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Drone-Aided Healthcare Services for Patients with Chronic Diseases in Rural Areas

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Abstract This paper addresses the drone-aided delivery and pickup planning of medication and test kits for patients with chronic diseases who are required to visit clinics for routine health examinations and/or refill medicine in rural areas. For routine healthcare services, the work proposes two models: the first model is to find the optimal number of drone center locations using the set covering approach, and the second model is the multi-depot vehicle routing problem with pickup and delivery requests minimizing the operating cost of drones in which drones deliver medicine to patients and pick up exam kits on the way back such as blood and urine samples. In order to improve computational performance of the proposed models, a preprocessing algorithm, a Partition method, and a Lagrangian Relaxation (LR) method are developed as solution approaches. A cost-benefit analysis method is developed as a tool to analyze the benefits of drone-aided healthcare service. The work is tested on a numerical example to show its applicability.

Keywords Drone · Healthcare · Delivery · Chronic disease · Rural health

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1 Introduction

According to the Centers for Disease Control and Prevention (CDC), chronic diseases are a major concern in terms of their economic and social aspects among the government and patients [1]. The cost of chronic diseases is an overwhelming component of overall healthcare expenses. In the United States (US), about 117 million people have had one or more chronic diseases in 2012, which means that about half of all adults are carrying chronic diseases that include heart disease, diabetes, arthritis and obesity [2]. Patients with chronic diseases are required to visit medical institutions for routine checkups or medicine refills. These periodic visits incur out-of-pocket expenses and medical costs that can be several times higher compared to patients without chronic diseases (Fig. 1). In Fig. 1, patients with a chronic disease (1 CD = \$2,915) spend almost 2.5 times more than those without chronic diseases (0 CD = \$1,177) due to regular clinic visits, prescriptions, home health visits and inpatient stays. In general, the presence of

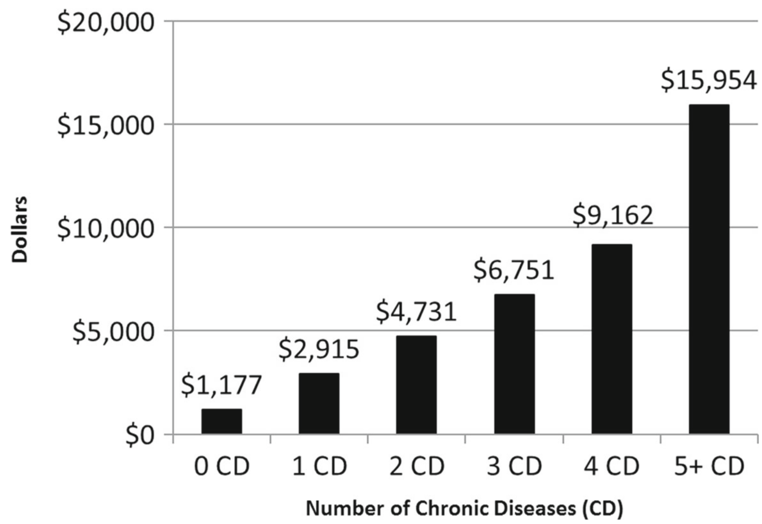

Fig. 1 Annual medical cost with number of chronic conditions, 2010, US [3]

more chronic diseases increases a patient's burden. In addition to the costs mentioned above, incidental costs are accrued such as transportation expenses to attend medical appointments and time off from work to seek medical service or take routine tests. These factors result in additional out-of-pocket expenses for patients.

The additional out-of-pocket expenses represent a greater burden for patients living in rural areas than for those living in urban areas. Rural areas have distinct barriers to accessing healthcare such as transportation to/from medical facilities and general availability of medical facilities [4]. Even though residents of rural areas have the same types and number of chronic diseases as those in urban areas, they face more out-of-pocket expenses due to their different geographical limitations. Even if they are willing to pay more to treat their diseases, they cannot easily access clinics due to lack of medical facilities within their vicinity [5]. This variation among populations is called health disparities [6].

To alleviate financial burdens and health disparities, the Federal Communications Commission (FCC) had proposed a project to develop the telemedicine infrastructure to enhance healthcare accessibility [7]. Using this broadband infrastructure, patients in rural areas can receive medical service without facing restrictions regarding time and space. Pilot programs combined with homecare delivery service are underway across the U.S. that allow teams of doctors to monitor and share patients' previous medical information and test results.

