Transportation Research Part C 90 (2018) 198–212

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

A range-restricted recharging station coverage model for drone delivery service planning

Insu Hong[a,*], Michael Kuby[b], Alan T. Murray[c]

[a] Department of Geology and Geography, West Virginia University, United States
[b] School of Geographical Sciences and Urban Planning, Arizona State University, United States
[c] Department of Geography, University of California at Santa Barbara, United States

ARTICLE INFO

Keywords:
Unmanned aerial vehicles
Spatial optimization
Euclidean Shortest Path
GIS
Location modeling

ABSTRACT

Unmanned Aerial Vehicles (UAVs) are attracting significant interest for delivery service of small packages in urban areas. The limited flight range of electric drones powered by batteries or fuel cells requires refueling or recharging stations for extending coverage to a wider area. To develop such service, optimization methods are needed for designing a network of station locations and delivery routes. Unlike ground-transportation modes, however, UAVs do not follow a fixed network but rather can fly directly through continuous space. But, paths must avoid barriers and other obstacles. In this paper, we propose a new location model to support spatially configuring a system of recharging stations for commercial drone delivery service, drawing on literature from planar-space routing, range-restricted flow-refueling location, and maximal coverage location. We present a mixed-integer programming formulation and an efficient heuristic algorithm, along with results for a large case study of Phoenix, AZ to demonstrate the effectiveness and efficiency of the model.

1. Introduction

Unmanned aerial vehicles (UAVs), or drones, have developed rapidly for commercial and personal uses, from military to surveillance/monitoring, journalism, scientific research, photography, emergency response, and recreational activities (Finn and Wright, 2012; Clarke, 2014; Sandbrook, 2015). Deploying drones for delivery service of small packages has attracted much attention, and several companies and public agencies have proposed or tested drone delivery service at a small scale (Hern, 2014; Murray and Chu, 2015; Ha et al., 2015a,b; Weise, 2017). Amazon (2017) is considering a premium delivery service called Amazon Prime Air, which would provide rapid delivery of packages within 30 min of ordering online. While not ready to completely replace the familiar delivery trucks, anytime soon, drones appear well-suited to augment existing road deliveries for high-margin, last-minute service to single-family homes and stand-alone businesses, and to bypass road congestion (Agatz et al., 2015). Another promising application is for reaching areas lacking road access, such as small islands and rainforest (Zhang and Kovacs, 2012; Hern, 2014; Toor, 2016).

To develop a stand-alone drone delivery service, a route planning strategy is necessary, based on efficient delivery routes in continuous two-dimensional space. Although a drone may not need to follow a pre-defined transportation network, barriers such as high-rise buildings, mountains and flight-restricted zones may impede a more direct flight path. In the literature, the problem of finding the best obstacle-avoiding route is known as the Euclidean Shortest Path (ESP) problem (Lozano-Pérez and Wesley, 1979; Asano et al., 1986; Hong and Murray, 2013).

* Corresponding author.
E-mail address: insu.hong@mail.wvu.edu (I. Hong).

https://doi.org/10.1016/j.trc.2018.02.017
Received 15 November 2016; Received in revised form 9 October 2017; Accepted 20 February 2018
Available online 22 March 2018
0968-090X/

Another factor to consider in path planning for delivery drones is the limited flight range of battery-powered or fuel-cell drones. Several logistical strategies have been proposed to deal with the range limitation in a drone delivery system. A multi-modal approach would combine drones with trucks, using the advantages of one to offset the disadvantages of the other, such as by launching drones from trucks for the “last-mile” only (Murray and Chu, 2015; Agatz et al., 2015; Ha et al., 2015a). Alternatively, a single-mode (drone-only) door-to-door drone delivery system from warehouse to customers would have to rely on single or multiple stops at battery-recharging, battery-replacing, or hydrogen-refueling stations (Sundar and Rathinam, 2014; Dorling et al., 2017; Yu et al., 2017). Our paper contributes to the development of the drone-only strategy by optimizing new locations of recharging stations for efficient drone delivery service without other modal needs.

A substantial literature has emerged for optimizing the locations of recharging facilities on a network for alternative-fuel vehicles. Kuby and Lim (2005) developed the Flow Refueling Location Model that explicitly takes into account the travel range of alternative-fuel vehicles when locating refueling or recharging stations on road or rail networks.[1] The flow refueling model locates a given number of stations to maximize the origin-destination flow volume that can travel without running out of fuel. The drone-recharging problem, however, is more complex. Unlike road or rail vehicles operating on a defined network, the designation of candidate station sites changes the potential routes over which drones may fly, from which optimal flight paths are derived. In addition, the potential service area of stations will be determined by the flight range of drones. Therefore, a coverage location model integrating the ESP is needed to optimize the location of stations for drone delivery service.

In this paper, we propose a new location model for optimally siting recharging stations to support commercial stand-alone drone delivery service in an area with obstacles. The new model combines elements of the ESP, the flow refueling, and the maximal cover location model to locate stations and construct a feasible and efficient delivery network in order to serve a region efficiently. A heuristic technique is developed that exploits spatial knowledge. Application results are presented to demonstrate the effectiveness of the proposed approach.

2. Background

The utility of UAVs has been rapidly expanding, especially in the civilian sectors (Finn and Wright, 2012; Clarke, 2014; Mohammed et al., 2014). The low operating cost of drones creates numerous opportunities for small-scale applications (Zhang and Kovacs, 2012; Sundar and Rathinam, 2014). UAVs have been deployed for data collection of disease propagation (Fornace et al., 2014), agricultural applications (Zhang and Kovacs, 2012; Pérez-Ortiz et al., 2015), vegetation analysis (Paneque-Gálvez et al., 2014), wildlife monitoring and conservation (Linchant et al., 2015; Sandbrook, 2015), nighttime lighting assessment (Murray and Feng, 2016), and many more. Other applications include disaster response (Adams and Friedland, 2011), disease control (Amenyo et al., 2014), traffic monitoring (Kanistras et al., 2014), urban planning (Mohammed et al., 2014), mapping (Tahar et al., 2012), and law enforcement (Finn and Wright, 2012; Clarke, 2014). The U.S. Federal Aviation Administration (FAA) prohibits commercial operations of drones but issues exemptions on a case-by-case basis for applications such as aerial surveying and photography, utility inspection, and filming (Dillow, 2015). Amazon, DHL Germany, and UPS have recently tested or attempted delivery service using drones (Hern, 2014; Amazon, 2017; Weise, 2017).

With growing commercial interest in drone delivery systems, researchers have begun developing operations research models for optimizing delivery systems. Several papers have proposed multi-modal drone-truck systems, where delivery trucks function as moving depots and drones launch from the trucks (Ha et al., 2015a,b). Murray and Chu (2015) coined the term “flying sidekick traveling salesman problem,” which first constructs traveling salesman truck routes and then substitutes drones that deliver to certain customers and return to the truck down-route. A variant allows customers close to the warehouse to be served directly by drones, which either return to the warehouse or meet a truck route (Murray and Chu, 2015). Agatz et al. (2015) studied the Traveling Salesman Problem with Drone, where the drone must follow the road network. Ha et al. (2015a) proposed two heuristics for the minimax delivery time traveling salesman with drone problem, while Ha et al. (2015b) proposed a cost-minimizing objective. Mathew et al. (2015) modeled the Heterogenous Delivery Problem, in which drones launched from trucks from a road endpoint deliver to isolated customers located off the road network.

A second but smaller group of drone delivery models focuses on drone-only strategies. Dorling et al. (2017) propose a vehicle routing and traveling salesman problem with a flight range restriction that allows UAVs to make multiple returns to the depot to pick up additional packages and swap for a fresh battery. Sundar and Rathinam (2014) optimize routes using the existing locations of recharging facilities away from the base. The model proposed in this paper extends this second group of drone-only approaches to the problem of locating a limited number of stationary recharging stations assuming that drones deliver to one customer per trip, consistent with the preliminary descriptions of Amazon Prime Air (2017) but with flying range extended via multiple recharging stops.

We know of no previous papers that optimize where to build a limited number of new stations for drone refueling during deliveries. The closest work is by Yu et al. (2017) who propose two generalized traveling salesman problems for drones capable of carrying multiple packages: one for multiple stationary charging stations and another for a single mobile charging station. Their stationary charging model, however, locates stations everywhere charging takes place, with no limit on the number that can be

[1] For the remainder of this paper, we will use the general term “recharging” for any method of restoring a drone’s energy storage system to 100%. The term “fuel” or “refueling” will only be used where it has become standard in the literature, such as alt-fuel vehicles or the flow-refueling location model. Nevertheless, these terms are interchangeable.

located or consideration of their cost. Stationary charging in their TSP is represented as a link from i to j with a cost equal to the travel time to j plus the landing, recharging, and takeoff times at j.

