+1 ($a \in A$, $j,j' \in J$, $t \in T$)

Mixed integer linear programming (P1)

Minimize

$$c_{AFC} \cdot \left(\sum_{a\in A}\sum_{j\in J} d_{ini\_AFC_a,j} \cdot Y_{aj}{}^{1} + \sum_{a\in A}\sum_{j\in J}\sum_{j'\in J}\sum_{t\in T, t\neq t_{\max}, t\neq 1} d_{jj'} \cdot U_{ajj'}{}^{t} \right) + c_{Shuttle} \cdot \sum_{a\in A}\sum_{s\in S}\sum_{j\in J}\sum_{t\in T} d_{sj} \cdot Z_{asj}{}^{t} + c_{UAV} \cdot \sum_{a\in A}\sum_{j\in J}\sum_{i\in I}\sum_{s\in S}\sum_{t\in T} (\alpha_{ji} \cdot d_{ji} + d_{is}) \cdot X_{ajis}{}^{t} \quad (5.1)$$

Subject to

$$\sum_{s\in S}\sum_{j\in J} Z_{asj}{}^{t} = 1 \qquad \forall a \in A, t \in T \cup O_a \quad (5.2)$$

$$\sum_{j\in J} Z_{a,ini\_Shuttle_a}^{o_{a,1}} = 1 \qquad \forall a \in A \quad (5.3)$$

$$\sum_{a\in A}\sum_{j\in J} Z_{asj}{}^{t} \leq NS_s \qquad \forall s \in S, t \in T \quad (5.4)$$

$$\sum_{a\in A}\sum_{j\in J}\sum_{s\in S} X_{ajis}{}^{t} = 1 \qquad \forall i \in I, t \in T_i \quad (5.5)$$

$$\sum_{i\in I}\sum_{s\in S} X_{ajis}{}^{t} \leq M \cdot Y_{aj}{}^{t} \qquad \forall a \in A, j \in J,\ t \in T \quad (5.6)$$

$$(\alpha_{ji} \cdot d_{ji} + d_{is}) \cdot X_{ajis}{}^{t} \leq SR_{UAV} \cdot Y_{aj}{}^{t} \qquad \forall a \in A, i \in I, j \in J,\ t \in T,\ s \in S \quad (5.7)$$

$$(d_{is}) \cdot x_{ajis}{}^{t} \leq SR_{SP} \qquad \forall a \in A, i \in I, j \in J,\ t \in T,\ s \in S \quad (5.8)$$

$$\sum_{j\in J} Y_{aj}{}^{t} = 1 \qquad \forall a \in A, t \in T \quad (5.9)$$

$$U_{ajj'}{}^{t} \geq Y_{aj}{}^{t} - (1 - Y_{aj'}{}^{t+1}) \qquad \forall a \in A, j \in J,\ j' \in J, t \in T : t \neq t_{\max} \quad (5.10)$$

$$\sum_{j\in J}\sum_{j'\in J} U_{ajj'}{}^{t} \leq 1 \qquad \forall a \in A, t \in T : t \neq t_{\max} \quad (5.11)$$

$$\sum_{s\in S}\sum_{j\in J}\sum_{i\in I}\sum_{t=1}^{o_{a,1}} X_{ajis}{}^{t} \leq UAV_{ini,a} \qquad \forall a \in A \quad (5.12)$$

$$\sum_{s\in S}\sum_{j\in J}\sum_{i\in I}\sum_{t=o_{a,e-1}+1}^{o_{a,e}} X_{ajis}{}^{t} \leq UAV_{\max,a} \qquad \forall a \in A, \forall e : e \neq 1 \quad (5.13)$$

$$\sum_{j\in J}\sum_{i\in I}\sum_{t=1}^{o_{a,1}} X_{ajis}{}^{t} \leq M \cdot \sum_{j\in J} Z_{asj}^{o_{a,1}} \qquad \forall a \in A, s \in S, e = 1 \quad (5.14)$$

$$\sum_{j\in J}\sum_{i\in I}\sum_{t=o_{a,e-1}+1}^{o_{a,e}} X_{ajis}{}^{t} \leq M \cdot \sum_{j\in J} Z_{as}^{o_{a,e}} \qquad (\forall a \in A, s \in S, \forall e : e \neq 1) \quad (5.15)$$

$$X_{ajis}{}^{t}, U_{ajj'}{}^{t}, Y_{aj}{}^{t}, Z_{as}{}^{t} \in \{0,1\} \qquad \forall a \in A, i \in I, j \in J, j' \in J, s \in S, t \in T \quad (5.16)$$

The FWSP aims to minimize the total operational cost of the AFC delivery system, as shown in (1). Specifically, the total operation cost consists of AFC, shuttle, and UAV operation costs. For each designated replenishment schedule, constraint (2) specifies that exactly one shuttle will perform replenishment per each AFC. If the proposed MILP is used for the rolling horizon approach, constraint (3) is required to properly return the UAV to the designated shuttle port. For instance, when there is a required change in the middle of an operation schedule, a new schedule is adjusted according to the change and previous schedule. Constraint (3) ensures that the UAVs are returning to the shuttle port that has been previously used in the last schedule so that the shuttle may depart from the one that has collected UAVs before it performs replenishment to AFC. Each shuttle port has a limited number of available shuttles, as shown in constraint (4). Via constraint (5), the proposed model should serve every service request. Constraint (6) ensures that all the UAVs are departing from the location where an AFC is currently located. The serviceable range of a UAV is restricted by constraint (7), which considers two UAV flights from AFC to a customer and a customer to a shuttle port at the same time. To properly address the descent travel of a UAV, the influence factor is used. In addition, this constraint ensures the safe return of the UAV by preventing the failure of the UAV from reaching the scheduled shuttle port due to the low battery. Constraint (8) represents the service range of the shuttle port for replenishment operation. Constraint (9) states, for each time period, an AFC should be positioned in only one of the possible locations. In constraint (10), the movement of AFCs is traced by updating the decision variable $U_{ajj'}^{t}$ which is equal to 1 when the Y_{aj}^{t}, and $Y_{aj'}^{t+1}$are both equal to 1. The movement of AFCs is limited to once per period by constraint (11). Constraint (12) and (13) ensure that the use of UAVs is not exceeding the number of available UAVs, $uav_{ini,a}$ and $uav_{max,a}$. Lastly, constraints (14) and (15) were developed to force the UAVs to return to the planned shuttle port for the next shuttle flight. Note that the proposed model is developed to use in the rolling horizon approach. Therefore, to derive operation schedules without using the rolling horizon approach, constraints (3), (12), and (14) are not necessary, and constraints (13) and (15) will cover the constraint (12) and (14) respectively by extending e to include a case of e=1. Note that the FWSP is an extension of the model that was proposed in a previous study conducted by Jeong et al., (2020)

5.3 Model verification and operation analysis

In this section, a case study is provided to verify the proposed MILP model and analyzed the AFC system through the experiment. The metropolitan area of Phoenix has been chosen, which has two Amazon fulfillment centers in the middle of the city. Figure 5.2 illustrates the problem instance, including 300 customer demand locations, 20 candidate AFC locations, and 2 MFHs. The location of customer demand and candidate AFC are randomly selected, and the location of the MFHs has been set as Amazon ground warehouses located in Phoenix. The serviceable range of a UAV was estimated based on the specification of a drone named Phantom 4 Advanced model of DJI can fly 72 km per hour and the flight time is 30 minutes (DJI (2018)). Therefore, the shuttle's serviceable range is estimated to be 36 km. The number of UAVs in the AFC was set to 100, and the influence factor for the UAV descent travel α_{ji} was set to 0.1. The operation cost of the UAV was set to \$0.03 per kilometer based on the cost estimation of Deutsche Bank (Business Insider, 2016). The operation costs of AFC and shuttle are set to \$30 and \$10 per kilometer. The proposed model and case study were tested with a personal computer with a 3.1-GHz processor and 4GB RAM.

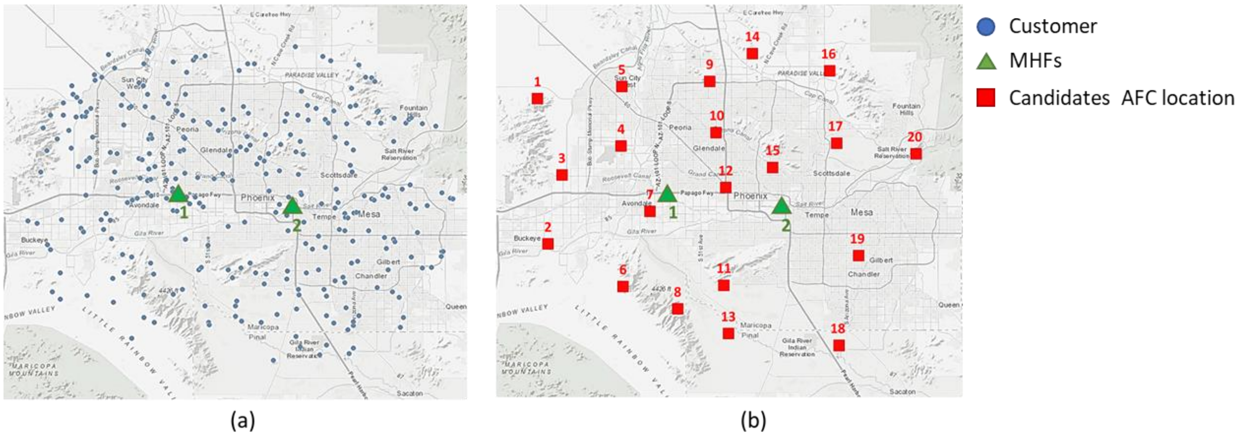


Figure 5.2. 300 Demand locations (a), 20 candidate AFC locations, and 2 shuttle ports locations (b).

