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A capacitated bi-objective location problem with uniformly distributed demands in the UAV-supported delivery operation

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Abstract

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. The performance of the algorithms, quality of solutions and the results are investigated and discussed.

Keywords: Facility Location, Supply Chain Management, Uniformly Distributed Demand, UAV, NSGA-II, NSGA-III

1. Introduction

It is incontrovertible that an efficient delivery system plays a vital role in the success of online retailers who spend vast sums of money in delivering the products to the customers (Shavarani et al. 2019a). The changes in fuel costs have resulted in the escalation of delivery costs which could be translated to a new challenge for online retailers in offering competitive prices. In order to refrain from spending enormous time in malls and shopping centers, customers dominantly prefer the home delivery (Magretta 2002). Considering the increasing demand for delivery operations and competitive nature of this market, reducing the delivery time is another matter that adds to the complexity of this challenge. As retailers strive to provide faster and cheaper delivery services, they have to overcome serious obstacles, especially in highly populated areas. (Zeithaml et al. 1985) and (Shavarani et al. 2018) mentioned that traffic jams in highly populated urban areas and the high fuel costs are the items that negatively affect the efficiency of the delivery operations. Many attempts have been made to tackle these complications. Among many solutions, Unmanned Aerial Vehicle (UAV) aided delivery system is placed under the spotlight during the past recent years (Murray and Chu 2015).

The drone technology has experienced impressive improvements in recent years which qualify it for a legion of applications. The previous studies highlight the potentials of UAV drones in delivering medical payloads (Meier and Soesilo 2015), disaster relief packages (Chowdhury et al. 2017; Shavarani 2019), post parcels (The Guardian 2015), and online purchased goods (Shavarani et al. 2018). 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 (Kwon et al. 2017). The efficiency of UAV-supported delivery systems depends on several factors such as the number of drones, their payload, endurance and the speed of drones, the capacity of delivery systems, the routes

of delivery missions, etc. Although there are several studies focusing on these factors such as (Murray and Chu 2015) to optimized the routing of delivery missions and (Mourelo Ferrandez et al. 2016) to minimize the delivery time and the number of delivery stations, as it has been shown by (Dorling et al. 2017), the proper consideration of the mentioned affecting factors mainly boils down to selecting locations of delivery stations. As a result, this paper investigates a new formulation for determining the locations of UAV-based delivery stations such that the total operating cost of the system comprising the establishment cost of stations and drone procurement cost, and the total number of uncovered demands are minimized simultaneously.

The structure of this study is as follows. Next section briefly reviews the literature. Section 3 describes the problem and the mathematical model. The proposed solution method is explained in Section 4. Section 5 presents a case study. The numerical results are discussed in Section 6 and the conclusions are drawn in section 7

2. Related works

Facility location problem (FLP) plays a major role in devising strategic plans in a wide spectrum of areas such as supply-chain management (Miranda and Garrido 2006; Hamad and Fares Gualda 2008; Shahabi et al. 2013; Tsao and Linh 2016), healthcare management (Daskin and Dean 2005; Shishebori et al. 2014b; Ghaderi 2015), and disaster management (Yushimito et al. 2012; Kim and Ryerson 2017). As it is mentioned by (Rahman and Smith 2000), location analysis improves the accessibility of facilities to the demands.

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 (Farahani et al. 2009; Bozkaya et al. 2010). 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 (Suzuki and Hodgson 2003; Correia et al. 2014).

FLPs could be studied on discrete or continuous space (Azarmand and Neishabouri 2009; Dantrakul et al. 2014). While in the continuous space problems any point in the plane could be opted for establishing the facilities (Brimberg et al. 2008; Brimberg and Drezner 2013), in discrete space problems, the locations of facilities are selected among a set of candidate points (ReVelle et al. 2008). As it is explained by (Charikar et al. 2001), in the discrete FLP, each candidate location is associated with an establishment cost and the problem aims to select a subset of candidate locations such that the service costs and/or the establishment costs are minimized. Based on the essence of servers, FLPs could be categorized as mobile or immobile server facility location problems. In the case of mobile servers, servers travel to the location of customers (Baptista and Oliveira 2012) while in immobile server, customers are supposed to visit the servers (Torrent-Fontbona et al. 2013).