There is a rich literature on location models for fueling or charging stations on a rail or road network that evaluates the feasibility of routes given a driving range. Building on the flow capturing (or intercepting) models pioneered by several researchers (e.g., Hodgson, 1990; Berman et al., 1992), the flow refueling problem treats demands for fuel stations as paths between origin and destination (O-D) pairs on a network, with the added stipulation that vehicles on the shortest O-D path must be able to complete their round trips without running out of fuel given the driving range of vehicles (Kuby and Lim, 2005; Upchurch et al., 2009). The range restriction means that multiple fuel stops may be needed on longer round trips, which Xie and Jiang (2016) referred to as a "relay" requirement—a useful term we adopt here for drone recharging. The flow refueling problem has been formulated with both maximal and complete covering objectives (Wang and Lin, 2009), and has been solved using a variety of heuristics and exact approaches (Kuby et al., 2009; MirHassani and Ebrazi, 2012; Capar et al., 2013), and extended (He et al., 2015; Riemann et al., 2015). The Deviation Flow Recharging Model (see Jiang et al., 2012; Kim and Kuby, 2012; Huang et al., 2015) is one such extension, allowing for realistic detours to refuel at stations off the shortest path, while Nourbakhsh and Ouyang (2010) detail an extension for locomotive refueling.

The Euclidean shortest path problem is well-suited for flight path planning and distance measurement in the presence of barriers (Asano, 1985). A number of derivation algorithms have been proposed, including visibility graphs and variations thereof (Lozano-Pérez and Wesley, 1979; Ghosh and Mount, 1991; Zhang et al., 2005; Gao et al., 2011), shortest path maps (Mitchell, 1999), and Voronoi diagrams (Papadopoulou and Lee, 1998), among others. Since it has been mathematically proven that the optimal ESP will pass through vertices of obstacles in a given region, most approaches are based on deriving a graph consisting of such vertices (Viegas and Hansen, 1985; de Berg et al., 2008). The most widely applied approach is the visibility graph. Recently, Hong and Murray (2013) and Hong et al. (2015) developed a new method to derive the ESP with significantly improved performance by exploiting spatial knowledge and GIS functionality, vastly expanding computing capabilities to enable practical planning problems to be solved in real-time.

This paper draws from these works to address the problem of locating recharging stations for UAVs in a package delivery service assuming drones can serve one customer at a time across Euclidean space while avoiding polygonal obstacles. The drone refueling station location problem resembles flow refueling in some ways and differs in others. Similarities include a limited travel range based on on-board energy storage and use, the need to recharge multiple times on longer round trips, and the use of stationary charging stations. The biggest difference is that, in flow refueling for ground transport, the network arcs are given based on the roads or railways, whereas drones operate in continuous space. While a network can be extracted from continuous space based on ESP properties, its structure will depend on the locations of the warehouse, the demand nodes, the candidate sites, and the obstacles. Second, in the drone refueling problem, the vehicle's range changes significantly after delivering a package. Third, the mixed integer program (MIP) for flow refueling requires pregeneration of the shortest paths on each O-D pair, while the MIP for the deviation flow refueling requires a finite set of deviation paths. In contrast, the MIP proposed here requires no paths to be generated before or during solution.

3. Routing

Air travel through a region is modeled using the ESP in order to avoid obstacles, barriers and restricted air space. The method here is based on the convexpath algorithm developed by Hong and Murray (2013) and Hong et al. (2015). Like other ESP methods, the convexpath algorithm constructs a graph based on obstacles and O-D points in continuous two-dimensional space, but utilizes spatial knowledge and GIS functionality to improve computational capabilities. Specifically, it uses the convex hull and intelligent spatial filtering to evaluate only relevant obstacles for given O-D pairs and constructs a minimal-sized graph that guarantees inclusion of the optimal ESP.

Given origin and destination points and a polygon obstacle that impedes straight line travel between them, it has been proven that the ESP for an O-D pair lies on a graph that consists of the convex hull for the O-D points and the obstacle (Hong and Murray, 2013; Hong et al., 2015). In the case of multiple obstacles, the convexpath algorithm derives a graph by iteratively constructing convex hulls around impeding obstacles. The graph is expanded systematically by replacing impeded arcs of the graph with sub-convex hulls. Fig. 1 shows an example of the associated graph as well as the ESP.

Drone delivery planning uses the ESP in two ways. First, the ESP derives flight paths to measure distances between locations, which in turn are needed to calculate the area that candidate recharging station locations could cover. Second, the ESP constructs the feasible delivery network. Fig. 2 presents an ESP flight path from a recharging station to a customer that avoids an obstacle between them. If desired, buffers can be applied around barriers to decrease the potential for collision or violation of flight-restricted zoning. Fig. 2 also shows that, without accounting for barriers, using a simple Euclidean buffer would erroneously estimate that the customer can be covered, whereas the ESP distance actually exceeds the coverage threshold. In contrast, the shaded area of Fig. 2 (ESP coverage) depicts the true service coverage based on the ESP metric considering obstacles. It can be seen that the highlighted customer would not, in fact, be covered by such a station.

4. Model

To provide delivery by electric (battery or fuel-cell) drone-only service over a large area, a constellation of recharging stations could extend flight range in order to cover more customers. A location model for recharging station system design must consider: (1) the flight range of drones under different conditions; (2) delivery service coverage of recharging stations; and (3) construction of a

Fig. 1. Euclidean Shortest Path (ESP).

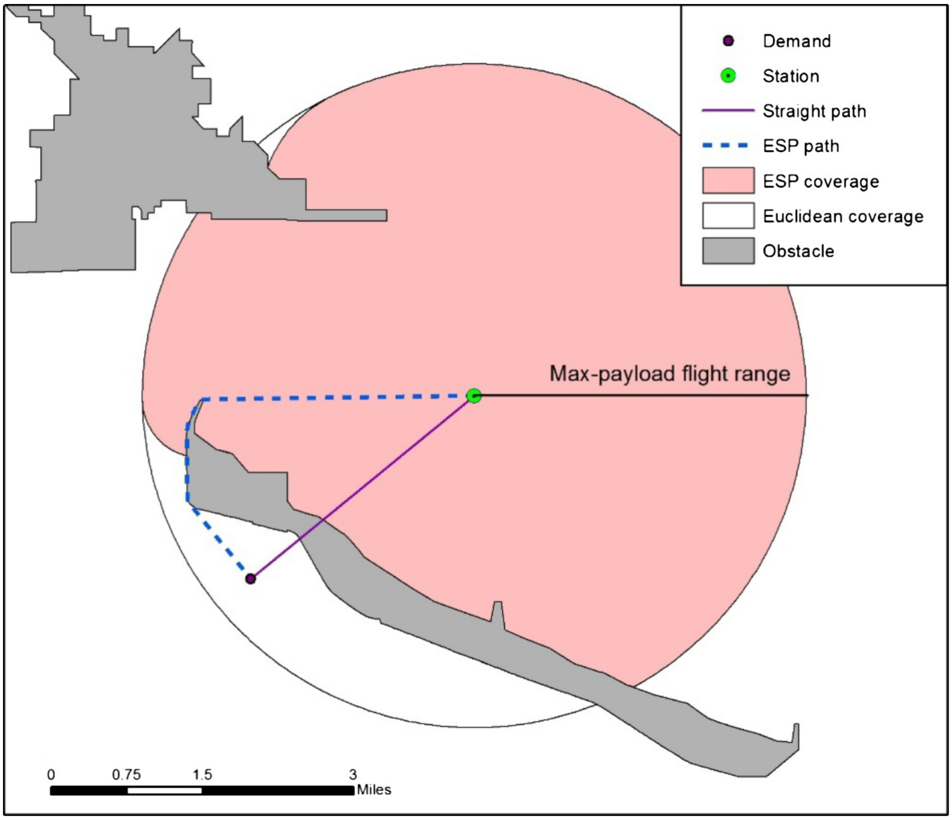

Fig. 2. Single-station ESP coverage.

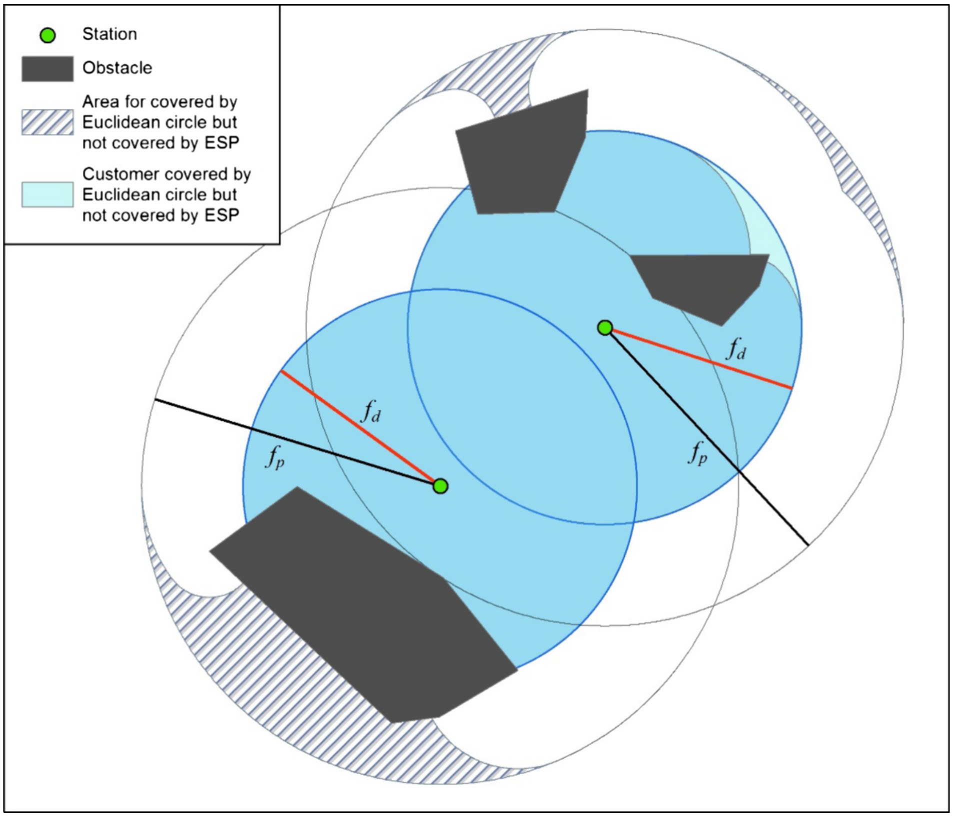

Fig. 3. Delivery flight range (f_d) and max-payload flight range (f_p) of a drone with Euclidean and ESP coverage.

feasible delivery network consisting of warehouses and recharging stations.