5.3.1 Single AFC case

The AFC's persistent operation without visiting the ground warehouse necessitates the shuttle's replenishment operation. The shuttle supplies products, fuels, and returned UAVs, as well as supports the commute of pilots and employees who work inside an AFC. However, for the work hour of the pilots and employees in the aircraft, Federal Aviation Administration (FAA) strictly limits the consecutive flight hours of crew members. The FAA's 14 CFR 91.1057 (FAA, 2018) and 14 CFR 91.1059 (FAA, 2012) regulations limit pilot and flight attendant flight time as follows:

- For flight attendants: Each flight assignment must provide for at least 10 consecutive hours of rest during the 24-hour period that precedes the completion time of the assignment (14 CFR 91.1057).
- For pilots: During any 24 consecutive hours the total flight time may not exceed 8 hours for a flight crew consisting of one pilot; or 10 hours for a flight crew consisting of two pilots (14 CFR 91.1059).

To control flight crew exhaustion and avoid an accident, certain regulations should be obeyed. Therefore, the replenishment operation of the shuttle, in this numerical analysis, assumes to have 6 hours interval, which is strictly less than 8 hours. To efficiently support such operations, we used an hour as a unit for '*t*' index during the numerical study. Please note that the shuttle operation period and time unit can be changeable based on the managerial situation. The proposed MILP is used to derive optimal schedules for the AFC, shuttle, and UAV operation. The schedule is summarized in Table 5.1, with blue cells indicating the replenishment operation of shuttles. The AFC may move the operation area or stay in a particular area to provide delivery service. There are four times of regular shuttle supplement when $t = 6, 12, 18$, and 24. Depending on the location of the AFC and the shuttle port, the system decides which shuttle port to perform the replenish job on. In the derived schedule, the AFC and shuttle will meet at AFC locations 4, 20, 3, and 15 for inbound and outbound replenishment at periods t = 6, 12, 18, and 24, respectively. The AFC utilizes 75 % of UAVs on average to serve 300 customers during 4 periods. The proposed MILP successfully derives the operation schedule of AFC, shuttles, and UAVs with a relatively short computation time of 20.53 seconds. The total operation cost of the AFC delivery system was $9753.42, and most of the operation costs come from the movement of AFC and shuttles. However, please note that the current total cost is a virtual value due to the opaqueness in the operation cost of the AFC and shuttle. In addition, the provision of quick delivery through the AFC service extends Amazon's ecosystem by contributing to the increase in the number of Amazon Prime members and allows additional benefits through membership fees. Therefore, the operation cost is somewhat covered by the expansion of their ecosystem and Amazon Prime membership fee. The proposed mathematical model is able to derive operation schedules of a variety of data structures, including different operation costs.

Table 5.1. Detailed operation of AFC system components with the 6 hours interval replenishment.

Period	1						2						3						4					
hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
AFC location	4	4	4	4	4	4	15	15	15	15	15	20	4	4	4	2	3	3	18	18	18	18	18	15
Usable UAVs	88	72	60	52	40	32	88	75	57	39	28	23	90	75	64	49	30	18	91	79	68	55	43	27
Shuttle port	1						2						1						2					
#Serve tasks	68						77						82						73					

5.3.2 Use of the rolling horizon approach.

Even during the scheduled operation, unexpected changes such as new delivery requests, order cancellations, drone failures, etc., may occur. In particular, aerial transportation is highly influenced by climate or air traffic, so it needs to be more flexible to change. For the resilient adaptation to these systemic changes, we implement the rolling horizon approach to the proposed MILP that derives a new operation schedule in the middle of the ongoing schedule according to changes. When a systemic change is observed, the original schedule at the time of the change, as well as the changed system variables, are used as new inputs in the model. A new operation schedule is derived along with the new input based on the current AFC's position, resource state, and shuttle replenishment schedule.

In this section, we suppose that there are certain regions of the target that area cannot be delivered by the AFC system formed from t = 20 to 36 due to unexpected circumstances such as heavy rain, as shown in Figure 5.3. Such a situation forces revision of the previous schedule. As a result, all deliveries that belong to an undeliverable area must be replaced with alternative delivery methods such as traditional delivery or wait until aerial delivery can resume. Therefore, the demands of customers who are unable to deliver are automatically returned by the system. At the same time, AFC accepts new customer demand due to the occurrence of situations such as umbrellas because of heavy rain. In this experiment, a new schedule was drawn up to time horizon 36 with the situation in which customer demand changes overall from t=20 according to environmental changes.

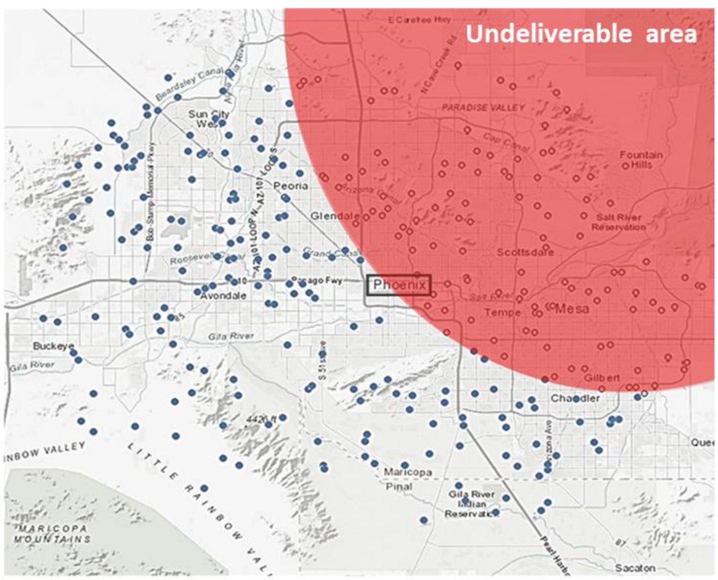


Figure 5.3. The undeliverable area from t = 20 to 30.

Appendix A1 shows the original and newly derived schedules with the rolling horizon approach. The green cells denote the changed schedule compared to the previous, and the red cells show a new schedule until t =36. During t= 20 to 30 periods when the no-delivery zone was formed, AFC appeared to be carrying out new incoming deliveries avoiding the affected area. More importantly, the new schedule is successfully derived in 12.92 seconds with a rolling horizon approach. This can be seen as computationally reasonable for real-time use, assuming that one time period is set as an hourly unit in this model. As a result, this model FWSP is capable of continuous use for AFC delivery systems as it has the ability to handle dynamic system changes in real-time. In conclusion, this model, FWSP, has the capability to handle dynamic system changes in real-time, making it possible to operate persistently in AFC delivery systems in a practical manner.

5.3.3 Multiple AFCs case

The proposed MILP is capable of operating multiple AFCs simultaneously. This section will investigate the use of two AFCs for the service area described in section 5.1. Table 5.2 shows the operation schedules of two AFCs, shuttles, and UAVs with 300 customer service requests. With two AFCs, AFCs divide the service area to minimize the movement of AFCs. AFC 1 is mainly located in candidate locations 1, 2, 4, and it moves only two times during the service periods. AFC 2, on the other hand, moves relatively frequently to serve customers, but its movement is limited mainly to candidate locations 15, 14, 18, 19, and 20. The roles of AFC 1 and 2 are clearly distinguished. AFC 1 is primarily responsible for western Phoenix and is supplied by shuttle port 1. AFC 2, on the other hand, is supplied by shuttle port 2 and is dedicated to the eastern part of Phoenix. However, the total cost is $ 9727.69, which is not much different from that of a single AFC case. This is probably due to the increase in shuttle operation while the total AFC movement distance has decreased. The total computation time was 585.93 seconds, which is relatively short for the derivation of operation schedules for two AFCs, shuttles, and UAVs.

Table 5.2. Operation schedules with simultaneous use of two AFCs.

AFC 1	Period	1						2						3						4					
	hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
	AFC location	1	1	2	2	2	2	2	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
	Usable UAVs	92	84	81	78	74	70	90	87	84	83	80	74	86	73	67	56	48	42	98	89	84	80	70	67
	Shuttle port	1						1						1						1					
	#Serve tasks	30						26						58						33					
AFC 2	Period	1						2						3						4					
	hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
	AFC location	19	19	19	19	19	19	19	19	20	19	15	18	18	19	19	19	19	19	19	17	19	19	19	19
	Usable UAVs	95	93	86	77	72	65	97	85	75	60	54	43	100	99	91	90	87	82	85	83	74	61	61	57
	Shuttle port	2						2						2						2					
	#Serve tasks	35						57						18						43					

5.4 Quantitative decisions on managerial issue

The proposed mathematical model can be a powerful tool for managerial issues in the AFC delivery system. In this chapter, some managerial issues will be quantitatively addressed by the use of the proposed MILP and the development of a new MILP for the existing system.

5.4.1 Service resource design

Service resource design is an important managerial issue for the setup and operation of a new service. In the AFC delivery system, a promising number of AFCs and UAVs will hugely affect the system cost. In this chapter, such issues will be quantitatively addressed by running the proposed MILP to find a minimal system configuration that satisfies service feasibility. In detail, with 100 customers, 10 AFC candidate locations, 24 time periods with 4 shuttle supplements, the number of UAVs meeting the service feasibility and operation cost were derived by increasing the number of AFCs one by one. Table 5.3 summarizes the results.