Despite the introduction of these programs, many limitations still exist in telemedicine and homecare delivery service for patients living in rural areas. First, telemedicine is no substitute for in-person hands-on care or delivering medicine. Although telemedicine can monitor and provide enrolled patients with qualified medical service through two-way streams of voice-and-video, it cannot deliver medicine and exam kits to patients. Second, it does not provide additional transportation methods for rural patients to visit healthcare facilities. The lack of transportation is one of factors for the failure of medication adherence [8]. Finally, in order to implement these programs widely and continuously, the participation of many providers is required. The population of rural residents is smaller than urban populations, and rural residents are more likely to be uninsured than urban residents [9]. As a result, the providers often hesitate to invest in projects like this because returns on investment from rural areas are estimated to be smaller when compared to urban areas. Even if the providers are willing to invest in such healthcare projects, it is often difficult to find, recruit and retain caregivers due to the geographical conditions. Moreover, according to American Association of Retired Persons, 89% of Americans over the age of 50 want to receive healthcare service in their own homes [10]. As they get older and face increased problems with mobility, they may have difficulty visiting medical clinics and prefer to be seen in a more comfortable place such as their own home. This trend is requiring providers to hire more caregivers to satisfy their patients' demands.

This paper aims to determine ways to overcome limitations of the current healthcare delivery methods in rural areas and to alleviate health disparities providing patients in rural areas with drone-aided healthcare delivery and pickup services. Drones as a substitute for currently limited transportation and caregivers can deliver routine test kits, refill drugs and pick up patients' exam kits such as blood and urine samples. Drones reduce the travel time and workload of a caregiver sharing simple care tasks. Compared to other transportation modes such as a postman and commercial courier services, drones can be a competitive alternative for delivery and pickup of time-sensitive items, regardless of the ground level road conditions. We note, however, that drones may not be dispatched in severe weather conditions and this aspect is beyond the scope of this paper. In our proposed work (Fig. 2), drones are utilized to deliver and pick up exam kits and medicine for patients located in rural areas while caregivers visit with patients who need in-person hands-on care. Therefore, the patients who need to obtain test kits or medicine do not need to drive, hence a saving on transportation expenses. Since the workload of the already limited available caregivers is reduced, they can concentrate on in-person hands-on care; thereby improving the quality of a caregiver's service.

This study proposes two planning models: strategic planning (SP) and operational planning (OP). The purpose of the SP model is to find the optimal locations for drone centers to provide its services to all patients in a given area. In the OP model, taking service range from centers into consideration, the optimal number of drones per drone center and their optimal delivery and pickup schedules are determined to satisfy the specific demands of patients within possible flying times. This study also suggests a cost-benefit ratio method for sensitivity analysis to help decision makers in providing an economically viable healthcare delivery service to patients using drones.

This paper contributes to the existing body of literature as follows:

– To propose a concept of drone-aided healthcare delivery and pickup service for chronic disease patients in rural areas: drones can provide aerial healthcare delivery and pickup services to assist the limited number of caregivers and reduce the out-of-pocket expenses for the patients in rural areas who need routine healthcare services.
– To develop two planning models in drone-aided healthcare delivery and pickup service: strategic planning to optimally decide where to place drone centers and how many centers, and operational planning for optimal drone flight schedule for each center.

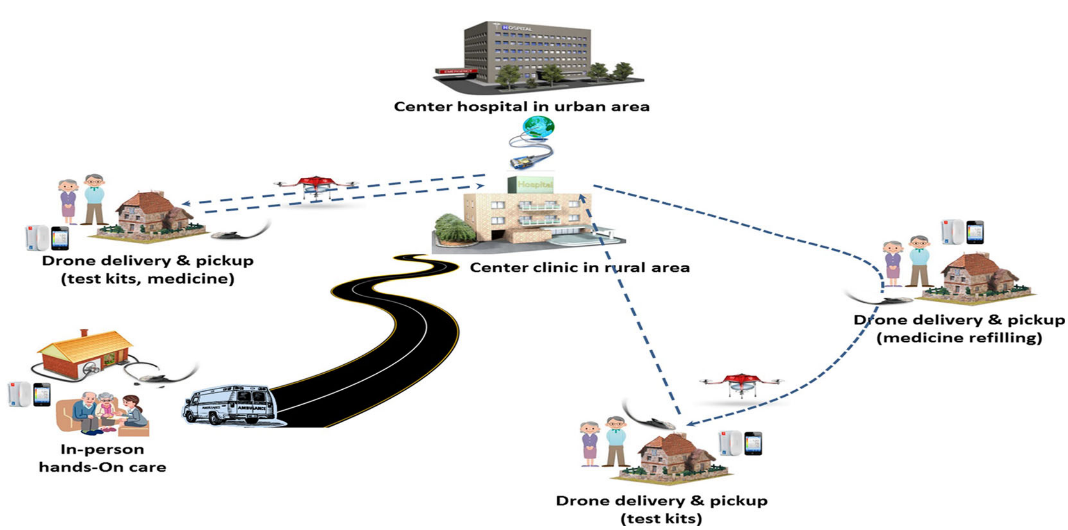

Fig. 2 Proposed concept of drone-aided healthcare delivery and pickup service in rural area

- To provide decision makers with an economic analysis tool (cost-benefit analysis method) for using drones in healthcare delivery: decision makers can analyze their investments on aerial delivery and pickup service using drones.
- To provide a preprocessing algorithm and bounds generation methods to reduce computational time to solve the proposed models.

