Logistics of Aerial Delivery Systems

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ABSTRACT

In the last decade, aerial delivery systems have been considered as a promising response to increasing traffic jams and incremental demand for transportation. In this thesis, the logistics of a droned-based delivery system is investigated aiming to optimize the costs of the system, waiting times, total travel distance, efficiency of the system, routing of the drones, locations of the facilities and lost demands. Distance-constrained mobile hierarchical facility location problem is investigated for finding the optimal number and locations of launch and recharge stations such that the total cost of the system is minimized. System costs include establishment costs for launch and recharge stations, drone procurement, and drone usage costs. To address the waiting times a congested model is provided and to account for the variability of the data and non-deterministic nature of the problem, fuzzy programming is incorporated into the models. It is supposed that the demand occurs according to Poisson distribution, is distributed uniformly along the network edges and is satisfied by the respective closest open facility. Since the drone flying distance is limited to its endurance, the drone may visit one or more recharge stations to reach the demand point. This route is calculated by the shortest path algorithm. Solution methods are developed to solve the proposed models. To illustrate the applicability of the methods case studies are presented and the results are discussed.

Keywords: Hierarchical Facility Location, Drone Delivery System, Hybrid Genetic Algorithm, Edge-Based Stochastic Demand, Supply Chain Management

ÖZ

Trafik tıkanıklıklarına ve ulaşımdaki talep artışına en uygun çözümün havadan gönderme sistemleri olduğu düşünülmektedir. Bu çalışmada insansız hava aracı (İHA) temelli sevkiyat sisteminin lojistiği, maliyet, bekleme süreleri, taşıma süresi, sistemin verimliliği, İHA'ların güzergahları, tesislerin lokasyonu ve talep kayıplarının eniyilenmesi (optimizasyon) amacıyla incelenmiştir. Mesafe-kısıtlı hiyerarşik (sıradüzensel) mobil tesis yeri problemi, sistemin maliyeti en düşük olacak optimal kalkış ve şarj istasyon sayıları ve lokasyonlarının tespiti amacıyla incelenmiştir. Maliyet hesaplamalarında kalkış ve şarj istasyonlarının inşası ve ilgili techizatın tedariki, İHA'ların edinilmesi ve kullanımından kaynaklanan harcamalar gözönüne alınmıştır. Bekleme süreleri için bir tıkalı (congested) model ve problemin veri değişkenliği ile belirgin olmayan (nondeterministic) doğasından dolayı modellerde bulanık programlama kullanılmıştır. Talebin Poisson dağılımına göre oluştuğu ve ağ kenarları boyunca uniform (birbiçimli) dağıldığı öngörülmüştür. İHA'ların uçuş mesafesi sınırlı olduğundan, talebe ulaşıncaya kadar bir veya daha fazla şarj istasyonuna uğramaları sözkonusu olabilecektir ve bu güzergah da en kısa yol algoritması ile hesaplanmaktadır. Önerilen modelleri çözecek yöntemler geliştirilmiş ve bu yöntemlerin uygulanabilir olduklarını göstermek amacıyla örnek olay incelemesi (case study) sunulmuş ve sonuçları da tartışılmıştır.

Anahtar Kelimeler: Hiyerarşik (sıradüzensel) Tesis Lokasyonu, İHA Gönderme Sistemi, Melez Genetik Algoritma, Kenar-Esaslı Rassal Talep, Tedarik Zinciri Yönetimi

To my beloved family

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Chapter 1

INTRODUCTION

Due to their speed, reduced costs and efficiency, drones had been under the spotlight in recent years. The utilization of the drones has been considered in many fields including disaster management and humanitarian relief distribution, communications, transportation, logistics operations for economical or healthcare sectors, survey and surveillance and military purposes. In his manuscript, Gregory has investigated the pros and cons of using drones in military section to provide information, surveillance, targeting and so forth (Gregory, 2011). As (Byman, 2013) indicated, only in his four years of presidency, Obama signed off more than 400 drone based operations in different countries such as Pakistan and Yemen. However, aside from its dark side and their misusage in privacy theft and terrorism and its application as a weaponry, drones have been used to the good of the mankind frequently. Drones have various application in healthcare. Considering the emergency nature of medical care and health care, and with heavy congested traffic on any metropolitan city, utilization of drones are going to be an integrated part of healthcare systems. (Scott & Scott, 2017) presented several applications of drones in health care including blood delivery. They investigate existing policies in drone delivery and claim that drones can provide timely care and consequently save lives. (T. Amukele, Ness, Tobian, Boyd, & Street, 2017) scrutinized the conditions such as temperature and physical properties that should be provided to enable the delivery of blood by drones. Their finding corroborate the potential of drones in this field and confirm their benefits to the health care. They performed a similar study on drone transportation of microbiological specimens found in blood and once again the capabilities of drones were approved (T. K. Amukele, Street, Carroll, Miller, & Zhang, 2016). Also, (Claesson et al., 2017) investigated the drone's application with the focus on cardiac arrests and emergency medical services. They proved that the response time is significantly lower compared with EMS and there is no technical issues in the process.

The applications of drones in post-disaster response and humanitarian relief distribution have been rampantly discussed. (Sandvik & Lohne, 2014) reviewed and discussed different applications of drones, from wars to the cargo delivery and finally investigated the emerging relief drones. (Tanzi et al., 2016) consider drones as an important part of disaster management and mention time and human resource as the most important factors that would cause disaster managers consider their utilization. In their study, they evaluate autonomy level and the reliability of the drones for such missions. (Gutierrez et al., 2015) proposed the collaboration of drones, robots and mobile stations for relief distribution, surveillance and rescue missions in post-disaster period and scrutinized the technical and technological issues in this regard. The most important criteria for commercial usage of drones is cost, and battery and its life time along with electricity usage for recharging these batteries are considered as the most costly elements of a drone delivery system by (Park, Zhang, & Chakraborty, 2016a). Consequently they have performed discrete event simulation analysis to evaluate the effect of different designs of the battery configuration, batter characteristics and integration methods, speed, endurance and etcetera on delivery time and operating costs.

Such studies made the drones faster, more reliable, smaller, smarter and most importantly more domestic and more economic which makes them preferable over many options in different fields and applications. Business and commercial companies also would not miss such an opportunity. In recent years many commercial institutes, logistics companies, retailers, post offices, and even fast food restaurants have thought of drones as an option for delivery of their products and services. There had been critics for mass utilization of drones. Most of these critics are resulted from the long association of drones with military purposes and address the privacy issues. The cons and pros, social impacts and policies which are applied on the management of public acceptability are discussed in (Boucher, 2015). According to (Dorling, Heinrichs, Messier, & Magierowski, 2017) drones can decrease the time and costs of the delivery operations. They have provided a vehicle routing for drones with consideration of the effects of the battery weight and configurations that can actually effect energy consumption and relevant costs. They developed and simulated annealing algorithm to solve the problem and observed a diverse relation between costs of the design for drone and battery and the resulting delivery times. (Murray & Chu, 2015) proposed the application of the drones beside trucks for the last mile delivery.

As a result of vast applications of drones, many studies has focused on optimization of different features and characteristics of drones and owing to these studies drones have experience a great deal of improvements in every aspect. (Minh-Duc Hua, Hamel, Morin, & Samson, 2009) provided models to simulate the interaction of drones with fluids surrounding them and investigate the consequences of such interactions. (Apvrille, Roudier, & Tanzi, 2015) studied the integrated on drones with several tools, platforms and systems such as SysML-Sec/TT and Parrot platform to increase the safety and security in their missions and guarantee a successful autonomous control.

In this thesis the application of the drones for delivery of products from retailers to customers is studied. Online retailers spend an enormous amount of their resources to deliver their sold products to the customers. By the increase in fuel rates the costs of delivery have increased and has brought new challenges to retailers and hinders their goal to offer competitive prices. Many retailers aim to utilize the drone-based aerial delivery system as an alternative solution to overcome the problems related to the high transportation costs and traffic jams in large cities. This thesis provides mathematical models for aerial delivery systems and addresses issues such as minimizing the total costs of the aerial delivery system related to refuel stations, warehouses, drones' procurements, and transportations and waiting time of the customers based on M/G/K queueing systems. The fuel stations and warehouses are the main components of the network. The demand (occurring at the lowest level) is ultimately satisfied via launching stations (the network's highest level). Launch stations serve as a control unit to load drones, control the drones throughout their flight including take off, landing and cruising the distance which is mostly done autonomously. Refuel stations are to support drones along their long routes between launch stations and demand points. In case of electronic drones, refuel stations or recharge stations are units spread in the area which provide drones with fully charged batteries or may provide platforms which enable drones to recharge their batteries remotely and without change of the batteries which of course is more time consuming. To account for different levels of facilities, multi-level facility location or hierarchical facility location approach is utilized.

The cost of the system is heavily affected by logistics decisions. Thus here the economics of the system, best location of refuel station, recharge stations and the best routes for fulfilling a demand is studied. In the first chapter a model is provided to minimize the whole costs of the systems including the costs of the establishments for stations and usage costs of the drones which is incurred by each distance unit travelled. The data required for this study have a great variability in their nature. It is obvious that the demand rates, establishment costs and usage costs are affected by huge number of factors and cannot be calculated in an exact method. Hence in the second chapter this issue is addressed by utilizing the fuzzy programming concepts. Furthermore an important criteria in any delivery system is the time that a customer should wait to receive the products purchased. Hence this issue is addressed by a congestive model in an effort to minimize this waiting time within an acceptable incurred costs. The third chapter presents a multi-objective model to account for different objectives that exist within this context, objectives such as costs, total travel distance, maximum waiting time, number of stations to be established, total number of drones to be procured and so forth.

This thesis is structured as follows; in the next chapter a hierarchical facility location problem is utilized to determine the best combination of launching and refuel stations in order to satisfy demand and minimize the total costs of the system. Chapter three introduces a fuzzy congested multi-level facility location model to capture the un-deterministic nature of the data required for such an infrastructure. Also the model tires to minimize the total waiting time, hence the title ‘congested’. Chapter four presents a multi-objective model to incorporate various objectives that would be important to decision makers and managers in this field.

Chapter 2

APPLICATION OF HIERARCHICAL FACILITY LOCATION PROBLEM FOR OPTIMIZATION OF A DRONE DELIVERY SYSTEM

2.1 Introduction

Drones, as aerial transportation vehicles, have attracted a lot of attentions in recent years as a solution to high traffic jams and increasing transportation needs. With the advancements achieved in drones' capabilities such as their endurance, speed, payload and automated navigation systems, their application seem promising in this field (Lee, 2017). The use of drones has been investigated in recent studies for rescue operations (Xiang, Hardy, Rajeh, & Venuthurupalli, 2016), relief distribution (Golabi, Shavarani, & Izbirak, 2017a), delivery systems (Hong, Kuby, & Murray, 2017a; M. Kim & Matson, 2017) and healthcare (Scott & Scott, 2017). Additionally, (Goodchild & Toy, 2017) compared the carbon dioxide emissions of truck and drone delivery vehicles and resulted that drones can reduce the amount of carbon dioxide emissions. (Haidari et al., 2016; Scott & Scott, 2017) studied the use of drones for fast and efficient delivery of blood and vaccines. Drone based delivery systems are being initiated in distribution centers and online retailers like "Amazon prime air" and "Google wing" projects, fast-food delivery, and transportation networks (D'Andrea, 2014; Sanjab, Saad, & Başar, 2017). As a result, many studies have addressed different aspects of this phenomenon such as the one by (Vempati, Crapanzano, Woodyard, & Trunkhill, 2017), wherein a linear model is presented to maximize the profit of Amazon's Prime Air project, and many others have focused on the logistics aspect of the problem. As an instance, (Hong, Kuby, & Murray, 2017b) used the FLP to locate the recharge stations for a drones delivery network to cover a large city. There is no study on the locations of both recharge and launch stations to the best of our knowledge, which results in a reduced feasible region of the problem and losing potential benefits.

Facility location problem is of great importance in economics and functionality of an organization, and improper selection of location would lead to problems in the delivery of services and accessibility of facilities (Rahman & Smith, 2000). Thus many forms of facility location problems have been investigated in the literature. (Rahmati, Hajipour, & Niaki, 2013) considered a multi-service FLP where each facility presents more than one service. (Basti & Sevkli, 2015) studied a p-median facility location problem which aims to minimize the maximum distance between nodes and facilities. (Li, Chu, & Prins, 2009) investigated a capacitated FLP where there exists an upper bound for the services presented by each facility. (Karkazis & Boffey, 1981) investigated the multi-commodity FLP wherein each facility provides several services. In the hierarchical FLP (HFLP) each facility provides different levels of services (Helber, Böhme, Oucherif, Lagershausen, & Kasper, 2016; Şahin & Süral, 2007). The single-flow network is defined in the context of HFLP wherein demand occurs at the lowest level and is finally satisfied at the highest level (Farahani, Hekmatfar, Fahimnia, & Kazemzadeh, 2014). Based on the availability of services HFLP can be nested network wherein a facility at highest level provides all the services to lower levels while in a non-nested network only a certain kind of services are provided to lower levels. Set covering HLP aims to satisfy all the demand with a minimum number of facilities. In the fixed charge problems, the objective is to minimize total facility construction costs in addition to transportation costs. According to (Teixeira & Antunes, 2008), the models of closest assignment constraint guarantee that the nodes are assigned to their closest facility.

It has been shown that FLPs are NP-hard and only small instances of the problem can be solved with exact methods (Owen & Daskin, 1998). Thus in many studies, metaheuristic algorithms have been applied to solve various FLP models (Basti & Sevkli, 2015; Ho, 2015; Maríc, Stanimirovíc, Milenkovíc, & Djeníc, 2015). As a result of their efficient performance, evolutionary algorithms have been predominantly used in this field (Fernandes et al., 2014; Gon??alves & Resende, 2015; Guo, Cheng, & Wang, 2017).

In this study, a distance-constrained single-flow hierarchical facility location model is developed to find the best spatial distribution of facilities in two levels of launch and recharge stations for a drone delivery system. The facilities can be either launching facility, which is the distribution center from where the drones are launched and parcels are sent, or recharge facility, which is used to recharge drones on their long routes to the demand points.

In the following section, assumptions are explained, and the problem is formulated. In section 2-3, an alternative solution method based on metaheuristic algorithms is developed. Section 2-4 presents a case study. In section 2-5, the results are elaborated, and finally, section 2-6 presents conclusions and sets directions for future research.

2.2 Problem Definition and Assumptions

In this study a mobile hierarchical facility location problem is investigated in order to find the best locations for launch/recharge stations. It is supposed that demands are ultimately satisfied by launch stations. The refuel stations are used to recharge drones on their long trips to demand points. The demand is assumed to arise according to Poisson distribution and is uniformly distributed along the network edges. Furthermore, due to of drone's capacity, it is assumed that only one demand is satisfied in each trip and in order to do that, a drone should perform a round trip from the nearest launch station to the demand point. Each demand is allocated to its nearest facility ignoring its type and each refuel station is itself allocated to nearest launch station. Several refuel stations may be visited in order to reach the designated launch station, this path is calculated according to shortest path algorithm. In order to use the shortest path algorithm for computing the shortest path parameter between pairs of potential facility locations, Euclidean distances between locations that are within the endurance of the drone are considered as feasible paths which prohibits the violation of endurance constraint. Since it is supposed that all the demand should be covered, the distance between any node and its closest facility should be within the endurance of the drones, otherwise the problem would be infeasible. This constraint also holds for refuel stations, which means that the distance between a refuel station and its closest facility should not be greater than the drone's endurance and there should be feasible path to at least one launch station. Endurance is defined as the distance that a drone can traverse without requiring to refuel/recharge. The words refuel station and recharge station are used equivalently in this study, the same goes for words demand and customer. Also it is obvious that the price of a refuel station is considered significantly lower than a launch station. Each drone has a distance capacity in the planning period which indicates the total distance that a drone can traverse within a given time or planning period. The number of drones assigned to each facility is determined based on the total demand assigned to that facility and the travel distance required for covering this demand. The number of open facilities is a decision variable. The potential locations of facilities are predetermined and discrete, and it can be used to establish either launching or recharge stations. There is a usage cost associate with each vehicle. The utilization cost of the drones is a function of drone life cycle, battery cost and life cycle (if applicable), fuel consumption, maintenance and so forth. The utilization cost is considered per distance unit and is incurred by the assignment of demands to the facilities based on the required travel distance.

2.3 Model Formulation

To model the problem the following variables, parameters and sets should be defined.