FLPs can be categorized base on the deterministic or probabilistic nature of the parameters (Golabi et al. 2018). As it is addressed by (Snyder 2006; Özdağoğlu 2012; Hosseiniou and Bashiri 2012; Wen et al. 2015; Srinivasan and Khan 2017), deterministic models are marred with inadequacies resulting from neglecting the uncertainties associated with the demands, costs, and travel times. As a result, the output of these models will be unrealistic. Congested location problems in which customers have to wait in a queue to receive the service, are a branch of stochastic location problems that incorporate the uncertainties of demand generation and service time (Boffey et al. 2007).

Based on the type of the objective function, FLPs are categorized into the center, covering, and median problems. The objective function of center problems is to minimize the maximum travel distance. Center problems are generally applied in emergency location problems such as locating ambulance stations. (Revelle and Hogan 1989) developed a center model to determine the locations of emergency service centers such that the maximum distance between demand and facilities is minimized. (Talmar 2002) studied a center problem for locating the search and rescue helicopters for responding to the emergency calls from tourist accidents in Alpine mountain ranges. Due to the NP-hardness of center problems (Garey and Johnson 1979; Kariv and Hakimi 1979), several metaheuristic or heuristic

algorithms have been developed to solve them. Covering models that are often found in emergency location problems (Pereira et al. 2007), aim to maximize the number of covered demands. (Hong et al. 2017) presented a new coverage model to determine the locations of recharging stations for delivery drones. (Kim et al. 2017) studied a two-stage optimization model for the drone-based delivery operation of medical supplies. The first stage considers a set covering problem to find the location of launch stations, while the second stage studies a multi-drone vehicle routing problem. (Farahani et al. 2012) compiled different versions of covering problems. The objective function of median problems is to minimize the traveling or waiting times/costs. (Berman and Drezner 2007) studied a multiple-server median FLP to minimize the sum of the travel time and the average time spent at the server, for all customers. Since the median problem is Np-hard on a general graph (Kariv and Hakimi 1979), the application of heuristic or metaheuristic algorithms as the solution methods is inevitable. Many studies developed local search (Arya et al. 2004), genetic (Alp et al. 2003), simulated annealing (Golabi et al. 2017b), and tabu search (Brimberg and Drezner 2013) algorithms to solve the median problems. (Mladenović et al. 2007) compiled different metaheuristic algorithms used for solving the median problems.

Capacitated FLP is another type of location problems in which each facility has a limited capacity to serve the demands (Wu et al. 2006). (Pagès-Bernaus et al. 2019) studied a stochastic capacitated FLP under a set of sampled scenarios to minimize the fixed costs of opening the facilities, the expected cost of serving the customers, and the expected costs of outsourcing part of demand. They solved the model by developing a simheuristic approach that hybridizes an iterative local search technique with the simulation. Capacitated mobile FLP was first introduced by (Demaine et al. 2009). (Raghavan et al. 2019) studied a capacitated mobile FLP to relocate a set of existing facilities and allocate demands to them. Their proposed objective function minimizes the weighted sum of facility movement costs and the clients' travel costs. Considering the UAV battery and payload constraints, (Chauhan et al. 2019) developed an integer linear formulation for a capacitated FLP with the objective of maximizing the coverage in a drone-based delivery system. They solved the model by a three-stage heuristic approach that involves a facility location and allocation problem, multiple knapsack subproblems, and a final local search stage.

As it is reviewed by (Ortiz-Astorquiza et al. 2018), hierarchical FLPs involve different types of interacting facilities that provide services to a set of customers. Considering three layers of services comprising automatic teller machines (ATMs), branch bank offices, and main banks, (Min and Melachrinoudis 2001) studied a hierarchical location problem of banking facilities. Their model incorporates some level of uncertainty stemming from the location factors such as interest rates, inflation, taxes, wages, utilities, demography, market competition, and loan policy. Considering drones as the delivery vehicles, (Shavarani et al. 2018) proposed a mixed integer non-linear mathematical model for a distance-constrained mobile hierarchical facility location problem to determine the best number and locations of launch and recharge stations. They used some metaheuristic algorithms to solve the problem with hybrid genetic algorithm being the most efficient. Using the M/G/K queuing framework, (Shavarani et al. 2019b) studied a congested capacitated hierarchical location problem for the drone-based delivery systems. They used fuzzy variables to tackle the nondeterministic nature of the problem. As the solution method, they developed a genetic algorithm.