The flight range of drones is a critical factor as it determines the delivery service area, limits the length of maximum feasible connections between facilities, and ultimately impacts the location configuration of recharging stations. The maximum flying range varies by drone type and depends on the interaction of a host of technological factors, weather conditions, and payload size. For spatial modeling purposes, the range reflects the distance a fully loaded drone can travel to the next station under the worst-case conditions or with an acceptably low probability of running out of charge. Warehouses are also considered stations, assuming that drone batteries are recharged/replaced before loading. There are, however, three additional considerations that complicate basic coverage.

First, drones, like all vehicles, can be recharged as many times as needed to reach their destination. As Fig. 3 illustrates, if the customer destination is not within the payload flying range of a warehouse, then the drone must be refueled at a station within the warehouse's payload flying range. From there, it must be able to reach another station, and so on, until finally reaching the final destination within the payload flying range of the last station.

Second, unlike most covering models (such as for fire stations), it is not enough to simply arrive at the customer's location within the maximum distance, travel time, or in this case flying range. A drone must be able to return to a station or the warehouse after delivery of its payload without exceeding its remaining fuel range.

A third complicating factor is that once the payload is delivered, the weight of the drone decreases and its flight range increases. Thus, delivery drones do not need to arrive at their destination with at least 50% state of charge to return to the last station, as assumed in standard flow-refueling approaches, because the return trip will use less fuel. The exact percentage will depend on the weight of the payload relative to the weight of the aircraft, wind speeds and direction, and wind resistance of the aircraft with and without a payload. Here, for simplicity and caution, the model assumes that the fully loaded trip from the last station to the final destination could require as much as twice the energy for an empty return trip to the last station visited. Under these assumptions, the loaded drone must arrive with 2/3 state of charge fuel level, keeping 1/3 in reserve for the return trip. Thus, the delivery flight range (f_d in Fig. 3) for the final delivery step would be 2/3 of the normal max-payload flight range (f_p in Fig. 3) in this case. The model is flexible, however, and these assumptions can be adjusted as necessary.

The drone delivery recharging location model (DDRLM) proposed here is an ESP-based maximal covering problem with obstacles and recharging. This model can be thought of as an extension to the work of Church and ReVelle (1974), incorporating routing, range, and round-trip considerations as well as obstacles to travel. As mentioned above, the uniqueness of the DDRLM is along two lines: its distance metric and dual coverage standard. The DDRLM utilizes ESP distance as the distance metric to reflect the presence of obstacles. Fig. 4 shows the effect of the distance metric in the covering model. With the simple Euclidean distance metric (ignoring

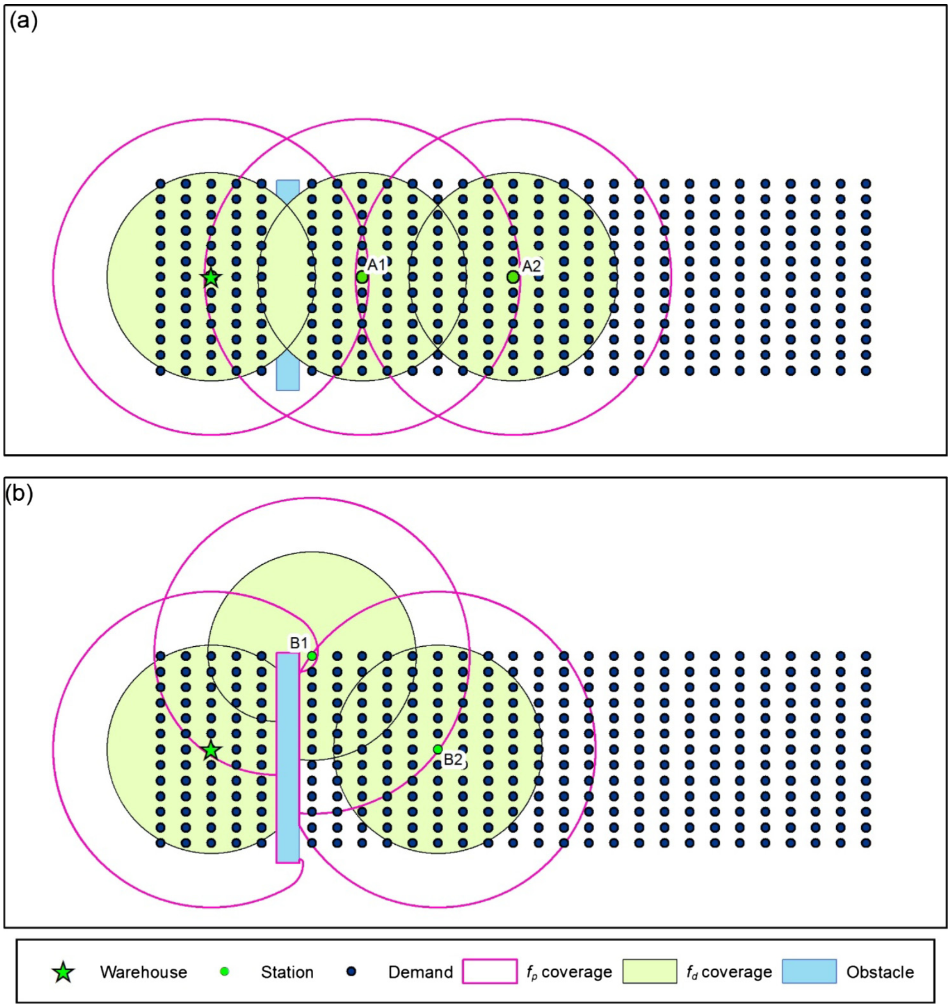

Fig. 4. Impact of distance metric and coverage standard in coverage model: (a) Euclidean metric; (b) ESP metric.

obstacles), a maximal coverage model like the MCLP (Church and ReVelle, 1974) would select two locations such as in Fig. 4a, which would be erroneous not only in terms of demand coverage, but also for the feasibility of the delivery network. Coverage in Fig. 4a includes demand that cannot actually be covered because of the travel obstacle. Also, a drone is not able to reach Station A1 from the warehouse because it has to fly around the obstacle along a detour that is 161% longer than drone's max-payload flight range, assumed to be 5 miles in this example. The optimal location and coverage considering the obstacle along with the ESP metric are presented in Fig. 4b. The station near the warehouse (Station B1) is now located closer to the warehouse as travel from the warehouse must skirt around the obstacle. Due to the obstacle, this solution covers 20% fewer demand than in Fig. 4a, but the demand coverage and delivery network now more accurately reflects actual service characteristics.

The second innovative aspect of the DDRLM is that it utilizes two coverage standards to determine (1) station-to-station "relay" coverage based on the max-payload flight range (f_p), and (2) final demand coverage using the delivery flight range (f_d), which ensures safe return of a drone after drop-off. As Fig. 4 shows, intermediate stations double as both relay stations and final delivery stations. For instance, in Fig. 4b, Station B1 can deliver to a local service area defined by the shorter radius f_d around it, while at the same time it relays drones to Station B2, which is located at a distance of f_p away from Station B1.