Sets:

V: Set of nodes ($v, v' \in V$)

J: Set of candidate locations ($j, j', j'' \in J, J \subseteq V$)

A: Set of network edges ($A \subseteq V \times V, (v, v') \in A$)

Scalars:

M: A large positive number

Parameters:

c_j^l: Cost of opening a new launching station in candidate location j

c_j^r: Cost of opening a new recharge station in candidate location j

c_d: Price of each drone

c_g: Usage cost of drones

$d_{jj'}$: Euclidean distance between facility j and facility j'

d_{jv}: Euclidean distance between facility j and node v

w_j: The weight of the j^{th} facility in computations of the shortest path

$l_{vv'}$: Length of edge (v, v')

$\lambda_{vv'}$: The demand located on edge (v, v')

ρ: Distance capacity of each drone in the planning period

M_t: The maximum acceptable length of the route from a refuel station to its assigned launching station

Variables:

$L_j = 1, if\ a\ launching\ station\ is\ established\ in\ location\ j; 0, otherwise$

$R_j = 1, if\ a\ refueling\ station\ is\ established\ in\ location\ j; 0, otherwise$

$y_j = 1, if\ a\ facility\ is\ established\ in\ location\ j; 0, otherwise$

$z_{jj'} = \begin{cases} 1 & if\ the\ facility\ j\ has\ the\ minimum\ Euclidean\ distance\ to\ facility\ j' \\ 0 & otherwise \end{cases}$

$u_{jj'} = \begin{cases} 1 & if\ the\ facility\ j\ has\ the\ minimum\ shortest\ path\ to\ launch\ station\ \ j' \\ 0 & otherwise \end{cases}$

$x_{jv} = 1, if\ node\ v\ is\ assigned\ to\ facility\ j; 0, otherwise$

n_d: Total number of required drones

n_g: Aggregate utilization of drones (total kilometers traversed)

$\delta_{vv'jj'}$: The distance between decomposing point of edge (v, v') and facility j when the closest facilities to nodes v and v' are j and j', respectively

$b_{vv'jj'}$: The distance between node v and the decomposing point of edge (v, v') when the closest facilities to nodes v and v' are j and j', respectively

$\bar{d}_{vv'jj'}$: The average distance from facility j to the decomposed segment vv' when the closest facilities to nodes v and v' are j and j', respectively

$t_{jj'}$: The length of the shortest path from facility j to facility j'

w_j: The weights used to compute the shortest path such that $w_j - w_j' = d_{jj'}$

If the vertices of an edge are assigned to two facilities, the edge is decomposed into two segments, and the demand on each segment is satisfied through its assigned facility. When node v is assigned to facility j and node v' is assigned to facility j', the distance between node v and the decomposition point is denoted by $b_{vv'jj'}$ and calculated according to Eq.(20) and Eq. (21), furthermore the distance between the decomposing point and its corresponding facility is obtained by Eq.(23) (Golabi, Shavarani, & Izbirak, 2017b).

Using the described assumptions and definitions, the problem can be modeled as follows:

$$Min \sum_j c_j^l L_j + \sum_j c_j^r R_j + n_d c_d + n_g c_g \qquad (2\text{-}1)$$

Subject to:

$$L_j + R_j = y_j \qquad \forall\, j \in J \qquad (2\text{-}2)$$

$$\sum_j x_{jv} = 1 \qquad \forall\, v \in V \qquad (2\text{-}3)$$

$$\sum_j z_{jj'} = 1 \qquad \forall\, j' \in J \qquad (2\text{-}4)$$

$$\sum_j u_{jj'} = 1 \qquad \forall\, j' \in J \qquad (2\text{-}5)$$

$$x_{jv} \le y_j \qquad \forall\, j \in J, v \in V \qquad (2\text{-}6)$$

$$u_{jj'} \le L_{j'} \qquad \forall\, j, j' \in J \qquad (2\text{-}7)$$

$$z_{jj'} \le y_{j'} \qquad \forall\, j, j' \in J \qquad (2\text{-}8)$$

$$2\delta_{vv'jj'}x_{jv}x_{j'v'} \leq E \qquad \forall\, j \in J, v \in V \tag{2-9}$$

$$\sum_{j'} d_{jj'}R_j y_{j'} z_{jj'} \leq E \qquad \forall\, j \in J \tag{2-10}$$

$$2d_{jv}x_{jv} \leq E \qquad \forall\, j \in J, v \in V \tag{2-11}$$

$$t_{jj'} = (w_j - w_{j'}) \qquad \forall\, j, j' \in J \tag{2-12}$$

$$w_j - w_{j'} \leq d_{jj'} \qquad \forall\, j, j' \in J | d_{jj'} \leq E \tag{2-13}$$

$$w_j - w_{j'} = M \qquad \forall\, j, j' \in J | d_{jj'} > E \tag{2-14}$$

$$t_{jj'}u_{jj'} \leq M_t \qquad \forall\, j, j' \in J \tag{2-15}$$

$$\sum\nolimits_{j' \in J} d_{j'v}\, x_{j'v} \leq d_{jv} + M(1 - y_j) \qquad \forall\, j \in J, v \in V \tag{2-16}$$

$$\sum\nolimits_{j' \in J} d_{jj'}\, z_{jj'} \leq d_{jj''} + M(1 - y_{j''}) \qquad \forall\, j, j'' \in J \tag{2-17}$$

$$\sum\nolimits_{j' \in J} t_{jj'}\, u_{jj'} \leq t_{jj''} + M(1 - y_{j''}) \qquad \forall j, j'' \in J \tag{2-18}$$

$$b_{vv'jj'} = \frac{l_{vv'}\left({d_{j'v}}^2 - {d_{jv}}^2\right)}{{d_{jv'}}^2 - {d_{j'v'}}^2 + {d_{j'v}}^2 - {d_{jv}}^2} \qquad \forall\, j, j' \in J | j \neq j', v, v' \in V \tag{2-19}$$

$$b_{vv'jj} = max\left(\frac{d_{jv'} - d_{jv}}{|d_{jv'} - d_{jv}|}, 0\right) l_{vv'} \qquad \forall\, j \in J, v, v' \in V \tag{2-20}$$

$$\bar{d}_{vv'jj'} = \left(d_{jv}x_{jv} + \delta_{vv'jj'}x_{jv}x_{j'v'}\right) + 2\sum\nolimits_{j'' \in J} t_{jj''}\, u_{jj''} \qquad \forall\, j, j' \in J, v, v' \in V \tag{2-21}$$

$$\delta_{vv'jj'} = \sqrt{\frac{b_{vv'jj'}{d_{jv'}}^2 + (l_{vv'} - b_{vv'jj'}){d_{jv}}^2 - b_{vv'jj'}(l_{vv'} - b_{vv'jj'})l_{vv'}}{l_{vv'}}} \qquad \forall\, j, j' \in J, v, v' \in V \tag{2-22}$$

$$n_j \geq \sum_{j'}\sum_{j''}\sum_{(v,v')} \lambda_{vv'}b_{vv'jj'}\bar{d}_{vv'jj}x_{jv}x_{j'v'}u_{jj''}/\rho l_{vv'} \qquad \forall\, j \in J \tag{2-23}$$

$$n_g = \sum_{j}\sum_{j'}\sum_{j''}\sum_{(v,v')} \lambda_{vv'}b_{vv'jj'}\bar{d}_{vv'jj}x_{jv}x_{j'v'}u_{jj''}/l_{vv'} \tag{2-24}$$

$$n_d = \sum_{j} n_j \tag{2-25}$$

$$y_j \in \{0,1\} \tag{2-26}$$

$$x_{jv} \in \{0,1\} \tag{2-27}$$

$$z_{jj'} \in \{0,1\} \tag{2-28}$$

$u_{jj'} \in \{0,1\}$ (2-29)

$L_j \in \{0,1\}$ (2-30)

$R_j \in \{0,1\}$ (2-31)

$b_{vv'jj'} \geq 0$, $w_j \geq 0$, $\bar{d}_{vv'jj'} \geq 0$, (2-32)

The objective function (2-1) aims to minimize the total costs incurred by the system. Constraint (2-2) prohibits the assignment of multiple facilities to a unique location. Constraint (2-3) assigns each node to only one facility. Constraints (2-4) and (2-5) along with constraints (2-16) - (2-18) ensure the assignments is done to closest facilities. Constraints (2-6) - (2-8) ensure that no demand is directed to closed facilities. Constraints (2-9) - (2-11) guarantee that the endurance capacity of the drones is observed. Constraints (2-12) - (2-14) belong to the dual form of the shortest paths mathematical formulation for finding routes from refuel stations to launch stations. Constraint (2-15) limits the maximum allowed distance from the recharge station to its nearest launching station. Constraints (2-16) - (2-18) determined the closest facility to demand point, and for recharge stations. Constraints (2-19) - (2-20) determine the position of the partitioning point of the segments. The average distance of the round trip from each segment to its assigned launch facility is provided by constraint (2-23). Constraint (2-22) determines the distance between partitioning point and the nearest facility. The minimum number of drones for each facility is specified by constraint (2-23). Total travel distance and a total number of required drones for satisfying the demands are determined by constraints (2-24) and (2-25), respectively. Integer and positive variables are defined by Constraints (2-26) - (2-32).

2.4 Solution Method

The proposed mixed integer nonlinear programming model for the considered FLP is proved to be NP-hard (Owen & Daskin, 1998). Therefore, the exact solutions failed to solve even small size instances of the problem. Previously many metaheuristics algorithms have been applied to solve the FLP problems. Among these algorithms evolutionary algorithms, specifically Genetic Algorithm and Memetic Algorithm have been of proper performance. Inspired by the evolution of species through generations found in nature Holland (Holland, 1975) devised GA and since then and due to its efficiency, it has been frequently and successfully used as the solution method to FLPs (Camacho-Vallejo et al., 2014; Fernandes et al., 2014; Guo et al., 2017). Thus, a genetic algorithm (GA) is proposed to solve the model. GA starts with a population of randomly generated solutions. Each solution is represented by a chromosome. The structure of the chromosomes in this study contains n genes, where n is equal to the number of candidate locations. As illustrated in Fig. 2.1, The i^{th} gene in the chromosome indicates the situation of the i^{th} candidate location which can have three different positions: L (launching station), R (recharge station) and C stands for closed. In this incomplete representation, the location of launching and recharge stations are expressed explicitly, the number of launch and recharge stations implicitly, the required number of drones and their total usage are not stated at all.

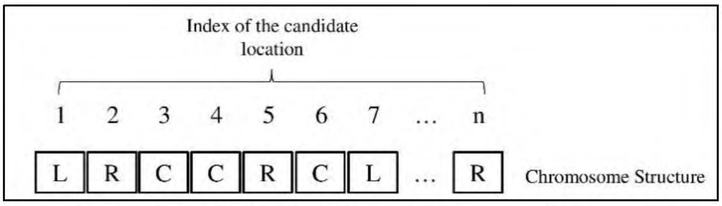


Figure 2.1: Solution Representation

Since each demand is assigned to its closest facility, by identification of the open facilities, the demand assignments are performed automatically by the algorithm. Consequently, according to the total demand assigned to each facility and required travel distance for satisfying it, the total number of required drones is calculated for each facility. Finally, the objective function in calculated by the summation of the incurred costs. A penalty function is applied if the distance between a demand point and its assigned/nearest facility violate the distance constraint, or in other words if the distance is greater that the drone's endurance. The same penalty function applies if the distance constraints are violated in the routes between recharge statins and their nearest launch station.

By the construction of initial population and computation of objective functions, the iterations of GA starts. In each iteration, the population size increases through producing offspring by crossover and mutation operators. The number of crossover and mutation operations is predetermined parameters of the GA. To perform these operations, parents are selected according to roulette wheel selection method which gives higher probabilities of selection to parents with better fitness values. The crossover operation starts with two selected parents. A crossover point is randomly generated along the length of the chromosomes. The second part of the chromosomes after the crossover point is interchanged and 2 offspring solutions are generated and added to the population. The crossover operation repeats as specified in the algorithm. The mutation operation starts with one selected parent. Based on the length of the chromosome, a number of parent's genes are selected and changed randomly. The schematic illustration of the crossover and mutation operations are presented in Fig.2.2 and Fig.2.3, respectively. The offspring solutions created by mutation operator are added to the population. At each iteration of GA, the population is sorted based on the fitness value and the best solutions are selected as the next generation to participate in the next iteration of the algorithm. The GA is finished when a predetermined number of iterations are performed. The pseudo code of GA is illustrated in Fig. 2.4.a.

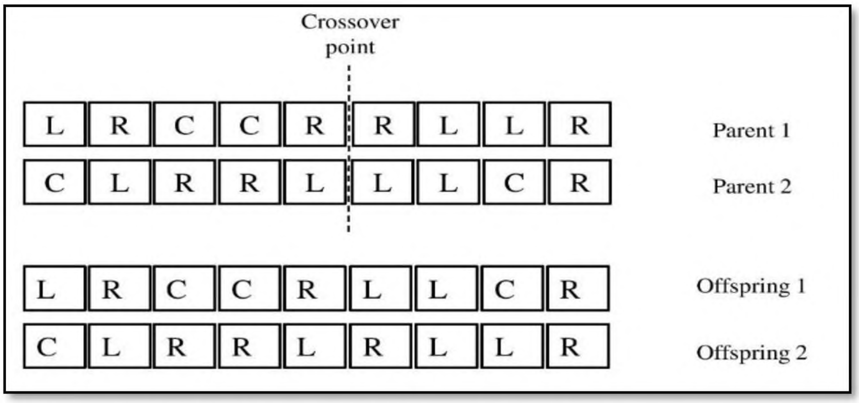


Figure 2.2: The Schematic Illustration of Crossover Operation

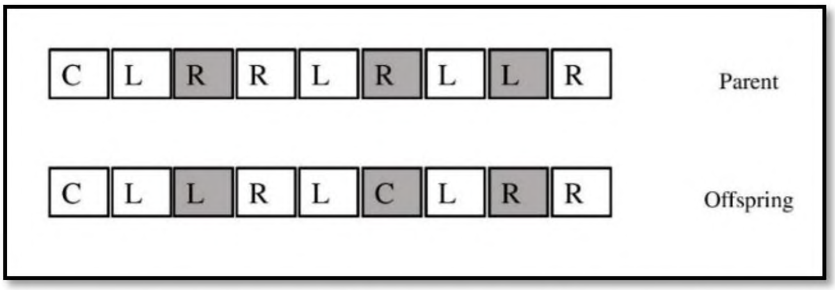


Figure 2.3: The Schematic Illustration of Mutation Operation

In the course of experiments with GA, it was observed that many locations remain open without any significant contribution to the objective function. This encouraged the authors to add a greedy algorithm to the GA in order to identify these locations and close or change them. Thus a local search was incorporated into the proposed GA to produce a hybrid GA. At the end of each iteration, the local search randomly selects some genes and lowers they level. The proposed hybrid GA is observed to be fast and gives better solutions. The pseudo code of the local search added to the GA is illustrated in Fig. 2.4.b.

a)

```
t ← 0
P(t) ← Randomly generated individuals
Eval[P(t)]; {evaluate the fitness value of the individuals}
Best ← Best individual
While t < Itmax do
    S ← select individuals ∈ P(t)
    Q ← Crossover(S) ∪ Mutation(S); {Creat offspring}
    P(t) ← [P(t) ∪ Q]
    Eval[P(t)]
    Update Best
    [P(t + 1)] ← select best individuals ∈ [P(t)]
    t ← t + 1
End while
Retrun Best;
```

b)

```
S ← Solution ∈ Population
I ← set of randomly selected locations ∈ S
For i ∈ I
    If allele(i) = L
            allele(i)=R
        Else
            allele(i) = C
    EndIf
    If Cost(S) < Cost(P)
            P ← S
        Else
            S ← P
    EndIf
End For
```

Figure 2.4: a) The Pseudocode of Genetic Algorithm b) The Pseudo Code of Local Search

The Taguchi method is used to tune the parameters of the proposed algorithms to improve their performance by finding the best combination of the parameters. The factorial design which was proposed by Fisher is generally used to investigate the effect of several factors on a response. The factors being investigated here are the parameters of the algorithm and the response is the fitness value. Taguchi reduced the required number of experiments by introducing the fractional factorial design (Roy, 1990). In this method, the factors are categorized into controllable factors (*S*) and noise factors (*N*) and the method seeks to control the effect of noise factors with an orthogonal design. The signal to noise ratio (*S/N*) is used for analyzing the results of the experiment with replications. The more the ratio of *S/N* the better is the parameter settings. The parameters to be tuned and their levels are brought in table 2.1, where *Np*, *It*, *Pc* and *Pm* indicate the population size, maximum iterations, crossover rate and permutation rate, respectively. Five replications are performed for each combination of the parameters, and the average of the fitness values obtained is used as the response.

The Taguchi design and the results for GA are displayed in Table 2.2 and Fig. 2.5.a), respectively.

Table 2.1: The parameters of the genetic algorithm and their corresponding

Parameters	Levels			
Np (Population size)	50	75	100	150
It (# Iterations)	50	100	150	200
Pc (Crossover rate)	0.3	0.5	0.7	0.8
Pm (Mutation rate)	0.2	0.3	0.5	0.3

Table 2.2: Taguchi design and corresponding data for genetic algorithm

Taguchi Design				Fitness values (for five iterations)		
Np	It	Pc	Pm	Average	Min	Max
50	50	0.3	0.2	469478041.4	406489108.1	552614080.9
50	100	0.5	0.3	460940012.9	402476718.0	522370757.7
50	150	0.7	0.5	393029127.7	351290288.3	458637618.9
50	200	0.8	0.7	396412076.2	365190898.8	429556203.0
75	50	0.5	0.5	350891405.4	326076933.5	382615819.5
75	100	0.3	0.7	376584260.4	342045786.4	424681780.4
75	150	0.8	0.2	356337262.2	323388920.0	380923717.6
75	200	0.7	0.3	374086193.2	332831457.1	419123473.9
100	50	0.7	0.7	338121203.1	317562615.0	350892253.5
100	100	0.8	0.5	344977198.4	317596614.0	382219945.4
100	150	0.3	0.3	346132795.7	334891393.6	354040417.4
100	200	0.5	0.2	370008371.7	344239917.4	407741033.2
150	50	0.8	0.3	327331502.5	315820513.2	349072118.3
150	100	0.7	0.2	347535250.2	319134731.6	359578554.4
150	150	0.5	0.7	340122109.6	325067012.9	360620640.1
150	200	0.3	0.5	326218991.8	318470658.4	336225494.7

The results of the Taguchi analysis suggest that the best configuration for GA algorithm is obtained by setting the Population size, Number of Iterations, Crossover rate and Mutation rate at 150, 150, 0.8 and 0.5, respectively.