Table 5.3. System configuration and resource design of AFC delivery system

Num of AFCs	Service feasibility	Operation cost				CPU time
		AFC	Shuttle	UAV	Total	
1	Infeasible	-	-	-	-	-
2	Feasible	2203.73	961.83	69.19	3234.75	72.11
3	Feasible	1765.75	1394.10	68.72	3228.58	229.92
4	Feasible	1251.30	1685.92	68.34	3005.57	228.22

At least two AFCs are required to serve the service region. As the number of AFC increases, the operation cost of AFC decreases because the AFCs divide service region to minimize their movement. However, each AFC requires supplements by the shuttles. Therefore, as the number of AFC increases, the operation cost of the shuttle also increases. Please note that in the AFC delivery system, each AFC requires regular shuttle supplements, at least for commuting of human staff. Figure 5.4 specifically depicts the shift in operation costs of each component as the number of AFC increases. In consequence, the operation of 3 AFCs and 18 UAVs was found to be an optimal resource design in this case study. Also, it has been found that the proposed MILP can be successfully used as a managerial tool for system resource design.

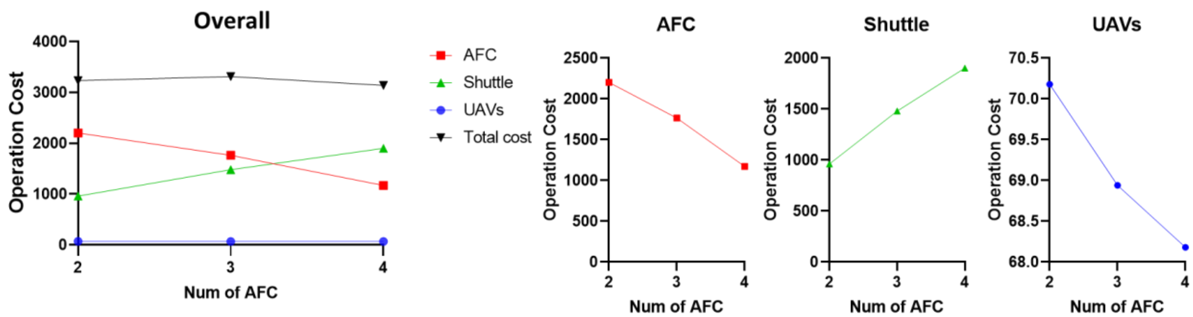


Figure 5.4. Operation cost of each component in AFC system with different numbers of AFCs.

5.4.2 Service area clustering for multiple AFCs

Simultaneous use of multiple service resources can lead to managerial problems such as confusion of jurisdiction and responsibility shifting. From a managerial perspective, identifying service areas for each resource can help forestall these problems. For multiple AFCs delivery services, we can resolve the complexity issue by simply applying the clustering approach (*K*-means) with the proposed MILP (Yadav and Sharma, 2013). Specifically, we can divide our service area into $|A|$ number of clusters and assign a single AFC for each cluster. The proposed MILP with a single AFC setting will be repeatably run $|A|$ times to provide the service schedule of each AFC – cluster pair. This combination of *K*-means clustering, and a single AFC model will prevent managerial and operational conflict between multiple AFCs. In addition, it provides computational efficiency for deriving service schedules, albeit there are some optimality losses.

Algorithm 2. K-mean clustering (pseudo code)

Select the the centroids arbitrary among customer locations
While (centroid converge)
  For each customer location *i*
    Find nearest centroid *c*
    Assign customer *i* to the centroid *c*
  For each cluster *c*
    Update centroid according to assigned customer
Return centroid, assignment

The derivation of the global optimal solution is guaranteed from the mathematical model. However, it usually requires hundred seconds of computational time. On the other hand, the combination of *K*-mean clustering and the single AFC model loses optimality of 18.98% on average. However, it derives such solutions within a second. The more system components there is, the greater impact on computational efficiency. Furthermore, it will enable the operation of the AFC delivery system by deriving a qualified solution even in situations where the derivation of the global optimality schedule is limited.

Table 5.4. Computational result of applying clustering approach and single AFC model.

Num of AFCs	Multiple AFCs model: Operation cost: AFC	Shuttle	UAV	Total	CPU time	*K*-mean clustering & Single AFC model: Operation cost: AFC	Shuttle	UAV	Cluster total	Sum	CPU time
2	2203.73	961.83	69.19	3234.75	72.11	870.50	668.77	29.73	1569.00	3824.71	7.11
						1826.09	389.08	40.52	2255.71		
3	1765.75	1394.10	68.72	3228.58	229.92	870.50	668.77	26.20	1565.47	3801.21	4.45
						633.47	668.07	24.10	1325.65		
						362.35	529.55	18.18	910.08		
4	1251.30	1685.92	68.34	3005.57	228.22	0.00	668.77	19.21	687.98	3899.06	3.65
						633.47	668.07	19.11	1320.66		
						0.00	713.30	15.34	728.65		
						617.83	529.55	14.38	1161.76		

5.4.3 Cooperation of AFC and stationary UAV delivery service

The main advantage of the AFC delivery system comes from its mobility. The warehouse with mobility offsets the limited serviceable range, which is a fundamental disease of delivery drones, and provides advanced delivery service to a wide operation area. However, behind these advantages, there are side effects such as continuous replenishment and high operating costs. The conventional warehouse with no mobility can also be used for drone delivery. One illustration is the stationary UAV (SUAV) delivery system suggested by Jeong et al., (2020). In the Stationary Unmanned Aerial Vehicle (SUAV) system, the drones are released from a warehouse in a fixed location, serving local clients, and then return to the warehouse. Figure5.5 depicts the SUAV system servicing customers in a metropolitan area.

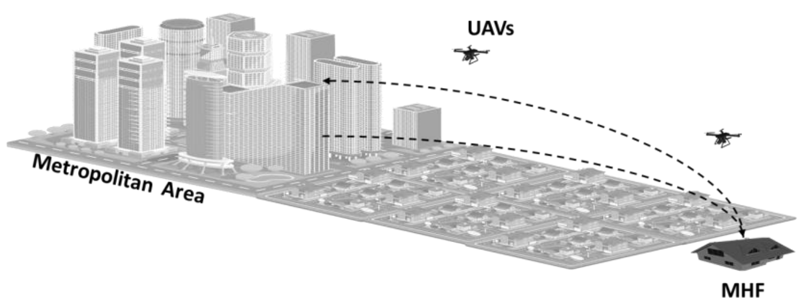
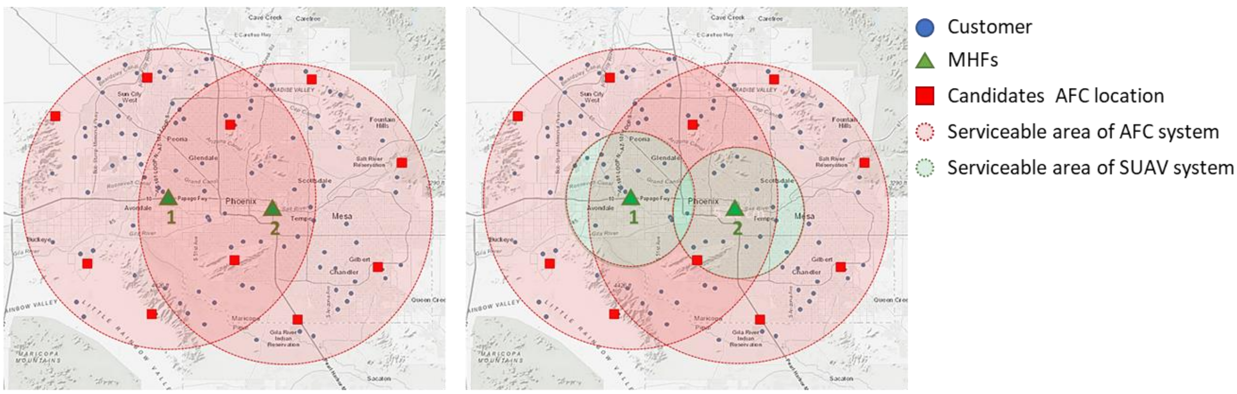


Figure 5.5. Operations of SUAV delivery system.

The AFC system can serve a broad customer area due to its high mobility, while the SUAV delivery service is only open to consumers who live near the fulfillment center. However, since the use of an airship and shuttle would not necessitate, it has low operation costs and a simple distribution network system. This section suggests a complementary scheme of the AFC system and the stationary systems and discusses their strengths and disadvantages using case studies. For the cooperation system, two mathematical models are used, FWSP for the AFC system and a MILP model for the SUAV proposed by Jeong et al., 2020 but with a modified objective function that minimize the operation cost. The notations and optimization model for the SUAV system can be found in Appendices A and B. Since the DJI Phantom series has a maximum flight period of 30 minutes or less, the case study set NR= 2 for each time period (hour), and the serviceable range SR_{MHF} was set to 15 km. Figure 5.6 graphically illustrates the serviceable range of both systems. Table 5.5 describes the result of the multi-AFC system and the combined system.



(a) (b)

Figure 5.6. Serviceable range of each system. (a) AFC system, (b) cooperation system.

Table 5.5. Results of multi-AFC system and cooperation system with different numbers of AFCs.

Num of AFCs	Multiple AFCs model					AFC & SUAV cooperation system					
	Operation cost				CPU time	Operation cost					CPU time
						AFC system			SUAV	Sum	
	AFC	Shuttle	UAV	Total		AFC	Shuttle	UAV			
2	2203.73	961.83	69.19	3234.75	72.11	2203.73	961.83	66.51	5.61	3237.69	28.82
3	1765.75	1394.10	68.72	3228.58	229.92	1765.74	1394.10	66.00	5.61	3231.45	67.16
4	1251.30	1685.92	68.34	3005.57	228.22	1251.30	1685.92	65.39	5.61	3008.22	53.42

The result shows that there was little difference in operation costs between the two systems. The traveling costs of AFC and shuttle, in particular, were exactly the same in each system. This ensures that even though SUAV acquired some customers through cooperation, the movement of AFC remains unchanged. The same trajectory of AFCs not only results in the same AFC operation cost but also the same shuttle operation cost that varies depending on the AFC location. As a result, the difference between the two systems depends on the use of the UAV. Of the 100 total customers used in the case study, only 7 are available to be served by SUAV's serviceable area. And the result means that the shipping cost of UAVs using AFC is subtly cheaper than using SUAV. This can be interpreted as the advantage of flexible mobility of the AFC mentioned above. In addition, the SUAV has a relatively simple operation procedure compared to AFC, and it is a model with relatively low computational complexity. Therefore, the number of customers divided in a collaborated system showed drastically reduced calculation time from 20% to 40%.