The application of bi-objective models is a sought approach in FLPs. (Badri et al. 1998) studied a model with 11 conflicting objective functions to find the best locations for establishing the fire stations in Dubai. They solved the proposed model by using a goal programming approach. (Drezner et al. 2006) developed a multi-objective location model with 5 objectives to locate the casualty collection points in the case of a large-scale disaster. A descent heuristic and a tabu search procedure were proposed for its solution. (Araz et al. 2007) studied a multi-objective covering problem to maximize the primary coverage as the first objective, the back-up coverage as the second objective, and minimize the traveled distance as the third objective. They used a lexicographic linear programming and a fuzzy goal programming as the solution approaches. (Beheshtifar and Alimoahmadi 2015) used the non-dominated sorting genetic algorithm (NSGA-II) to solve a healthcare facility location problem that minimizes the total travel cost, the inequality in access to clinics, the land-use incompatibility, and the cost of land acquisition in four objective functions. They used chromosomes of variable lengths to optimize both the number and the location of clinics. (Golabi et al.

2017a) proposed a multi-objective location problem to locate the ATMs such that the establishment costs, the surcharge costs, the interchange costs, and the number of lost customers are minimized simultaneously. They used a weighted-sum approach to combine the objective function into a single one. (Karatas and Yakıcı 2018) incorporates the objectives of median, covering, and center problems in a multi-objective facility location problem. As the solution method, they developed an algorithm that combines branch and bound with an iterative goal programming approach.

In the majority of FLPs studied in the literature, the demands are considered to be located at the network nodes. In order to present a more realistic model, (Arkat and Jafari 2016) studied on a single server facility location problem in which demands are uniformly distributed along the network edges. (Golabi et al. 2018) expanded the previous study by considering M/M/C queuing systems to optimize the location of facilities and the number of servers assigned to each facility. Using the concept of distributed demands, (Golabi et al. 2017b) proposed a facility location problem in humanitarian relief logistics using UAV drones. They assumed that afterward a large-scale earthquake, the demand of the inaccessible or collapsed network edges is covered by UAV drones. (Shavarani et al. 2018) expanded the previous model by considering two levels of services. Inspired by these studies, this paper studies a bi-objective facility location problem with stochastic demands distributed along the network edges. Each facility is a distribution center with limited capacity 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 (Owen and Daskin 1998; Javadian et al. 2014; Shishebori et al. 2014a). Furthermore, the proposed model is mixed-integer nonlinear which adds up to the complexity of the problem (Pasandideh et al. 2013a). Thus, a metaheuristic method is used to solve the proposed mathematical model.

3. Problem definition and formulation

As mentioned in previous sections, the efficiency of a delivery system significantly depends on the location of distribution centers. Determining the best locations for establishing the distribution centers has obsessed many researchers in the field of logistics and supply chain management. Although the classical node-based location problems have been extensively studied in the previous works, as far as the authors know, the edge-based capacitated location problem with mobile servers has not been considered in the literature. It should be mentioned that none of the few studies which focused on uncapacitated edge-based location problems with mobile servers have considered optimizing more than one objective function by developing multi-objective mathematical models. Since it is incontrovertible that in the real-life cases the customers are distributed along the network edges and the delivery operation is subject to capacity restrictions, the necessity of studying this problem will be more highlighted. Therefore, this paper studies a bi-objective stochastic mobile facility location problem in order to locate distribution centers in a delivery system. It is assumed that the delivery operation is performed by means of UAV drones assigned to each distribution center. The considered problem is a discrete location problem in which distribution centers are selected among a set of candidate locations. In addition to the number and the locations of distribution centers, the number of drones assigned to each center is also a decision variable. It is premised that the customers are uniformly distributed along the network edges. For each network edge, the demand generation follows the Poisson distribution. Based on the proximity of the endpoints to the opened facilities, each network edge is decomposed into two different segments each assigned to its nearest facility. 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. Therefore, the capacity of each facility is defined as the total travel distance that can be traversed by its 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 optimize the 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 clear that minimizing the number of

uncovered customers is a matter of great interest for all the capacitated delivery systems. 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. Figure 1 represents the problem schematically.

Figure 1: Schematic representation of the problem

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 ($A \subseteq I \times I, (i, i') \in A$)
- J : the set of candidate locations ($j, j' \in J$)

Scalars:

- k : the maximum allowed number of opened facilities
- N : the maximum number of drones to be purchased
- M : a large positive number
- E : the endurance of each drone
- P : 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')
- f_j : the cost of establishing j^{th} facility
- t_{ji} : the Euclidian distance between node i and facility j

Decision variables:

- y_j : $\begin{cases} 1 & \text{if facility } j \text{ is open} \\ 0 & \text{otherwise} \end{cases}$
- x_{ij} : $\begin{cases} 1 & \text{if the closest open facility to node } i \text{ is facility } j \\ 0 & \text{otherwise} \end{cases}$
- 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 and formulated by (Golabi et al. 2017b), each network edge is decomposed into two different segments, each assigned to its closest open facility. Figure 2 illustrates a network edge in which facilities j and j' are the closest open facilities to nodes i and i' respectively. Since demands are uniformly distributed along the network edges, the customers distributed between node i and the decomposing points are assigned to facility j , while the remaining customers are assigned to j' . It is assumed that the decomposing point has the same aerial distance with facilities j and j' . As illustrated in Figure 2, the aerial distance between the decomposing point and facility j which is shown by $g_{ii'jj'}$ could be calculated as:

Figure 2: Partitioning a network edge

$$t_{ji}^2 = d_{ii'jj'}^2 + g_{ii'jj'}^2 - 2d_{ii'jj'}g_{ii'jj'}\cos\theta \quad (1)$$

$$t_{ji'}^2 = d_{i'i'j'j}^2 + g_{ii'jj'}^2 + 2d_{i'i'j'j}g_{ii'jj'}\cos\theta \quad (2)$$

Substituting $\cos\theta$ from Eq. 1, it follows:

$$t_{ji'}^2 = d_{i'i'j'j}^2 + g_{ii'jj'}^2 + 2d_{i'i'j'j}g_{ii'jj'}\left(\frac{g_{ii'jj'}^2 - t_{ji}^2 + d_{ii'jj'}^2}{2d_{ii'jj'}g_{ii'jj'}}\right) \quad (3)$$

Solving Eq. 3 for $g_{ii'jj'}$ yields:

$$g_{ii'jj'} = \sqrt{\frac{d_{i'i'j'j}t_{ji}^2 + d_{ii'jj'}t_{ji'}^2 - d_{ii'jj'}d_{i'i'j'j}l_{ii'}}{l_{ii'}}} \quad (4)$$

Using the same logic to calculate $g_{i'i'j'j}$ and then making it equal to $d_{i'i'j'j}$ yields:

$$d_{ii'jj'} = \frac{l_{ii'}(t_{ji'}^2 - t_{ji}^2)}{t_{ji'}^2 - t_{ji}^2 + t_{ji}^2 - t_{ji}^2} \quad (5)$$

If the closest open facilities to nodes i and i' are identical, the edge is not decomposed and would be assigned entirely to that facility. In this case, based on the proximity of i or i' to the closest facility, $d_{ii'jj'}$ is either equal to zero or $l_{ii'}$ and is calculated according to Eq. 6.

$$d_{ii'jj} = \max\left(\frac{t_{ji'} - t_{ji}}{|t_{ji'} - t_{ji}|}, 0\right) l_{ii'} \quad (6)$$

Using similar calculations, the aerial distance between facility j and the midpoint of the designated segment of edge (i, i') that is shown by $\tau_{ii'jj'}$ is calculated as follows:

$$\tau_{ii'jj'} = \sqrt{\frac{2g_{ii'jj'} + 2t_{ji'}^2 - d_{ii'jj'}}{4}} \quad (7)$$

Using the discussed calculations, the proposed mathematical model is as follows:

$$\text{Min} \sum_{j \in J} f_j y_j + P n_j \quad (8)$$

$$\text{Min} \sum_{(i, i') \in A} L_{ii'jj'} \quad (9)$$

$$\sum_{j \in J} y_j \leq k \quad (10)$$

$$\sum_{j \in J} n_j \leq N \quad (11)$$

$$n_j \leq c_j \quad \forall j \in J \quad (12)$$

$$x_{ij} \leq y_j \quad \forall i \in I, j \in J \quad (13)$$

$$n_j \leq M y_j \quad \forall j \in J \quad (14)$$

$$\sum_{j \in J} x_{ij} = 1 \quad \forall i \in I \quad (15)$$

$$\sum_{j' \in J} x_{ij'} t_{j'i} \leq t_{ji} + M(1 - y_j) \quad \forall i \in I, j \in J \quad (16)$$

$$d_{ii'jj'} = \frac{l_{ii'}(t_{ji'}^2 - t_{ji}^2)}{t_{ji'}^2 - t_{ji}^2 + t_{ji}^2 - t_{ji'}^2} \quad \forall (i, i') \in I, (j, j') \in J \quad (17)$$

$$d_{ii'jj} = \max\left(\frac{t_{ji'} - t_{ji}}{|t_{ji'} - t_{ji}|}, 0\right) l_{ii'} \quad \forall (i, i') \in I, j \in J \quad (18)$$