For the Hybrid GA, the levels are the same as the GA levels, with only one difference which is the substitution of 200 iterations with 20. This decision was made based on the speed and convergence rate of the Hybrid GA. The results of the Taguchi design and results for hybrid GA are brought in Table 2.3 and Figure 2.5. Considering the output of Taguchi analysis for hybrid GA, the values of Np, It, Pc and Pm are set to 150, 50, 0.8 and 0.5 respectively.

Table 2.3: Taguchi design and corresponding data for hybrid genetic algorithm

Taguchi Design				Fitness values (for five iterations)		
Np	It	Pc	Pm	Average	Min	Max
50	50	0.3	0.2	324109457	308344245.8	333049557.5
50	100	0.5	0.3	323032143	316032490.2	329777349.4
50	150	0.7	0.5	327541200	314468553.4	342259902.6
75	50	0.5	0.5	317510686	304456020.6	329013329.8
75	100	0.3	0.7	331549381	323695035.8	345894090.0
75	150	0.8	0.2	325128689	318410757.3	334383484.8
100	50	0.7	0.7	320742057	305134059.9	333371545.4
100	100	0.8	0.5	315020113	304772032.5	326957197.8
100	150	0.3	0.3	324935016	312820475.6	333489412.4
150	50	0.8	0.3	310950350	299177744.9	319126806.5
150	100	0.7	0.2	318972719	307886191.6	335969540.2
150	150	0.5	0.7	316018585	307742074.2	330351399.0
50	20	0.8	0.7	319043965	302579930.5	341554004.0
75	20	0.7	0.3	324559447	305584076.0	353534468.1
100	20	0.5	0.2	330322943	313374486.7	361196920.2
150	20	0.3	0.5	317506207	305255948.5	340597810.4

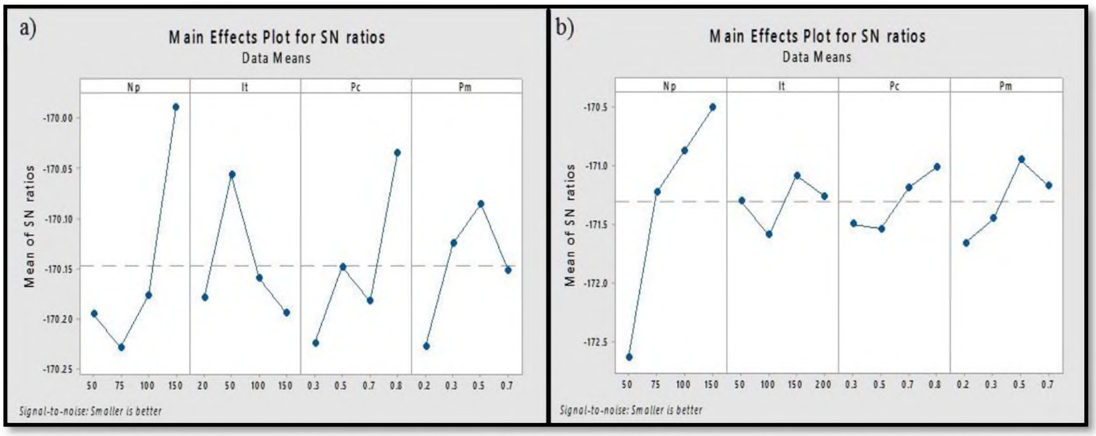


Figure 2.5: a) Main Effects Plot for SN Ratios Related to GA b) Main Effects Plot for SN Rations Related to Hybrid GA

To evaluate the performance of the two tuned algorithms, a problem is solved ten times with each algorithm and the mean of the fitness values are compared. The experiment's data is brought in Table 2.4. The assumption of equal means for the results of two methods are tested using t-test and the results are provided in Table 2.5. The results indicate that the performance of the proposed hybrid GA is significantly better than the GA (P-Value = 0.000).

Table 2.4: The comparison of GA and HGA

# run	Costs*										Average Costs	Average Solution Time
	1	2	3	4	5	6	7	8	9	10		
GA	350	331	327	342	328	338	343	343	325	352	338	1658 (seconds)
Hybrid GA	293	330	317	310	318	304	307	297	321	330	3.13	538 (seconds)
*The cost are in million dollars												

Table 2.5: Two-sample T for GA vs Hybrid GA (obtained by Minitab 16)

	N	Mean	StDev	SE Mean
GA	10	337998002	9565716	3024945
Hybrid GA	10	312639984	12546988	3967706

Difference = mu (GA) - mu (Hybrid GA)

Estimate for difference: 25358018

95% CI for difference:(14781203, 35934834)

T-Test of difference = 0 (vs not =): T-Value = 5.08, P-Value = 0.000, DF = 16

2.5 Case Study

As one of its missions, Amazon is committed to offer prices which are competitively lower than other retailers. The increase in the fuel costs in recent years has led to the increase in transportation costs by logistics companies, including FedEx and UPS that deploy Amazon's delivery operations. By the increase of the costs, Amazon is now facing new challenges to keep the prices comparatively low. As a solution to this problem Amazon has announced that a new drone delivery system is going to be launched by this company. In this way, third party transportation companies are eliminated from the chain, leaving the benefits to Amazon. This benefit is emphasized by comparing the price of ground and aerial transportation (Welch, 2015). As mentioned by (Smith, 2015), the delivery cost of a package of 2 Kilograms over a distance of 9.7 Kilometers is only 10 cents, which is way lower than ground transportation ranging from 2 to 8 dollars. Consequently, the cost of aerial delivery over one kilometer is approximated by one cent in this study.

As described by (Welch, 2015), Amazon has reported that the drones which are going to be used for delivery have the speed of 50 miles/hour (80 Km/hour) and travel a radius of 16 kilometers, which is equivalent with the endurance of 32 Kilometers, considering the round trips for delivery of the products. The distance capacity of each drone in an 8 hours' shift would be 640 Kilometers based on the speed of the drone. For each delivery mission, 6 minutes is spent for loading, unloading, landing and so forth which reduces the distance capacity of each drone to 215 kilometers in an 8-hour shift. Also, the cost of each drone is mentioned to be 4000 dollars on average. There is no accurate information on the structure and price of recharge stations, but there are few solutions on the market offered for automatically and wirelessly recharge the drones, such as the Dronebox or the Skysense Charging Pad which are around 5000 dollars. These charging pads can be placed on top of buildings or there may be towers built for them. Considering factors such as the number of charging pads and installment costs, the price of each recharge station is considered fifty thousand dollars. There is no accurate data on the costs related to a fulfillment center, therefore the cost of establishing a launching station is roughly estimated around thirty-five million dollars which may account for the costs related to the site, the construction, drone pilot station, warehouse and so forth.

San Francisco with a population around 850 thousand is selected for the case study. The geographical data of the San Francisco transportation network (Fig. 2.6.a) was extracted from ArcGIS 10 software which includes 68374 polylines and 47266 points associated with information such as coordinates of the points and lengths of the lines. Among existing nodes, 110 nodes were selected to be used as potential locations (Fig. 2.6.b).

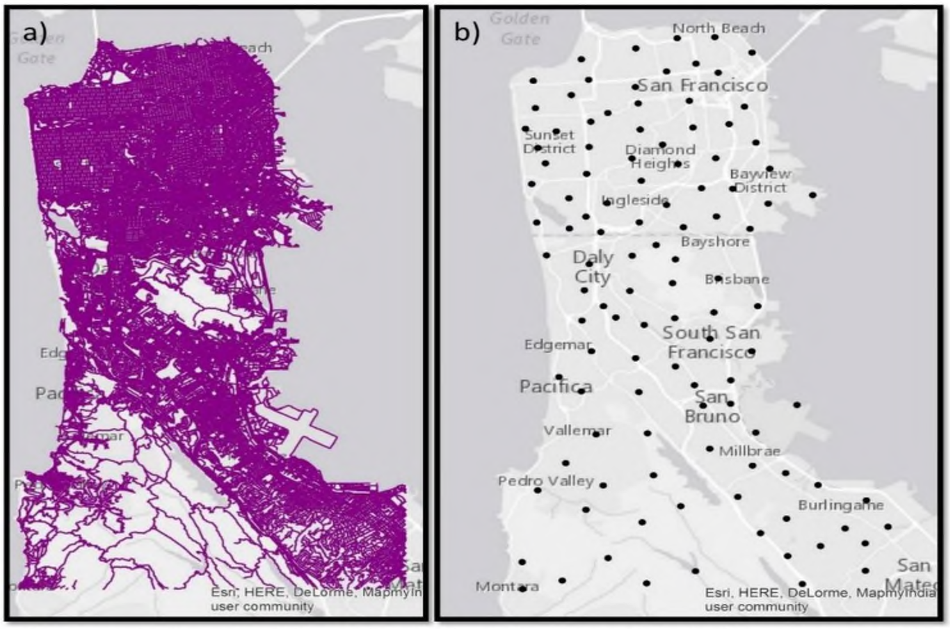


Figure 2.6: Acquired from ArcGIS; a) San Francisco's Open Street Map
b) Candidate Locations

2.6 Discussion

Considering the data related to the city of San Francisco, the problem was solved with the tuned hybrid GA. Among the selected candidate locations, two launch stations and twenty-two recharge stations are selected to support the delivery system, as illustrated in Fig. 2.7. This combination of the stations is the best found solution with the total cost of the system equal to 298491684 dollars for covering all the demands in planning horizon. Let's be reminded that this is the total costs of the system including the costs of station establishments, drone procurement and usage costs. According to (Welch, 2015) an average of delivery for each person in USA per day is 0.122295 and considering the population of San Francisco, the average daily delivery for this city would be 103950.75. Since each trip is on average 10 miles or 16.0934 kilometers, Therefore, everyday an average of 1672921 Kilometers is travelled every day. By using the drone system Amazon would benefit 0.49 dollars per kilometers which is equivalent with 819731.2900245 dollars per day for the city of San Francisco. Thus the capital of 298491684 dollars would return in just 365 days. Considering the longer travel distances of ground transportation compared with aerial transportation, the justification of this investment would be even clearer. Many studies in this area have only considered the construction of refuel stations without considering the construction of launch stations/warehouses which could lower the costs due to the decreased travel distance. This study also accounts for investments in this area for both launch stations and refuel stations.

From another point of view, the number of drones is dependent on the number of shifts or working hours in each day. In this solution, the number of drones is 54345 according to one shift delivery. This accounts for 217380000 out of 298491684 dollars. If the working hours increase to 16 hours/day or two shifts, the total capita would decrease to 189801684 which makes this investment more desirable. Also, it may be interesting that by increasing the speed of the drones by 25 percent, from 80 to 100, the capita would decrease from 298491684 to 255015684. These kinds of analysis would help decision makers to decide on the configurations of the drones and other parameters under decision with regard to their prices and weigh their benefits and costs.

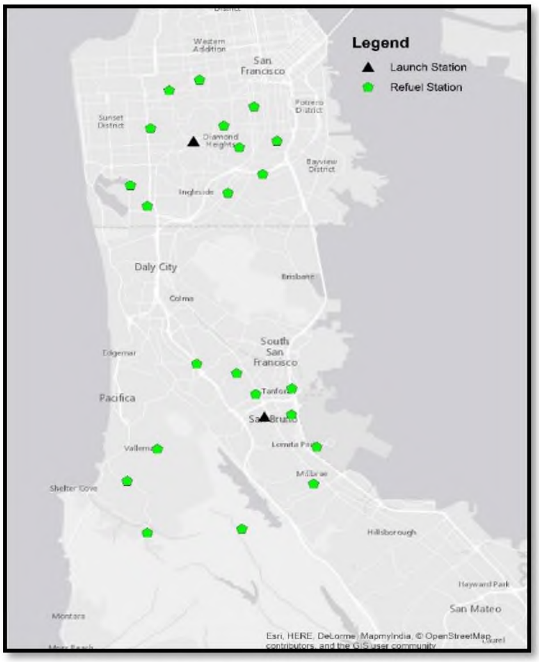


Figure 2.7: The Outcome of the Proposed Algorithm for San Francisco

2.7 Conclusion

In this study, a hierarchical facility location model was applied to a delivery system where the objective function is minimizing the total costs incurred by the system. It is assumed that the demand is uniformly distributed along the network edges. The demand is satisfied by round flights of the drones. To satisfy a demand, a drone should have a round flight from the launch station/warehouse to and from the demand point. If the flight duration is greater than the endurance of the drone, a drone may visit one or more recharge stations. The proposed model minimizes the total costs related to launch and recharge stations, and drones' procurement and usage costs. Two metaheuristic algorithms including GA and a Hybrid GA were developed and their results were compared. The performance of the hybrid genetic algorithm was proved to be better than the GA. Therefore, the hybrid GA was used to perform the case study. The data required for the case study was acquired from ArcGIS 10 and the results were discussed. The feasibility and also the profitability of the investment for a drone delivery system was also investigated to some extent. This study provides a proper vision for companies seeking to establish an aerial delivery system which seems to be vital for surviving in the competitive market of todays.

With improvements in the technology of the drones and their payload, they can serve more than one demand in each trip which calls for models to monitor this situation. Furthermore, due to uncertainty in several parameters of the problem, including the costs of the stations and drone's capabilities and specifications, future studies can either use fuzzy models to give a more realistic vision of the problem or perform a sensitivity analysis to account for the outcome of different options. Also one of the goals aimed by Amazon is to decrease the delivery time under thirty minutes and this can be a subject of future studies to account for waiting times using the queuing theory.

Chapter 3

A CONGESTED CAPACITATED MULTI-LEVEL FUZZY FACILITY LOCATION PROBLEM: AN EFFICIENT DRONE DELIVERY SYSTEM

3.1 Introduction

In the modern market of today's, management of supply chain and efficient delivery of goods and services to the customers has turned into the most essential, challenging components of a successful business. This relatively new issue has raised a heavy competition among the major players in the global market. Considering the current tremendous pool of demand, the companies always try to find a more effective delivery option which is faster, cheaper, and more convenient. Having the time when the customers had to go to the market for procurement long passed; the indoor delivery for numerous categories of goods and services is becoming the mainstream delivery means in current societies. (Magretta, 2002).

On the other hand, there are major obstacles in the delivery of services/goods to the customers in populated metropolises. The difficulties associated with the transportation (particularly the traffic jams in large cities and fuel costs) cause them to be less satisfactory and more expensive with more delay (Zeithaml, Parasuraman, & Berry, 1985). In the past few years, myriad pieces of research tried to come up with effective solutions for the mentioned setbacks in various principles, specifically in supply chain management and logistics.

According to ("The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery," 2015), one of the propositions to tackle this complication is utilizing the drones for delivery of products or services. This solution has attracted the interest and investment of many reputable companies such as Amazon, Google, and DHL. The core idea of the majority of the studies in utilizing aerial delivery systems is to develop an accurate model to optimize the routing of the drones and to schedule the operations efficiently. Interestingly, drone delivery applications are cultivated to cover a wider variety of applications from pizza delivery in large cities to document delivery in Emirates. Recently, even drone-taxi is being initiated in some cities (Kwon, Kim, & Park, 2017).

While using drones for delivery purposes seems to be a promising solution for many enterprises, enabling the decision maker to design an effective delivery system is at the stake of contemplating an important set of parameters. Some of the most prominent variables in this regard are the number of launching and relaunching facilities, the capacity of the launching sites, the number of drones in each facility, and the endurance of the drones. Whether the organization is a service provider or a product provider, proper deliberation of the mentioned factors is at the stake of determining the best locations from where the service or goods must be delivered to the customers (Dorling et al., 2017).

The above-mentioned problem is addressed by Facility location problems (FLP) in the literature. The FLP deals with the problem of spotting a set of facilities - normally from a set of candidate locations - to satisfy the demand as efficient as possible under a set of constraints. Generally, this problem aims to minimize the total weighted distances between the providers and customers. In the literature, the weights normally express the difficulty degree of the transportation or simply the travel distance. A solution to this problem is expected to apprehend the facility locations such that maximum profit and customer satisfaction is acquired.

According to Melo, Nickel, and Saldanha-Da-Gama (2009), deciding on the location of a facility is an imperative factor in the strategic planning of delivery networks. This subject has attracted plentiful attention to proposing models for determining the most profitable locations for the facilities (Melo et al., 2009). A typical facility location problem usually includes a set of customers as well as service/goods providers in which the distances and traveling time (or transportation costs) between facilities and clients is measured by a specific criterion. In these problems, the answer to the following three questions has a fundamental significance: (i) how many facilities are required? (ii) Which target customers are to be served by each facility and, (iii) which strategy delivers the minimum amount of cost (Klose & Drexl, 2005; ReVelle, Eiselt, & Daskin, 2008)? According to (Wen, Qin, Kang, & Yang, 2015a), FLP was first studied by Cooper in 1963 trying to determine the location of several warehouses with respect to the demand points that had to be met through each warehouse. Sarraj, Ballot, Pan, Hakimi, and Montreuil (2014) are the first individuals who implemented this concept in network design. The economic advantages of drone utilization for commercial purposes was addressed by Park, Zhang, and Chakraborty (2016). They investigated the various battery configurations to minimize the costs related to electricity and battery purchases. Mourelo Ferrandez *et al.* (2016) minimized the delivery time as well as the total number of facilities in a drone-truck delivery system.