The paper is organized as follows. A literature review is presented in Section 2. Section 3 describes the problem in detail and presents the mathematical models applied to find a solution. In Section 4, the preprocessing algorithm and the bounds generation methods are introduced to improve computational performance. The cost-benefit analysis method is described in Section 5. In Section 6, an example is used to illustrate the effectiveness of the proposed model in practice and a cost analysis is also conducted. Finally, Section 7 concludes with a discussion of the highlights in this paper and the potential extension of this work.

2 Literature Review

The aging population and increasing numbers of patients have presented a huge economic burden on not only themselves, but the government and providers as well [11, 12]. Because of this, there have been many different healthcare models and methods produced over the years.

For example, the homecare model [13] provides patients with certain types of care in their own homes. Homecare emerged over a century ago when the home was one of the workplaces for nurses. This model has evolved and developed over time due to changes in the demands of patients and technology [14, 15]. The homecare model has many challenges such as temporal precedence, demanding skilled treatments, increasing operating cost and unmet service level [16–19].

In rural areas, furthermore, homecare services have faced many difficulties obtaining benefits due to different environments encountered than those within urban areas. Some of the factors may be due to lower population, a lack of transportation, medical facilities and pharmacies as well as long distances between patients and medical facilities [20, 21].

Video-based treatment (called videoconferencing) is another model that provides two-way video services and voice contact between patients and doctors or patients and their relatives. Using devices with a touch screen, patients can easily consult with doctors or relatives when they need to [22]. This method enables patients who are far from urban areas or centralized hospitals to receive video therapy, recovery support and specialty services. Doctors can collect and share patients' data and information (such as blood pressure and heart rate) to make an accurate and rapid diagnosis with specialists in other areas.

The Medical Home model, which was first introduced in 1967 for pediatricians, has been applied in many states [23]. This service is performed mainly to perform primary care and is patient-centered, comprehensive, team based, coordinated, accessible, and focused on quality and safety. The medical team for a patient shares his/her medical information to ensure the patient receives pertinent care at the right time and place in the manner that best suits his/her needs. Hence, the patient does not have to retake tests because the information is being shared and provided by the different healthcare providers. Therefore, the patients have access to relevant medical services which in turn, saves time and money [24].

Overall, these models and methods are not applicable to all patients and face many barriers for patients who require periodic hands-on care due to limited physical situations [25]. Patients living in rural areas have limited or no access to transportation methods or caregivers who are able to deliver or pick up medicine and test kits for them. Recently, some researchers have proposed the use of drones for healthcare services [26–28]. However, they are not applicable to patients who need routine healthcare services as we consider in this paper. Therefore, a new healthcare model should be developed to ease the burden for patients with chronic diseases living in rural areas.

3 Problem Description and Formulations

The proposed decision-making process to deliver and pick up medical supplies for patients with chronic

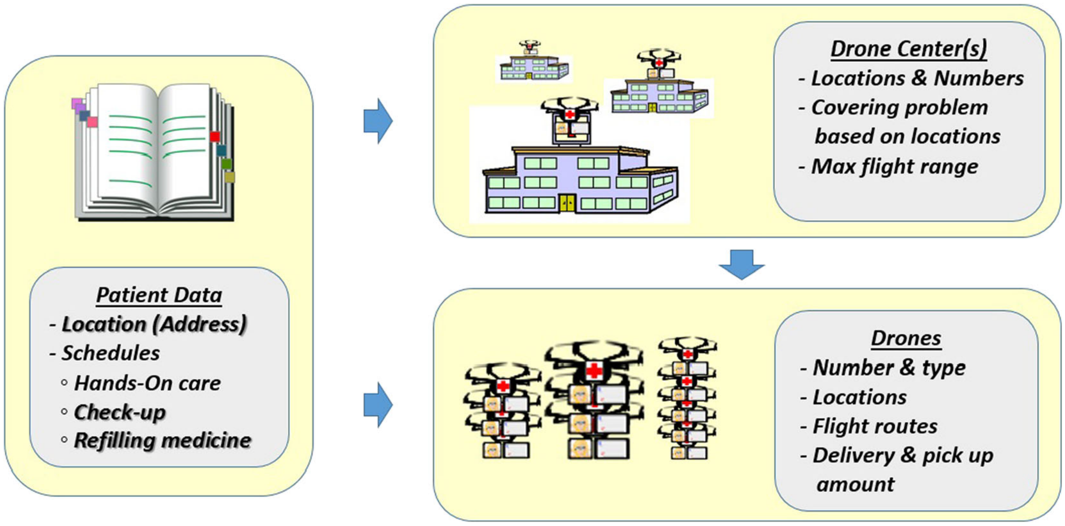

Fig. 3 Decision-making process

diseases in rural areas is shown in Fig. 3. Based on patient data that ranged from schedules for hands-on care, regular checkups and medicine refills as well as their residences, patients can be divided into two groups: one group that needs in-person hands-on care and the other who needs only simple testing or drug refills. This study focuses on the second group of patients where drones can provide simple test kits and drugs. Next, the locations and number of centers are determined to cover all patients within this second group. The property of this process is a long-term SP. Once the locations of the centers are determined, implementation of a SP begins requiring time, money and efforts. Lastly, the optimal number of drones and their routes are determined to deliver and pick up orders in a short-term OP.

