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Optimizing the spatial location of medical drones

Aaron Pulver[a], Ran Wei[b,*]

[a] Department of Geography, University of Utah, Salt Lake City, United States
[b] Center for Geospatial Sciences, School of Public Policy, University of California, Riverside, United States

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ABSTRACT

Unmanned aerial vehicles (UAVs) or drones are increasingly proposed for medical uses due to their potential to transport medical supplies quickly and efficiently. A prototype medical drone that is equipped with an on-board automated external defibrillator (AED) was announced recently to significantly reduce the time it takes for an AED to arrive to a patient's side. As drones are battery-operated and have limited service range, a network of medical drones is required to adequately provide service to a large area. This paper developed a new spatial optimization model, the backup coverage location problem with complementary coverage (BCLP-CC), to aid in the deployment of a network of AED enabled medical drones. By explicitly integrating backup coverage and continuously distributed demand, the BCLP-CC can optimally place drones and the corresponding launch sites while significantly improving backup coverage with minimal loss of primary coverage. Our results show that 90.4% of historical out-of-hospital cardiac arrests in Salt Lake County can be responded to within 1 min by using 71 drones and 68 launch sites. In addition, 58.9% of incidents can be served by two or more drones, a significant improvement over existing models. This study shows that drones could significantly reduce life-saving equipment travel times for victims of cardiac arrest by appropriately siting them, which will motivate further research in using UAVs or drones for emergency medical purpose.

1. Introduction

Unmanned aerial vehicles (UAVs) have routinely been used for remote sensing, aerial imagery collection, and military purposes (Everaerts, 2008). UAVs may soon be used to transport goods quickly, safely, and efficiently to both accessible and inaccessible terrain (Misener, 2014; Thiels, Aho, Zietlow, & Jenkins, 2015). Using UAVs or drones for medical purposes has only recently been seriously considered. Thiels et al. (2015) discuss how drones can potentially be used to transport medical supplies such as blood derivatives and pharmaceuticals to hospitals, remote areas, and mass causality incidents. In addition to transporting medical supplies, drones may have the ability to provide other medical treatments and equipment.

Out-of-hospital cardiac arrest is a major issue in health care. It is estimated that between 180,000 and 400,000 deaths occur due to sudden cardiac arrest (SCA) in the United States each year (Kong et al., 2011). Most of these deaths occur outside of the hospital and only one to five percent of patients survive (Becker, Pat Ostrander, Barrett, & Kondos, 1991; Caffrey, Willoughby, Pepe, & Becker, 2002; Cummins, Ornato, Thies, & Pepe, 1991; Galea et al., 2007). It has been shown that automated external defibrillator (AED) use can significantly improve cardiac arrest survival rates (Caffrey et al., 2002; Cummins, Bergner, Eisenberg, & Murray, 1984; Marenco, Wang, Link, Homoud, & Estes, 2001). In addition to AED use, emergency medical service (EMS) response time has been tied to survival rates. It is estimated that reducing response times by 1 min can improve the odds of survival by 24% (O'Keeffe et al., 2010). It has also been shown that there is a sharp decline in survival during the first 5 min after a cardiac arrest (De Maio, Stiell, Wells, Spaite, & Ontario Prehospital Advanced Life Support Study Group, 2003). The majority of people who suffer a cardiac arrest have no history of cardiac problems, making prevention difficult. Therefore, many efforts have been made to improve pre-hospital care by reducing response times and improving access to AEDs (Caffrey et al., 2002; Cummins et al., 1991; Pell, Sirel, Marsden, Ford, & Cobbe, 2001; Tsai, KobHuangc, & Wen, 2012).

A prototype medical drone was announced in 2014 (Communication, 2014). Equipped with an on-board AED and having speeds up to 100 km/h, this drone has the capability to significantly reduce the time it takes for an AED to arrive to a patient's side. The detailed drone deployment procedure is given in Appendix. Since drones are not bound by road networks and have similar speeds to traditional ground transport EMS vehicles, they have the potential to drastically reduce equipment travel time for time critical emergencies such as sudden cardiac arrest.

* Corresponding author. 900 University Ave., Riverside, CA 92521, United States.
E-mail address: ran.wei@ucr.edu (R. Wei).

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Drones are battery-operated and have limited service range. In order to minimize response times, a network of medical drones is required to adequately provide service to a large area. This network must be located in such a way to minimize travel delays, minimize cost, and maximize service coverage. Pulver, Wei, and Mann (2016) investigated locating a network of medical drones using the maximal covering location problem (MCLP), which is a well-established spatial optimization model for siting emergency service facilities (Brotcorne, Laporte, & Semet, 2003; Church & ReVelle, 1974; Eaton, Daskin, Simmons, Bulloch, & Jansma, 1985). However, there are three major limitations raised in that study. First, the backup service provision for medical emergencies was not considered, despite the fact that planning for backup service is essential for the design of an emergency service system in order to ensure public safety in the case where the closest facility is unavailable to provide services (Hogan & Revelle, 1986; Jia, Ordóñez, & Dessouky, 2007; Pirkul & Schilling, 1988). Second, the continuously distributed demand that requires emergency medical services was abstracted as discrete demand points (e.g., the centroids of block groups). Such oversimplification of spatial representation could introduce significant errors and bias into the service coverage assessment and the final identified locations for medical drones (Miller, 1996; Murray, Tong, & Kim, 2010; Wei & Murray, 2015). Finally, the study relied on estimated incidence rates rather than empirical medical data to assess the demand for medical drones. In an effort to address these issues, we developed a new spatial optimization model that explicitly takes into account backup service provision and mitigates representation errors to locate a network of medical drones in the greater Salt Lake City area using empirical OOHCA incidence rates.

