Deviation flow refueling location model for continuous space: commercial drone delivery system for urban area

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Abstract

Recently, drones, which refer a range of small-size unmanned aerial vehicles propelled by multiple rotors, have been utilized for various purposes, such as for military, surveillance, photography, and entertainments. Commercial delivery service for small products is one of the potential applications, and optimal path planning is essential for operational efficiency of the delivery service. As a drone's movement is not limited to existing transportation network, path planning needs to be conducted in continuous space with taking into account obstacles for flight. However, due to limited flight range of battery-powered drones, multiple recharging stations are required to complete delivery without running out of the power in large urban area. In this research, we developed a new coverage model that can optimize location of recharging stations for delivery drones, as well as ensure construction of a feasible delivery network that connects the stations and covered demands based on continuous space shortest paths. A heuristic solution technique is utilized for the optimization of station location. Application results show the effectiveness of our model for construction of drone delivery network that covers large urban area.

Keywords: UAV, drone, coverage location model, Euclidean shortest path.

1. Introduction

Drones, or small-size, battery-powered unmanned aerial vehicles propelled by multiple rotors, have been in the news in recent years. Drones are increasingly utilized for purposes ranging from military to surveillance, photography, and entertainment, and civilian usage of drones are increasing rapidly in public and private sectors (Finn and Wright 2012, Clarke 2014).

Among potential civilian applications, commercial drone delivery service for small products draws attention from public and private sectors. Several private companies and public agencies around the world have proposed or tested drone delivery system (Clarke

2014). Drones have potential for fast and low cost delivery for short distance, and alternatives for an area of poor transportation infrastructure such as small islands.

For drone package delivery system, path derivation method in continuous space and location model for recharging stations for drone are crucial. Since a drone is able to move in airspace, its movement does not limited to transportation network. However, barriers, such as obstacles and flight restricted zones, may impact on drone's flight path. Therefore, considering obstacles for continuous space movement is essential for route derivation method for drones. To cover large urban area, however, a method to extend drone's limited flight range must be considered. Battery-replacing recharging stations for drones can be answer for this issue. A new location model that optimizes spatial configuration of recharging stations while considering feasible delivery network is necessity.

In this research, we propose a new location model for commercial drone delivery system in urban area. Recently developed obstacle-avoiding path derivation technique is utilized for route construction and distance measurement. A coverage optimization model is developed for locating recharging stations with a spatial heuristic solution technique. Application result is presented to demonstrate capability and efficiency of the new location model and solution technique.

2. Route derivation: convexpath algorithm

Route planning for drone needs to reflect several considerations. First, movement of drone is not confined to a transportation network. However, obstacles such as mountains and high-rise buildings may impede drone's flight. Also, flight restricted areas such as airports and military installations can act as obstacles. Lastly, flight path of a drone can be assumed as 2 dimensional route, since maintaining altitude will be ideal strategy for battery efficiency.

This 2 dimensional, obstacle-avoiding shortest path in continuous space has been referred to as Euclidean shortest path (ESP), and several ESP derivation methods have been developed (Lozano-Pérez and Wesley 1979, Asano *et al.* 1986, Hershberger and Suri 1993, Mitchell 1999). Recently, Hong and Murray (2013a), (2013b) developed the convexpath algorithm for efficient derivation of the ESP. Convexpath exploits spatial knowledge and GIS functionality to identify relevant obstacles and construct a graph that includes the ESP. The notion of convexpath and the shortest path spatial filter efficiently identify obstacles that impact on the ESP for given origin and destination points.