We have developed the optimal scheduling model by making some assumptions using rotor wing drones that can fly up to 60 *mph* [29]. First, maximum flight times are not affected by the amount of load to be carried by a drone because most delivery items in this application are light weighted and have minimal impact on the flight time. Second, flight times between two nodes (two patients or a center and a patient) include actual flight time and average landing/pickup times of an item(s). Third, the drones are equipped with a proper device to land and pick items as intended.

3.1 Strategic Planning (SP)

The purpose of this planning is to decide the minimum number of drone centers based on the patient's residence data. The plan should ensure that all selected centers are able to reach all patients regardless demand levels and the number of chronic diseases experienced. All patients are placed at equal priority to receive service regardless of their circumstances. Unlike other services, healthcare services experience failure at a higher cost which is why selected centers must be mapped in a way where all patients are covered by at least one center. Hence, the solution to this problem requires geographical locations of all participating patients.

We propose to use the set-covering approach to solve this problem [30]. The set-covering problem determines the locations and optimal number of centers to cover all patients. The candidate sites for centers are assumed to be the locations of currently existing local medical institutes and some vacant lots that are adjacent to roads in order to avoid infeasible locations such as the middle of a lake or the top of a mountain. The criterion for deciding center locations is the maximum possible service distance (*MPSD*, i.e. the maximum possible one-way flight time of a drone) determined by the battery life of drones [31, 32].

The following notation is used in developing the SP model.

Sets

I	Set of patients ($i \in I$)
R_c	Set of candidate locations of centers ($r \in R_c$)
R_i	Set of centers covering patient i, i.e., $R_i \subseteq R_c$

Parameters

c_r	Initial cost to open a center at location r
d_{ir}	Distance between patient i and location r
MPSD	Maximum Possible Service Distance determined by maximum flight time of drones

Decision Variable

x_r	1 if location r is selected as a center, 0 otherwise

The goal of the SP model is to determine drone center locations with the minimum initial investment cost. Hence, our base model to accomplish this goal is given below:

$$\text{Minimize} \quad Z_{SP} = \sum_{r \in R_c} c_r x_r \tag{1}$$

$$\text{Subject to:} \quad \sum_{r \in R_i} x_r \geq 1, \qquad \forall i \in I \tag{2}$$

$$x_r \in \{0, 1\},$$

The objective function (1) is to minimize the initial cost of setting up drone centers. Let R_i in Constraint (2) be the set of centers covering a patient i (i.e., $R_i = \{r | d_{ir} \leq MPSD\}$). Constraint (2) ensures that each patient is served by at least one center.

3.2 Operational Planning (OP)

The goal of OP is to find the optimal number of drones and their routes for delivery and pickup orders. Once the locations of each center are decided, the number of drones per center can be determined by the number of patients served. The number of patients assigned to each center can be determined as a result of SP, but does not guarantee the assignment of patients to be optimal since some patients can be covered by more than one center. Therefore, the flight routes of drones are required by the OP to decide the number of drones allocated to each center.

Determination of the optimal number of drones for a given area is based on the worst case scenario (i.e., the largest estimated number of patients to be served at one schedule time window). The specific hourly flight routes for other cases are planned using OP model within the optimal number of drones.

The goal is to minimize the number of drones while covering all patients. We assume the cost for operating and maintaining a drone remains the same regardless of the flight distance (time) and loading amount which includes delivery and pickup packages.

Each patient is served only once by a drone and there is no priority in visiting patients. Each drone has to return to base after completing an assigned task. Some limitations of drones include flight time (range) and loading amount. In developing a drone's route, one must check the possible loading amount at each patient site. When finding the path, the net loading amount (i.e., net loading amount = delivery amount - pickup amount) is considered.

The following notation is used in developing the OP model.