The following notation is used:

S = *set of station candidate sites, including warehouses*
W = *set of warehouses*
C = *set of customer nodes*
p = *number of stations to be located*
i,j = *station index*
k = *customer index*
a_k = *service demand at customer location k*

f_d = *final delivery flight range that ensures safe return of a drone after payload drop-off*
f_p = *maximum payload flight range for one-way flights between stations*
N_k = *candidate sites within an ESPdistance of* f_d *of customer k*
Ω_i = *set of candidate sites within an ESP distance* f_p *of site i*
M = *large number (at least the number of candidate sites)*

$$Y_k = \begin{cases} 1 & \textit{if customer } k \textit{ is covered} \\ 0 & \textit{otherwise} \end{cases}$$

$$X_j = \begin{cases} 1 & \textit{if candidate site } j \textit{ is selected} \\ 0 & \textit{otherwise} \end{cases}$$

Z_{ij} = *a non - negative integer for tracking path flow from site i to site j*

Based on this notation, the objective function and constraints of the DDRLM are as follows:

$$\text{Maximize} \sum_{k \in C} a_k Y_k \tag{1}$$

Subject to:

$$\sum_{j \in N_k} X_j \geqslant Y_k \quad \forall\, k \in C \tag{2}$$

$$\sum_{i \in S} X_i = p \tag{3}$$

$$\sum_{j \in \Omega_i} Z_{ij} \leqslant (M-1)X_i \quad \forall\, i \in S \tag{4}$$

$$\sum_{j \in \Omega_i} Z_{ij} - \sum_{j \in \Omega_i} Z_{ji} \geqslant X_i \quad \forall\, i \in S \backslash W \tag{5}$$

$$\sum_{j \in \Omega_i} Z_{ij} - \sum_{j \in \Omega_i} Z_{ji} \leqslant X_i - M \quad \forall\, i \in W \tag{6}$$

$$X_j, Y_i \in \{0,1\} \tag{7}$$

$$Z_{ij} \geqslant 0 \tag{8}$$

The objective function (1) maximizes covered demand. Constraints (2) define demand covered: if at least one station is located that is a member of cover set N_k, then demand k is covered. Cover set N_k includes all station sites within f_d of the customer, which means a drone with maximum payload can leave any of those stations with a full payload, drop off the package, and be able to return to the station empty. Constraint (3) limits the number of drone charging stations to p, which includes the warehouse station. Constraints (4)–(6) use Z_{ij} as non-negative integer path variables in order to indicate that a feasible link from i to j can eventually lead to the warehouse. "Flow" on these paths indicates a kind of cumulative topological connectedness that builds towards a root node. In Constraints (4), if a site i has any outflow to a node in set Ω_i, that is, within max-payload flying range of i, then a station must be built there. The constraint works in both directions: if no station is built at i, there can be no outflow from i. In this constraint, if M is the total number of candidate station sites, $(M-1)$ is the total number of *other* candidate sites, which is the theoretical maximum amount of accumulated flow through i. In Constraints (5), if a station is built at i, the flow out of node i to stations within range must exceed the flow into i from stations within range by at least 1 unit. Likewise, if no station is built at i, then no outflow is required. Because the outflow from every node must go somewhere, another station within range must have an inflow, and by its instance of Constraint (5), its outflows must exceed its inflows by at least 1. Constraints (6) create an exception for the root node station, which in this case is fixed at the warehouse(s), allowing it to have more inflow than outflow.[2] Integer conditions are imposed in Constraints (7). Constraints (8) define the Z_{ij} as non-negative: logically they should be integers, but the integrality constraints can be relaxed and they will still solve to integer values.

The DDRLM can also be viewed as related to the contiguous land parcel acquisition model structured in Wu and Murray (2008) in terms of ensuring connectedness from a warehouse to a customer, and is significant in two important ways. First, the original Wu and Murray (2008) model is complicated by the fact that the root node of the adjacency path is unknown because any land parcel may not be part of land acquisition. In this drone-delivery context, however, the warehouse can serve as the fixed root node, simplifying the formulation. Second, for drone recharging, stations do not have to be strictly adjacent to each other. Rather, they only need to be within flying range of another station and have a feasible path via other stations to the warehouse. Thus, in the constraints above, the adjacency conditions in Wu and Murray (2008) are replaced with coverage by a station within the maximum payload flight range, f_p, allowing a drone to hop from the warehouse station via any number of other relay stations to the customer and back.

Fig. 5 illustrates how Constraints (4)–(6) work. Let's start at a selected station as far as possible (in a topological sense) from the

[2] Note that in models where the root node is not pre-determined, such as in Wu and Murray, the big M in (6) is multiplied by a binary variable indicating whether that node serves as the root or not. As such, the outflow-inflow ≥ 1 requirement is not relaxed unless the root node binary variable = 1 for the node in question.

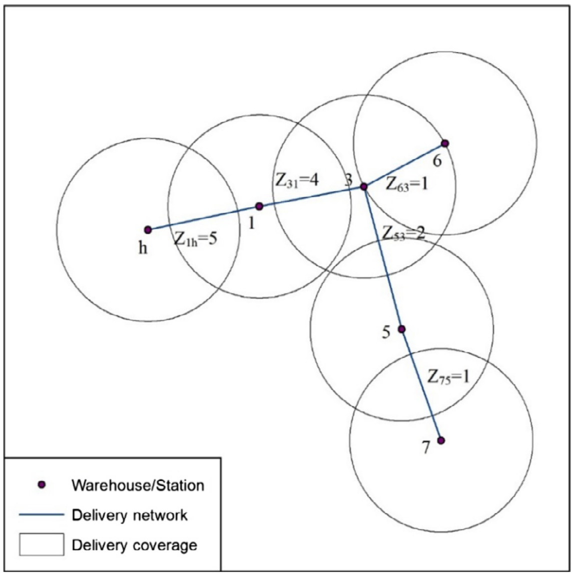

Fig. 5. Flow constraint of DDRLM. The radius of the circles shown here is f_d, the shorter flying range that allows a max-payload delivery and return to base. For one-way max-payload flights to another station, the f_p flying range is 50% farther, and all of these stations are within range of the one earlier in the path from the warehouse *h*.

warehouse *h*. Station 7, in this case, is not required as a recharging stop by any other station. It therefore has no path inflows, and can have an outflow of $Z_{75} = 1$. Station 5's outflows must exceed its inflow, so Z_{53} must be at least 2. Station 3 has an inflow of 2 from node 5 and an inflow of 1 from node 6, so its outflow Z_{31} must be at least 4. Finally, Z_{1h} must be at least 5. In addition, the *X* variables for nodes, 7, 5, 6, 3, 1, and *h* on this path must all equal 1, that is, $X_7 = X_5 = X_6 = X_3 = X_1 = X_h = 1$.

To test the validity of DDRLM formulation, a sample dataset is utilized consisting of 364 demand and a single warehouse (Fig. 6a). All demand points also serve as candidate sites for recharging stations. A single rectangular obstacle is located near the warehouse. The max-payload flight range of a drone is assumed to be 5 miles and the delivery flight range is 3.3 miles. The sample dataset was designed purposely to have an optimal $p = 5$ (including the warehouse) solution, depicted in Fig. 6a. Given the delivery flight range of 3.3 miles, each vertical column of demand measures 6 miles, in order to force stations to locate in the exact middle of a column to be able to serve both its northern and southern extremities. To minimize overlaps with the customer service areas of stations and to maintain a feasible delivery network between stations, the stations need to be located as far as possible from each other given the 5-mile radius, as shown in Fig. 6a. One exception is station S1, which is the farthest reachable point from the warehouse using ESP distances, due to the detour caused by the obstacle. Fig. 6b shows the MIP solution generated by the DDRLM. The model successfully identifies the optimal locations while constructing a feasible delivery network connected to the warehouse.

5. Spatial heuristic solution approach

The DDRLM integrates features of the ESP, flow refueling, dual flight range of a drone, and round-trip restriction into a maximal coverage approach. The MIP for the DDRLM is difficult to solve optimally especially with realistically large problem sizes, as it generates an extremely large number of arcs that connect candidate sites and demand nodes to be evaluated. Connectivity constraints, reflected as a form of in- and out-bound flow between candidate sites, doubles the number of candidate sites constraints to the model. Therefore, even for the small test dataset with five stations used in the previous section, the MIP required more than 17 min to derive the solution (using Gurobi 5.1 on a computer with an Intel i7 CPU with six physical cores and 16 GB memory). Therefore, a new heuristic solution technique is needed.

The proposed heuristic uses greedy and interchange heuristics to generate a solution at each iteration. Simulated annealing—originally developed by Kirkpatrick (1984) and modified for the maximal cover problem by Murray and Church (1996)—is applied here as a meta-heuristic to escape local optima. Finally, the heuristic exploits spatial knowledge to improve solution quality and computational efficiency in novel ways.

Spatial knowledge is used for efficient construction and improvement the quality of solutions. To evaluate candidates for both greedy and interchange algorithms, only the sites reachable by a drone with payload from a current solution set are considered in the heuristic process, reflecting the distance restriction and connectivity constraints of the DDRLM. For removing a station in the interchange step, relay connectivity must be maintained: the algorithm does not consider a station for removal from the solution unless it can be substituted by a facility capable of relaying drones to the same set of other stations as the removed station.