$$g_{ii'jj'} = \sqrt{\frac{d_{ii'jj'} t_{ji'}^2 + (l_{ii'} - d_{ii'jj'}) t_{ji}^2 - d_{ii'jj'} (l_{ii'} - d_{ii'jj'}) l_{ii'}}{l_{ii'}}} \quad \forall (i, i') \in I, j \in J \quad (19)$$

$$\tau_{ii'jj'} = \sqrt{\frac{2g_{ii'jj'} + 2t_{ji'}^2 - d_{ii'jj'}}{4}} x_{ij} x_{i'j'} \quad \forall (i, i') \in I, (j, j') \in J \quad (20)$$

$$\left(s_{ii'jj'} + L_{ii'jj'} - \lambda_{ii'} \frac{d_{ii'jj'}}{l_{ii'}}\right) x_{ij} x_{i'j'} = 0 \quad \forall (i, i') \in I, (j, j') \in J \quad (21)$$

$$2 \sum_{(i,i') \in A} S_{ii'jj'} \tau_{ii'jj'} \leq \omega n_j \quad \forall (j,j') \in J \quad (22)$$

$$x_{ij}, y_j \in \{0,1\} \quad \forall i \in I, j \in J \quad (23)$$

$$\tau_{ii'jj'}, L_{ii'jj'}, S_{ii'jj'} \geq 0 \quad \forall (i,i') \in I, (j,j') \in J \quad (24)$$

$$d_{ii'jj'} \text{ free in sign} \quad \forall (i,i') \in I, (j,j') \in J \quad (25)$$

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 (10) and (11) set an upper bound for the total number of opened facilities and purchased drones respectively. Constraint (12) restricts the number of drones assigned to each facility. Constraints (13) and (14) assure that no assignment is done for the close facilities. Constraints (15) and (16) guarantee each network node is assigned to the closest facility. Constraints (17) and (18) define the length of each segment. The distance between the partitioning point and its corresponding facility is determined by constraint (19). Constraint (20) defines the average distance between each segment and its assigned open facility. Constraint (21) guarantees the equality of covered and uncovered demands to the total demands of each segment. It is noteworthy to mention that since the demand generation of each network edge follows the Poisson distribution and due to this fact that demand is uniformly distributed along the edges, the demand of each designated edge segment is $\lambda_{ii'} \frac{d_{ii'jj'}}{l_{ii'}}$. Constraint (22) assures that the capacity constraint of each facility is not violated. Constraints (23), (24), and (25) enforce the binary, non-negative, and free in sign restrictions on decision variables.

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 (Deb et al. 2002; Deb and Jain 2014).

4.1. NSGA-II

As an efficient evolutionary multi-objective optimization algorithm, NSGA-II has been applied to solve a plethora of location problems (Bhattacharya and Bandyopadhyay 2010). NSGA-II initiates with a randomly generated population of solutions with size N . Each individual solution in the population is called a chromosome. In this study, each chromosome is a vector consisting of $2m$ elements where m represents the number candidate locations. The first m elements are binary numbers where 1 indicates that the corresponding facility is opened. The second half of the chromosome indicates the number of assigned vehicles which is randomly generated between 0 and c_j , the maximum number of drones for facility j . It is needless to mention that no drone is assigned to the closed facilities. 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 a random number of units. This operation continuous until the constraint (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. The structure of the chromosome is illustrate in Figure 3.a.

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 there is either no unsatisfied demand or no capacity left to satisfy further demands. Now the computation of objective functions according to Eq. 8 and Eq. 9 is straightforward.

In the next step, the solution population is sorted based on non-dominance. Since in multi-objective optimization the complete sorting of the solutions is not possible, the concept of non-domination is used to sort the population of solutions. As it has been described by (Coello et al. 2007), the solution u dominates solution v ($v < u$) if and only if:

$$f_i(u) \leq f_i(v) \quad \forall i \in \{1, \dots, n\} \quad (26)$$

$$f_i(u) < f_i(v) \quad \exists i \in \{1, \dots, n\} \quad (27)$$

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 sorting procedure continues by excluding the rank 1 solutions. In this step the non-dominated solutions are ranked 2 and the process continues till all the solutions are ranked.

The selection process of the algorithm is performed based on the rank of the solutions. First the solutions of the first rank are selected and added to the pool. If the size of the pool is reached to $2N$ the selection stops, otherwise the solutions with rank 2 are selected and so on. 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 this study 2 type of cross overs are performed; two-point crossover and uniform crossover. The probability of two types of crossover is equal. In the crossover operations two parents are selected.