Sets

I	Set of patients ($i, j \in I$)
R	Set of selected centers from SP model (i.e., $R \subseteq R_c$)
K	Set of drones ($k \in K$)

Parameters

p_k	Operating cost of drone k
P_i	Pickup amount at patient i
D_i	Delivery amount to patient i
T_k	Maximum flight time of drone k
M	Sufficiently large number

Decision Variables

x_{ijk}	1 if drone k flies from patient i to j, 0 otherwise
h_k	1 if drone k is utilized to serve, 0 otherwise
L_{ik}	Net loading amount on drone k when taking off from patient i
μ_i	The order of sequence of visiting patient i in a path

The mathematical model of OP is expressed below:

$$\text{Minimize} \quad Z_{OP} = \sum_{k\in K} p_k h_k \tag{3}$$

$$\text{Subject to:} \quad \sum_{i\in I\cup R}\sum_{k\in K} x_{ijk} = 1, \qquad \forall j \in I \tag{4}$$

$$\sum_{j\in I\cup R}\sum_{k\in K} x_{ijk} = 1, \qquad \forall i \in I \tag{5}$$

$$x_{iik} = 0, \qquad \forall i \in I \cup R,\ k \in K \tag{6}$$

$$\sum_{j\in I} x_{rjk} - \sum_{i\in I} x_{irk} = 0, \qquad \forall r \in R,\ k \in K \tag{7}$$

$$\sum_{r\in R}\sum_{j\in I} x_{rjk} = h_k, \qquad \forall k \in K \tag{8}$$

$$\sum_{i\in I}\sum_{r\in R} x_{irk} = h_k, \qquad \forall k \in K \tag{9}$$

$$\sum_{i\in I\cup R} x_{iuk} - \sum_{j\in I\cup R} x_{ujk} = 0, \qquad \forall u \in I,\ k \in K \tag{10}$$

$$\sum_{i\in I\cup R}\sum_{j\in I} x_{ijk} D_j = L_{rk}, \qquad \forall r \in R,\ k \in K \tag{11}$$

$$L_{rk} - D_j + P_j - M(1 - x_{rjk}) \leq L_{jk}, \qquad \forall r \in R,\ j \in I,\ k \in K \tag{12}$$

$$L_{jk} \leq L_{rk} - D_j + P_j + M(1 - x_{rjk}), \qquad \forall r \in R,\ j \in I,\ k \in K \tag{13}$$

$$L_{ik} - D_j + P_j - M(1 - x_{ijk}) \leq L_{jk}, \qquad \forall i, j \in I,\ k \in K \tag{14}$$

$$L_{jk} \leq L_{ik} - D_j + P_j + M(1 - x_{ijk}), \qquad \forall i, j \in I,\ k \in K \tag{15}$$

$$L_{rk} \leq C_k h_k, \qquad \forall r \in R,\ k \in K \tag{16}$$

$$L_{ik} \leq C_k h_k, \qquad \forall i \in I,\ k \in K \tag{17}$$

$$\sum_{i\in I\cup R}\sum_{j\in I\cup R} x_{ijk}\, d_{ij} \leq T_k, \qquad \forall r \in R,\ k \in K \tag{18}$$

$$\mu_i - \mu_j + m\sum_{k} x_{ijk} \leq m - 1, \qquad \forall i, j \in I \tag{19}$$

$$x_{ijk}, h_k \in \{0, 1\},\ \mu_i \geq 0,\ m = |I|,\ R \subseteq R_c,$$

The objective function (3) is to minimize the sum of operating cost of drones, which helps to minimize the number of drones. Constraints (4) and (5) ensure that each patient is served only once. Constraint (6) is set to prevent a drone from revisiting the same patient or center and Constraint (7) guarantees a drone will return to where it departed from. Constraints (8) and (9) describe the utilization condition of the drones. Constraint (10) is used to conserve the flow of drone flight at both patients as well as centers. The aforementioned specifications of a drone are expressed in Constraints (11)–(18). The initial load amount on drone k at center r (L_{rk}) is determined by the demands of patients who are visited by drone k (Constraint (11)). Checking the net loading amount at each patient's site before taking off is a necessary condition reflecting the drone's property. Constraints (12) and (13) are set for visiting the first patient j from a center to describe the varying load due to different delivery (D_j) and pickup (P_j) amounts (i.e., net loading amount) and Constraints (14) and (15) are set for serving the next patients. Constraints (16) and (17) limit the loading amount on a drone to prevent overloading. The maximum possible flight time is also represented in Constraint (18). The Miller-Tucker-Zemlin formulation [33] is used in Constraint (19) to eliminate sub-tours.

Furthermore, the SP model ensures that each selected center has at least one patient to serve. This logical constraint is expressed below:

$$\sum_{j \in I} \sum_{k \in K} x_{rjk} \geq 1, \qquad \forall r \in R \qquad (20)$$

where for each selected center (r), at least one drone is assigned to serve patients. Constraint (20) is added in this OP model.

4 Solution Approach

The OP model is similar to the Multi-Depot Vehicle Routing Problem (MDVRP) that requires a considerable effort to obtain a good solution. This section presents a preprocessing algorithm (Section 4.1) to reduce the search space first and bounds generation methods (Section 4.2) to help improve convergence of the solution algorithm to find a solution.