Similarly, the application of drone delivery has been discussed in the context of rescue operations (Xiang et al., 2016), relief distribution (Golabi et al., 2017b), delivery (Hong et al., 2017b; M. Kim & Matson, 2017) and healthcare (Scott & Scott, 2017). Recently, Hong *et al.* (2017) tried to optimize the location of recharging stations for UAVs in order to cover the demand in the context of large cities.

Congested facility location problem is another ilk of location problems in which customers have to wait in a queue to receive the service. Boffey, Galvão, and Espejo (2007) reviewed different versions of congested location problems with immobile servers. In the case of mobile servers, the service time accounts for the round-trip time between the facility and the location of demand plus the probable on-scene and off-scene service time (Berman, Larson, & Chiu, 1985) and considering a general distribution for service time is essential (Batta & Berman, 1989). In this field, Berman *et al.* (1985) studied a single-server single-facility location problem using M/G/1 queuing systems. Considering the same queuing framework, Berman and Mandowsky (1986) expanded the previous study to locate n facilities on a network. Applying M/G/k queuing systems, Batta & Berman (1989) proposed a model for the general k-servers n-facility location problem. Using discrete event simulation, they showed that the approximation method devised by Nozaki & Ross (1978) is adequate for a congested location problem in an M/G/k environment. The queuing system discussed in this study follows the M/G/k model.

3.2 The Impact of Uncertain Factors

As described by Wen, Qin, Kang, and Yang (2015b), a general flaw in the majority of current studies on FLP is considering them as deterministic problems which means the customers' demands are assumed to be known, the variation in the travel durations is neglected, and the cost is considered as linear functions. However, without considering the uncertainties associated with the problem the proposed models are unable to represent effective realistic solutions to the actual problems. This inadequacy is addressed by incorporating stochastic nature of the variables into the model by several researchers (Logendran & Terrell, 1988; Sabri & Beamon, 2000; Zhou & Liu, 2007).

Although stochastic models can be effective in a large range of cases, they still are unable to represent the majority of the scenarios where the probability distributions of the uncertain parameters are entirely or partially unknown. In such cases, the best applicable approach for obtaining a better understanding of the problem as well as the appropriate modeling approach is to consult the experts (more precisely; the person(s) who has enough knowledge about the topic) and collect the data from the professional point of view (Klir & Yuan, 1996). The empirical data acquired from experts is normally contaminated with some degree of uncertainty. Such characteristic of the uncertain variables may be reflected by employing the fuzzy variables in the representative model of the problem (Zadeh, 1965). In fuzzy theory, when an uncertain variable such as customer's demand is stated as "around 93", a fuzzy variable must be utilized to illustrate the concept of "around 93". In reality, "around 93" might be anything between 85 and 100. Thus, a corresponding hypothetical trapezoidal membership function can be defined to show the membership degree of the demand to a specified interval. This method has been a common practice to reflect the uncertainty of the problems for many decades (U. Bhattacharya, Rao, & Tiwari, 1993; Darzentas, 1987; Zhou & Liu, 2007). Unfortunately, Interpretation of such membership functions and utilizing them for solving a problem is not an easy task (Wen et al., 2015b). This complication has been the motive for many researchers to come up with new solution approach dealing with uncertain problems (Niroomand, Mosallaeipour, Mahmoodirad,

& Vizvari, 2018). One of the best methods for dealing with this category of problems is the “uncertainty theory” introduced by Liu (2007, 2010) which has attracted lots of attention recently(Cui, Cui, & Yang, 2014; Baoding Liu, 2016; J. N. K. Liu & Zhang, 2014). Similarly, (Mosallaeipour, Mahmoodirad, Niroomand, & Vizvari, 2017) utilized the concept of uncertainty theory, the expected value of the fuzzy variables, and the degree to which an independent fuzzy variable is greater than or equal to another independent fuzzy variable in a fuzzy possibilistic programming approach for solving an uncertain supplier-material selection problem successfully.

In this study, the **customer’s demands**, **costs of opening a new facility**, **costs of drone procurement** and the **distance capacity** of the drones are considered as uncertain variables for which fuzzy variables are employed to reflect their uncertain characteristics. These characteristics create a suitable problem setting for utilizing the possibilistic approach, however, slight modifications might be required before this method can be utilized (Mosallaeipour et al., 2017). It should be noted that the possibilistic approach does not provide the crisp equivalent of the fuzzy relations in the case of nonlinearity or dependent fuzzy variables; however, utilizing the concept of expected value in such relations solves this problem easily. This modification is incorporated into the original model for dealing with the complex formulation of the current Congested Capacitated Multi-Level Fuzzy Facility Location Problem. Some of the most significant advantages of possibilistic programming approach which makes it a suitable solution approach for this problem are the followings: it is easy to implement, may employ trapezoidal and triangular fuzzy variables, enables the decision maker to obtain the optimal solution depending on the desirable feasibility degree, and more importantly, it uses strong mathematical concepts such as expected interval and expected value of the fuzzy numbers. This method apprehends the crisp equivalent of the mentioned fuzzy formulation which is solvable by the regular approaches.

The remaining of this chapter is organized as follows: In section 3-2, a brief description of the problem along with some essential preliminaries is laid out. In sections 3-3, the fuzzy mathematical formulation of the problem is proposed. Section 3-4, provides details on the application of fuzzy possibilistic approach for transforming the proposed fuzzy model into its crisp equivalent. Section 3-5 illustrates the performance and effectiveness of the proposed methodology through a case study. The 6^{th} section of this chapter pertains to the conclusion and directions for future research.

3.3 Preliminaries and Problem Formulation

3.3.1 Definitions and Preliminaries

Before proceeding any further, the following definitions must be considered:

Warehouses: Warehouses are the initial takeoff location for the drones. They are considered as the main nest for the drones. Opening a Launch center requires more infrastructure in comparison with the refuel stations.

Refuel stations: These centers are designed for extending the coverage of the drones by giving them the possibility to refuel/recharge on their way to demand points.

Capacitated facilities: the capacity of each facility is determined by the total number of assigned drones. The model seeks the best configuration to fully satisfy the demand. It is supposed that the set of candidate locations is known and thus the problem is defined as discrete FLP.

The demand occurrence on each node is assumed to follow the Poisson distribution. The distance between the launching point and the landing of a drone, no matter the warehouse or refueling station is called a trip. The length of trips cannot be greater than the endurance of the drones. Each mission of the drone could consist of as many as trips needed. A drone may visit one or more refueling stations on its route to satisfy a demand. The distances between facilities are Euclidean and the length of the total route from warehouse to the demand point is calculated based on Dijkstra algorithm. Each drone has a distance capacity during the planning period. The number of drones assigned to each facility is determined based on the total demand assigned to that facility and the travel distance required for covering this demand. Each drone is considered as a server. If drones are available, they are immediately dispatched to the demand point. If drones are busy, customers wait in a queue within an M/G/k framework. The number of open facilities is a decision variable. It is assumed that the average waiting time at each open facility should not exceed a predetermined threshold. The potential locations of facilities are predetermined and discrete and can be used to establish launching or refueling stations. The establishment cost of refueling stations is supposed to be significantly lower than launching stations. Finally, a usage cost associates each drone mission.

3.3.2 Problem Specifications

In this study, optimization of a drone delivery system comprised of refuel stations and warehouses is considered. Since the warehouses also serve as the launch stations, the words warehouse and launch station are used equivalently in this article. To cover the whole area of the city, the refuel stations should be established in specific locations in the area. A drone may visit one or more refuel stations during its journey between the warehouses and customers. The frequency of the refuels depends on drone endurance and the distance traversed. The endurance of a drone is defined as the maximum distance that can be flown by a drone without being refueled. The length of the shortest path from a demand to the nearest warehouse is equal to the Euclidean distance if no refueling required, otherwise, this length is acquired using the shortest path algorithm. Since the location of refuel stations is a decision variable, the length of the shortest path is variable as well. Similarly, the total number of facilities to be established is a decision variable for both refuel stations and warehouses. Moreover, the price of refuel stations is significantly lower than warehouses and customer is served by the closest warehouse. Furthermore, all demand should be covered.

Four major costs could be addressed in these problems: establishment costs of the lunch stations, establishment costs of refuel stations, and procurement and usage costs of the drones. Usage costs care normally addressed as maintenance, fuel and depreciation cost. They have a direct relation with the distance traveled thus they are all calculated per distance unit. It is imperative to integrate such costs in the objective function as a coefficient multiplied by the aggregate travel distance. The speed of drones is fixed and identical. Therefore, minimization of the usage costs would be equivalent to minimizing the traveling time.

In each working shift, a drone can travel a maximum distance according to its specifications such as speed and endurance. This distance is considered as the distance capacity of a drone. Consequently, the distance capacity of a facility is defined as the total distance that can be covered by a facility and is equal to the sum of distance capacities of the drones assigned to that facility. Thus, the number of drones assigned to each facility is a function of the demands assigned to it and the total travel distance required for satisfying them.

3.4 Fuzzy Mathematical Formulation

In this section, the fuzzy mathematical formulation is presented based on the characteristics and assumptions of the problem mentioned in the previous sections. In this model, the uncertainty of the variables is reflected through fuzzy variables; a tilde over the variables indicates their fuzziness. The following notations are used to introduce the mathematical formulation of the problem.

Sets:

V: The set of nodes ($v, v' \in V$)

J: The set of candidate locations ($j, j' \in J, J \subseteq V$)

Scalars:

M: A large positive number

Parameters:

$\widetilde{cl_j}$: The cost of opening a new launching station at candidate location j

$\widetilde{cr_j}$: The cost of opening a new refueling station at candidate location j

$\widetilde{c_d}$: The price of each drone

c_g: The usage cost of drone vehicles per distance unit

$d_{jj'}$: The Euclidean distance between facility j and facility j'

d_{jv}: The Euclidean distance between facility j and node v

$\widetilde{\lambda_v}$: The demand located on node v

$\widetilde{h_v}$: The fraction of total demands originated from node v

$\tilde{\vartheta}$: The speed of drones

$\tilde{\rho}$: The distance capacity of each drone during the planning period

E: The endurance of each drone

τ_j: The maximum allowed waiting time at facility j

M_t: The maximum allowed length of the route from demand point to its assigned launching station

Variables:

$L_j = 1$, if a launching station is established at location j; 0, otherwise

$R_j = 1$, if a refuelling station is established at location j; 0, otherwise

$y_j = 1$, if a facility is established at location j; 0, otherwise

$x_{jv} = 1$, if node v is assigned to facility j; 0, otherwise

$w_j =$ The shortest path weight of node j

t_{jv}: The length of the shortest path from facility j to demand node v

n_j: The total number of required drones in facility j

n_d: The total number of required drones

n_g: The aggregate utilization of drones

$\widetilde{\gamma_j}$: The request for service at facility j

$\overline{S_j}$: The first moment of service time at facility j

$\overline{S_j^2}$: The second moment of service time at facility j

$\overline{T_{jv}}$: The first moment of service time for demand node v at facility j

$\overline{T_{jv}^2}$: The second moment of service time for demand node v at facility j

ω_j: The expected waiting time at facility j

Since the demand generation is according to Poisson distribution, the request for service at each open facility j is a Poisson process with the following intensity:

$$\widetilde{\gamma_j} = \sum_{v \in V} \widetilde{\lambda_v}\, x_{jv} \tag{3-1}$$

The fraction of total demands originating from demand node v is calculated according to Eq. 3-2.

$$\widetilde{h_v} = \widetilde{\lambda_v} / \sum_{t \in V} \widetilde{\lambda_t} \tag{3-2}$$

For M/G/k queuing systems, the expected waiting time at each facility j is calculated as (Batta & Berman, 1989):

$$\omega_j = \frac{\widetilde{\gamma_j}^{n_j}\ \widetilde{\widetilde{S_j}}^2\ \widetilde{\widetilde{S_j}}^{k_j-1}}{2\,(n_j-1)!\,[n_j-\gamma_j\overline{S_j}]\sum_{i=0}^{k_j-1}\left((n_j-i)(\widetilde{\gamma_j}\widetilde{\overline{S_j}})^i/i!\right)} \qquad if\ \widetilde{\gamma_j}\widetilde{\widetilde{S_j}} < n_j \tag{3-3}$$

The first and second moments of service time at each facility j are calculated as (Jamil, Baveja, & Batta, 1999):

$$\widetilde{\widetilde{S_j}} = \sum_{v \in V} h_v \overline{T_{jv}}\, x_{jv} \tag{3-4}$$

$$\widetilde{\widetilde{S_j}}^2 = \sum_{v \in V} h_v \overline{T_{jv}^2}\, x_{jv} \tag{3-5}$$

The first and second moments of service time for demand node v at facility j are calculated by Eq. 3-6 and Eq. 3-7 respectively (Moghadas, Monabbati, & Kakhki, 2013).

$$\widetilde{\overline{T_{jv}}} = \frac{2d_{jv}}{\widetilde{\vartheta}} + \overline{z_v} \tag{3-6}$$

$$\widetilde{\overline{T_{jv}^2}} = \left(\frac{2d_{jv}^2}{\widetilde{\vartheta}}\right) + 2\left(\frac{2d_{jv}}{\widetilde{\vartheta}}\right) + \overline{z_v}^2 \tag{3-7}$$

$\overline{z_v}$ is the expected on-scene and off-scene service time at demand node v which according to the essence of this study could be neglected.

Using the described assumptions and definitions, the problem can be modeled as the following fuzzy formulation:

$$Min \sum_{j} \widetilde{c_j^l} L_j + \sum_{j} \widetilde{c_j^r} R_j + n_d \widetilde{c_d} + \widetilde{n_g} c_g \tag{3-8}$$

Subject to:

$$L_j + R_j = y_j \qquad \forall\, j \in J \tag{3-9}$$

$$\sum_j x_{jv} = 1 \qquad \forall\, v \in V \tag{3-10}$$

$$x_{jv} \leq y_j \qquad \forall\, j \in J, v \in V \tag{3-11}$$

$$t_{jv} = (w_v - w_j) \qquad \forall\, j \in J, v \in V \tag{3-12}$$

$$(w_j - w_{j'}) y_j y_{j'} \leq d_{jj'} \qquad \forall\, j, j' \in J|_{d_{jj'} \leq E} \tag{3-13}$$

$$(w_v - w_j) y_j \leq d_{jv} \qquad \forall\, j \in J, v \in V|_{d_{jv} \leq E} \tag{3-14}$$

$$t_{jv} x_{jv} \leq M_t \qquad \forall\, j \in J, v \in V \tag{3-15}$$

$$\sum_{j' \in J} t_{j'v} x_{j'v} \leq t_{jv} + M\big(1 - y_j\big) \qquad \forall\, j \in J, v \in V \tag{3-16}$$

$$n_j \geq \sum_{(v)} \widetilde{\lambda_v} t_{jv} x_{jv} / \tilde{\rho} \qquad \forall\, j \in J \tag{3-17}$$

$$n_g = \sum_{j} \sum_{(v)} \widetilde{\lambda_v} t_{jv} x_{jv} \tag{3-18}$$

$$n_d = \sum_{j} n_j \tag{3-19}$$

$$\omega_j \leq \tau_j \qquad \forall\, j \in J \tag{3-20}$$

$$y_j, x_{jv},, L_j, R_j \in \{0,1\} \tag{3-21}$$

$$w_j, t_{jv}, n_j, n_g, n_d \geq 0 \tag{3-22}$$

The objective function of the model (3-8) minimizes the total costs of the system. Constraint (3-9) refrains from establishing both launches and refuel stations at a single candidate location. Constraint (3-10) ensures that each node is assigned to one station.

Constraint (3-11) assures that demand is only assigned to opened facilities. Constraints (3-12) - (3-15) define the length of the shortest path between launch stations and demand points. The assignment of demands to the facility with the shortest path is guaranteed by constraint (3-16). Constraint (3-17) determines the minimum number of required drones for each facility. Drone utilization is reflexed in constraint (3-18). The total number of drones is specified by equation (3-19). Constraint (3-20) guarantees that the waiting time does not exceed a predefined threshold. Binary and positive variables are defined in constraints (3-21) and (3-22) respectively.

The possibilistic programming approach is employed for defuzzification of the proposed fuzzy model. In this approach, each parameter with epistemic uncertainty has a possibility distribution which means the occurrence of each data value has a possibility degree that is determined by the knowledge of the experts. In the next section, the procedure of transforming the fuzzy model to its crisp equivalent using possibilistic programming approach is discussed.