However, due to flight range and network connectivity constraints, the spatial configuration of candidate sites and obstacles can influence heuristic solution quality. For instance, if the shape of the region, the locations of candidate sites, or the spatial configuration of obstacles create narrow "corridors," as is the case for the Paradise Valley area shown in Fig. 7, the heuristic solution

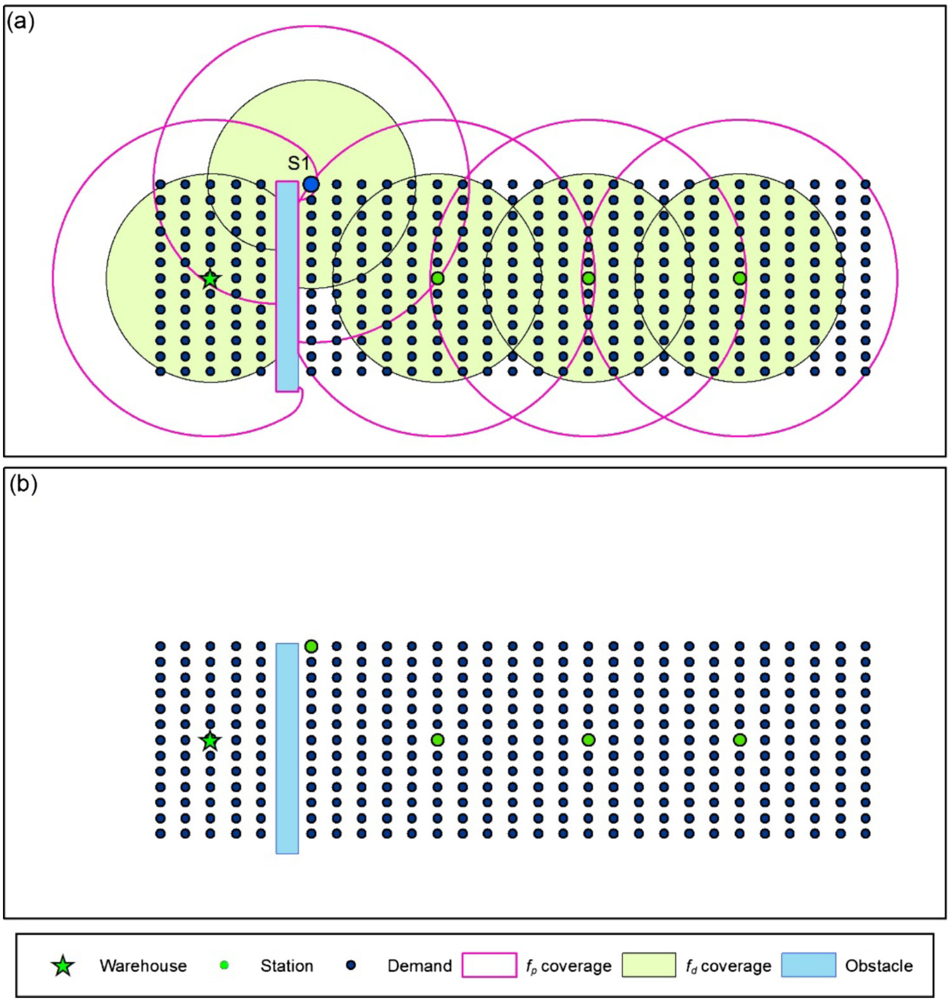

Fig. 6. (a) Model test dataset with the purposely constructed optimal solution; (b) MIP solution generated by the DDRLM for $p = 5$.

process may be trapped *spatially* in a local optimum: the greedy algorithm or randomized choice algorithm is not likely to pick candidates in the corridor area unless they cover a large volume of demand or a large enough number of stations is to be located. The proposed spatial heuristic utilizes spatial knowledge such as demand distribution over space to avoid being trapped in *spatial pitfalls*. Temporary over-expansion of the solution beyond the given number of stations (p) and randomized greedy algorithm are repeated every iteration of the heuristic process to prevent and escape spatial local optima and thus improve solution quality.

The pseudo-code for the solution algorithm is as follows:

1. Initialize a solution with p stations (includes warehouses) without considering connectivity constraints, using a non-spatial greedy algorithm;
2. Generate a minimum spanning tree that connects the p sites. For arcs that exceed flight range, add more sites to make the network feasible (ignoring p);
3. Reduce the size of solution to p by a greedy drop algorithm while maintaining connectivity;
4. Improve solution quality using a spatial interchange heuristic;
5. Compare current and new solution, and determine acceptance of a new solution based on simulated annealing acceptance criteria (function of cooling); and
6. Repeat Steps 2 to 5 until termination criteria are satisfied.

6. Case study results

The study area is the central core of the Phoenix, Arizona Metropolitan Area, including most of the cities of Phoenix, Tempe, Mesa, Scottsdale, Chandler, Gilbert, Glendale, and others, with a total population of 2.2 million people (Fig. 7). The centroids and populations of 32,940 census blocks are used as the customer demand nodes. The location of a single warehouse was randomly

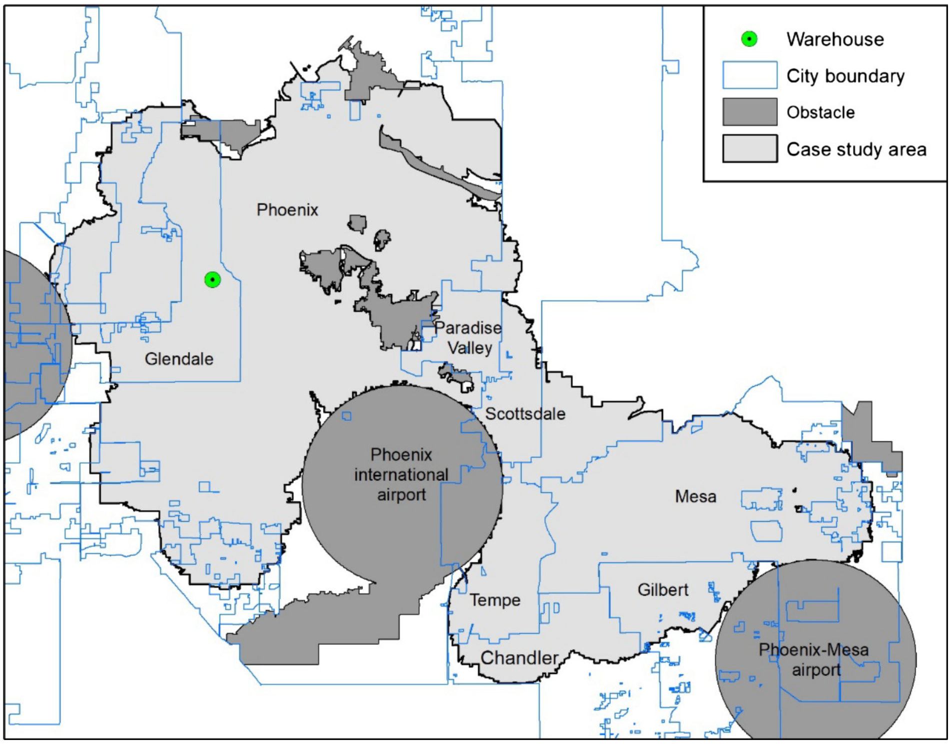

Fig. 7. Phoenix case study area.

chosen for illustration purposes; the warehouse is assumed to have its own recharging station, so that drones leave the warehouse fully charged and can return empty. There are 499 sites considered as candidates for recharging stations. Obstacles for this case study include federally controlled land (mostly parks) and three major airports. For reasons of air traffic control, a 5-mile buffer is imposed around each airport. The resulting ESP network requires 975,663 individual arcs to connect these 32,940 demand nodes to the 499 candidate sites and one warehouse around these 14 obstacles.

Determining a realistic flight range for package delivery drones was challenging in the absence of corporate or published information. Pogue (2016) quotes an Amazon executive saying "the range has to be over 10 miles," but stations would most likely have to be spaced much closer together to minimize the risk of drones being stranded due to incomplete charging, battery degradation, wind resistance, cold temperatures (which reduce battery capacity), and other factors. We therefore conservatively assume a max-payload one-way range f_p of 5 mi, and round-trip delivery range f_d of 3.3 miles, but we also present results for $f_p = 10$ and $f_d = 6.6$.

To test the quality of the heuristic solution technique developed in this research, mixed integer programing (MIP) solutions are found for problems with a small number of stations varying from $p = 5$ to 10. The heuristic solution is implemented in Python 2.7 and the MIP solutions are generated using Gurobi 5.1 on a computer with an Intel i7 CPU with six physical cores and 16 GB memory. The MIP has 103,259 constraints and 69,318 variables, including 33,440 binary variables.

Table 1 compares the solution quality and computing time of the heuristic and MIP solutions for locating 5–10 recharging stations, with $f_p = 5$ and $f_d = 3.3$. For each parameter setting of the heuristic, 30 solutions are derived and the average computing time and the best solution are taken for evaluation. The quality of the heuristic solution is very high, varying between 98.3 and 100% of the optimal solution: for $p = 5$, 6, and 7, the heuristic finds the optimum. MIP computing time increases dramatically with the number of the stations to be located, and takes more than 87 h to find the optimal solution for the instance of $p = 10$, whereas the

Table 1
Solution computing time and quality.

p	MIP		Heuristic	
	Computing time (seconds)	Objective	Computing time (seconds)	Solution quality
5	71.95	778,743	87.41	100% (778,743)
6	248.53	870,897	155.81	100% (870,897)
7	421.21	953,149	261.09	100% (953,149)
8	3,013.34	1,025,287	392.56	99.9% (1,025,053)
9	322,72.56	1,129,034	395.5	98.3% (1,109,665)
10	313,611.88	1,252,745	494.75	98.4% (1,232,444)