4.1 A Preprocessing Algorithm

Drones have a limited loading capacity and flying time. These restrictions motivated us to develop a preprocessing algorithm to eliminate easily identifiable and infeasible situations from the search space. As a result, computational performance of the models can be improved due to a reduced search space. To eliminate redundant and infeasible paths, two factors are considered to further reduce the search space: (1) flight distance between consecutive flight locations, i.e., between a depot and a patient or between two patients in case of stopping at multiple locations, and (2) loading amounts at a depot and/or destinations. Considering a real flight environment, winds and obstacles can influence the actual flight time. Hence, we consider two cases for estimating flight distance: symmetric and asymmetric. In the symmetric distance case, flight times between two adjacent locations are considered the same (i.e., $d_{ij} = d_{ji}$), while it is treated unequal ($d_{ij} \neq d_{ji}$) in the asymmetric case.

Algorithm 1 A preprocessing algorithm to generate paths with symmetric flight distances

Inputs:
A set of patients I, $(i, j \in I)$, and a set of centers R, $(r \in R)$.
Flight distance information between two locations (i.e., d_{ir} and d_{ij}).
Delivery and pickup amounts at each patient location (i.e., D_i and P_i).
Drone (k) information: maximum loading capacity (C_k) and flight distance (T_k).
Step 1 - Search space reduction:
for all (patient $i, j \in I$ and center $r \in R$)
  if distance $d_{ir} > \frac{T_k}{2}$
    Eliminate arc (x_{irk}) from the path generation (i.e., $x_{irk} = 0$)
  end if
  if distance $d_{ij} > \frac{T_k}{2}$
    Eliminate arc (x_{ijk}) from the path generation (i.e., $x_{ijk} = 0$)
  end if
end for
Step 2 - Calculate the maximum number of patients in a path:
Calculate the maximum number of patients (MNP_k) to be served on a path using D_i, P_i, and C_k:
$MNP_k = \left\lfloor \frac{C_k}{\max[\min_i(D_i), \min_i(P_i)]} \right\rfloor, \forall k \in K$

Symmetric Flight Distance Assumption Algorithm 1 is developed under the symmetric flight time assumption, and it has two main steps. Step 1 follows two separate screening processes to identify and eliminate flight leg assignments that are not possible considering the maximum flight distance (T_k). The first screening process is associated with flights between a center and a patient only. In this case, flight leg (i, r) is eliminated from the search space ($x_{irk} = 0$) if distance from center r to patient i is greater than a half of the maximum flight distance, i.e., $d_{ir} > \frac{T_k}{2}$. The second elimination process is for flights involving more than one patient in one path. Hence, leg (i, j) will be eliminated from the search space ($x_{ijk} = 0$) if distance from patient i to patient j is greater than a half of the maximum flight distance, i.e., $d_{ij} > \frac{T_k}{2}$. This logic can be easily proved by the triangular inequality: $d_{ri}+d_{jr} \geq d_{ij} > \frac{T_k}{2}$ [34].

Step 2 calculates the maximum number of patients that a path can take in one complete flight path. Given D_i, P_i, and C_k, the maximum number of patients (MNP_k) in a path is defined as

$$MNP_k = \left\lfloor \frac{C_k}{\max\{\min_i(D_i), \min_i(P_i)\}} \right\rfloor, \qquad \forall k \in K. \tag{21}$$

For example, the loading capacity of drone k is assumed to be 100 (=C_k), the minimum delivery amount among all patients is 10 (=$\min_i(D_i)$), and the minimum pickup amount among all patients is 20 (= $\min_i(P_i)$). Then, the drone can visit at most five patients on a path.

Algorithm 2 A preprocessing algorithm to generate paths with asymmetric flight distances

Inputs:
A set of patients I, $(i, j \in I)$, and a set of centers R, $(r \in R)$.
Flight distance information between two locations (i.e., d_{ir} and d_{ij}).
Delivery and pickup amounts at each patient location (i.e., D_i and P_i).
Drone (k) information: maximum loading capacity (C_k) and flight distance (T_k).
Step 1 - Search space reduction:
for all (patient $i \in I$ and center $r \in R$)
  if distance $(d_{ri} + d_{ir}) > T_k$
    No more than one arc between arc (r, i) and arc (i, r) can be selected on a path (i.e., $x_{rik} + x_{irk} \leq 1$)
  end if
end for
Step 2 - Calculate the maximum number of patients in a path:
Calculate the maximum number of patients (MNP_k) to be served on a path using D_i, P_i, and C_k:
$MNP_k = \left\lfloor \frac{C_k}{\max[\min_i(D_i), \min_i(P_i)]} \right\rfloor, \forall k \in K$

Asymmetric Flight Distance Assumption Algorithm 2 is for the case of asymmetric flight distance, in which flight times between two locations are assumed to be different depending on the flight direction. The difference betwen Algorithm 2 and Algorithm 1 is in Step 1. Because $d_{ri} \neq d_{ir}$, if the total distance of a round trip flight time exceeds T_k (i.e., $(d_{ri} + d_{ir}) > T_k$), then it is impossible for drone k to return back to center r using leg (i, r). Hence, the two legs cannot be selected in one path at the same time (i.e., $x_{rik} + x_{irk} \leq 1$).