3.5 The Crisp Equivalent of the Fuzzy Model Using Fuzzy Possibilistic Uncertainty Theory

Since this formulation utilizes the fuzzy variables, it must be converted to its crisp equivalent before solving the problem. In this step, the concepts and definitions of the possibilistic method are described before it is employed to transform the fuzzy formulation:

Definition 1. Let $\tilde{\ell} = (\ell^1, \ell^2, \ell^3, \ell^4)$ be a trapezoidal fuzzy number with the following membership function:

$$\mu_{\tilde{\ell}}(x) = \begin{cases} \frac{x-\ell^1}{\ell^2-\ell^1} & \ell^1 \le x \le \ell^2 \\ 1 & \ell^2 \le x \le \ell^3 \\ \frac{\ell^4-x}{\ell^4-\ell^3} & \ell^3 \le x \le \ell^4 \\ 0 & Otherwise \end{cases} \qquad (3-23)$$

The expected interval and expected value (EI & EV respectively) of a trapezoidal fuzzy number $\tilde{\ell} = (\ell^1, \ell^2, \ell^3, \ell^4)$ are defined as follows (Jimenez *et al.*, 2007):

$$EI(\tilde{\ell}) = [E_1^{\ell}, E_2^{\ell}] = \left[\frac{\ell^1 + \ell^2}{2}, \frac{\ell^3 + \ell^4}{2}\right] \qquad (3-24)$$

$$EV(\tilde{\ell}) = \frac{E_1^{\ell} + E_2^{\ell}}{2} = \frac{\ell^1 + \ell^2 + \ell^3 + \ell^4}{2} \qquad (3-25)$$

Definition 2. According to Jimenez (1996), for any pair of fuzzy numbers ℓ and Υ, the degree to which ℓ is bigger than Υ is defined as:

$$\mu_M(\tilde{\ell}, \tilde{\Upsilon}) = \begin{cases} 0 & E_2^{\ell} - E_1^{\Upsilon} < 0 \\ \frac{E_2^{\ell} - E_1^{\Upsilon}}{E_2^{\ell} - E_1^{\Upsilon} - (E_1^{\ell} - E_2^{\Upsilon})} & 0 \in [E_1^{\ell} - E_2^{\Upsilon}, E_2^{\ell} - E_1^{\Upsilon}] \\ 1 & E_1^{\ell} - E_2^{\Upsilon} > 0 \end{cases} \qquad (3-26)$$

For the cases $\mu_M(\tilde{\ell}, \tilde{\Upsilon}) \geq \alpha$, it is said that $\tilde{\ell}$ is bigger than or equal to $\tilde{\Upsilon}$ at least in degthe ree of α. This relation is represented by $\tilde{\ell} \geq_{\alpha} \tilde{\Upsilon}$.

Definition 3. For a pair of fuzzy numbers like ℓ and Υ, the numbers are equal in degree of α (the feasibility level which is set by the decision maker) if the following relationship holds (Parra *et al.*, 2005):

$$\frac{\alpha}{2} \le \mu_M(\tilde{\ell}, \tilde{\Upsilon}) \le 1 - \frac{\alpha}{2} \qquad (3-27)$$

Definition 4 If ℓ is defined as a linear combination of $\widetilde{\Upsilon^1}$ and $\widetilde{\Upsilon^2}$, then mathematically it is true that EV (ℓ) = EV (linear combination of $\widetilde{\Upsilon^1}$ and $\widetilde{\Upsilon^2}$)

In order to illustrate how the possibilistic method converts a fuzzy model to its crisp equivalent, consider the following general mathematical formulation:

$$
\begin{array}{ll}
min\ \widetilde{c^T}\ x & \\
Subject\ to & \\
\widetilde{a_\iota}x \geq \widetilde{b_\iota} & i = 1,2,\ldots,l \\
\widetilde{a_\iota}x = \widetilde{b_\iota} & i = l+1,\ldots,m \\
\ell = p_1 \sum \widetilde{\Upsilon^1}/\widetilde{\Upsilon^2} & \\
x \geq 0 &
\end{array}
$$

According to Jimenez *et al.* (2007), Vector $x \in \mathbb{R}^n$ will be feasible with α degree if $min\ \{\mu_M(a_{\tilde{i}}x,\ b_{\tilde{i}}) = \alpha\ , i = 1,\ldots,m\}$. Hence, α is considered as the degree of feasibility for the model which is decided by the decision maker (DM). A higher value of α corresponds to smaller feasible solution space, accordingly the optimal solution becomes less interesting.

Conferring from (3-26) and (3-27), the relation $a_{\tilde{i}}x \geq b_{\tilde{i}}$ and $a_{\tilde{i}}x = b_{\tilde{i}}$ can be expressed as the followings:

$$\frac{E_2^{a_i x} - E_1^{b_i}}{E_2^{a_i x} - E_1^{b_i} - (E_1^{a_i x} - E_2^{b_i})} \geq \alpha \qquad i = 1,2,\ldots,l \qquad (3\text{-}28)$$

$$\frac{\alpha}{2} \leq \frac{E_2^{a_i x} - E_1^{b_i}}{E_2^{a_i x} - E_1^{b_i} - \left(E_1^{a_i x} - E_2^{b_i}\right)} \leq 1 - \frac{\alpha}{2} \qquad i = l+1,\ldots,m \qquad (3\text{-}29)$$

Substituting the equivalent equations into original model implies the following key relations:

$$\min[EV(c^{\sim T})]\,x$$

Subject to:

$$\left((1-\alpha)E_2^{a_i}+\alpha E_1^{a_i}\right)x \geq \alpha E_2^{b_i}+(1-\ \alpha)E_1^{b_i} \qquad i=\ 1,2,\dots,l$$

$$\left((1-\frac{\alpha}{2})E_2^{a_i}+\frac{\alpha}{2}E_1^{a_i}\right)x \geq \frac{\alpha}{2}E_2^{b_i}+(1-\frac{\alpha}{2})E_1^{b_i} \qquad i=\ l+1,\dots,m$$

$$\left(\frac{\alpha}{2}E_2^{a_i}+(1-\frac{\alpha}{2})E_1^{a_i}\right)x \leq (1-\frac{\alpha}{2})\alpha E_2^{b_i}+(\frac{\alpha}{2})E_1^{b_i} \qquad i=\ l+1,\dots,m$$

$$\mathrm{EV}(\ell)=\mathrm{EV}(p_1\sum \widetilde{\Upsilon^1}/\widetilde{\Upsilon^2})$$

$$x \geq 0$$

Based on the above-mentioned relations, the crisp equivalent of the given fuzzy objective function and constraints (17)-(18) above can be rewritten as the followings:

$$Min\ \sum_j\left(\frac{c_j^{l1}+c_j^{l2}+c_j^{l3}+c_j^{l4}}{4}L_j+\frac{c_j^{r1}+c_j^{r2}+c_j^{r3}+c_j^{r4}}{4}R_j\right)+\frac{c_d^1+c_d^2+c_d^3+c_d^4}{4}n_d+\frac{n_g^1+n_g^2+n_g^3+n_g^4}{4}c_g \tag{3-30}$$

Subject to constraints (9)-(16) and (19)-(22) and:

$$n_j \geq \sum_{(v)}\left(\alpha\left(\frac{\lambda_{vv'}^3+\lambda_{vv'}^4}{2}\right)+(1-\alpha)\left(\frac{\lambda_{vv'}^1+\lambda_{vv'}^2}{2}\right)\right)t_{jv}x_{jv}\Big/\left(\alpha\left(\frac{\rho^3+\rho^4}{2}\right)+(1-\alpha)\left(\frac{\rho^1+\rho^2}{2}\right)\right) \qquad \forall\, j \in J \tag{3-31}$$

$$n_g \geq \sum_j\sum_{(v)}\left(\alpha\left(\frac{\lambda_{vv'}^3+\lambda_{vv'}^4}{2}\right)+(1-\alpha)\left(\frac{\lambda_{vv'}^1+\lambda_{vv'}^2}{2}\right)\right)t_{jv}x_{jv} \tag{3-32}$$

$$n_g \leq \sum_j\sum_{(v)}\left(\alpha\left(\frac{\lambda_{vv'}^1+\lambda_{vv'}^2}{2}\right)+(1-\alpha)\left(\frac{\lambda_{vv'}^3+\lambda_{vv'}^4}{2}\right)\right)t_{jv}x_{jv} \tag{3-33}$$

Where:

$$\gamma_j = \sum_{v\in V}\left(\frac{\lambda_v^1+\lambda_v^2+\lambda_v^3+\lambda_v^4}{4}\right)x_{jv} \tag{3-34}$$

$$h_v = (\lambda_v^1+\lambda_v^2+\lambda_v^3+\lambda_v^4)/\sum_{t\in V}\left(\lambda_t^1+\lambda_t^2+\lambda_t^3+\lambda_t^4\right) \tag{3-35}$$

$$\overline{T_{jv}} = \frac{2d_{jv}}{\left(\frac{\vartheta^1+\vartheta^2+\vartheta^3+\vartheta^4}{4}\right)} + \overline{z_v} \tag{3-36}$$

$$\overline{T_{jv}^2} = \frac{2d_{jv}^2}{\left(\frac{\vartheta^1+\vartheta^2+\vartheta^3+\vartheta^4}{4}\right)} + 2\frac{2d_{jv}}{\left(\frac{\vartheta^1+\vartheta^2+\vartheta^3+\vartheta^4}{4}\right)} + \overline{z_v}^2 \tag{3-37}$$

$$\omega_j = \frac{\gamma_j^{n_j}\ \overline{S_j^2}\ (\overline{S_j})^{n_j-1}}{2\,(n_j-1)!\,[n_j-\gamma_j\overline{S_j}]\ \sum_{i=0}^{n_j-1}\left((n_j-i)(\gamma_j\overline{S_j})^i/i!\right)} \qquad if\ \ \gamma_j\overline{S_j} < n_j \tag{3-38}$$

3.6 Solution Method

Due to the extreme nonlinearity of the proposed mixed integer nonlinear mathematical model. The exact methods were unable to solve even the small instances of the problem. To overcome this problem, a genetic algorithm is developed to solve the problem. Inspired by the evolve of generations in nature, John Holland devised Genetic Algorithm in 1975 (Holland, 1975). Since then many researchers used this algorithm in their studies (Ghadiri Nejad, Shavarani, Vizvári, & Barenji, 2018; Guo et al., 2017). First random solutions are generated by the Genetic Algorithm (GA) to form the initial population. As illustrated in Fig. 3.1.a), each solution is represented by a chromosome and the n^{th} gene in the chromosome indicates the status of the n^{th} candidate location which can take 3 different forms; Closed (C), Warehouse (W) and Recharge Station (R). After determining the location of the facilities the assignment of demands is performed by the closest neighborhood assignment method. The distance between each node and any open facility is calculated by Dijkstra algorithm. In the calculation of the shortest path, the distances between recharge stations and other facilities which are in bounds of the expected value of their endurance are deemed as existing edges. If there exists a node whose closest facility is further than the endurance of the drones, a penalty is applied to prohibit such solutions in the next generation. The number of drones required for each facility is calculated based on the total demand assigned to that facility, the total travel distance to satisfy assigned demands, and the number of drones required to observe the constraint imposed by the maximum waiting time. Total costs of the system which is considered as the fitness value is obtained by multiplying each of the elements of the system by the expected value of their cost. Each solution is then ranked based on its fitness function. In the next step, some solutions are selected as parents to generated offspring's/children. The parents are selected by roulette wheel selection method which gives higher priority to individuals with higher rank. The children are then produced by mutation and crossover operators. In the mutation operator (Fig. 3.1.b) some genes of the selected parents are selected and their values (allele) are changed. In order to apply crossover operation (Fig. 3.1.c), two parents are selected and a crossover point is generated randomly across their length. The second parts of the chromosomes are then interchanged, giving birth to two new solutions. The increased population is then sorted based on their rank and the best individuals are selected as the next generation. The procedure repeats for a determined number of iterations. To improve the performance of the algorithm a greedy algorithm is incorporated which randomly selects a predetermined number of genes and downgrades the level of the selected gene/candidate location. If the solution is improved in terms of its fitness function, the original solution would be replaced with the superior one. This greedy algorithm is proved to improve the performance of GA in hierarchical FLP and accelerate the convergence of the algorithm towards better solutions (S.M. Shavarani, Nejad, Rismanchian, & Izbirak, 2017).

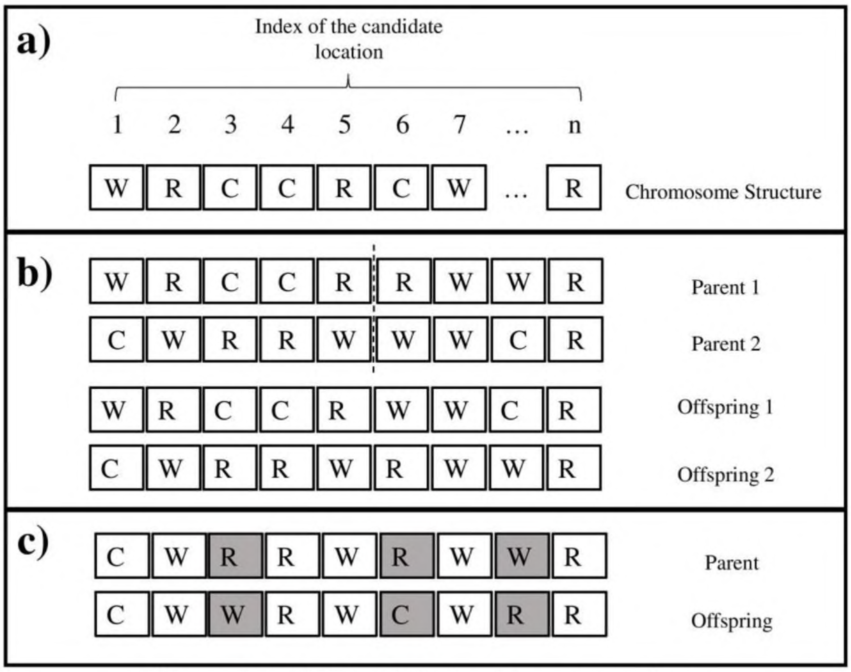


Figure 3.1: a) The Solution Representation,
b) Crossover Operation, c) Mutation Operation

3.7 Case Study

Online retailers are always coping with problems which stem from their logistics operations. The increase of the fuel costs in recent years, made the logistics companies increase their rates for the services they offer to retailers. To solve this problem and to continue offering competitive prices in the market, Amazon announced its Amazon Prime Air project to be launched in near future. The reason for this decision lies in the significantly lower costs of the aerial delivery compared to that of the ground delivery. As mentioned by (Smith, 2015) the cost of delivery for a package of 2 kilograms over a course of 10 kilometers is approximately 0.1 USD by air and 5 USD through the ground which translates to 0.49 USD savings for each kilometer traveled. On the other hand, Amazon has claimed that they intend to deliver the purchased packages in **half an hour** of the issue date for the users of Prime Air service. Thus, waiting time is calculated to monitor this issue. It is obvious that minimizing the waiting times would directly affect the number of drones required to serve the demand.

Considering a daily worldwide shipping of 15.6 million packages for Amazon (Cheredar, 2012) and on the premise that 25% of these items are shipped inside the U.S., (Welch, 2015) calculated the daily average number of delivery as 0.0122295 packages per person.

In this study, in order to reflect a more realistic image of the daily demand in the U.S., the fraction of domestic shipping packages is considered to be 10%, 20%, 30%, and 40%. Using these rates and according to this fact that 86% of orders shipped by Amazon weights less than 5 pounds and could be delivered by drones (E. Kim, 2016), the daily number of shipping items could be calculated as 0.004207, 0.008414, 0.012621, and 0.016828 packages per person. The city of San Francisco with 850,000 inhabitants is considered for the case study of this research. The transportation network of the city, depicted in Fig 3.2.a, with 40326 nodes and 68609 edges is provided using Esri maps and the ArcGIS software. AS illustrated in Fig 3.2.b, 110 nodes are selected as the potential locations for launch and refueling stations.

Considering the population of San Francisco, the different levels of daily demand of the city would be 3576, 7152, 10728, and 14304 packages. According to the U.S. regulations, drones should fly no faster than 100 mph and no higher than 400 feet (Federal Aviation Administration, 2016). Taking these regulations into account, Amazon would initiate drone delivery operation for the items that weight less than 5 pounds (Lavars, 2015). The endurance of each drone varies from 10 (Whitwam, 2016) to 15 miles (Johnson, 2017). The speed of each drone is assumed to be 50 mph (E. Kim, 2016), 60 mph (Johnson, 2017), and 80 mph (Betters, 2016). Using these specifications, the price of each drone ranges from \$3000 to \$5000 (Welch, 2015). Here, in order to account for different possibilities, the endurance of drones is assumed to be 10, 13, 15, and 18 miles and the speed of each drone is supposed to be 50, 60, 70, and 80 mph. Considering these specifications, four different price levels of drones could be assumed as \$3000, \$4000, \$5000, and \$6000. Considering a planning period of 10-years and on the premise that the drones have a useful life of 5 years (Swope, 2013) and using an interest rate of 2% per year (Bankrate, 2018), the annual cost for purchasing each drone could be calculated according to Eq. 3-39:

$$Annual\ Cost = Purchasing\ cost * \left(1 + \left({}^{P}/_{F}, 2\%, 5\right)\right) * \left({}^{A}/_{P}, 2\%, 10\right) \qquad (3\text{-}39)$$

A, ***P***, and ***F*** are the annual, present, and future value of the money respectively (Blank & Tarquin, n.d.). Using Eq. 3-39, four different levels for the annual purchasing cost of drones are calculated as \$637, \$849, \$1061, and \$1273.