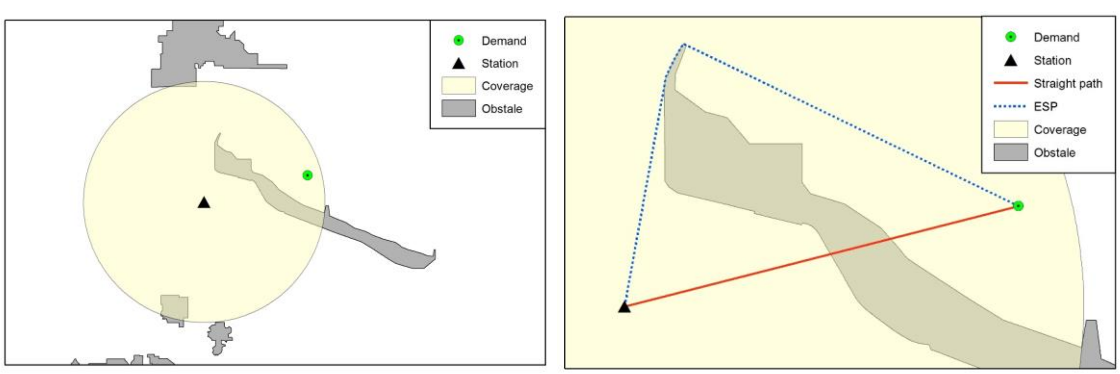

Figure 1. Example of ESP route planning

Example of obstacle-avoiding route from a station to a demand is shown in Figure 1. Given demand is in the coverage of the station if consider Euclidean distance. However, the ESP distance to demand exceeds drone's maximum flight range with payload. Therefore, given recharging station cannot cover the demand.

3. Distance restricted maximal coverage location model

To extend limited flight range of battery-powered drones, battery swapping recharging stations will be required. Recharging station extends flight range of drone by replacing depleted battery to fully-charged one. From warehouse or station, a drone fly either to next station to reach destination or to a demand within distance of safe return. Therefore, each recharging station is considered providing service for demands in a given area.

Furthermore, the location model for drone delivery system considers construction of network for delivery. Recharging stations must be located under consideration of drone's flight range with payload. Stations are linked if their ESP distance is shorter than maximum flight range with payload, and this arcs form the delivery network.

To construct location model for efficient drone delivery network, we assume as follows: 1) a drone departs from a warehouse with fully-charged battery, and returns to identical warehouse; 2) drone makes single delivery; 3) with payload, drone's flight range is reduced to half of remaining; 4) distance metric is ESP distance; 5) to satisfy demands, warehouses and recharging stations need to be fully connected through network; and 6) location of warehouses is given, and included as recharging stations.

In this research, a new coverage location model is proposed, referred to as distance restricted maximal coverage location model. This model has two objectives: 1) maximizing demand coverage; and 2) minimizing average flight distance from warehouses to recharging stations, via constructed network. To construct feasible delivery network, maximum distance restriction between stations and warehouses is applied, that is the half of maximum flight range. Consider following notion:

$j, k =$ index of potential facility sites where $j, k = 1,2, \dots, m$
$l =$ index of warehouse locations where $l = 1,2, \dots, r$
$i =$ index of demand units where $i = 1,2, \dots n$
$h_i =$ demand at i
$d_{ij} =$ ESP distance between i and j
$s_{ij} =$ network shortest distance between i and j
$f_{max} =$ flight range with maximum payload
$f_0 =$ flight range with empty payload
$N_i = \{\text{a set of sites that can cover demand } i\}$
$M_j = \{\text{a set of sites that within } f_{max} \text{ from site } j\}$

$$X_j = \begin{cases} 1, & \text{if a facility is located at potential site } j \\ 0, & \text{if not} \end{cases}$$

$$Z_i = \begin{cases} 1, & \text{if a demand } i \text{ is covered by at least one facility} \\ 0, & \text{if not} \end{cases}$$

$$C_{lj} = \begin{cases} 1, & \text{if a site } j \text{ is connected to source } l \\ 0, & \text{if not} \end{cases}$$

Objective function

$$maximize\ \sum h_i Z_i \frac{r(p-r)}{\sum_{l=1}^{r}\sum_{j=1}^{m} X_j s_{lj}} \quad (1)$$

Subject to:

$$\sum_{j\in N_i} X_j \geq Z_i \qquad \forall i \quad (2)$$

$$\sum_{k\in M_j} X_k - X_j \geq 0 \qquad \forall j \quad (3)$$

$$C_{lj} = X_j \qquad \forall l, j \quad (4)$$

$$\sum_{j=1}^{m} X_j + \sum_{l=1}^{r} X_l = p \quad (5)$$

$$X_l = 1 \quad \forall l \quad (6)$$

$$X_j, Z_i, C_{lj} = \{0,1\} \quad (7)$$

Objective function (1) is to maximize covered demand while minimizing average network distance from each warehouse to each selected facility site. Constraint (2) defines coverage. Constraint (3) is for minimum connectivity constraint, to prevent isolation of stations that separated from warehouses. Constraint (4) is source connectivity constraint, which ensure connection of demands to every warehouse via delivery network. Constraint (5) and (6) are for reflecting given warehouses.