Apart from comparing the AFC system and the cooperative system, the operation cost of SUAV accounted for a minimal amount, about 0.2% of the total collaborative approach. In comparison, despite the costly operation, the AFC system can benefit from extended serviceable capacity, over five times broader coverage, securing customers, and quicker distribution by partially overcoming the flight range limitations of UAVs, which is unquestionably a viable and competitive delivery method. In this respect, two distribution mechanisms may mitigate shortcomings and optimize benefits in the appropriate case. Delivery services for customers located densely near MHF, for instance, maybe prioritized through SUAV delivery services. In addition, in the opposite case, the customer's point is spread over a large area, the AFC delivery system can manage the service needs. As a result, the situational operation of both systems will optimize the usability of UAV delivery services.

5.5 Concluding remarks

Technology advancement contributes to the creation of previously unimaginable services. One of them is Amazon's AFC system, which seeks to innovate last-mile delivery. The successful operation of this system provides the benefit of minutes delivery to more consumers. On the other hand, the AFC system is complicated since it is a dynamic system that needs simultaneous coordination between multiple components.

In this study, we investigate the AFC delivery system quantitatively and qualitatively through various analyses. First, we proposed an extended mathematical model designed to drive optimal schedules that are simultaneously coordinating the multi-components operation, AFC, shuttle, and UAVs. By implementing the rolling horizon approach, the proposed model enables real-time applications and is tested through scenarios in which undeliverable areas by unexpected events. The model was also evaluated in a scenario where the number of AFCs increased. In all cases where resources are not scarce, the model has successfully generated an optimal schedule. However, as the number of AFCs increased, the complexity of the problem increased significantly. Accordingly, we presented and tested an efficient computational approach in the form of divide-and-conquer through k-means clustering. In addition, the cooperation of the AFC system and stationary UAV delivery service has been proposed and tested with comparative analysis with the AFC system. The results implicitly present the advantages and disadvantages of each system from managerial aspects.

This study was performed not only by optimization of the AFC operation but also by a quantitative approach that investigated the delivery system. Since the AFC system has not yet been implemented and has few related studies, there are myriad opportunities for future research. For example, an extension FWSP can be developed, modeling the impact of payload on power consumption or by monitoring AFC's fuel consumption. Furthermore, it is feasible to suggest a model that has flexible AFC's replenishment operation depending on the amount of remaining inventory or fuel. It would be interesting to investigate the schedule for larger instances further. There could be insights gained from a greater range of target customers, the number of MHFs, and AFCs. This problem can be handled more efficiently with solution approaches with strong computational capacity, such as heuristics or machine learning.

CHAPTER 6 . COMPARATIVE ANALYSIS BETWEEN DELIVERY SYSTESMS

The above chapters investigate the operation optimization method and performance measurement of two-hybrid systems, truck-drone, and airship-drone, through quantitative analysis. Although the analysis provides numerical values which represent the characteristics of each system, in practice, it may not be sufficient to support decision-makers about which systems are superior to each situation. In this chapter, we perform the performance measurement of the hybrid and conventional delivery systems through a comparative analysis in terms of operational cost and delivery latency. By conducting the experiment on various problem instances with different systemic environments, this analysis can provide managerial guidelines for decision-makers regarding the advantage and disadvantages of the systems according to each situation.

6.1 Performance measurement

This experiment exploits two performance measures for the evaluation of the delivery systems, operational cost and mean latency. The operational cost represents travel expenses which contain fuel, maintenance charges, yearly depreciation, registration, and other miscellaneous charges. However, in the experiment, we assume the operational cost is linearly proportional to the travel distances of each vehicle to simplify the calculation.

The operational cost for the truck is set to 1.026 USD per km, which is designed based on an analysis of the operational costs of trucking reported by the American Transportation Research Institute (ATRI) in 2020 (Williams & Murray, 2020). The report presents the weighted average marginal cost per mile (CPM) based on the data for the trucking industry. The cost of drone operation was estimated to be US$ 0.03 per km following the research by Deutsche (Kim, 2016; Lauryn, 2019), which is over 30 times cheaper than trucks. The difference gets even bigger considering the operational cost of the airship. To Prentice et al. (2004), the operation cost for an airship is estimated to be US$ 40 per km, assuming it is carrying a 200MT capacity. Along with the operational cost, the velocity of each vehicle has assumed to be fixed and Table 6.1 shows the specification of each vehicle.

Table 6.1. Specification of vehicles.

	Drone	**Truck**	**Airship**
Operational cost (US$ / km)	0.03	1.026	40
Speed (km/ hr)	23	15	223

The latency is chaptered to evaluate the delivery systems. Latency stands for the waiting time of recipients. The last-mile delivery is a customer-oriented supply chain that latency at the point of demand has a large impact on customer satisfaction. Therefore, minimizing latency should be considered a primary goal. The minimum latency problem can also be classified as a traveling repairman problem (TRP), which minimizes the time to service all repair requests. In the delivery system, the latency is the waiting time of the end customer, so the experiment records the time difference between the departure time of the vehicle and the time when the customer received their order. For intuitive analysis understanding, we used average latency, but in Section 6.5, the latency distribution graph is proposed, which gives further insight into each system.

6.2 Optimization approach

The experiments consider three delivery systems, truck-only, truck-drone, and airship drone. The truck-only system is the one that has been extensively studied as TSP. The truck-drone hybrid system has discussed in Chapter 2 as FSTSP-ECNF and DRP-T. Since the DRP-T has further flexibility in its operation and the number of drones, we adapted the DRP-T model and used MA-CH as a solution approach. For the airship delivery system, the FWSP is adopted since it has the multi-airship capability. The objective function of the system is to minimize the operational cost of each system, and the latency is evaluated by simply calculating the delivery arrival time for each customer location. The following subsections discuss the mathematical model for each system as MILP.

6.2.1 Truck-only system

Minimize
$$c_{Truck} \cdot \sum_{i \in I} \sum_{j \in J} d_{i,j} \cdot x_{i,j} \tag{6.1}$$

Subject to
$$\sum_{i \in I_0} x_{i,j} = 1 \qquad \forall j \in I_+ \tag{6.2}$$

$$\sum_{j \in I_+} x_{i,j} = 1 \qquad \forall i \in I_0 \tag{6.3}$$

$$u_j - u_i \geq 1 - n \cdot (1 - x_{i,j}) \qquad \forall 1 \leq i \neq j \leq n \tag{6.4}$$

$$0 \leq x_{i,j} \leq 1 \qquad \forall i, j \in N \tag{6.5}$$

$$0 \leq u_i \leq n \qquad \forall i \in N \tag{6.6}$$

The mathematical model for the truck-only system is developed based on a general TSP model with an objective function (1), aiming to minimize the traveling cost. Constraint (2) ensures that the truck should depart from all locations, including starting depot and customers. Similarly, constraint (3) makes the truck arrive at all customers and return depot exactly one time each. Finally, constraint (4) is a sub-route elimination constraint to derive desired single tour.

6.2.2 Truck-drone system

Minimize
$$c_{truck} \cdot \sum_{j \in J} \sum_{\substack{j' \in J \\ j \neq j'}} x_{jj'} + c_{UAV} \cdot \sum_{k \in K} \sum_{n \in N} \sum_{\substack{n' \in N \\ n \neq n'}} y_{hnn'}^{k} \tag{6.7}$$

Subject to
$$\sum_{\substack{j \in J \\ j \neq 0}} x_{0j} = 1 \tag{6.8}$$

$$\sum_{\substack{j \in J \\ j \neq |J|}} x_{j|J|} = 1 \tag{6.9}$$

$$\sum_{j \in J} x_{jj'} = \sum_{j \in J} x_{j'j} \qquad \forall j \in J^{+} \tag{6.10}$$

$$\sum_{n \in N} y_{jn}^{k} \leq M \cdot \sum_{j' \in J} x_{j'j} \qquad \forall k \in K, j \in J \tag{6.11}$$

$$\sum_{\substack{n \in N \\ n \neq j}} y_{nj}^{k} \leq M \cdot \sum_{\substack{j' \in J \\ j \neq j'}} x_{j'j} \qquad \forall k \in K, j \in J \tag{6.12}$$

$$\sum_{\substack{n \in N \\ n \neq i}} \sum_{k \in K} y_{ni}^{k} = 1 \qquad \forall i \in I \tag{6.13}$$

$$\sum_{\substack{n \in N \\ n \neq i}} y_{nik} = \sum_{\substack{n' \in N \\ n' \neq i}} y_{in'k} \qquad \forall k \in K, i \in I \tag{6.14}$$

$$z_{0j}^{t} = |K| \qquad \forall t \in T, j \in J, j \neq 0 \tag{6.15}$$

$$\sum_{\substack{j'' \in J \\ j'' \neq j'}} z_{j'j''} = \sum_{\substack{j \in J \\ j \neq j}} z_{jj'}^{t} - \sum_{k \in K} \sum_{i \in I} y_{j'i}^{k} + \sum_{k \in K} \sum_{i \in I} y_{ij'}^{k} \qquad \forall j' \in \{J : j' \neq 0\} \tag{6.16}$$

$$\sum_{k \in K} \sum_{\substack{i \in I \\ i \neq j'}} y_{j'i}^{k} \leq z_{jj'} \qquad \forall j, j' \in \{J : j \neq j\} \tag{6.17}$$

$$b_{i}^{k} \geq \tau_{ij}^{d} - M \cdot (1 - y_{ji}^{kt}) \qquad \forall k \in K, i \in I, j \in \{J : j \neq 0\} \tag{6.18}$$

$$b_{n}^{k} \geq b_{i}^{k} + \tau_{in}^{d} - M \cdot (1 - y_{in}^{k}) \qquad \forall k \in K, i \in I, n \in N, n \neq 0 \tag{6.19}$$

$$0 \leq z_{jj'} \leq |\mathrm{K}| \qquad \forall j, j' \in \{J : j \neq j\} \tag{6.20}$$

$$0 \leq b_{n}^{k} \leq \mathrm{E} \qquad \forall k \in K, n \in N \tag{6.21}$$

The truck-drone system adopted the DRP-T model but with operational cost minimization, as seen in the objective function (7). The overall model is very similar to the DRP-T, but the equation (9)-(12) is excluded since the time synchronization is no longer needed due to the different objective functions. The time synchronization is needed only in consideration of waiting time between drone and truck. For a detailed explanation of the above model, please refer to Section 3.