The average area of Amazon's delivery stations is estimated 84389 square feet (MWPVL International Inc., 2018). Since it is assumed that the delivery station at the city would not be unique, the area of each station is considered equal to 42000 square feet. Since the land price in the San Francisco fluctuates from \$400 to \$1200 per square feet (Trulia, 2017) and the average construction cost of logistic centers is estimated equal to \$88 per square feet (COMPASS, 2017), four different levels of the establishment cost for each delivery center is premised as 22.6, 33.1, 43.6, and 54.1 million dollars. Each refueling station is considered to have an area of 10000 square feet equipped with 200 extra batteries each costing \$200. The different levels of the establishment cost of refueling stations are supposed to be 5, 7.9, 10.4, and 12.9 million dollars. Considering a planning period of 10 years and 2% interest rate and assuming the salvage value of the land as 95% of its purchasing price, the annual cost of opening launching stations is calculated according to Eq. 3-40.

$$Annual\ Cost = (land\ price + construction\ cost) * \left({}^{A}/_{P}, 2\%, 10\right) - land's\ salvage\ value * \left({}^{A}/_{F}, 2\%, 10\right) \tag{3-40}$$

On the premise that each battery could be used for a 2-year period, the annual cost of refueling stations is calculated according to Eq. 3-41.

$$Annual\ Cost = (land\ price + construction\ cost) * \left({}^{A}/_{P}, 2\%, 10\right) + battries\ cost * \left({}^{A}/_{P}, 2\%, 2\right) - land's\ salvage\ value * \left({}^{A}/_{F}, 2\%, 10\right) \tag{3-41}$$

Using Eq. 3-40, four different levels of the annual opening cost for each delivery station is calculated as 0.8757, 1.1337, 1.3916, and 1.6496 million dollars. Based on Eq. 3-24, four different levels of the annual opening cost for each refueling station is calculated as 0.2291, 0.2905, 0.3519, and 0.4133 million dollars.

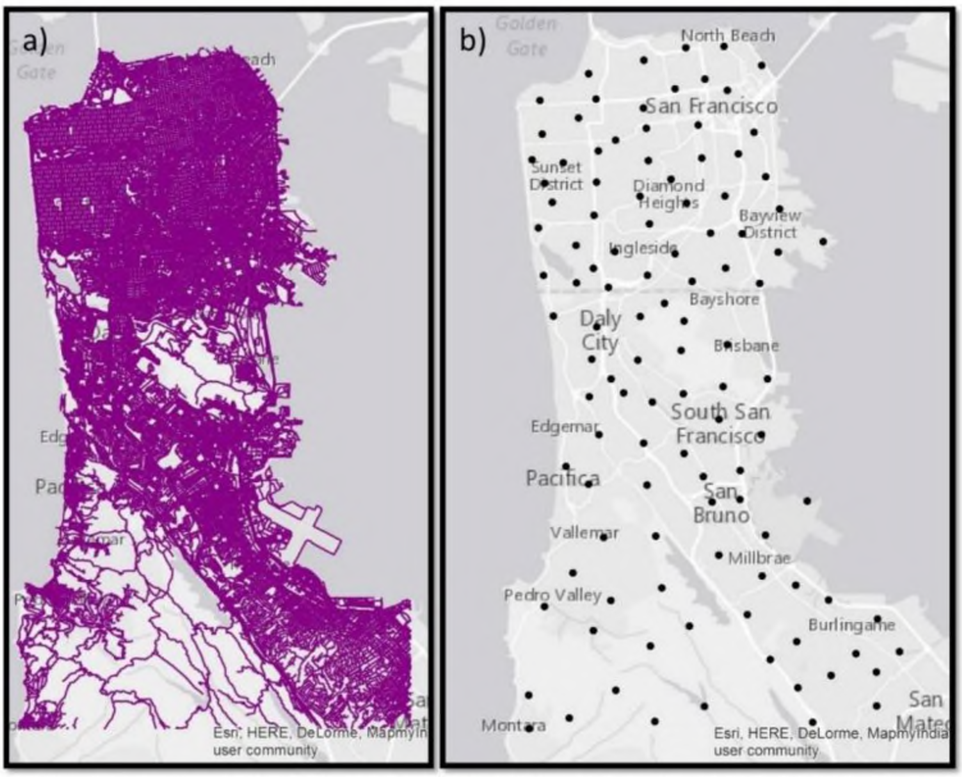


Figure 3.2: Acquired from ArcGIS; a) San Francisco's Transportation Network b) Candidate Locations

3.8 Results and Discussion

As previously mentioned, the feasibility level "α" in a fuzzy mathematical formulation is decided by the decision maker and varies from 0.6 to 1. Logically, the α level is changed if the obtained solution didn't satisfy the decision maker until a satisfactory result is obtained. In strategic decisions, it is particularly important that the solution is processed from the minimum acceptable level to the maximum due to the cost that would be imposed on the system in higher feasibility level. Hence, in the present study, α is set equal to 0.6 and the results are elaborated on that basis and with regards to the factual information (discussed in section 4). Table 3.1 represents the required infrastructure for a specific intended lead time (delay) in delivery. Since the obtained solution is satisfying, proceeding to higher levels of α is not necessary.

Table 3.1: The outcomes of the problem for different values of waiting time

Maximum acceptable Waiting time (min)	Total Number of the warehouses	Total Number of the recharge stations	Total Number of the Drones	Travel Distance (km)	Total Cost ($)	CPU Time (sec)
30	2	38	1502	312,008	17,981,761	2412
60	2	32	1550	310,841	16,096,009	24789
90	6	10	361	175,690	13,720,939	30127
120	7	5	309	177,280	13,655,123	9821
150	6	5	321	162,950	12,028,811	8914
180	7	6	289	166,610	13,917,069	8267
210	6	10	356	192,540	13,779,604	20497
240	6	5	352	183,220	12,134,699	8539
270	6	5	281	150,820	11,944,968	7156
300	**6**	**8**	**298**	**160,331**	**12,960,599**	**22296**
360	6	7	350	189,698	12,799,565	22439
420	6	5	284	155,605	11,965,846	20794

Table 3.1 illustrates the required infrastructure (number of drones, a total number of warehouses, a total number of recharge stations) as well as total distance traveled and cost in each setting. The significant cost saving in this solution approach is due to two important factors:

a. Using an aerial delivery system ($0.49 save / kilometers)
b. Considering both launch and refuel stations in optimizing the problem that directs to a cost saving up to 50 million dollars in a year.

The importance of the second factor becomes even more prominent by considering the fact that application of a simple facility location problem in which launch stations are disregarded, would make the problem infeasible for small values of maximum waiting time.

Based on this calculation, the total costs incurred by the system generally is expected to increase by reduction of the waiting times. In order to account for this issue, the topography of the problem instance for waiting time of 300 minutes is chosen to examine the effect of the maximum waiting time on the costs of the system. The results of this experiment are provided in table 3.2. As expected, the waiting time does not affect anything but the number of servers, that is the more the waiting time, the less is the required number of servers (drones in this study).

Table 3.2: Effect of waiting time on a specific solution

Maximum acceptable Waiting time (min)	Total Number of the Drones	Travel Distance (km)	Total Cost ($)
30	332	**160,331**	12,993,069
60	321	**160,331**	12,982,564
90	316	**160,331**	12,977,789
120	311	**160,331**	12,973,014
150	308	**160,331**	12,970,149
180	306	**160,331**	12,968,239
210	303	**160,331**	12,965,374
240	301	**160,331**	12,963,464
300	298	**160,331**	12,960,599
360	295	**160,331**	12,957,734
420	293	**160,331**	12,955,824
1440	278	**160,331**	12,941,499

3.9 Conclusion

There are many studies involved with optimization of drone-based delivery systems focusing on various criteria such as fuel consumption, endurance, hijacking, battery weight and obstacle avoidance. Nevertheless, only a few of them are concerned about the operational aspects of the problem. Similarly, there has been nearly no study on economics and logistics aspects of the drone delivery system comprised of launch and relaunch stations. On the other hand, decision making about the number of launch and relaunch stations is highly affected by the uncertainty of the parameters of the problem. Therefore, any optimization problem should be concerned about dealing with such uncertainties. Filling these gaps in the literature, all mentioned factors are taken into consideration in this study. Utilizing the fuzzy variables, the optimization model proposed in this study accommodates the factor of uncertainty in the solution procedure for determining the correct number of launch stations, refueling stations, and drones for an intended delivery time with minimum cost. Fuzzy possibilistic approach as one of the most useful tools for defuzzification of the problem is employed to apprehend the crisp equivalent of the proposed model. The resulting problem has a strong nonlinear nature hence the Genetic Algorithm is utilized as the solution method.

The proposed solution methods in this study provide a proper tool for managers to establish an aerial delivery system with a proper setting which is essential in the current competitive market.

This study accounts for waiting times of the customers and it is assumed that the products purchased by the customers in a working shift would be delivered in the same shift based on the goals announced by Amazon to decrease the delivery time to thirty minutes and less. Future studies may involve vehicle routing for the case where the payload of the drones allows for more than one demand to be satisfied in each trip of the drone.

Chapter 4

AN EDGE-BASED CAPACITATED BI-OBJECTIVE LOCATION PROBLEM IN UAV-SUPPORTED DELIVERY OPERATION: A CASE OF SAN FRANCISCO

4.1 Introduction

In recent years, small unmanned aerial vehicles have been used to deliver medicine and goods as a solution to high traffic jams and to serve the purpose of fast and effective delivery especially for medical and emergency applications where time is vital. On the other hand, in the competitive market of today, retailers are considering the use of drones to minimize the customers' waiting times and as a way to lower their transportation costs. This study aims to develop a bi-objective mathematical model to account for the optimum number and spatial location of facilities among a set of candidate locations such that the total travel distance, costs, and lost demands are minimized simultaneously. It is assumed that the demand occurrence is according to Poisson distribution and is uniformly distributed along the network edges. The proposed bi-objective capacitated facility location model is NP-hard, thus Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and Reference-Point Based Non-dominated Sorting Genetic Algorithm (NSGA-III) are applied to solve the problem.

4.2 Literature Review

Facility location problem (FLP) plays a major role in devising strategic plans applied in a wide spectrum of areas such as supply-chain management (Hamad & Fares Gualda, 2008; Miranda & Garrido, 2006; Shahabi, Akbarinasaji, Unnikrishnan, & James, 2013; Tsao & Linh, 2016), healthcare management (Daskin & Dean, 2005; Ghaderi, 2015; Shishebori, Snyder, & Jabalameli, 2014), and disaster management (H. Kim & Ryerson, 2017; Yushimito, Jaller, & Ukkusuri, 2012). It has been observed that poor location planning of facilities has made them inaccessible for the majority of the population. Methods such as facility location can be used to tackle such problems (Rahman & Smith, 2000).

There have been many variations of FLP since its introduction by Weber (Weber, 1929). In single FLP only one facility should be located whereas multi-facility location aims to locate several facilities simultaneously (Bozkaya, Yanik, & Balcisoy, 2010; Farahani, Abedian, & Sharahi, 2009). Based on the variety of services that facilities provide, location problems are categorized into single service and multi-service problems where one or more than one service is provided by facilities, respectively (Correia, Nickel, & Saldanha-da-Gama, 2014; Suzuki & Hodgson, 2003). Facilities are assumed to have unlimited or limited supply and the models concerning these problems are categorized as un-capacitated and capacitated FLP, respectively (Cromley & Mrozinski, Jr., 2002; Melkote & Daskin, 2001; Miralinaghi, Keskin, Lou, & Roshandeh, 2017). Furthermore, FLPs can be categorized base on the deterministic or probabilistic nature of the parameters (Hosseinijou & Bashiri, 2012; Özdağoğlu, 2012; Snyder, 2006; Srinivasan & Khan, 2017). As it has been categorized by (Azarmand & Neishabouri, 2009), the set of candidate locations have three different representations: in continuous space model the candidate locations are generated by the model in specified space, in discrete space model a number of locations should be selected among existing candidate locations. Network models are the third type of the problems wherein the locations are represented by a network. Network model itself can be categorized as continuous or discrete depending on whether the locations can be considered on network edges or only on nodes.

As it is explained by (Charikar, Khuller, Mount, & Narasimhan, 2001) in the discrete FLP, each candidate location is associated with an establishment cost and this problem aims to select a subset of candidate locations such that the service costs and/or the establishment costs are minimized. Generally, service cost is considered to be equivalent to the summation of the distances between nodes and their corresponding facilities. In k-median problems, the establishment costs are generally neglected and the objective function minimizes the service costs. Thus in the k-median problem, the total travel distance is minimized. The objective function of k-center problems is to minimize the maximum travel distance. As another type of FLPs, covering problems aim to maximize the number of covered demands (Church & ReVelle, 1974; Curtin, Hayslett-McCall, & Qiu, 2010; Ghodratnama, Tavakkoli-Moghaddam, & Azaron, 2013).

Crowded cities are exposed to high traffic jams, which makes ground transportation a challenge. Thus, many attempts have been performed to find alternative approaches for the delivery and transportation operations. Among many solutions, Unmanned Aerial Vehicle (UAV) aided delivery system is placed under the spotlight during the past recent years. UAV drones have been already used for delivery of medicines, medical samples, first aid cares, relief, online purchased goods, post parcels and so forth.

The drone technology has experienced an impressive improvement in recent years which qualifies it for a legion of applications. The specifications of drones have advanced to an extent which has made them an appropriate option not only for delivery operation (Kimchi et al., 2017) but even for passenger transportation (Storch, Storch, & Johnson, 2017). Having observed the drone delivery systems in Amazon, Google and DHL, (Murray & Chu, 2015) developed a model to optimize and schedule routing of the delivery system and operations. (Mourelo Ferrandez et al., 2016) considered using drones alongside the traditional truck system. They proposed a mathematical model to minimize the delivery time and the total number of facilities. (Hong et al., 2017a) tried to optimize the location of recharging stations for UAV drones in order to cover the demands.

In the majority of FLPs studied in literature, the demands are considered to be located at the network nodes. In order to present a more realistic model, (Arkat & Jafari, 2016) studied on a single server facility location problem in which demands are uniformly distributed along the network edges. Using the concept of distributed demands, (Golabi et al., 2017b) proposed a facility location problem in humanitarian relief logistics using UAV drones. Inspired by these studies, here a bi-objective facility location problem with stochastic demands distributed along the network edges is studied. Each facility is a distribution center which uses drones to deliver the demanded items to the customers. It has been proved that FLPs are generally NP-hard and heuristic and metaheuristic algorithms are frequently used to solve such problems (Javadian, Tavakkoli-Moghaddam, Amiri-Aref, & Shiripour, 2014; Owen & Daskin, 1998; Shishebori, Dayarian, Jabbarzadeh, & Barzinpour, 2014). Furthermore, the proposed model is mixed-integer nonlinear which adds up to the complexity of the problem (Pasandideh, Niaki, & Hajipour, 2013). Thus a metaheuristic method is used to solve the proposed mathematical model.

The structure of this chapter is as follows. Next section describes the problem and the mathematical model. The proposed solution method is explained in Section 4-3. Section 4-4 presents a case study. The numerical results are discussed in Section 4-5 and the conclusions are drawn in section 4-6.

4.3 Problem Definition and Formulation

This study scrutinizes a stochastic discrete mobile facility location problem in order to locate distribution centers. Each center is equipped with a number of UAV drones used as delivery vehicles. It is premised that the customers are uniformly distributed along the network edges. For each network edge, the demand generation follows the Poisson distribution. It is supposed that only one demand is covered in each drone flight. On the premise that the weight of delivered items is compatible with the payload of the drones, the only restriction imposed on drone flights is their endurance which determines the maximum flight distance. The capacity of each facility is defined as the total travel distance that can be traversed by assigned drones in the planning period. The effective capacity of each facility which accounts for load/unload and charging times in the planning period is considered to be a function of the number of assigned drones and their flight speed. The total costs of the system are composed of the establishment costs of the facilities and costs of drone purchases. Since the number of open facilities and assigned drones are considered as decision variables, one of the objective functions of the model is to determine the optimum number of facilities and drones in order to minimize the total costs. Due to the capacity restriction, it may be impossible to cover the entire demand. It is incontrovertible that satisfying each demand requires a fraction of the facility's capacity. Considering the limited capacity of the facility, minimizing the uncovered customers can be translated into a knapsack problem such that the closer customers have a higher priority for receiving the services. Thus the minimization of uncovered customers is equivalent to the minimization of aggregate travel distance. Fig. 4.1 represents the problem schematically.

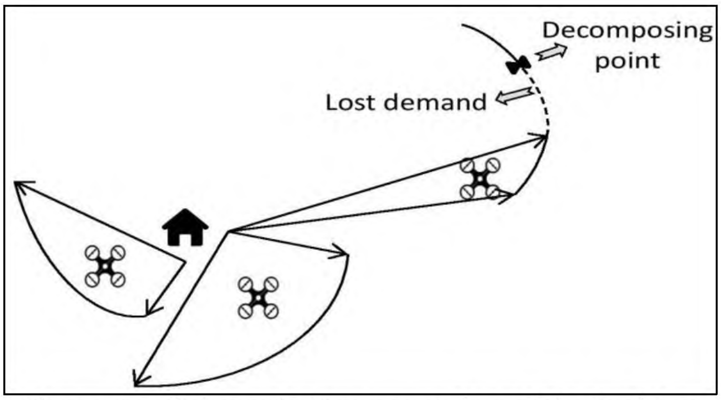


Figure 4.1: Schematic Representation of the Problem

4.3.1 Mathematical Formulation

In order to develop the mathematical model for the discussed problem, the following sets, parameters, scalars and decision variables are used:

Sets:

$G(I, A)$: a network including the set of nodes (I) and the set of edges (A)

I: the set of nodes

A: the set of network edges $(A \subseteq \mathrm{I} \times \mathrm{I}, (i, i') \in A)$

J: the set of candidate locations $(j, j' \in J)$

Scalars:

k: the maximum allowed number of open facilities

N: the maximum number of drones to be purchased

M: a large positive number

E: the endurance of each drone

DC: the price of each drone

ω: The effective flying distance that can be covered by each drone in the planning period

Parameters:

c_j: the maximum number of drones that can be assigned to facility j

$\lambda_{ii'}$: the demand occurrence rate on edge (i, i')

$l_{ii'}$: the length of edge (i, i')

fc_j: the cost of establishing j^{th}facility

t_{ji}: the Euclidian distance between node i and facility j

Decision variables:

y_j: $\begin{cases} 1 & if\ facility\ j\ is\ open \\ 0 & otherwise \end{cases}$

x_{ij}: $\begin{cases} 1 & if\ the\ closest\ open\ facility\ to\ node\ i\ is\ facility\ j \\ 0 & otherwise \end{cases}$

n_j: the number of assigned drones to j^{th}facility

$d_{ii'jj'}$: the distance between node i and the partitioning point of edge (i, i') if j and $j'$are the closest open facilities to nodes i and i' respectively

$\tau_{ii'jj'}$: the average distance between facility j and the assigned segment of edge (i, i') if j and $j'$are the closest open facilities to nodes i and i' respectively

$s_{ii'jj'}$: the number of covered customers on assigned segment of edge (i, i') if j and j' are the closest open facilities to nodes i and i' respectively

$L_{ii'jj'}$: the number of uncovered customers on assigned segment of edge (i, i') if j and j' are the closest open facilities to nodes i and i' respectively

As it has been described by (Golabi et al., 2017b), if the closest open facilities to nodes i and i' are not the same, the edge (i, i') is partitioned into two segments and each segment receives the services through its corresponding facility. In this case, the distance between node i and partitioning point of edge (i, i') is calculated by Eq. 4-10; otherwise it is calculated by Eq. 4-11. Also, the distance between partitioning point to its corresponding facility is obtained from Eq. 4-12.