In the two-point crossover, a crossover point h , is randomly generated between 1 and m . The second point is set to $m+h$. This makes sure that the feasibility of the chromosome is maintained; i.e. no vehicle is assigned to closed facilities and open facilities are assigned vehicles. Two offspring are generated by swapping the part between the two crossover points the two-point crossover is illustrated in Figure 3.b. Occasionally Constraint (11) can be violated by crossover operation; therefore, the application of the repair function may be necessary.

In uniform crossover a vector of random binary numbers with size m is generated. The vector is copied and concatenated to produce a vector of size $2m$ called mask. Again this is to make sure the vehicles are assigned to open facilities and avoid extra repair function. Two parents are selected then. Offspring one is generated by taking those elements of parent 1 which correspond to the elements of the mask which are equal to 1, and those elements of parent 2 which correspond to the elements of the mask which are equal to 0. The second offspring is generated similarly and with exchanging the roles of parent 1 and 2. Again application of a repair function may be inevitable. The uniform crossover operation is depicted in Figure 3.c.

In order to perform the mutation operation, a parent is selected. A random number of alleles are selected randomly from the first part of the chromosome; i.e. alleles with index between 1 and m . The binary value of these alleles is changed and the corresponding alleles in the second part of the chromosome are also changed accordingly. If the allele in the first part changes from 0 to 1, the corresponding allele in the second part indicating the number of chromosomes

is changed to some random number between 1 and c_j . If it changes from 1 to 0, its corresponding allele in the second part is changed to zero. Application of a repair function may be necessary. The mutation operation is displayed in Figure 3.d.

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 ($F_1, F_2, \dots, F_{l-1}$) whose cumulative number of members does not exceed N 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.

The algorithm evolves the population through generation for a pre-determined number of iterations. The codes for NSGAII were acquired from (Francesco Biscani Dario Izzo 2019) and adopted to the problem at hand.

Index of the candidate location Binary part							Index of the candidate location Integer part for assigned number of drones							a
1	2	3	4	5	...	m	1	2	3	4	5	...	m	
0	1	0	0	1	...	0	0	8	0	0	17	...	0	
														b
0	1	0	0	1	...	0	0	8	0	0	17	...	0	Parent 1
1	0	0	1	0	...	1	12	0	0	6	0	...	32	Parent 2
0	1	0	1	0	...	1	12	0	0	0	17	...	0	Offspring 1
1	0	0	0	1	...	0	0	8	0	6	0	...	32	Offspring 2
														c
0	1	0	1	1	...	0	0	1	0	1	1	...	0	mask
0	1	0	0	1	...	0	0	8	0	0	17	...	0	Parent 1
1	0	0	1	0	...	1	12	0	0	6	0	...	32	Parent 2
1	1	0	0	1	...	1	12	8	0	0	17	...	32	Offspring 1
0	0	0	1	0	...	0	0	0	0	6	0	...	0	Offspring 2
														d
1	0	0	1	0	...	1	12	0	0	6	0	...	32	Parent
1	1	0	0	1	...	1	12	22	0	0	17	...	32	Offspring

Figure 3: a) Structure of the chromosome, b) two-point cross over operation, c) uniform crossover operation, d) mutation operation

4.2. NSGA-III

It has been shown that many-objective problems several challenges are imposed. Firstly, the number of non-dominated solutions become very large. Therefore, any elitist preserving algorithm would have problems in accommodating new solutions in the pool and the search process slows down. Second, calculating diversity metrics such as crowding distance becomes computationally expensive (Deb et al.). Therefore (Kukkonen and Deb 2006), (Deb and Jain 2014) introduced reference-point-based NSGAII, namely NSGA-III, for many objective problems. This method priorities solutions that are non-dominated and close to some pre-determined reference points. Originally the algorithm was proposed for handling many objective problems; i.e. problems with 4 to 15 problems. However, it was shown that the method works well for with different kinds of problem (Deb and Jain 2014).