2. Background

In emergency planning, it is often necessary for EMS personnel to be able to reach a certain percentage of people or homes within a set distance or time threshold. For example, the National Fire Protection Association (NFPA) established a guideline of 9 min between EMS notification and EMS arrival at the patient's side for 90% of distress calls in urban areas (NFPA, 2010). These constraints are the basis for coverage location models. In general, coverage location models have three main parts: the demand, the facilities that provide the service, and the demand-service constraints. In emergency planning, demand may be the total population per area unit, the number of historic emergency calls per area unit, or other related measures. The facilities represent the locations that provide some level of service to the demand. For example, these may be fire stations, hospitals, or in our case drone launch sites. Finally, the service constraints connect the facilities to the demand units by imposing restrictions on the minimum amount of demand that must be appropriately served by a configuration of facilities within a pre-specified distance or time threshold. For example, the total percentage of population that can be reached by an ambulance within 5 min must be at least 80%. Coverage models have been extensively used to address emergency service planning issues and examples can be found in Eaton et al. (1985), Erkut, Ingolfsson, and Erdoğan (2008), Foo, Ahghari, and MacDonald (2010), Yin and Mu (2012), Murray (2013), Pulver et al. (2016) and Røislien, van den Berg, Lindner, Zakariassen, Aardal, and Theresia van Essen (2017).

Pulver et al. (2016) investigated the use of MCLP to site a network of medical drones. The MCLP, developed by Church and ReVelle (1974) is a widely used location model to site emergency medical services. The intent of this model is to maximize the service coverage given limited resources (Church & ReVelle 1974; Church & Murray, 2009). Although the MCLP is widely used, it relies upon several major assumptions. The first assumption is that only one type of facility can be used. Often times it may be more cost effective to renovate existing infrastructure than to build new facilities. To address this issue, Schilling, Revelle, Cohon, and Jack Elzinga (1980) presented an extension of MCLP known as the *capital improvement model* which considers siting multiple types of facilities that have different costs.

A second major assumption of the MCLP is that it relies on binary coverage, meaning that a demand unit is either completely covered or it is not covered at all. This is not an issue when point data are used for analysis, however often times, such as in this study, demand is represented as polygons where partial coverage of the polygons are possible. Many previous studies have demonstrated that significant errors in assessing service coverage and identifying optimal facility location configuration can result if partial coverage is ignored (Cromley, Lin, & Merwin, 2012; Tong, 2012; Wei & Murray, 2015). A few MCLP extensions, including the MCLP-explicit proposed by Tong and Murray (2009) and Murray et al. (2010), the MCLP-implicit developed by Alexandris and Giannikos (2010) and Murray et al. (2010), and the MCLP-complementary coverage (MCLP-CC) proposed by Tong (2012), have been developed to take into account partial coverage. Among these models, the MCLP-CC is considered to be the most promising modelling approach because of its capability of identifying facility configuration that achieves largest coverage with reasonable computational efforts (Wei, 2016).

Third, the MCLP does not explicitly consider backup coverage which is important in EMS facility allocation, where a facility may be busy and unable to respond to a second event in its service area (Daskin & Stern, 1981). In order to account for backup coverage, Hogan and Revelle (1986) developed a multi-objective optimization model, which is an extension of the MCLP and known as the *backup coverage location problem* (BCLP) to maximize both primary and secondary service coverage. Several other extensions of the BCLP are also discussed in detail in Hogan and Revelle (1986). Although these models account for backup coverage, they do not work well with continuously distributed demand, such as population. It has been shown that actual primary and secondary coverage could be overestimated or underestimated based on the binary nature of the BCLP (Kim & Murray, 2008). Given this, Kim and Murray (2008) developed the BCLP-Actual Area (BCLP-AA) model, also referred to as the BCLP-Explicit by Murray et al. (2010), to deal with continuously distributed demand. However, the resulting number of constraints and variables in the BCLP-Explicit is usually very large and beyond the computational capability of existing optimization packages (Kim & Murray, 2008). Such high computational requirements prohibit its application to realistic planning problems.

As described earlier, it is essential to integrate backup coverage and continuously distributed demand into the location decision making of medical drones. Given these issues associated with existing coverage models, there is a need to develop a new spatial optimization approach that explicitly takes into account backup service provision and continuously distributed demand to locate a network of medical drones.

3. Methodology

We propose a new multi-objective model, the *Backup Coverage Location Problem with Complementary Coverage* (BCLP-CC), to identify the optimal locations for a network of medical drone launch sites. The BCLP-CC is an extension of both the BCLP and MCLP with some constraints similar to the MCLP-CC. This model accounts for partial coverage of continuously distributed demand as well as backup coverage. Before continuing on, it is necessary to consider the following notation:

j = index of potential drone launch sites where $j = 1,2,\ldots m$
i = index of demand units where $i = 1,2,\ldots n$
d_i = amount of demand in unit i
p = number of drones (or launch sites) to locate
h = maximum backup coverage level
b_{ij} = the amount of service provided to demand i by the drone launched at j
t = the maximum response time used to determine service areas
N_i = the set of drone launch sites that provide some service to demand i within t