6.2.3 Airship-drone system

The FWSP already has minimizing operation cost as its objective function, so we used the same model in the experiment. However, there are some changes to adapt to the experiment environment. First, the Ti in constraint (10) is replaced with T so that all the customers can be served at any time, minimizing the total operation cost. Second, the time period does not have a fixed unit of time so that the latency of each customer can be more precisely derived. Lastly, shuttle replenishment is neglected in this experiment.

6.3 Experiment settings

The performance of a delivery system is the subject of many discussions in the logistics industry. Due to the heterogeneity of vehicle types, their performance might be diverse in different systemic environments. Trailers are proven to be efficient for long-distance travel of large and heavy loads. However, because of the size, it is not suitable for last-mile delivery, which has a short distance and many visit points with small capacity. In this experiment, the performance of the three delivery systems introduced above is compared and analyzed according to the change in the quantity of demand, the distribution of demand reflecting the city structure, the size of the city, and the change in the number of delivery vehicles.

The demand refers to the number of customers that should be served. The high demand case can represent the situation of a sudden surge in demand due to special events such as anniversaries. A small demand can be considered a consistent but low volume demand in a small town with a low population. This experiment is not to simply increase the problem size but to find out the systemic changes of each system with a different density of demand. The result should be considered with the map size so that a more precise conclusion can be derived.

The customer distribution reflects the city structure. For instance, the centroid distribution represents a general metropolitan area that consists of a central urban area with surrounding suburban areas. Therefore, this customer distribution possibly affects delivery performance compared to different customer distributions such as random distribution. In the experiment, we considered three types of customer distributions patterns, Random, Centroid, and Quadrants. Figure 6.1 illustrates the example of customer distributions. The Random represents randomly distributed customers with a uniform distribution; the Centroid simulates a large city with an urban area with suburb zones; the Quadrant represents a collection of small towns located on the side of the main road, river, or river valley. For the detail of distribution patterns, please refer to Crainic T.G., et al, (2010).

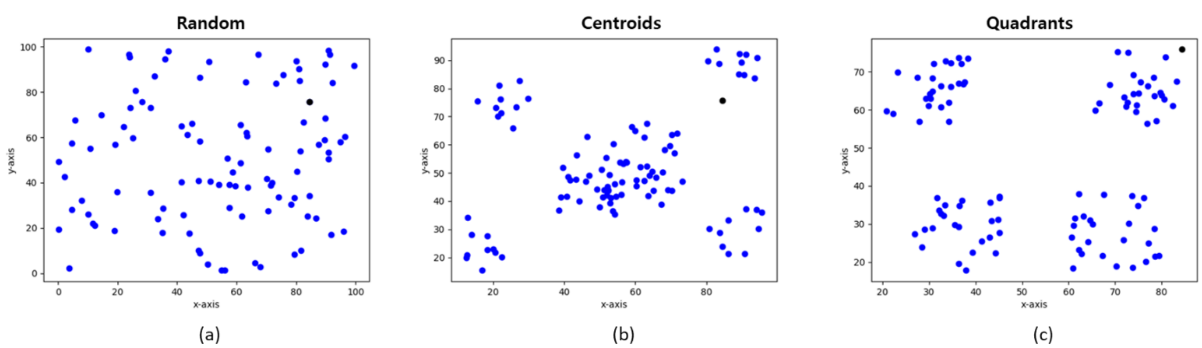


Figure 6.1. Examples of 3 types of customer distribution: (a) Random, (b) Centroids, (c) Quadrants.

Lastly, the size of the map is considered another factor in the experiment. Some delivery systems might have superior or inferior capabilities with small size maps since the drones have limited delivery coverage. Especially considering the drone's limited flight range due to its battery capacity, the map size has further importance in the drone-related delivery system. The map with discretely scattered which has a large average distance between each customer, might not be the best option considering the feasibility of drone usage.

The problem instances have 4 different demand amounts from 25,50,75,100 with 3 different map size 10x10,25x25,50x50 km2.With 10 replications of these three systemic variables, 360 problem instances have been generated for the experiment.

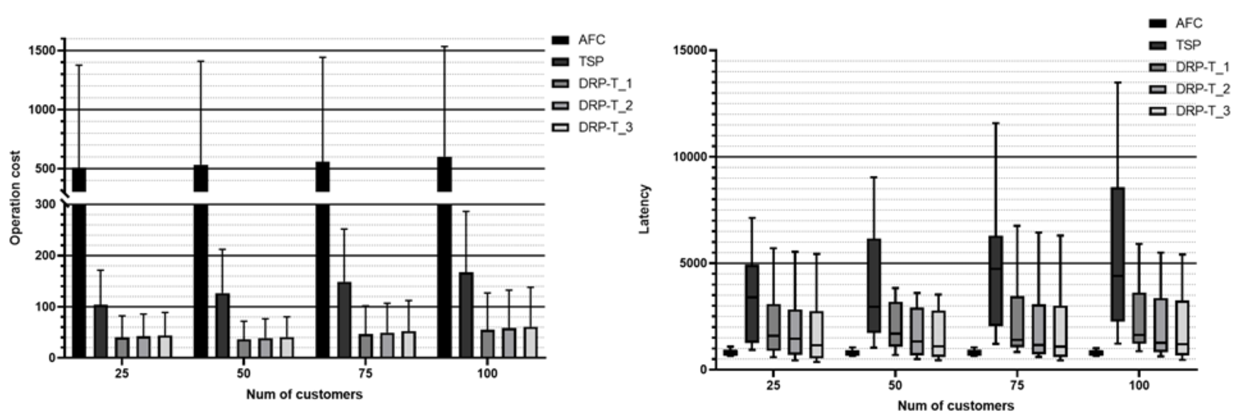
6.4 Numerical experiment-single carrier

The experiment was conducted in the abovementioned environments. In this section, the numerical result of the experiment has been analyzed from customer demand, distribution, and map size. The analysis is based on two performance measures, operation cost, and latency. The AFC, TSP, DRP-T represents the airship-drone, truck-only, truck-drone system, respectively, and the following number represents the number of drones used in DRP-T.

6.4.1 Result from different number of customer demand

A large number of customer demand inevitably increase travel distance. As the distance has increased, the latency may go higher since the customer who is assigned on the later order have to wait longer until the prioritized customers have been served. The result clearly follows this intuition but not for the AFC. In Figure 6.2 (a), the operation cost tends to be increased slightly along with the customer increase. However, the latency in Figure 6.2 (b) did not really show that tendency. This is mainly because the airship-drone system deploys multiple drones at the same time, which prevents accumulating latency like the traditional system. Even though the latency accumulates with airship movement, it affects much less than the others. This is clearly indicated by the result that other systems' latency increases as the number of customers. Comparing TSP and DRP-T, the truck-drone hybrid system always shows shorter latency, especially with a greater number of drones. But the latency of AFC has always shown the lowest in every case.

In terms of operation cost, the AFC system always shows significantly high compared to others, as shown in Figure 6.2 (a). But interestingly, the increasing amount of the AFC was relatively small along with the number of customers. The DRP-T system always guarantees noticeably lower operation costs compared to others. However, its operation cost goes slightly higher when the number of drones increases, but at the same time, the latency decreases greatly. So that DRP-T has a clear trade-off between 1 drone and multi-drones with higher cost and lower latency.



(a) (b)

Figure 6.2. Computational result from different number of customers.

6.4.2 Result from different customer distribution

The customer distribution reflects the population distribution of the target area. In a centroid or quadrant area, the customer locations are more likely to have high density. The high density indicates that it is a better environment for drones since they are freer from the flight limitations of the battery. Therefore, the experiment result from Figure 6.3 shows that the gap between TSP and DRP-T is noticeably large in centroid and quadrant with both operation cost and latency. Although AFC is also a drone-related system, it still shows significantly high operation costs due to the expensiveness of airship operations. Compared to the centroid, quadrants show slightly lower operation cost and latency, mainly because they have a lower number of customer swarms but no big difference between them.

The latency distribution represents the expected waiting time distribution. To be specific, the customer order with the AFC system has a very consistent waiting time. However, the customer orders in TSP or DRP-T have highly varied waiting times. According to Figure 6.3 (b), an order from TSP can be either 20 minutes later or 5 hours later in random customer distribution. Therefore, the delivery performance is hardly measurable from the customers' view. DRP-T shows a narrow range compared to TSP but is still much larger than AFC. This is mainly caused by the latency cumulation effect. Customers who got served first will have short latency, but the last customer should wait long to get their service. So, the TSP and DRP-T is not the best option to perform special delivery service such as quick 15-minute delivery.