4. Solution technique: simulated annealing

To obtain solution for the distance restricted coverage model, a heuristic solution technique that utilizes spatial knowledge is developed. Greedy algorithm is utilized to generate feasible solutions. Interchange algorithm (Teitz and Bart 1968) improves quality of solutions from the greedy algorithm. What is novel in this approach is utilization of spatial knowledge for efficient evaluation of candidate sites while preserving feasibility. In the greedy process, only candidate sites that can be reached from current solution set are evaluated, to facilitate the process. Once solution set and delivery network are generated, the interchange algorithm improves solution quality while maintaining feasibility of the network. The interchange process also uses spatially restricted candidates, but more strategically. If a station is critical for preserving feasibility of the network, the interchange algorithm evaluates candidates around it that are able to keep connectivity of stations.

Simulated annealing (Kirkpatrick 1984) is applied for the distance restricted coverage model to prevent the solution process stops in local optimum. To improve solution quality, we enhance the simulated annealing with a solution memory. It ‘remembers’ the best solution so far, but accepts inferior solutions based on temperature condition. However, if resulting solution after termination is inferior to the memorized one, stored best solution is selected.

This spatial simulated annealing derives a solution like followings: 1) initial solution is generated in random, considering distance restriction and warehouse connectivity; 2) randomly remove given number of stations from solution; 3) generate new solution using the greedy algorithm; 4) improve solution using the interchange algorithm; 5) determine acceptance of new solution based on simulated annealing criteria; and 6) repeat step 3 to 5 until termination condition is satisfied.

5. Application results

To assess efficiency and solution quality of the distance restricted coverage model for the drone delivery system, a test application in large urban area is assumed. A part of Phoenix Metropolitan area is utilized for the test application. Centroids of census blocks represent demands for the delivery service, and total 32,940 demand points are utilized. For candidates for recharging stations, 500 points are randomly selected from the demands, including 3 warehouses. Flight range of drone is assumed 10 mi for empty payload, and 5 mi for full payload. Demand coverage of each station is 3.3 mi, which ensures safe return of a drone to the station after finishing delivery. Heuristic solution technique is implemented in Python 2.7 using open source spatial library. The analysis is carried out on Intel i7 CPU with 8 GB memory system.

Figure 2 shows a solution with 25 stations including 3 warehouses. This solution covers 91.5% of total population in this area. This takes 1,353 second to compute the solution.

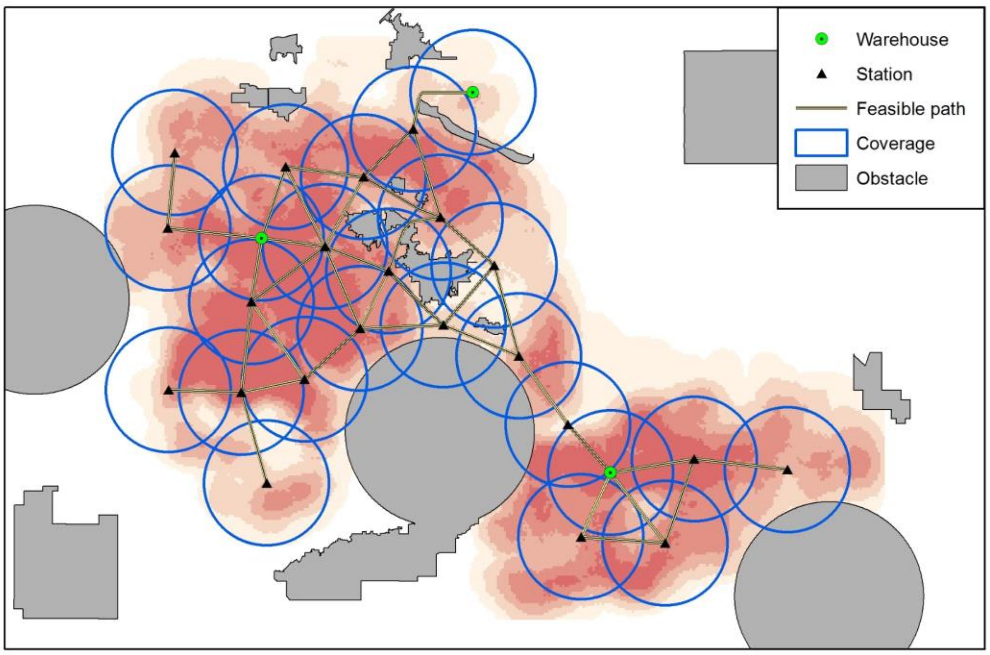

Figure 2. Solution for 25 recharging stations in Phoenix area

To assess solution quality and computational performance, commercial solver will be used to derive integer programing solution.

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