According to discussed definitions and assumptions, the developed mathematical model is as follows:

$$Min \sum_{j \in J} fc_j y_j + DCn_j \quad (4\text{-}1)$$

$$Min \sum_{(i,i') \in A} L_{ii'jj'} \quad (4\text{-}2)$$

$$\sum_{j \in J} y_j \leq k \quad (4\text{-}3)$$

$$\sum_{j \in J} n_j \leq N \quad (4\text{-}4)$$

$$n_j \leq c_j \qquad \forall\ j \in J \quad (4\text{-}5)$$

$$x_{ij} \leq y_j \qquad \forall\ i \in I\ ,\ j \in J \quad (4\text{-}6)$$

$$n_j \leq My_j \qquad \forall\ j \in J \quad (4\text{-}7)$$

$$\sum_{j \in J} x_{ij} = 1 \qquad \forall\ i \in I \quad (4\text{-}8)$$

$$\sum_{j' \in J} x_{ij'}\, t_{j'i} \leq t_{ji} + M(1 - y_j) \qquad \forall\ i \in I\ ,\ j \in J \quad (4\text{-}9)$$

$$d_{ii'jj'} = \frac{l_{ii'}\left({t_{j'i}}^2 - {t_{ji}}^2\right)}{{t_{ji'}}^2 - {t_{j'i'}}^2 + {t_{j'i}}^2 - {t_{ji}}^2} \qquad \forall\ (i,i') \in \mathrm{I}, (j,j') \in J \qquad (4\text{-}10)$$

$$d_{ii'jj} = max\left(\frac{t_{ji'} - t_{ji}}{\left|t_{ji'} - t_{ji}\right|}, 0\right) l_{ii'} \qquad \forall\ (i,i') \in \mathrm{I}, j \in J \qquad (4\text{-}11)$$

$$g_{ii'jj'} = \sqrt{\frac{d_{ii'jj'}{t_{ji'}}^2 + (l_{ii'} - d_{ii'jj'}){t_{ji}}^2 - d_{ii'jj'}(l_{ii'} - d_{ii'jj'})l_{ii'}}{l_{ii'}}} \qquad \forall\ (i,i') \in \mathrm{I}, j \in J \qquad (4\text{-}12)$$

$$\tau_{ii'jj'} = \sqrt{\frac{2g_{ii'jj'} + 2{t_{ji}}^2 - d_{ii'jj'}}{4} x_{ij} x_{i'j'}} \qquad \forall\ (i,i') \in \mathrm{I}, (j,j') \in J \qquad (4\text{-}13)$$

$$\left(s_{ii'jj'} + L_{ii'jj'} - \lambda_{ii'} \frac{d_{ii'jj'}}{l_{ii'}}\right) x_{ij} x_{i'j'} = 0 \qquad \forall\ (i,i') \in \mathrm{I}, (j,j') \in J \qquad (4\text{-}14)$$

$$2 \textstyle\sum_{(i,i') \in A} s_{ii'jj'}\, \tau_{ii'jj'} \leq \omega n_j \qquad \forall\ (j,j') \in J \qquad (4\text{-}15)$$

$$x_{ij}, y_j \in \{0,1\} \qquad \forall\ i \in I, j \in J \qquad (4\text{-}16)$$

$$\tau_{ii'jj'}, L_{ii'jj'}, s_{ii'jj'} \geq 0 \qquad \forall\ (i,i') \in \mathrm{I}, (j,j') \in J \qquad (4\text{-}17)$$

$$d_{ii'jj'} \ \textit{free in sign} \qquad \forall\ (i,i') \in \mathrm{I}, (j,j') \in J \qquad (4\text{-}18)$$

The first objective function minimizes the total cost of facility establishment and drone procurement. The total number of uncovered customers is minimized by the second objective function. Constraints (4-3) and (4-4) set an upper bound for the total number of opened facilities and purchased drones respectively. Constraint (4-5) restricts the number of drones assigned to each facility. Constraints (4-6) and (4-7) assure that no assignment is done for the close facilities. Constraints (4-8) and (4-9) guarantee each network node is assigned to the closest facility. Constraints (4-10) and (4-11) define the length of each segment. The distance between the partitioning point and its corresponding facility is determined by constraint (4-12). Constraint (4-13) defines the average distance between each segment and its assigned open facility. Constraint (4-14) guarantees the equality of covered and uncovered demands to the total demands of each segment. Constraint (4-15) assures that the distance capacity of each facility is not violated. Constraints (4-16), (4-17), and (4-18) enforce the binary, non-negative, and free in sign restrictions on decision variables.

4.4 Solution Methods

Although the mathematical model was coded in General Algebraic Modeling System (GAMS), even the small generated instances could not be solved due to the NP-hardness of the developed model. Thus, the application of a metaheuristic algorithm as the solution method is inevitable. As the result, the Non-dominated Sorting Genetic Algorithm (NSGA-II) and Reference-Point Based Non-dominated Sorting Genetic Algorithm (NSGA-III) are applied to solve the problem.

4.4.1 NSGA-II

As an efficient multi-objective optimization algorithm, NSGA-II has been applied to solve a plethora of location problems (R. Bhattacharya & Bandyopadhyay, 2010). NSGA-II initiates with a randomly generated population of size N. Each individual in the population is called a chromosome. In this study, each chromosome is a matrix consisting of two rows and m columns where m is a random number such that $m \in [1, k]$. Each allele of the first row indicates an index of the candidate location selected for establishing the facility and the allele below illustrates the number of assigned drones which is generated randomly between one and c_j. If the total assigned drones exceed its upper bound, a repair function is applied in order to reduce it. The repair function iteratively selects random alleles of the second row and deducts them by random a number of units. This operation continuous until the constraint (4-4) is satisfied. After generating each chromosome, the capacity of each open facility is determined based on the pertinent number of assigned drones and their effective flying distance. In the next step, each network edge is decomposed according to the open facilities. Segments are sorted ascendingly based on their average distances to their closest facility. The assignment starts with the first segment and continues until the capacity of one facility is not adequate to satisfy further demands. At this point this facility is deleted from further calculations and the remaining demand is reassigned to other facilities. This procedure repeats until there is no unsatisfied demand or no capacity left to satisfy further demands. Now the computation of objective functions according to Eq. 4-1 and Eq. 4-2 is straightforward.

In the next step, the solution population is sorted based on non-dominance. As it has been described by (Coello, Lamont, & Veldhuisen, 2007), the solution u dominates solution v if and only if:

$$f_i(u) \leq f_i(v) \qquad \forall\, i \in \{1, \ldots, n\} \qquad (4\text{-}19)$$

$$f_i(u) < f_i(v) \qquad \exists\, i \in \{1, \ldots, n\} \qquad (4\text{-}20)$$

Where f_i denotes the i^{th} objective function and n is the number of objective functions. A solution that is not dominated is defined as non-dominated solution and is ranked as the first Pareto-optimal front. The selection process of the algorithm is performed based on the rank of the solutions. The crowding distance is used to make the selection from the solutions of the same rank. In order to preserve the diversity of the solutions in each front, the solutions with greater crowding distance are preferred. To calculate the crowding distance for i^{th} objective function, the solutions are first sorted by their front rank and then by their fitness value of i^{th} objective function, then the crowding distance for the i^{th} objective function and the j^{th} solution in the front is defined as $cd_i(j) = \frac{f_i(j-1)-f_i(j+1)}{\max(f_i)-min(f_i)}$. The same procedure is performed for the rest of the objective function. Then the crowding distance of the j^{th} solution is calculated as $cd(j) = \sum_i cd_i(j)$.

To carry out the crossover and mutation operations, parents are selected by Roulette Wheel procedure which enhances the selection chance of better solutions. The solutions with lower ranks and higher crowding distances have a greater probability of being selected.

In the crossover operations two parents are selected. For each parent, a crossover point is randomly generated along the length of its chromosome which decomposes each parent into two parts. The first offspring is generated by merging the first part of the first parent with the second part of the second parent. The first part genes of the second parent are used to replace the repeated genes in the offspring, if any. The second offspring is generated in the same manner by exchanging the role of first and second parents. Since each offspring inherits the number of drones from the parents, occasionally Constraint (4-4) can be violated; therefore, the application of the penalty function may be necessary. In order to perform the mutation operation, a parent is selected. A random number of first row alleles are selected randomly and exchanged with the candidate location indices that are not present in the solution. The corresponding alleles of the second row are replaced by a feasible random number. After performing the mutation operation, application of repair function may be needed. Figs. 4.2 and 4.3 illustrate the crossover and mutation operations respectively.

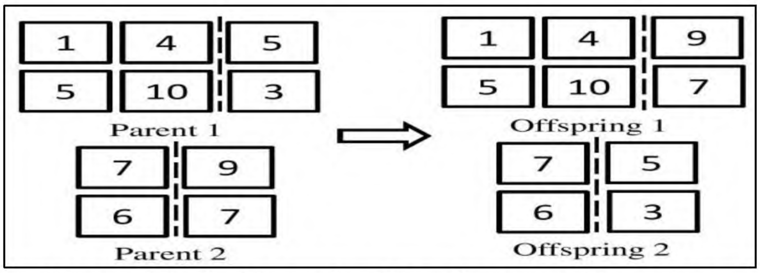


Figure 4.2: An Example of the Crossover Operation

At each generation of NSGA-II, the mutation and crossover operations are performed repeatedly until the population, called the combined population (C_t), is doubled in size $(2N)$. After sorting the combined population based on non-domination, fronts whose cumulative number of members does not exceed N $(F_1, F_2, \ldots, F_{l-1})$ are fully selected to generate the new population (P_{t+1}). In order to have a new population of size N, the remaining members, if any, are selected from the last front (F_l) members with the highest crowding distance values. This procedure is continued for a pre-determined number of iterations.

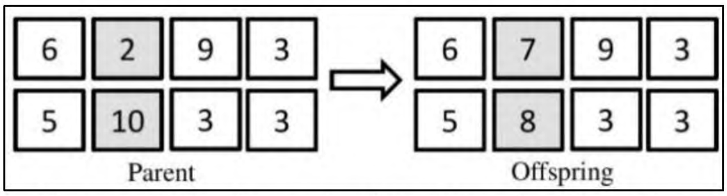


Figure 4.3: An Example of the Mutation Operation

4.4.2 NSGA-III

Since it has been shown that the crowding distance does not estimate the diversity in the many-objective type of problems (Kukkonen & Deb, 2006), (Deb & Jain, 2014) introduced NSGA-III in order to have a more reliable analysis for selecting the last front members by using the reference points. The reference points that ensure the diversity in obtained solutions can be defined by using a designed method such as the manner proposed by (Das & Dennis, 1998) or by the preferences of the decision maker. In this algorithm, the ideal point of the population P_{t+1} is a vector consisting of the minimum values of each objective function. In the next step, each objective value of this population is normalized by subtracting its pertinent minimum value so the ideal point becomes a zero vector. For each reference point, the reference line is considered as the line joining the point to the origin. Then, based on the proximity to the reference lines calculated by the perpendicular distance of each member of the population, each member would be associated to a reference point. The reference points with minimum number of associations according to $F_1, F_2, \dots, F_{l-1}$ members are considered for an association in F_l members. These members are then added at time to fill the population.

4.4.3 Parameter Tuning

It is incontrovertible that the parameters affect the results obtained by developed metaheuristic algorithms. Therefore, calibrating the parameters is a matter of paramount importance in advance to implement the algorithms. In this study, Taguchi method is used to calibrate the parameters and enhance the efficiency and effectiveness of solution methods. Taguchi is an efficient method which uses orthogonal arrays to scrutinize a multitude of controllable factors with few experiments (Mousavi, Niaki, Mehdizadeh, & Tavarroth, 2013). This method determines the optimum level of each parameter by minimizing the effect of noise. The variation of the response is determined via the signal to noise (S/N) ratio which is calculated using Eq. 4-21 in which Y and n denote the response and number of orthogonal arrays respectively.

$$ {}^{S}/_{N} = -10 \times \log(S(Y^2)/n) \tag{4-21} $$

Table 4.1 shows the applied parameters of developed solution algorithms along with their relative ranges. In order to evaluate the performance of proposed metaheuristic algorithms four multi-objective metrics are introduced as diversity, mean ideal distance (MID), the number of solutions found (NOS), and the required CPU time. Diversity and mean ideal distance measure the extension and convergence of Pareto fronts (Zitzler & Thiele, 1998) while the number of solutions found counts the number of solutions in Pareto optimum front (Rahmati et al., 2013). The main objectives of

Pareto-based metaheuristic algorithms are the good convergence and diversity (Salmasnia, Hasannejad, & Mokhtari, 2017). In order to evaluate both convergence and diversity of algorithms simultaneously in a unique response, the combined metric (cm) is calculated by Eq. 4-22.

$$cm = \frac{Mean\ Ideal\ Distance}{Diversity} \qquad 4\text{- }(22)$$

For each parameter combination shown in Table 4.2 and the data for the case of San Francisco which is described in Section 4, the proposed problem is solved 10 times to acquire the average response. The Taguchi method is performed by Minitab 16, and the algorithms are coded in Matlab (R2016a) programming language and implemented on Intel Xeon E5-2660v2@2.5 GHz computers with 8 GB RAM and 25 MB Cache. Fig. 4.4 illustrates the S/N ratios attained from NSGA-III and NSGA-II algorithms respectively. Using these results, the best parameter combination for each algorithm is determined. For example according to Fig. 4.4a the NSGA-III parameters A, B, C, and D are better to be at their first, third, second, and first levels respectively.

Table 4.1: Parameter levels

Algorithms	Parameters	Parameter range	Low(1)	Medium(2)	High(3)
	$Itmax$ (A)	200 - 400	200	300	400
NSGA-II	$Npop$ (B)	100 - 200	100	150	200
&	P_c (C)	0.6 - 0.8	0.6	0.7	0.8
NSGA-III	P_m (D)	0.1 - 0.3	0.1	0.2	0.3

Table 4.2: Computational results for tuning NSGA-II and NSGA-III

Run order	NSGA-II parameters				Response	Run order	NSGA-III parameters				Response
	A	B	C	D			A	B	C	D	
1	1	1	1	1	1.72593	1	1	1	1	1	3.60968
2	1	2	2	2	0.81807	2	1	2	2	2	2.42110
3	1	3	3	3	0.92891	3	1	3	3	3	2.72804
4	2	1	2	3	3.89391	4	2	1	2	3	4.00231
5	2	2	3	1	2.81853	5	2	2	3	1	3.89872
6	2	3	1	2	3.67693	6	2	3	1	2	3.49550
7	3	1	3	2	3.00290	7	3	1	3	2	3.98426
8	3	2	1	3	1.60209	8	3	2	1	3	2.43331
9	3	3	2	1	0.74424	9	3	3	2	1	0.88669

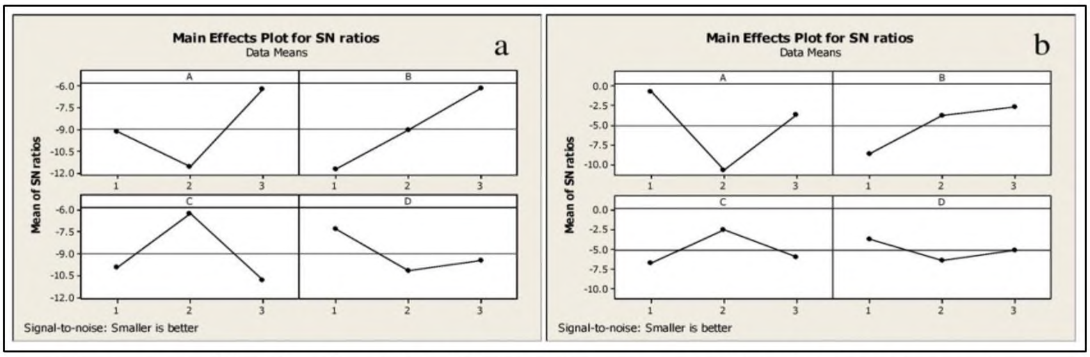


Figure 4.4: S/N Plot for: (a) NSGA-III Parameters; (b) NSGA-II Parameters

4.5 Case Study

According to (Chris Busch, 2016) the transportation problems in SF and expensive transportation options have led the community to use personal vehicles which in return has added to traffic congestion problems, making the Bay area the second congested network in the whole nation after Los Angeles. The report continues with mentioning the SF transportation as the greatest source of greenhouse gas emissions in the state. (Cauthen, 2016) Adds more highlights to the problem by the fact that there are more than 425,000 registered vehicles in the city, which translates to more than 50 percent of the population. Furthermore, more than 300,000 vehicles crowd onto streets from the south each day and the record is increasing every day, adding to the transportation problem. Since the aerial delivery is considered as a solution to traffic jams, the City of San Francisco, California with an estimated population of 850 thousand is considered for the case study. The transportation network of San Francisco is acquired by ArcGIS software. Fig 4.5b illustrates the network that consists of 68,609 edges corresponding to the main streets of the city and 53,738 nodes. As illustrated in Fig. 4.5a, among the existing nodes, 109 locations are selected to serve as candidate locations for establishment of facilities. Each location has a potential capacity, maximum number drones to incorporate and establishment cost. There is an upper limit for the total number of drones and open facilities that are presumed equal to 2,000 and 40 respectively. The speed of drones is supposed to be equal to 65 kilometers per hour. The working hours for delivery operations is a 10-hours shift a day. The efficient working hours of each drone is 70 percent of the shift, and 30 percent is considered for maintenance and loading/unloading. The demand on each edge is assumed proportional to the population on that edge. On the premise that the average daily delivery request for each person is 0.123 (Welch, 2015), the average number of daily deliveries of the city is estimated as 105,000. According to the extracted network of the city, the average length of each delivery trip is supposed to be 5 miles or 8 km which is equivalent to an average of 840,000 km per day. Considering $3,000 as the purchasing price of each drone and a cost between $500,000 up to $1,000,000 for establishing each facility in different candidate locations, the problem was solved with the tuned NSGA-II and NSGA-III Algorithms.