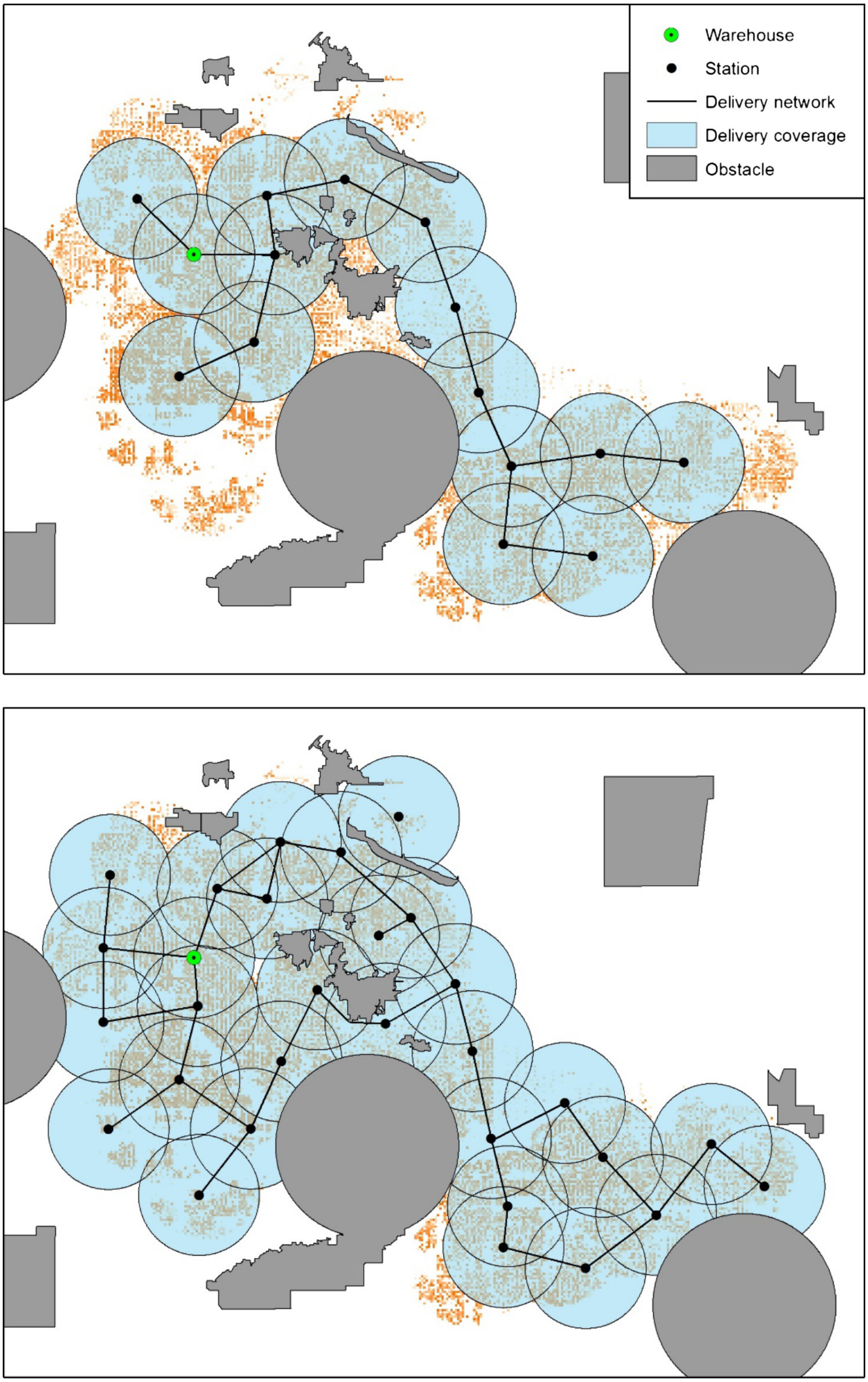

Fig. 8. Heuristic solutions with (a) 15 facilities; (b) 30 facilities. The circular buffers shown are for the round-trip max-payload flight range, f_p. Five-mile circular buffer surround (from east to west) Mesa Gateway Airport, Phoenix Sky Harbor Airport, and Luke Air Force Base.

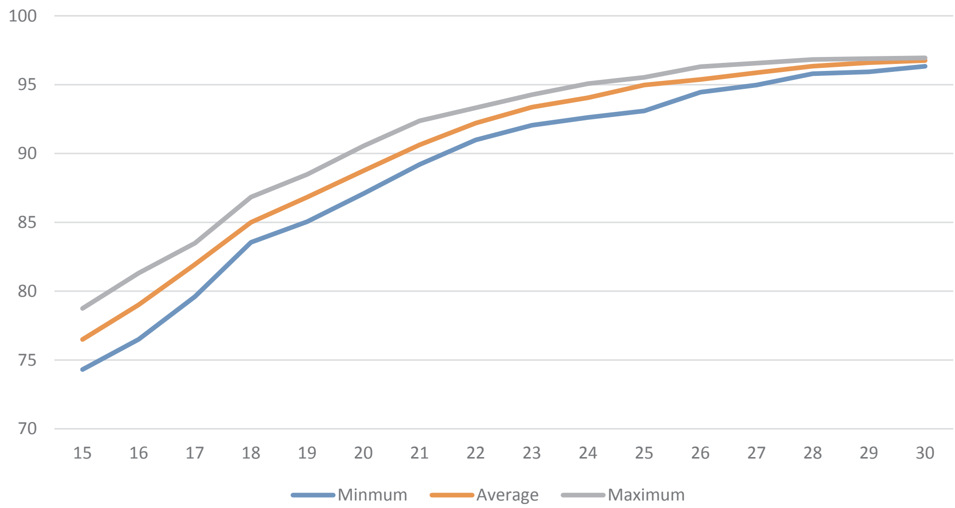

Fig. 9. Covered demand by stations.

heuristic takes only 494 s on average, roughly 0.16% of the MIP computing time.

Fig. 6 presents two heuristic solutions for the cases of $p = 15$ and 30 stations, with $f_p = 5$ and $f_d = 3.3$. Coverage of stations is derived based on ESP travel, and the delivery network is also presented for each solution. For 15 recharging stations (includes the warehouse), they are capable of serving 78.7% of total demand (Fig. 8a), while 30 stations are able to cover 96.9% of customer demand (Fig. 8b).

Fig. 9 graphs the coverage of customers for siting 15–30 stations (including the warehouse). For each parameter setting, 30 solutions were again generated. Fig. 9 presents maximum, minimum, and average population covered as a percentage of total demand.

Fig. 10 summarizes the computing time of the heuristic solution procedure, which fluctuates due to the nature of the heuristic. In general, computing time increases as the number of stations sited increases, requiring 1617–4426 s on average, but with some fluctuation due to the nature of the heuristic technique.

7. Discussion

The ability of the DDRLM to take into account the influence of travel barriers can be seen in the spacing of stations and the shape of the derived delivery network. In Fig. 8, the stations around obstacles are located closer to each other than other facilities and the delivery network detours around obstacles.

Like other optimization models, the DDRLM solution results in Fig. 9 show the tradeoffs associated with customer service coverage in terms of the number of recharging stations (p) sited. A network of 25 stations covers 95.5% of the entire customer demand in the study area. Beyond this, additional stations add less than 0.5% of customer demand. Of course, the ideal number of stations would depend on a host of other factors, such as the cost per station and alternative delivery methods.

The spatial simulated annealing heuristic developed in this research solves the DDRLM in 0.25–1.6 h, and most solutions are within a few percentage points of optimal. In comparison, obtaining the global optima using an exact approach (MIP in this case) can take days or even weeks to compute. For example, it takes 3.6 days to compute integer-feasible MIP solution for 10 stations, while the

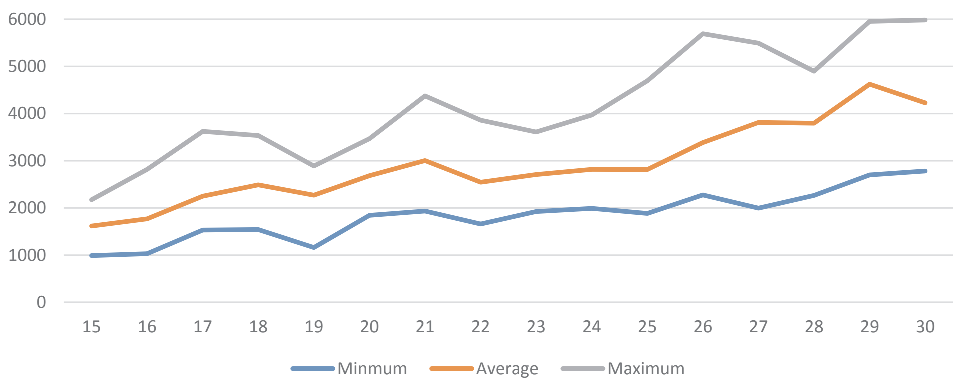

Fig. 10. Algorithm computing time.