The main part of the algorithm is similar to NSGAII and most of difference comes from the selection process in this algorithm. Preserving diversity in NSGAIII is aided by defining and updating some well-spread reference points. This is done by replacing the calculations of crowding distance with calculating the proximity to reference points. We have used the original idea of producing and updating reference points as proposed in (Das and Dennis 1998). If there are M objectives and p divisions on each objective axis, there would be $\binom{M+p-1}{p}$ reference points on the objective space. The points are located on a normalized hyper-plane which is equally inclined to all objective axes and has an intercept of one on each axis. The reference points could be also defined by the user if some preference information is at hand. NSGAIII uses non-dominated ranks and the proximity to reference points in order to sort the population. To do this, a vector is calculated from the origin to each reference point. The perpendicular distance of each solution to the vectors is calculated. A reference point is associated to a point if its vector has the minimum perpendicular distance to that point. Since these reference points are widely distributed on the hyperplane, the resulting solutions would well-distributed on/near the Pareto front.

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 the ideal point vector 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.

A members of F_t associated with reference points with minimum number of associations from $F_1, F_2, \dots, F_{t-1}$ (fronts added to the pool already) is add to the pool and the number of associations of that reference point is incremented by one. These members are then added one at a time to fill the population. The codes for NSGAIII were downloaded from (Tsung-Che Chiang 2014) and adopted to the problem at hand.

4.3. Parameter tuning

It is incontrovertible that the efficiency and effectiveness of metaheuristics algorithms are affected by the applied parameter levels and therefore, tuning the parameters prior to implementation of algorithms is necessary (Golabi et al. 2018). Although in the majority of studies, the parameters are fixed manually according to the reference values of previous similar researches, this study applies the Taguchi method to calibrate the parameters. In addition to reducing the computational effort of inefficient trial and error tuning method (Candan and Yazgan 2015), orthogonal arrays of the Taguchi method outperform the classical statistical optimization parameter tuning methods by investigating more decision variables in a smaller number of experiments (Mukherjee and Ray 2006). Taguchi classifies the factors into two main categories: controllable and noise (those that cannot be controlled directly) factors. The method aims to minimize the effect of noise while determining the optimal level of controllable factors (Phadke 1989). To do so, the signal-to-noise (S/N) ratio is calculated using Eq. 28, where signal (S) represents the desirable value (mean response variable), noise (N) represents the undesirable value (standard deviation), (Y) denotes the response value, and (n) shows the number of orthogonal arrays (Pasandideh et al. 2013b).

$$S/N = -10 \times \log(S(Y^2)/n) \quad (28)$$

Table 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 and Thiele 1998). Diversity or the maximum spread metric that measures the extension of Pareto solution is calculated by Eq. 29 in which l denotes the number of objective functions and $Min f_j$ and $Max f_j$ are the minimum and maximum values of each fitness function among all non-dominated solutions attained by the algorithm (Okabe et al. 2003). The higher value of Diversity is of interest (Arjmand and Najafi 2015).

$$Diversity = \sqrt{\sum_{j=1}^l (Min f_j - Max f_j)^2} \quad (29)$$

MID calculates the distance between the Pareto fronts and the ideal points. The value of this metric is calculated using Eq. 30 where n is the number of non-dominated solutions, $f1_i$ and $f2_i$ denote the first and second objective value of the i^{th} non-dominated solution respectively, and $f1_{total}^{min}$ and $f1_{total}^{max}$ are the smallest and the biggest values of the first fitness function among all non-dominated solutions that are resulted from an algorithm (Maghsoudlou et al. 2016). The smaller the value of MID, the better is the performance of the algorithm.

$$MID = \frac{\sum_{i=1}^n \sqrt{\left(\frac{f1_i - f1_{best}}{f1_{total}^{max} - f1_{total}^{min}}\right)^2 + \left(\frac{f2_i - f2_{best}}{f2_{total}^{max} - f2_{total}^{min}}\right)^2}}{n} \quad (30)$$

The NOS denotes the number of solutions in the optimal Pareto front that is obtained by each metaheuristic algorithm (Rahmati et al. 2013). A higher number of NOS shows more desirability (Arjmand and Najafi 2015). CPU time denotes the speed of running the algorithms to find near optimum solutions. It is clear that smaller values of CPU time have more credit.

The main objectives of Pareto-based metaheuristic algorithms are the good convergence and diversity (Salmasnia et al. 2018). In order to evaluate both convergence and diversity of algorithms simultaneously in a unique response, the combined metric (cm) is calculated by Eq. 31.

$$cm = \frac{Mean\ Ideal\ Distance}{Diversity} \quad (31)$$

For each parameter combination shown in Table 2 and the data for the case of San Francisco which is described in Section 5, 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. Figure 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 Figure 4a NSGA-II parameters A, B, C, and D are better to be at their first, third, third, and second levels respectively.