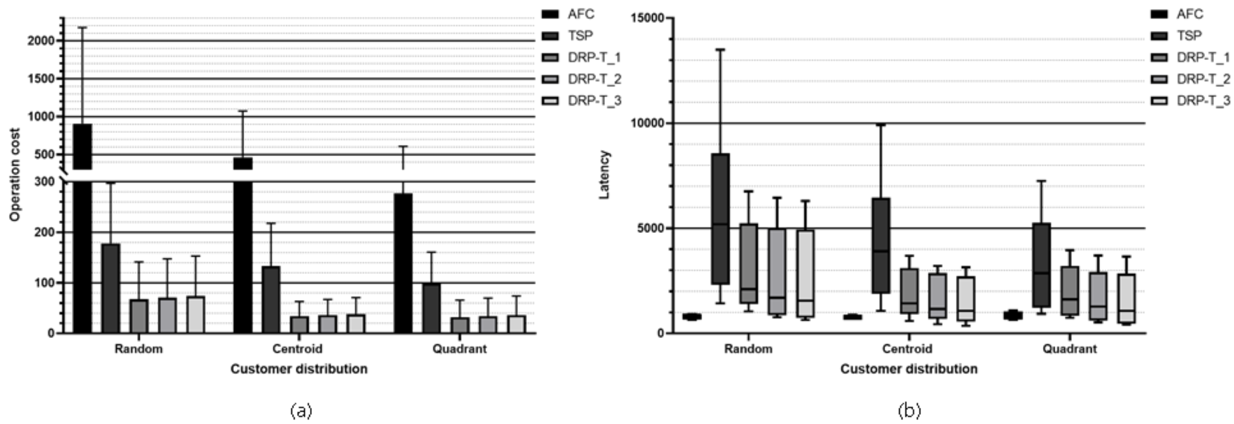


Figure 6.3 Computational result from different customer distributions.

6.4.3 Result from different map size

The map size plays a large portion in delivery performance. Obviously, a large map takes a much longer time for delivery completion with the high operation cost due to its long travel distance. The results in Figure 6.4 (a) clearly show the effect of increasing map size on high operating costs. Of particular note is the sudden change in AFC operating costs. The operation cost of AFC in a small map size is low, which is not have seen in the previous analysis, even smaller than TSP. This is caused by the small size of the map, which enables AFC to cover all areas without moving them. In this case, it is possible to cover all demands by moving only drones without bearing the expensive AFC operation cost. In the same vein as AFC, DRP-T also showed very low operation costs. This is even lower than that of the AFC because the moving distance of the UAV becomes longer due to the high altitude of the AFC. Despite these disadvantages, the latency of AFC still maintained the lowest position, as seen in Figure 6.4 (b). However, in the case of the smallest map size, the gap between AFC and DRP-T was unprecedentedly small. The gap between the two increased exponentially as the map size increased. However, when targeting a small target area, the latency of AFC and DRP-T is similar, so DRP-T, which has a low operation cost, seems to be the superior strategy.

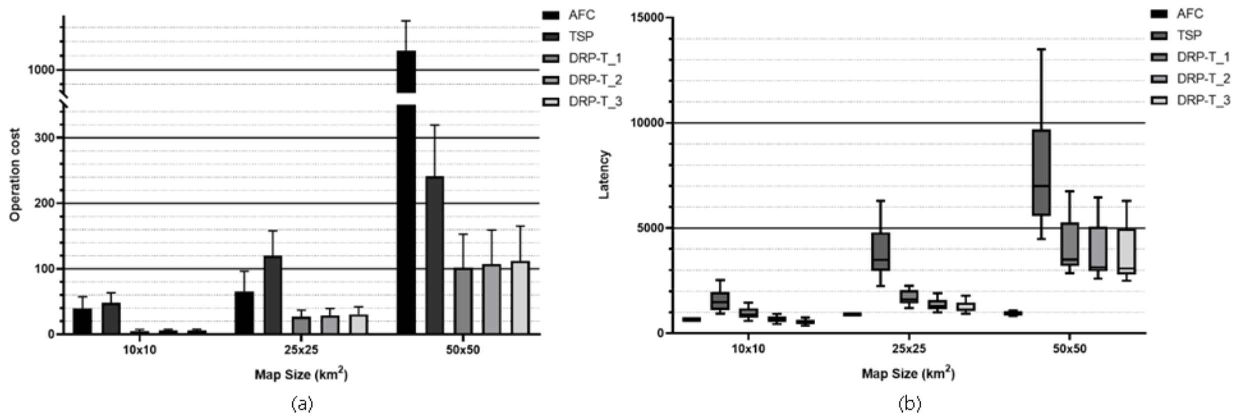


Figure 6.4 Computational result from different size of maps.

6.5 Numerical experiment-multiple carriers

The multi-carrier case has extremely high complexity compared to a single vehicle. Since the single carrier is already proven to be NP-hard in the above sections, multi-carrier is hardly solvable optimally, especially in large problem instances. Therefore, to mitigate the complexity of the problem, we adopted the divide and conquered strategy proposed in Section 5.4.2. The main idea of this approach is to divide the customers into several clusters based on their locations and assign each carrier to the clusters. Then the big chunk of the problem will be separated into sub-problems that has smaller size, which is more likely solvable. Each sub-problems are solved separately, and then the result of the sub-problem is summated at the end of the process. The summary of this approach is graphically demonstrated in Figure 6.5. The primary advantage of this approach is that it can offset the high computational complexity, as proven in the previous sections. On the other hand, there is a downside that the result may lose its relative optimality. Nevertheless, this approach is a suitable methodology for analyzing the trends in the results, so we adopted this in this section. For the dividing clusters, we developed the k-mean clustering method, which is demonstrated as pseudo-code in Algorithm 3.

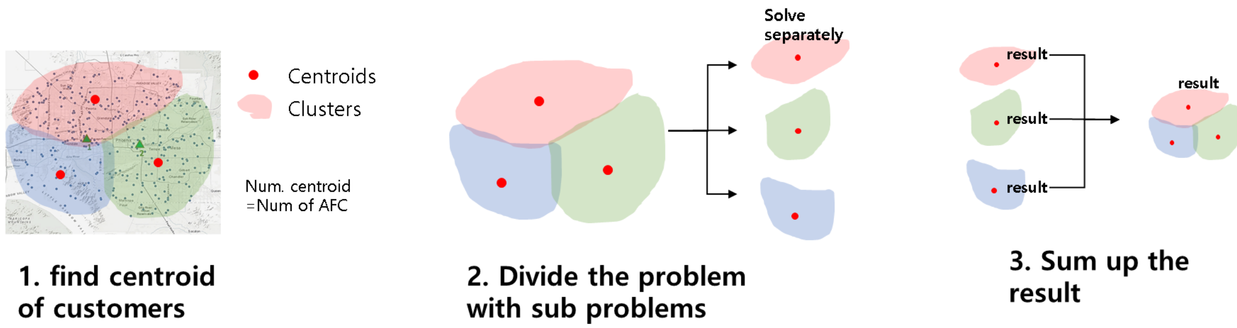


Figure 6.5 Process of divide and conquer strategy.

Algorithm 3. K-mean clustering (pseudo code)

Select the *centroids* arbitrary among *customer locations*
While (centroid converge**)**
  For each customer *location i*
    Find nearest *centroid c*
    Assign *customer i* to the *centroid c*
  For each *cluster c*
    Update *centroid* according to assigned *customer*
Return *centroid*, *assignment*

For the experiments, the carrier, which is an airship in AFC and a truck in TSP and DRP-T, has verified from 1 to 3, and the drone also varied from 1 to 3 as in the previous experiment. So as a result, 15 systems with different numbers of components were applied to the 360 problem instances.

6.5.1 Result from different number of customer demand

The increase in carriers inevitably forces higher operation costs. In the same way, the larger number of customers have positive effects on travel distance which leads to higher operation cost. The result from Figure 6.6 clearly shows these trends, especially the increased carrier in DRP-T.

Similar to the result from Section 6.4.1, the AFC always shows comparatively high cost, followed by TSP and DRP-T. The DRP-T has the lowest operation cost even when it cooperates 3 carriers and 3 drones in its system. So economically, DRP-T is always a superior option.

As more carriers and drones were involved in the DRP-T system, its latency decreased consistently until 3, although it will be converged at some point. However, even this continuously reduced latency showed a high value compared to AFC's. More importantly, the decrease in the range was comparably sluggish. This indicates that no matter how many carriers and drones are used, DRP-T cannot reach that latency that AFC has. In an extreme case, with numerous carriers, DRP-T might reach that latency level, but it will not be fairly economical or efficient.