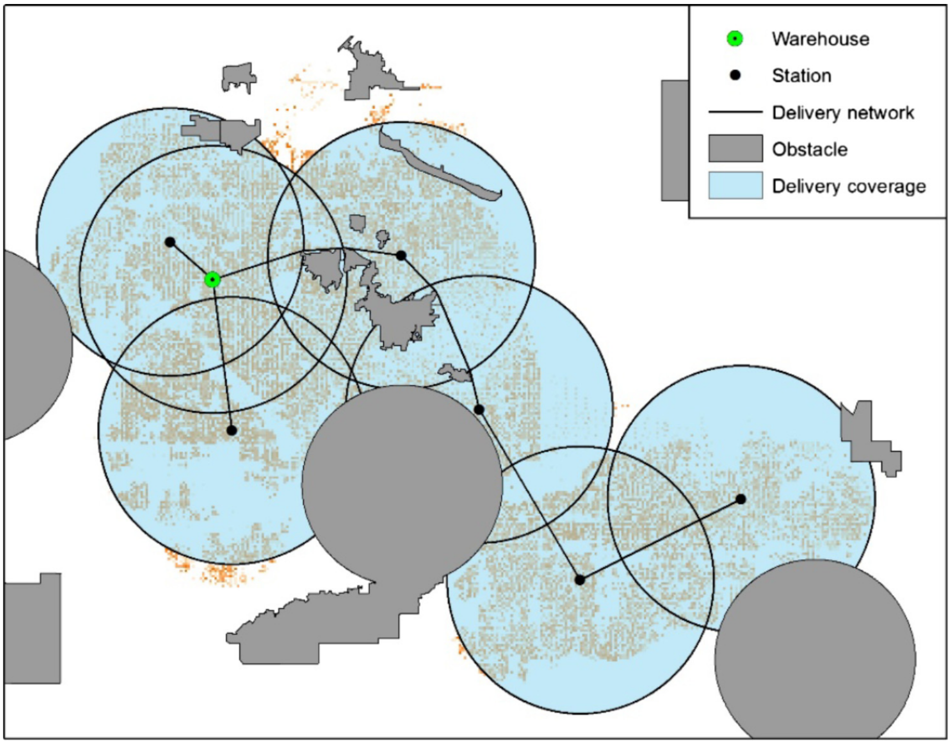

Fig. 11. Heuristic solution with 7 stations, for extended delivery distance.

simulated annealing approach takes only 494 s. This is generally impractical, especially when decision makers want to explore alternatives or vary model parameters. Therefore, the spatial simulated annealing heuristic shows significant potential for solving the DDRLM model for drone delivery service efficiently and providing valuable insights to decision-makers.

Finally, we present results for a scenario in which the flight range is doubled to $f_p = 10$ and $f_d = 6.6$ due to technological improvement and/or a less conservative safety margin. As shown in Fig. 11 for $p = 7$ stations including the warehouse, each station covers a larger area and relay stations can be spaced twice as far apart, With the flight range doubled, 7 stations can cover 97.6% of total demand, while the same level of coverage requires more than 30 stations with the shorter range parameter.

In these early days of UAVs in logistics, these scenarios have explored how a network of recharging stations could be deployed intelligently to extend coverage farther away from a warehouse than a drone can fly on a single charge, without needing to launch drones from trucks operating on congested roads. The scenarios illustrate what such a delivery network might look like, and how many stations and recharging stops would be needed under different flight range assumptions. These results help bring other questions into focus, such as whether delivery drones should be powered by batteries or fuel cells (Murray, 2017). How much does the battery weight reduce the range and/or payload? If batteries, should they be swapped instead of charged so that the drones can quickly continue their journey? If charged, should batteries be plugged in or charged wirelessly by landing on an inductive charging pad? If hydrogen, should tanks be refilled or would it be more efficient to swap in a filled cartridge? Each of these alternatives has implications for the need for a human attendant at each station, and for inventory of batteries or cartridges. While our initial model cannot definitively answer these questions, it could be used as a laboratory for estimating how these different technologies would perform in a real-world spatial setting. In addition, these scenarios raise a host of other questions that cannot be answered with the basic model developed here. These questions point toward model extensions worth developing in the future, which we explore at the end of the concluding section.

8. Conclusions

UAVs have the potential to provide fast, direct, low-cost delivery service of small packages in various situations, but several complications must be overcome. Obstacles in the landscape may prevent drones from flying in a straight-line path to customers. Their limited flying range creates the need for stations to recharge or refuel their power source en route in order to relay drones to the next station. A drone must not only be able to complete the delivery without running out of fuel but also be able to return to a station for the return trip. To further complicate matters, the flying range of the empty drone is considerably longer than when carrying a payload. Given these requirements, this paper proposed the Drone Delivery Recharging Location Model (DDRLM) for optimizing the location of the recharging stations to maximize the customer demand that can be served using a given number of drone recharging stations. The innovative MIP model draws on features of several location models to formulate this problem, including the obstacle-avoiding shortest path (ESP), flow-based refueling station location, maximal coverage, and contiguity-based area location models, and does not require pre-generation of any shortest or deviation paths.

An effective heuristic algorithm combining several heuristic techniques was developed to derive solutions for the DDRLM. The algorithm incorporates minimum spanning trees, greedy subtraction, spatial interchange, and simulated annealing. Application results showed that the DDRLM heuristic consistently achieved demand coverage within 2% of the best MIP solutions in a reasonable amount of computing time for a large-scale application in Phoenix, Arizona with nearly one million arcs in the network.

To improve applicability of the DDRLM, a number of enhancements should be investigated. First, it is possible that integration of a secondary network for returning drones could improve the overall efficiency of drone delivery service. Given that the non-payload flight range would be longer than the flight range with a payload, stations for the empty return trip to the warehouse could be spaced farther apart. Second, the stations in this model are uncapacitated, and optimized for maximum initial coverage. As demand grows, station capacities will become an issue, and the number of operable drones and the number of charging ports, batteries stored, or hydrogen tank size will need to be incorporated. One would expect some interesting possible model interactions between the wider spacing of a return network, the capacity of stations, and possibly scheduling aspects. Third, there is no explicit accounting, maximum, or penalty on the degree of detouring or the number of recharging events for any delivery. In Fig. 8b, several detours can be observed, mostly due to maximization of customer demand coverage. Tracking of routes, number of stops, deviations from the shortest possible route, and route distance and time windows (Keskin and Çatay, 2016) is an essential of future extension of the basic DDRLM. Lastly, a multi-warehouse extension will need to address new issues such as inventory that may not be available at all warehouses, and drone fleet management with the possibility of returning to a different warehouse.

Another set of extensions could focus on costs and profit, technological change, and comparison or integration of this drone-only system with a truck-based system. In this paper, we have developed a basic modeling approach for a drone-only system. The model adopts a covering approach, which makes sense for introducing a basic level of service. Extending this work to a monetary objective would open up a wide range of analyses, but would of course require detailed cost data. Once converted to a cost basis, the model could be augmented with any of the drone-truck options to enable it to determine the optimal delivery portfolio between air and ground service. With willingness-to-pay data, a profit-maximizing approach could be developed. Economies of scale and cost tradeoffs could be evaluated between building fewer larger stations and smaller stations or between smaller drones delivering one package to a single customer and larger drones that could conduct traveling salesman problem tours with multiple packages.

References

Adams, S.M., Friedland, C.J., 2011. A survey of unmanned aerial vehicle (UAV) usage for imagery collection in disaster research and management. In: 9th International Workshop on Remote Sensing for Disaster Response.

Agatz, N., Bouman, P., Schmidt, M., 2015. Optimization approaches for the traveling salesman problem with drone. ERIM Report Series Reference No. ERS-2015-011-LIS.

Amazon, 2017. Amazon Prime Air. Available at: https://www.amazon.com/Amazon-Prime-Air/b?node=8037720011 (accessed April 19, 2017).

Amenyo, J.-T., Phelps, D., Oladipo, O., Sewovoe-Ekuoe, F., Jadoonanan, S., Tabassum, T., Gnabode, S., Sherpa, T.D., Falzone, M., Hossain, A., 2014. MedizDroids Project: Ultra-low cost, low-altitude, affordable and sustainable UAV multicopter drones for mosquito vector control in malaria disease management. In: IEEE Global Humanitarian Technology Conference (GHTC), 2014. IEEE, pp. 590–596.

Asano, T., 1985. An efficient algorithm for finding the visibility polygon for a polygonal region with holes. IEICE Trans. (1976–1990) 68 (9), 557–559.

Asano, T., Guibas, L., Hershberger, J., Imai, H., 1986. Visibility of disjoint polygons. Algorithmica 1 (1), 49–63.

Berman, O., Larson, R.C., Fouska, N., 1992. Optimal location of discretionary service facilities. Transp. Sci. 26 (3), 201–211.

Capar, I., Kuby, M., Leon, V.J., Tsai, Y.-J., 2013. An arc cover–path-cover formulation and strategic analysis of alternative-fuel station locations. Eur. J. Operat. Res. 227 (1), 142–151.

Church, R., ReVelle, C., 1974. The maximal covering location problem. Papers Regional Sci. 32 (1), 101–118.

Clarke, R., 2014. Understanding the drone epidemic. Comput. Law Security Rev. 30 (3), 230–246.

de Berg, M., Cheong, O., Van Kreveld, M., 2008. Computational Geometry: Algorithms and Applications, second ed. Springer-Verlag.

Dillow, C., 2015. FAA approves more than 1,000 commercial drone permits. Fortune.

Dorling, K., Heinrichs, J., Messier, G.G., Magierowski, S., 2017. Vehicle routing problems for drone delivery. IEEE Trans. Systems, Man, Cybernet.: Syst. 47 (1), 70–85.

Finn, R.L., Wright, D., 2012. Unmanned aircraft systems: surveillance, ethics and privacy in civil applications. Comput. Law Security Rev. 28 (2), 184–194.