4.2 Tighter Bounds on the Objective Function

The proposed OP model is the MDVRP, which is known to be *NP–hard* in general [35]. Hence, we propose bound generation methods to help reduce computational time to solve the problem that is specifically designed for this application. We claim that an optimal solution is found when the gap between an upper bound and a lower bound on the objective function falls below a prespecified threshold value $\epsilon > 0$. In Section 4.2.1, a Partition method is introduced to find an upper bound and Section 4.2.2 proposes a method to find a lower bound.

4.2.1 Upper Bound Generation

The OP problem formulation is a minimization problem. Hence, any feasible solution can be used to generate an upper bound of the minimization problem. Although it may not be easy to find a feasible solution for some IP problems [36], we have developed a Partition method to efficiently generate a feasible solution to the OP model.

Partition Method 1

Step 1
Find an optimal solution (number and locations, R) of drone centers using the SP model (Section 3.1).
Step 2
Partition all patients in the planning area (A) into $|R|$ sub-areas: $A_1, A_2, \ldots, A_n$, if |R|=n (i.e., $A = \bigcup_{i=1}^{n} A_n$).
Step 3
Solve the OP model for each sub-area (Section 3.2).

The Partition method is comprised of three steps. First, an optimal solution is found by solving the SP model. The solution details the number of drone centers (R) and their locations. Second, based on the solution found in Step 1, partition all patients into R sub-regions. Finally, the OP model is solved for each of the sub-areas and a feasible solution is found that gives an upper bound on an optimal value of Z_{OP}.

Proposition 1 *Let Z^*_{OP-A} denote an optimal value of Z_{OP} for the planning area (A) and $Z^*_{OP-A_n}$ be an optimal value of Z_{OP} for the n^{th} sub-area (A_n), then the following inequality holds true:*

$$Z^*_{OP-A} \leq \sum_n Z^*_{OP-A_n} \tag{22}$$

Proof To prove the above, we consider two cases: 1) there is no patient that is covered by two or more centers (i.e., each patient is covered by only one center) and 2) there are patients who are covered by two centers or more (i.e., at least one patient is covered by two centers or more).

In Case 1, all sub-areas are distinctly divided without an overlap where each sub-area problem is the same as a single-depot vehicle routing problem. Hence the sum of the optimal values of all sub-areas ($\sum_n Z^*_{OP-A_n}$) is the same as the optimal value (Z^*_{OP-A}) of the planning area (i.e., $Z^*_{OP-A} = \sum_n Z^*_{OP-A_n}$).

In Case 2, the sum of the optimal values of all sub-areas ($\sum_n Z^*_{OP-A_n}$) is one of the feasible values because all patients are served by a drone from a center. But, there is no guarantee that this feasible value ($\sum_n Z^*_{OP-A_n}$) is the optimal value of the planning area (Z^*_{OP-A}). As a result, this feasible value provides an upper bound of Z^*_{OP-A} (i.e., $Z^*_{OP-A} \leq \sum_n Z^*_{OP-A_n}$). □

4.2.2 Lower Bound Generation

A Lagrangian Relaxation (LR) approach is used to generate a lower bound on Z_{OP}. We pose two questions when applying LR: (1) which constraints to relax? and (2) how to find the Lagrangian multipliers? Typically, the sub-tour elimination constraint (Constraint (19)) is the complicating constraint in vehicle routing problems [37]. Hence, the objective function of the OP model can be rewritten by moving the constraint to the objective function as below:

$$L(\phi) = \min \sum_{k \in K} p_k h_k + \sum_{i \in I} \sum_{j \in I} \phi_{ij} [\mu_i - \mu_j + m \sum_k x_{ijk} - (m-1)], \tag{23}$$

where, $\phi_{ij} \in \mathcal{R}$ is the Lagrangian multiplier, $\phi_{ij} \geq 0, \forall i, j \in I$ [38]. The reformulated objective function is solved with the remaining constraints (4)–(18) to find the Lagrangian multipliers and the corresponding lower bound using the subgradient algorithm outlined in Algorithm below.

Subgradient Algorithm (ϕ)

Initialization

Initial values of UBD (Section 4.2.1), θ, and ϕ;

Repeat

Set $\phi^{prev} = \phi$;

Solve the Lagrangian dual problem (23) with constraints (4)–(18) to obtain a lower bound (LBD).