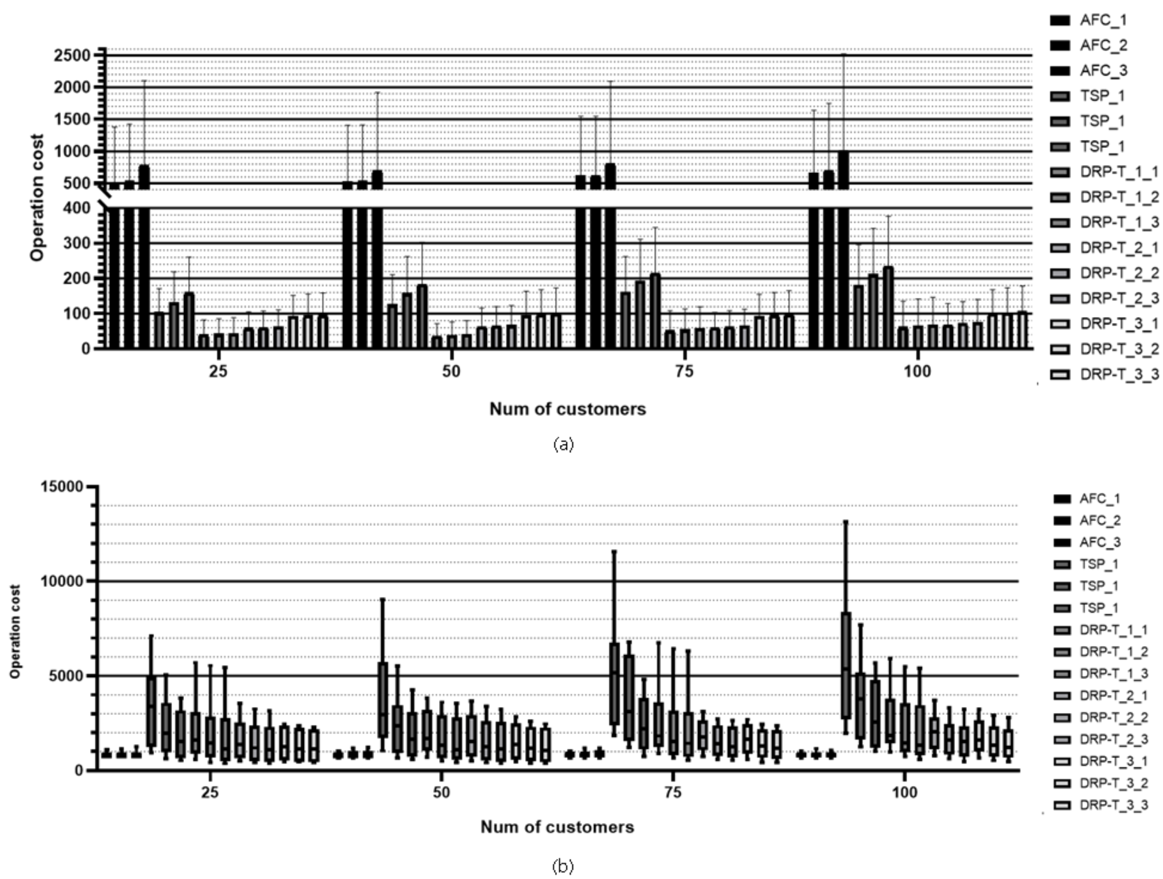


Figure 6.6 Result of multi-carrier operations from different number of customer demand

6.5.2 Result from different number of customer demand

The Figure shows the computational result of each system with the different customer distributions. The customer distribution also has a similar result to the single carrier analysis. In the case of AFC, the operation cost was seen to be extremely varied depending on the distribution of customers. Compared to random distribution, centroid or quadrant showed a cost difference of up to 1/3. This was also true for other delivery systems. Relatively low operating cost was found in centroid or quadrant.

This trend has also shown in the latency of the systems. The TSP and DRP-T had relatively short latency in centroid and quadrant. More specifically, the quadrant has a slightly better result. However, the AFC system has not been affected by customer distribution, unlike operation costs. The reason is mainly because of its unique delivery process that connects the warehouse and customer directly with drones which prevents latency cumulation.

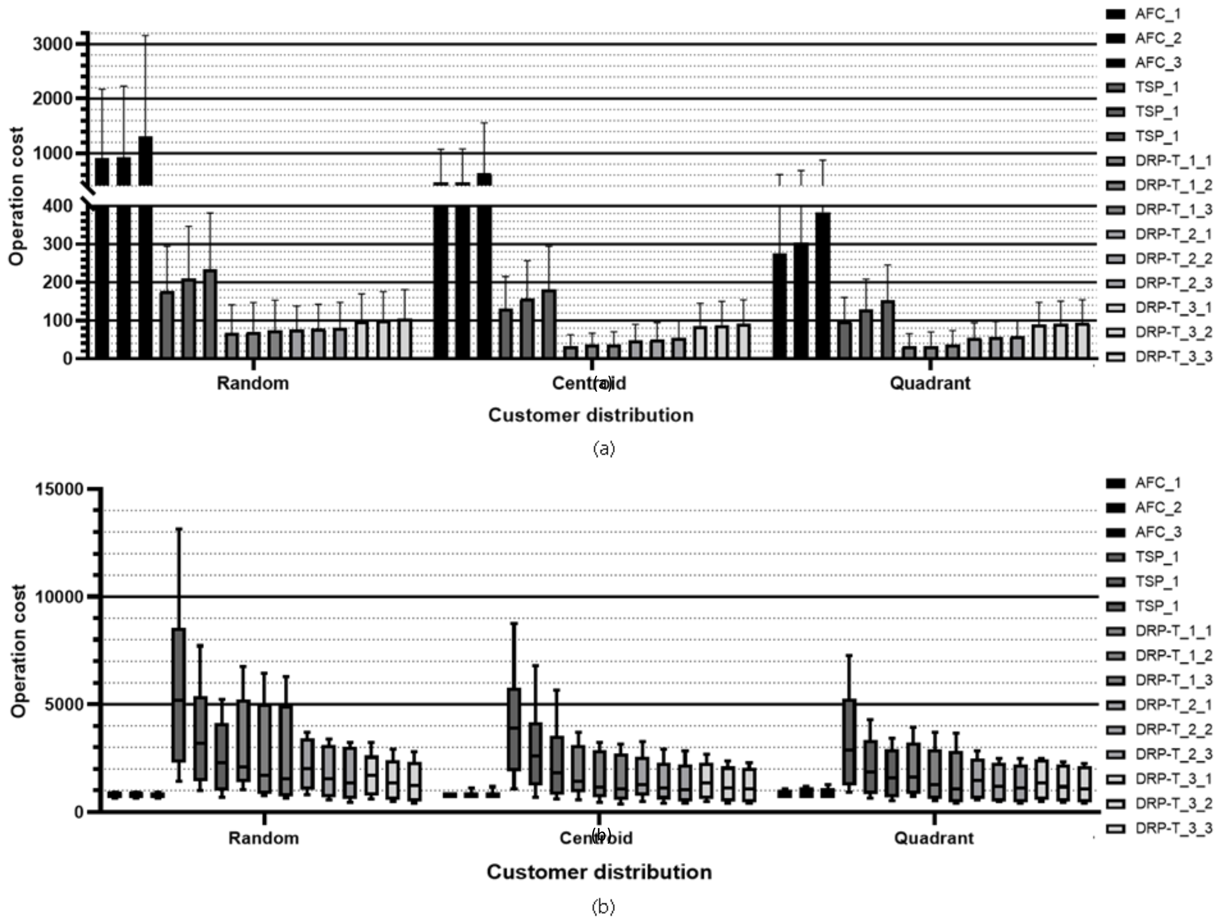


Figure 6.7 Result of multi-carrier operations from different customer distribution.

6.5.3 Result from different number of customer demand

Map size is the factor that has the most dramatic effects on the delivery system's performance. In Figure, the AFC operation cost varies from 15 in 10x10 km2 to 3000 in50x50 km2, which is 200 times higher. Also, in the previous analysis, AFC always showed high operating costs, but in this result, it can be seen that the AFC operating cost is smaller than TSP in the size of 10x10, 25x25, which represents a small city. This clearly demonstrates that the operation cost, especially of AFC, increases exponentially as the size of the target area is extended.

In the case of latency, we could see different results than before. In particular, it can be seen that the latency gap between AFC and DRP-T is very small in the smallest map size of 10x10 km2. As a result, it can be found that the difference between AFC and DRP-T is offset in the small size. However, the change in the amount of increase according to the map size change is notable. In the case of AFC, its latency is almost unaffected by the change in the map size, whereas, in other systems, it has been greatly affected by the increase in map size.

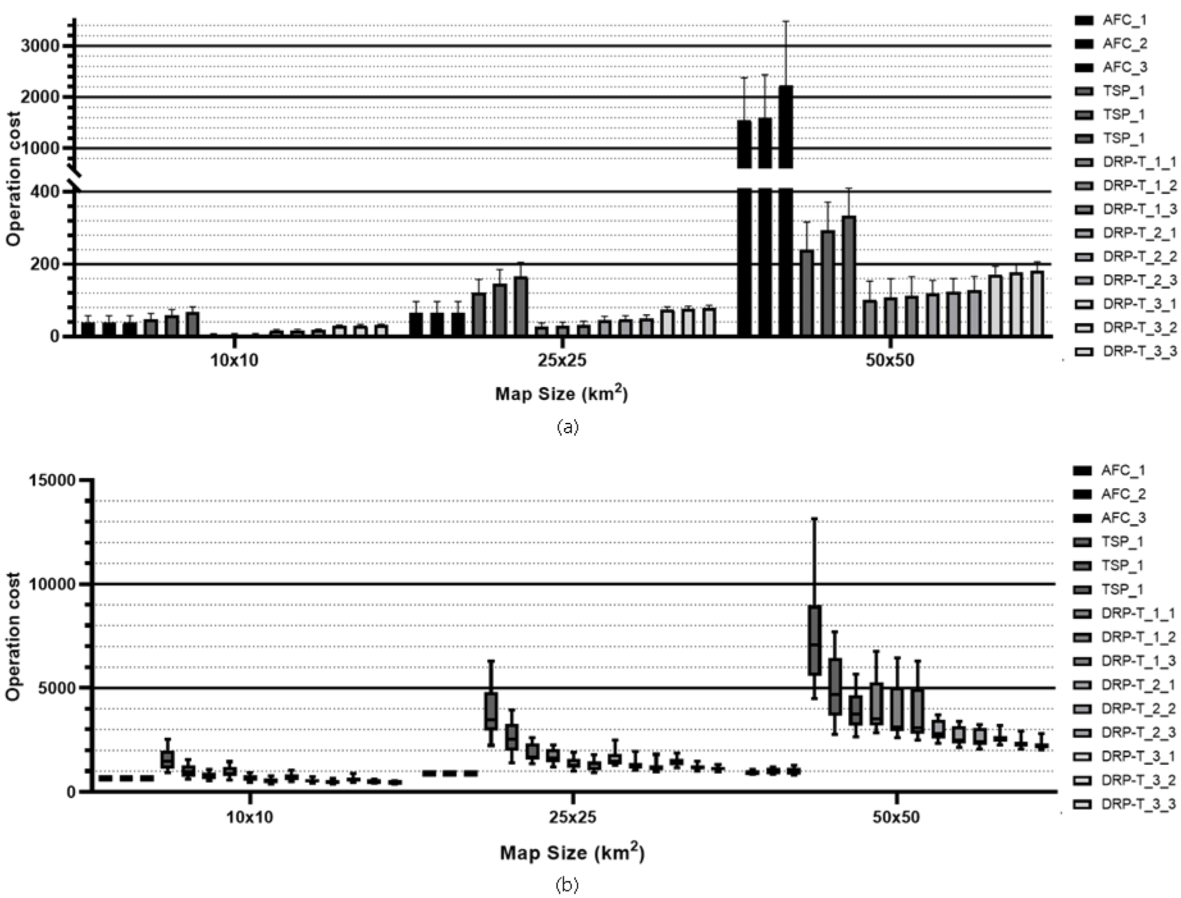


Figure 6.8 Result of multi-carrier operations from different map size.