Fornace, K.M., Drakeley, C.J., William, T., Espino, F., Cox, J., 2014. Mapping infectious disease landscapes: unmanned aerial vehicles and epidemiology. Trends Parasitol. 30 (11), 514–519.

Gao, Y., Yang, J., Chen, G., Zheng, B., Chen, C., 2011. On efficient obstructed reverse nearest neighbor query processing. In: Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems. ACM, pp. 191–200.

Ghosh, S.K., Mount, D.M., 1991. An output sensitive algorithm for computing visibility graphs. SIAM J. Comput. 20 (5), 888–910.

Ha, Q.M., Deville, Y., Pham, Q.D., Hà, M.H., 2015a. On the Min-cost Traveling Salesman Problem with Drone. arXiv preprint arXiv:1512.01503.

Ha, Q.M., Deville, Y., Pham, Q.D., Hà, M.H., 2015b. Heuristic methods for the traveling salesman problem with drone. arXiv preprint arXiv: 1509.08764.

He, F., Yin, Y., Zhou, J., 2015. Deploying public charging stations for electric vehicles on urban road networks. Transp. Res. Part C: Emerging Technol. 60, 227–240.

Hern, A., 2014. DHL launches first commercial drone 'parcelcopter' delivery service. The Guardian.

Hodgson, M.J., 1990. A flow-capturing location-allocation model. Geogr. Anal. 22 (3), 270–279.

Hong, I., Murray, A.T., 2013. Efficient measurement of continuous space shortest distance around barriers. Int. J. Geogr. Inform. Sci. 27 (12), 2302–2318.

Hong, I., Murray, A.T., Wolf, L.J., 2015. Spatial filtering for identifying a shortest path around obstacles. Geogr. Anal. 48 (2), 176–190.

Huang, Y., Li, S., Qian, Z.S., 2015. Optimal deployment of alternative fueling stations on transportation networks considering deviation paths. Networks Spatial Econ. 15 (1), 183–204.

Jiang, Y., Zhang, Y., Zhang, C., Fan, J., 2012. The capacitated deviation-flow fueling location model for siting battery charging stations. Proc. CICTP 2771–2778.

Kanistras, K., Martins, G., Rutherford, M.J., Valavanis, K.P., 2014. Survey of Unmanned Aerial Vehicles (UAVs) for traffic monitoring. Handbook of Unmanned Aerial Vehicles. Springer, pp. 2643–2666.

Keskin, M., Çatay, B., 2016. Partial recharge strategies for the electric vehicle routing problem with time windows. Transp. Res. Part C: Emerging Technol. 65, 111–127.

Kim, J.-G., Kuby, M., 2012. The deviation-flow refueling location model for optimizing a network of refueling stations. Int. J. Hydrogen Energy 37 (6), 5406–5420.

Kirkpatrick, S., 1984. Optimization by simulated annealing: quantitative studies. J. Statistical Phys. 34 (5–6), 975–986.

Kuby, M., Lim, S., 2005. The flow-refueling location problem for alternative-fuel vehicles. Socio-Economic Plan. Sci. 39 (2), 125–145.

Kuby, M., Lines, L., Schultz, R., Xie, Z., Kim, J.-G., Lim, S., 2009. Optimization of hydrogen stations in Florida using the flow-refueling location model. Int. J. Hydrogen Energy 34 (15), 6045–6064.
Linchant, J., Lisein, J., Semeki, J., Lejeune, P., Vermeulen, C., 2015. Are unmanned aircraft systems (UASs) the future of wildlife monitoring? A review of accomplishments and challenges. Mammal Rev. 45 (4), 239–252.
Lozano-Pérez, T., Wesley, M.A., 1979. An algorithm for planning collision-free paths among polyhedral obstacles. Commun. ACM 22 (10), 560–570.
Mathew, N., Smith, S.L., Waslander, S.L., 2015. Planning paths for package delivery in heterogeneous multirobot teams. IEEE Trans. Autom. Sci. Eng. 12 (4), 1298–1308.
MirHassani, S., Ebrazi, R., 2012. A flexible reformulation of the refueling station location problem. Transp. Sci. 47 (4), 617–628.
Mitchell, J.S.B., 1999. Geometric Shortest Paths and Network Optimization. In: Sack, J.R. (Ed.), Handbook of Computational Geometry, pp. 633–702.
Mohammed, F., Idries, A., Mohamed, N., Al-Jaroodi, J., Jawhar, I., 2014. UAVs for smart cities: opportunities and challenges. In: International Conference on Unmanned Aircraft Systems (ICUAS), 2014. IEEE, pp. 267–273.
Murray, A.T., Church, R.L., 1996. Applying simulated annealing to location-planning models. J. Heuristics 2 (1), 31–53.
Murray, A.T., Feng, X., 2016. Public street lighting service standard assessment and achievement. Socio-Econ. Plan. Sci. 53, 14–22.
Murray, C.C., Chu, A.G., 2015. The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery. Transp. Res. Part C: Emerging Technol. 54, 86–109.
Murray, J., 2017. Why this U.S. logistics giant will use drones powered by fuel cells. GreenBiz (March 30). Available at: https://www.greenbiz.com/article/why-us-logistics-giant-will-use-drones-powered-fuel-cells (accessed April 21, 2017).
Nourbakhsh, S.M., Ouyang, Y., 2010. Optimal fueling strategies for locomotive fleets in railroad networks. Transp. Res. Part B: Methodol. 44 (8), 1104–1114.
Paneque-Gálvez, J., McCall, M.K., Napoletano, B.M., Wich, S.A., Koh, L.P., 2014. Small drones for community-based forest monitoring: an assessment of their feasibility and potential in tropical areas. Forests 5 (6), 1481–1507.
Papadopoulou, E., Lee, D., 1998. A new approach for the geodesic Voronoi diagram of points in a simple polygon and other restricted polygonal domains. Algorithmica 20 (4), 319–352.
Pérez-Ortiz, M., Peña, J., Gutiérrez, P., Torres-Sánchez, J., Hervás-Martínez, C., López-Granados, F., 2015. A semi-supervised system for weed mapping in sunflower crops using unmanned aerial vehicles and a crop row detection method. Appl. Soft Comput. 37, 533–544.
Pogue, D., 2016. Exclusive: Amazon reveals details about its crazy drone delivery program. Yahoo! Tech (Jan. 18). Available at: https://www.yahoo.com/tech/exclusive-amazon-reveals-details-about-1343951725436982.html (accessed April 20, 2017).
Riemann, R., Wang, D.Z., Busch, F., 2015. Optimal location of wireless charging facilities for electric vehicles: flow-capturing location model with stochastic user equilibrium. Transp. Res. Part C: Emerging Technol. 58, 1–12.
Sandbrook, C., 2015. The social implications of using drones for biodiversity conservation. Ambio 44 (4), 636–647.
Sundar, K., Rathinam, S., 2014. Algorithms for routing an unmanned aerial vehicle in the presence of refueling depots. IEEE Trans. Autom. Sci. Eng. 11 (1), 287–294.
Tahar, K.N., Ahmad, A., Akib, W.A.A.W.M., Mohd, W.M.N.W., 2012. Aerial mapping using autonomous fixed-wing unmanned aerial vehicle. In: IEEE 8th International Colloquium on Signal Processing and its Applications (CSPA), 2012. IEEE, pp. 164–168.
Toor, A., 2016. This startup is using drones to deliver medicine in Rwanda (April 5). Available at: http://www.theverge.com/2016/4/5/11367274/zipline-drone-delivery-rwanda-medicine-blood (accessed April 19, 2017).
Upchurch, C., Kuby, M., Lim, S., 2009. A model for location of capacitated alternative-fuel stations. Geogr. Anal. 41 (1), 85–106.
Viegas, J., Hansen, P., 1985. Finding shortest paths in the plane in the presence of barriers to travel (for any l_p-norm). Eur. J. Operat. Res. 20 (3), 373–381.
Wang, Y.-W., Lin, C.-C., 2009. Locating road-vehicle refueling stations. Transp. Res. Part E: Logistics Transp. Rev. 45 (5), 821–829.
Weise, E., 2017. UPS tested launching a drone from a truck for deliveries. USA TODAY (Feb. 21). Available at: https://www.usatoday.com/story/tech/news/2017/02/21/ups-delivery-top-of-van-drone-workhorse/98057076/ (accessed April 19, 2017).
Wu, X., Murray, A.T., 2008. Spatial contiguity optimization in land acquisition. J. Land Use Sci. 2 (4), 243–256.
Xie, C., Jiang, N., 2016. Relay requirement and traffic assignment of electric vehicles. Computer-Aided Civil Infrastruct. Eng. 31 (8), 580–598.
Yu, K., Budhiraja, A.K., Tokekar, P., 2017. Algorithms for Routing of Unmanned Aerial Vehicles with Mobile Recharging Stations and for Package Delivery. arXiv preprint arXiv:1704.00079.
Zhang, C., Kovacs, J.M., 2012. The application of small unmanned aerial systems for precision agriculture: a review. Precision Agric. 13 (6), 693–712.
Zhang, J., Papadias, D., Mouratidis, K., Manli, Z., 2005. Query processing in spatial databases containing obstacles. Int. J. Geogr. Inform. Sci. 19 (10), 1091–1111.