Table 1
Parameter levels

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

Table 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	3.215696	1	1	1	1	1	0.574047
2	1	2	2	2	3.111688	2	1	2	2	2	0.531708
3	1	3	3	3	3.146800	3	1	3	3	3	0.526300
4	2	1	2	3	3.624216	4	2	1	2	3	0.555809
5	2	2	3	1	3.174152	5	2	2	3	1	0.601438
6	2	3	1	2	3.240528	6	2	3	1	2	0.531300
7	3	1	3	2	3.192296	7	3	1	3	2	0.623817
8	3	2	1	3	3.672952	8	3	2	1	3	0.594464
9	3	3	2	1	3.193696	9	3	3	2	1	0.581711

Figure 4: S/N plot for: (a) NSGA-II parameters; (b) NSGA-III parameters

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. Figure 5b illustrates the network that consists of 68,609 edges corresponding to the main streets of the city and 53,738 nodes which represent the crossroads. As illustrated in Figure 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 of 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 5: (a) candidate locations; (b) transportation network

6. Results and discussion

The computational results of employing the proposed metaheuristic algorithms on the case of San Francisco are shown in Table 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. Figure 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 Figure 6, the proposed NSGA-III flagrantly outperforms NSGA-II in terms of diversity, mean ideal distance, and combined metric (*cm*). 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 required CPU time. The attained p-values and interval plots of ANOVA test based on the required CPU time is shown in Figure 7. According to this figure, there is not a significant difference between the results of proposed algorithms on the basis of required CPU times. In order to exemplify the results' analysis, the non-dominated solutions of the proposed algorithms are schemed in Figure 8 To give a more clear illustration, Pareto fronts are depicted separately for each algorithm. 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 (Shavarani et al. 2018), the annual benefit of drone delivery system is estimated as \$100,150,000.

Table 3

Computational results of solving methodologies

RU N	NSGA-II					NSGA-III				
	Diversit	NO		Time	(s)	Diversi	NO		Time	(s)
	y	MID	S	cm		ty	MID	S	cm	

1	0.5372	1.4404	28	2.6811	16498	1.1841	0.5836	66	0.4928	16627
2	0.7460	1.5053	30	2.0178	16332	1.3168	0.7780	75	0.5908	16516
3	0.6569	1.4607	37	2.2237	16291	1.2154	0.6453	68	0.5310	15921
4	0.7988	1.3304	25	1.6655	16462	1.2610	0.8178	61	0.6486	16532
5	0.5142	1.3960	25	2.7147	16407	1.1848	0.5555	73	0.4688	16201
6	0.6272	1.3493	27	2.1512	16410	1.2764	0.5850	67	0.4583	16386
7	0.5231	1.3736	34	2.6260	16481	1.2052	0.5424	64	0.4500	15973
8	0.7882	1.3960	35	1.7711	16519	1.2874	0.5390	67	0.4187	16622
9	0.4914	1.4669	34	2.9849	16371	1.2947	0.8029	62	0.6202	16516
10	0.7302	1.3199	31	1.8075	16481	1.3071	0.6987	62	0.5345	15745
11	0.7434	1.6611	33	2.2346	16395	1.2446	0.6879	76	0.5527	16195
12	0.7593	1.6779	29	2.2098	16544	1.1676	0.5422	78	0.4644	16450
13	0.5162	1.4963	36	2.8989	16541	1.1981	0.7971	70	0.6653	16639
14	0.6139	1.4957	27	2.4363	16339	1.3418	0.7139	61	0.5321	16029

Figure 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

Figure 7: ANOVA and related interval plots for comparing the algorithms based on required CPU time

Figure 8: The Pareto optimal fronts acquired by each algorithm

6. Conclusion

On the premise that customers are uniformly distributed along the network edges, this paper 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. According to the obtained results, although there was not a significant difference between the results of proposed algorithms on the basis of required CPU times, NSGA-III outperforms NSGA-II based on diversity, mean ideal distance, combined metric (*cm*), and the number of Pareto solutions. The chromosome is consisted of 109 binary and 109 integer variables which makes the feasible space extremely large and non-smooth. As the result, authors suspect that NSGAII requires much more time to find solutions in different parts of the Pareto

front while the well-distributed reference points in NSGAIII helps this algorithm to find representative solutions in each region of the Pareto Front.

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. Alternatively, the queuing systems could be considered by adding new constraints reflecting the maximum allowed waiting time of customers. Another interesting research would be developing many-objective models accounting for more aspects of facility location such as tax scores, advantage scores and potential income of the facilities and compare the performance of the proposed algorithms when dealing with more than two objectives. 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 to make the model more realistic.

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