6.6. Conclusion remarks

The hybrid delivery system has distinct advantages in delivery latency in most cases compared to the traditional truck-only system. However, due to the computational complexity of the hybrid system, it is hard to precisely derive its schedule optimally in a reasonable time. This chapter adopted previously presented solution approaches that have computationally efficient in analysis and predict their delivery performance in terms of operation cost and delivery latency. In addition, by proposing a comparative analysis between hybrid delivery systems and truck-only systems, we have seen which system has more practicality in different operational environments.

The quantitative approach in comparative analysis provides a managerial guideline for the practical application of a hybrid delivery system. For instance, in a small operation area, the DRP-T has been seen to be a superior option considering its low operation cost with short enough latency. However, when the system has a very short latency limit with a large operation area, the AFC system would be the best choice since it shows consistently short latency in every case. Although AFC's high performance with low latency, it takes significantly high operation cost due to its inherent size of the carrier, an airship. So that in case of low budget operation, the AFC is no longer to be available.

Since this study focused on two hybrid delivery systems, airship-drone, and truck-drone, one promising area is to consider other delivery systems such as drone-only systems. In addition, an extension of the collaborative delivery system across the hybrid delivery system or traditional system can be another interesting study.

CHAPTER 7 FUTURE RESEARCH

This dissertation proposed a novel optimization problem of hybrid delivery systems with the application of delivery drones. Each problem is formulated as a mathematical model as MILP. The inherent complexity of those problems has been mitigated by adopting efficient computational approaches. Several numerical analyses have been presented to verify the systems, including a comparative analysis with a traditional truck-only system. The quantitative analysis provides the managerial guidelines for the operation of the hybrid delivery system.

The truck-drone hybrid delivery system represented by the DRP-T model appears as a cost-effective delivery method with low operation cost and latency. In particular, as the number of drones used increases, the efficiency tends to increase further. In addition, its performance shows superiority in a smaller target area. These characteristics are caused by collaboration with drones. The flexible and high mobility of the drone lowers the latency while taking advantage of the low operation cost of drones. Also, since drones have flight range limits due to their battery capacity, a smaller map works better, which is a relatively freer environment to use drones.

If the truck drone system was a combination of two different delivery systems, the airship-drone system is a combination of a warehouse and a delivery drone. However, it includes a gigantic flying warehouse that can move around the sky. Its fundamental characteristics make the operation cost to be measured inevitably high. On the other hand, its clear advantages of latency and service coverage. To be specific, the airship system always shows consistently low latency, whether the map is large or small, with many or few customers, whatever the customer distribution. Since it is less affected by the cumulative increase of the latency, it always maintains an overwhelmingly low value compared to other delivery systems. Therefore, to overcome same-day delivery and progress to stably performing 15-minute delivery, direct connection of warehouse-customer is essential.

In this dissertation, two different hybrid delivery systems are addressed with a case study for practical application. Since the hybrid delivery system is a new concept that is an emerging system that has not yet been commercialized, there are many opportunities for future research. The following sections describe the directions for the future work.

7.1 Different types of hybrid delivery system

According to the technical advances, there are different types of emerging transportation. For instance, the droid is one of the delivery methods that are already commercially available in the United States and Europe, represented by Starship (Starship, 2020). Currently, the Starship is operated as depot-based last-mile delivery, the same as standard truck delivery. The main advantage of the droid is the low operation cost of the fact that no pilot is needed. However, due to its low speed and congestion of the road network, it often takes too long for delivery. Therefore, future research can be the designing and proposing a new hybrid delivery system utilizing the advantage of droids while mitigating its disadvantages.

(a) (b)

Figure 7.1. Hybrid delivery system with droid-truck.

7.2 Collaborations across systems

In addition to the comparative analysis in Chapter 6., the analysis of collaboration across delivery systems can be a future work direction. As seen in the result, each system has a distinct advantage in a different situation. So, assigning each system in a suitable situation is expected to benefit using synergy advantages selectively. For example, one way to collaborate is to use DRP-T for customers close to the warehouse and use AFC for customers far away. Alternatively, in the process of AFC's operation, the collection using a truck can also be proposed as a new collaboration method to minimize the drone's battery usage. These collaborations may help find the application point of a more advanced and optimized method for the hybrid delivery system.

7.3 Computational complexity mitigation

The hybrid delivery system has inherent complexity, requiring a computationally efficient solution approach, especially in multi-carrier cases. Therefore, in this dissertation, the divide and conquer strategy has been adopted. Although it addresses the problems in a reasonable time, there is still optimality loss in the solution quality. For future work, we can consider additional fleets of carriers in operation with advanced algorithms to mitigate the high complexity. One possible solution is to develop a machine learning-based approach that allows learning from the previous solution to improve its quality and robustness. Recently, Jun. (2020) has applied the machine-learning-based solution approach to scheduling problems and proved that it could solve a high complexity problem in a reasonable time span. Similary, Kim et al., (2021) also showed that the learning algorithm could mitigate the complexity with higher optimality than general metaheuristics.

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VITA

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PUBLICATIONS

Journal Papers

1. Jeong, H. Y., Song, B. D. & Lee, S. (2019). Truck-drone hybrid delivery routing: Payload-energy dependency and No-Fly zones. *International Journal of Production Economics,* 214, 220-233.
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PRESENTATION

1. Jeong, H. Y., & Lee, S. (2018). Scheduling Hybrid Delivery System of Truck and Drone: Energy-Payload dependency and No-Fly Zone, *Institute of Industrial and Systems Engineers, Institute of Industrial and Systems Engineers (IISE) Annual meeting*, Orando, US.
2. Jeong, H. Y., & Lee, S. (2018). Vehicle-Carrier Routing Problem, *Institute for Operations Research and the Management Sciences (INFORMS) Annual meeting*, Peonix, US, 2018.
3. Song, B. D., Jun, S., Jung, H. Y., & Lee, S. (2019). Movable Unmanned Aerial System Optimization of System Resource Design and Drone Routing, *International Conference on Production Research 25th (ICPR25)*, Chicago, US, 2019.
4. Jeong, H. Y., & Lee, S. (2019). Optimization of Vehicle-Carrier Routing Mathematical Model and Comparison with Related Routing Models, *International Conference on Production Research 25th (ICPR25)*, Chicago, US, 2019.
5. Jeong, H. Y., & Lee, S. (2019). Airship-based drone delivery system: quantitative approach for managerial and operational guidelines., *Institute for Operations Research and the Management Sciences (INFORMS) Annual meeting*, Seattle, US, 2019.

ACADEMIC AWARD

1. The 1st Runner up paper on *International Conference on Production Research 25th (ICPR25)*, 2019.

RESEARCH EXPERIENCE

May 2019 - Current	**Visualization of Repair Operations Management for Networked Systems Resilience** Funded by **Navy Crane Center**, IN, United States Developed a simulation tool and optimization tools for military network resilience.
Jan 2018 – May 2019	**Resilience in Networked Systems using collaboration (RNSC) Project** Funded by **Navy Crane Center**, IN, United States Developed a user interface and optimization tools for military facility network.

SKILLS

Python, MATLAB, C#, R, ILOG CPLEX, Gurobi, ARENA

PUBLICATIONS

Journal Papers

1. **Jeong, H. Y**., Song, B. D. & Lee, S. (2019). Truck-drone hybrid delivery routing: Payload-energy dependency and No-Fly zones. International Journal of Production Economics, 214, 220-233.
2. **Jeong, H. Y**., David, J. Y., Min, B. C., & Lee, S. (2020). The humanitarian flying warehouse. Transportation research part E: logistics and transportation review, 136, 101901.
3. **Jeong, H. Y**., Song, B. D., & Lee, S. (2020). The Flying Warehouse Delivery System: A Quantitative Approach for the Optimal Operation Policy of Airborne Fulfillment Center. IEEE Transactions on Intelligent Transportation Systems.

Conference Proceeding

4. **Jeong, H. Y**., & Lee, S. (2019). Optimization of Vehicle-Carrier Routing: Mathematical Model and Comparison with Related Routing Models. Procedia Manufacturing, 39, 307-313.
5. Song, B. D., Jun, S., **Jung, H. Y**., & Lee, S. (2019). Movable Unmanned Aerial System: Optimization of System, Resource Design and Drone Routing. Procedia Manufacturing, 39, 300-306.
6. **Jeong, H. Y**., & Lee, S. (2021). Collaborative Hybrid Delivery System: Drone Routing Problem Assisted by Truck. In IFIP International Conference on Advances in Production Management Systems (pp. 33-42). Springer, Cham.
7. Kim, Y., **Jung, H**., & Lee, S. (2021). Drone Delivery Vehicle Routing Problem with Multi-flight Level. In IFIP International Conference on Advances in Production Management Systems (pp. 43-51). Springer, Cham.