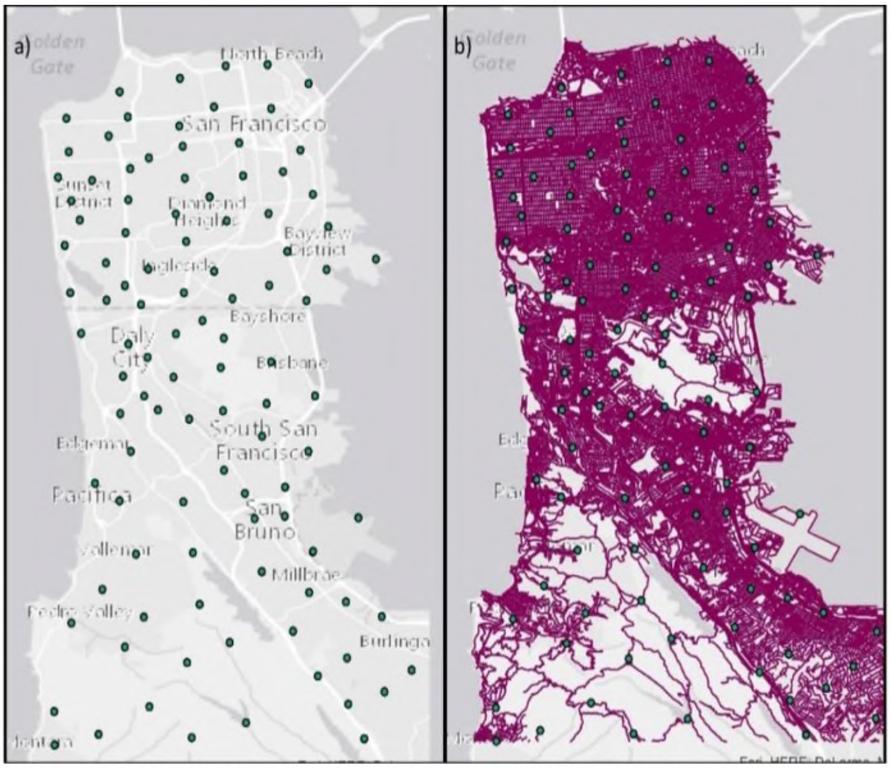


Figure 4.5: (a) Candidate Locations; (b) Transportation Network

4.6 Results and Discussion

The computational results of employing the proposed metaheuristic algorithms on the case of San Francisco are shown in Table 4.3. The main multi-objective metrics consisting of diversity, mean ideal distance, number of solutions, the combined metric (cm), and the required CPU times for 14 runs of each algorithm have been shown in this table. Fig. 4.6 illustrates the graphical comparison of deployed algorithms in terms of the mentioned metrics. The greater the diversity and the number of solutions and the smaller the mean ideal distance, the combined metric, and the required CPU time, the better is the performance of the proposed algorithm. According to Fig. 4.6e, the proposed NSGA-III flagrantly outperforms NSGA-II in terms of required CPU times. Moreover, the one-way analysis of variance (ANOVA) was performed by Minitab software in order to compare the performance of devised algorithms based on the obtained multi-objective metrics. The attained p-values and interval plots of ANOVA tests based on the applied metrics are shown in Fig. 4.7. According to this figure, although there is not a significant difference between the results of proposed algorithms on the basis of diversity, number of solutions, and the combined metric (cm), NSGA-II outperforms NSGA-III based on the mean ideal distance. In order to exemplify the results' analysis, the non-dominated solutions of the proposed algorithms are schemed in Fig. 4.8. For instance, the solution located at the middle of Pareto front of NSGA-II, indicates establishing 19 facilities with 1,410 drones which is equivalent to a total cost of almost $17,000,000 and leads to performing almost 70,000 deliveries per day. Considering an average benefit of $0.49 per km (Seyed Mahdi Shavarani, Nejad, Rismanchian, & Izbirak, 2017), the annual benefit of drone delivery system is estimated as $100,150,000.

Table 4.3: Computational results of solving methodologies

RUN	NSGA-II					NSGA-III				
	Diversity	MID	NOS	cm	Time	Diversity	MID	NOS	cm	Time
1	0.867	1.142	26	1.318	12619	1.116	1.283	25	1.150	12436
2	0.457	0.895	21	1.960	12532	0.865	1.155	22	1.336	12410
3	0.816	1.093	26	1.340	12551	0.558	1.235	24	2.214	12459
4	1.180	1.140	26	0.966	12616	0.757	1.021	27	1.349	12441
5	0.583	0.774	23	1.328	12619	0.476	1.246	26	2.617	12490
6	0.461	0.926	26	2.007	12594	0.567	1.229	25	2.166	12469
7	0.867	1.255	27	1.447	12686	1.414	1.312	25	0.928	12421
8	1.348	1.161	26	0.862	12534	0.900	1.372	24	1.525	12447
9	1.095	0.825	21	0.753	12560	0.424	1.174	25	2.768	12406
10	0.570	1.177	26	2.065	12673	0.479	1.324	23	2.762	12447
11	0.463	1.034	25	2.232	12681	1.176	0.984	20	0.836	12484
12	1.408	0.752	22	0.534	12563	0.456	1.205	24	2.639	12479
13	0.543	1.078	24	1.984	12623	1.270	0.887	26	0.698	12391
14	0.488	1.134	25	2.324	12527	0.550	1.235	26	2.246	12509

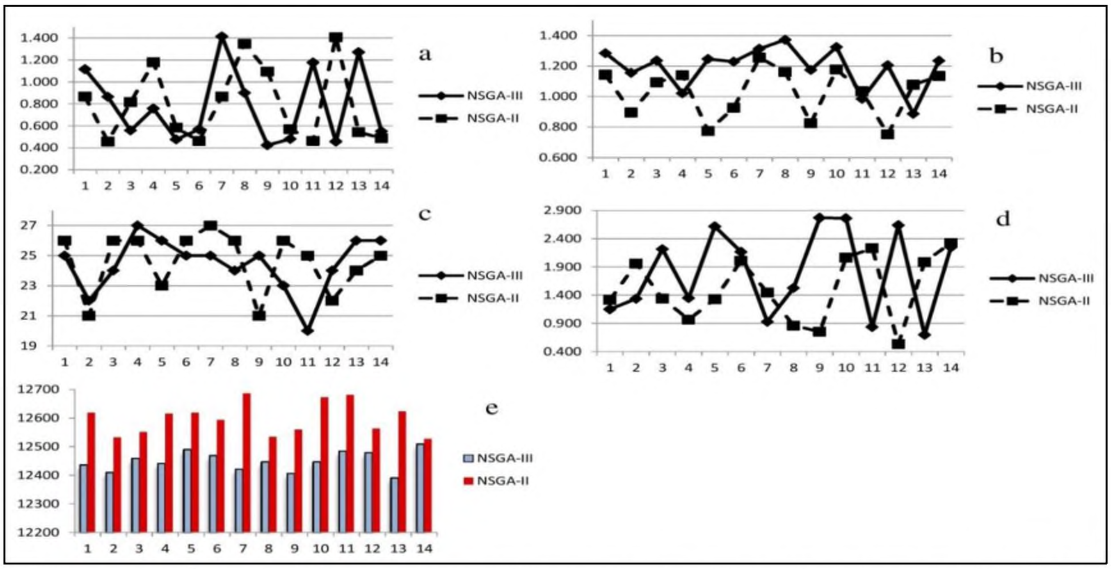
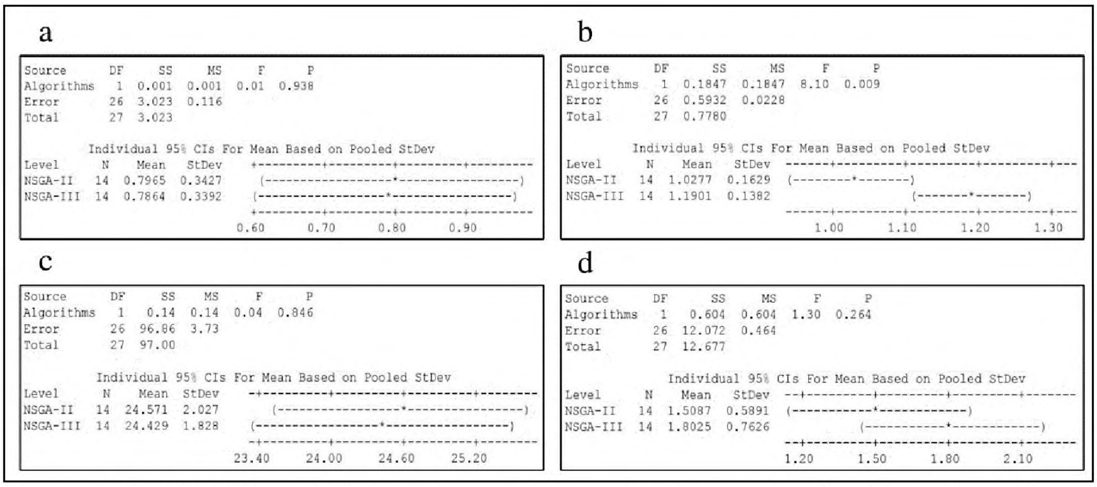


Figure 4.6:Graphical Comparison of Proposed Algorithms Based on: (a) Diversity; (b) Mean Ideal Distance; (c) Number of Solutions; (d) Combined Metric; (e) Required CPU Time



a

```
Source      DF     SS     MS     F      P
Algorithms   1  0.001  0.001  0.01  0.938
Error       26  3.023  0.116
Total       27  3.023

          Individual 95% CIs For Mean Based on Pooled StDev
Level      N    Mean   StDev    +---------+---------+---------+---------
NSGA-II   14  0.7965  0.3427     (------------------*-----------------)
NSGA-III  14  0.7864  0.3392    (------------------*------------------)
                                +---------+---------+---------+---------
                              0.60      0.70      0.80      0.90
```

b

```
Source      DF      SS      MS     F      P
Algorithms   1  0.1847  0.1847  8.10  0.009
Error       26  0.5932  0.0228
Total       27  0.7780

          Individual 95% CIs For Mean Based on Pooled StDev
Level      N    Mean   StDev  ------+---------+---------+---------+---
NSGA-II   14  1.0277  0.1629  (--------*-------)
NSGA-III  14  1.1901  0.1382                  (-------*-------)
                              ------+---------+---------+---------+---
                                  1.00      1.10      1.20      1.30
```

c

```
Source      DF     SS    MS     F      P
Algorithms   1   0.14  0.14  0.04  0.846
Error       26  96.86  3.73
Total       27  97.00

          Individual 95% CIs For Mean Based on Pooled StDev
Level      N    Mean  StDev    -+---------+---------+---------+--------
NSGA-II   14  24.571  2.027       (-----------------*-----------------)
NSGA-III  14  24.429  1.828    (-----------------*-----------------)
                               -+---------+---------+---------+--------
                             23.40     24.00     24.60     25.20
```

d

```
Source      DF      SS     MS     F      P
Algorithms   1   0.604  0.604  1.30  0.264
Error       26  12.072  0.464
Total       27  12.677

          Individual 95% CIs For Mean Based on Pooled StDev
Level      N    Mean   StDev  --+---------+---------+---------+-------
NSGA-II   14  1.5087  0.5891  (-----------*------------)
NSGA-III  14  1.8025  0.7626            (-----------*------------)
                              --+---------+---------+---------+-------
                              1.20      1.50      1.80      2.10
```

Figure 4.7: ANOVA and Related Interval Plots for Comparing the Algorithms Based on Attained: (a) Diversity; (b) Mean Ideal Distance; (c) Number of Solutions; (d) Combined Metric

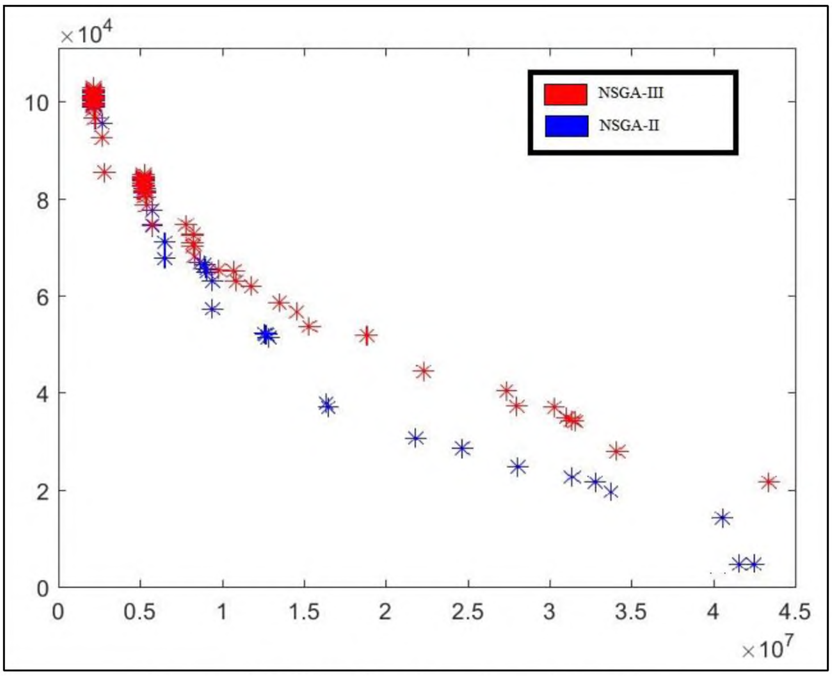


Figure 4.8: The Non-Dominated Solutions

4.7 Conclusion

On the premise that customers are uniformly distributed along the network edges, this study presents a stochastic bi-objective mixed integer nonlinear programming model for a discrete mobile facility location problem. For each network edge, demand generation follows the Poisson distribution. Each facility is considered as a distribution center equipped with a number of drones used as delivery vehicles. Based on the proximity to open facilities, each network edge may be decomposed to two different parts where each part is assigned to its closest open facility. The first objective function minimizes the total establishment cost of facilities by determining the number of open facilities and their concomitant number of assigned drones. Since it is considered that only one customer is covered in each drone flight, considering the endurance and the flying speed of each done results in the maximum flying distance of each center which yields the efficient capacity of each facility in terms of the total travel distance after subtracting the load/unload and charging times in the planning period. Considering the limited capacity of facilities, the second objective function minimizes the total number of uncovered customers which could be translated into the minimization of aggregate travel distance according to the knapsack problem. The proposed mathematical model was applied to the large-scale network of San Francisco, California consisting of 68909 edges and 53738 nodes extracted from ArcGIS software. Due to the NP-hardness of presented model, NSGA-II and NSGA-III algorithms were proposed as the solution methods. After tuning the parameters of proposed algorithms using Taguchi method, they were implemented for the case of San Francisco. Performing one-way ANOVA method on the computational results obtained from different runs of solution methods, the performance of algorithms based on some main multi-objective metrics was compared. According to the obtained results, although there was not a significant difference between the results of proposed algorithms on the basis of diversity, number of solutions, and the combined metric (cm), NSGA-II outperforms NSGA-III based on the mean ideal distance.

For the future research, the application of queuing systems in order to minimize the aggregate waiting time or servers' idle probabilities as the third objective function would be of great interest. Another interesting research would be developing other Pareto-based heuristic or metaheuristic algorithms to yield better solutions in shorter times. Also extending the model for considering different types of facilities providing different levels of services would be another line of research. Furthermore, the demand rate could be considered as fuzzy inputs.

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