Calculate G_{ij}, a gradient of $L(\phi)$

Calculate step size $S_{ij} = \theta \times \frac{(UBD - LBD)}{||G_{ij}||^2}$

Update Lagrangian multiplier: $\phi_{ij} = \phi^{new}_{ij} = max(0, \phi^{prev}_{ij} + S_{ij} G_{ij}), \forall i, j \in I$

Until satisfying the convergence condition ($\|\phi^{new} - \phi^{prev}\|_1 < \epsilon$)

Output: ϕ^* and $L(\phi^*)$

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5 Cost-Benefit Analysis Methodology

The costs associated with the drone center and its operation are mostly the responsibility of providers. The beneficiaries of the proposed healthcare delivery system are the patients and the providers, but it is not easy to quantify the benefits for the providers. To address this concern, the cost-effectiveness analysis (CEA) is widely used to compare the relative costs and the effects of two or more interventions in healthcare [39] in which the quality-adjusted life-year ($QALY$) is used to evaluate the effectiveness in healthcare instead of through monetary values. However, it is not easy to evaluate $QALY$ from patients with chronic diseases [40]. Hence, the cost-benefit analysis method (B/C ratio) is used to analyze the varying parameters to represent other interventions. Therefore, this section focuses on the costs healthcare providers incur and the benefits to patients (i.e., driving cost and copayment).

The Life Cycle Costs of each drone center is shown in Table 1. Initial investment costs for centers (c_r) and drones (c_k) are required at the beginning of this intervention. The operation and maintenance (OM) cost is incurred as a proportion (α) to the initial investment cost every year. In addition to the labor cost (c_{labor}), other costs (β) associated with labor such as recruitment, retainment, training, and insurance, are listed in Table 1. After the expected life years of centers (N_1) and drones (N_2), the increase (γ) in the re-acquisition cost of drones is reflected whereas no increase is reflected in the cost of centers.

As shown in Table 1, the cost evaluation periods are different and the life cycles of centers and drones are not the same. Usually, the life span of a centers (N_1) is longer than the life span of the drones (N_2). To facilitate the analysis, the analysis period assumes the duration of expected life of centers (N_1) to be the same for drones. The following factors are expressed in terms of annual cost as shown below:

Acquisition Cost
$$(c_r + c_k) \times (A/P, i\%, N_1) = (c_r + c_k) \times \frac{i(1+i)^{N_1}}{(1+i)^{N_1} - 1} \tag{24}$$

Operation & Maintenance Cost
$$\alpha(c_r + c_k) \tag{25}$$

Labor Cost
$$(1+\beta)c_{labor} \tag{26}$$

Drone re-acquisition Cost
$$\gamma c_k \times (A/F, i\%, N_2) = \gamma c_k \times \frac{i}{(1+i)^{N_2} - 1} \tag{27}$$

Annual interest rate is assumed at $i\%$, and no inflation or deflation is assumed for the life cycle of the centers. Equation 24 expresses the annual amount of the initial investment on centers and drones using the capital recovery concept [41], which is the annual equivalent of the initial investment cost (c_r and c_k). Equation 25 is the OM cost of all centers and drones and Eq. 26 is the labor cost which includes indirect labor cost, too. The re-acquisition cost of drones will incur every N_2 years during the analysis period of N_1 years, in which the future repurchase expenses can be divided into annual expenses (27). These costs incur every year during the N_1 period.

Additional benefits for patients come from the receipt of care from drone centers: reduction of driving cost (b_1) and copayment (b_2). The amount of B_1 corresponds to the driving cost incurred whenever patients drive to visit clinics or a pharmacy. The driving cost is calculated by multiplying the average driving distance of patients living in rural areas by driving cost/mile. The amount of b_2 is also the same as the amount of copayment for every visit. These reductions are made through the drones' delivery and pickup instead of a patient visiting medical facilities or pharmacy themselves. Using b_1 and b_2, the benefits are described as below:

Reduction of Driving Cost
$$Nmb_1 \times (F/A, i_e\%, D) = Nmb_1 \times \frac{(1+i_e)^D - 1}{i_e} \tag{28}$$

Reduction of Copayment
$$Nmb_2 \times (F/A, i_e\%, D) = Nmb_2 \times \frac{(1+i_e)^D - 1}{i_e}, \tag{29}$$

where N is the number of service schedules per day and m is the average number of patients in each service schedule. And i_e indicates the effective interest rate reflecting the compounding period of interest rates and one year is assumed to have D days. Equations 28 and 29 describe the annual saving amounts of driving cost and copayment, respectively. From an economic perspective, the B/C ratio should be at least 1 to determine the support and feasibility of implementing the proposed framework. The value of B/C is calculated using Eq. 30 below:

$$< B/C > = \frac{\text{Benefits}}{\text{Costs}} = \frac{\text{Reduction of Costs}}{\text{Incurred Costs}}$$
$$= \frac{\text{Reduction of Driving Cost} + \text{Reduction of Copayment}}{\text{Capital Recovery} + \text{Operation \& Maintenance} + \text{Drone re-acquisition} + \text{Labor}}$$
$$= \frac{Nm(b_1 + b_2) \times \frac{(1+i_e)^D - 1}{i_e}}{(c_r + c_k) \times \frac{i(1+i)^{N_1}}{(1+i)^{N_1}-1} + \alpha(c_r + c_k) + \gamma c_k \times \frac{i}{(1+i)^{N_2}-1} + (1+\beta)c_{labor}} \tag{30}$$

6 Numerical Experiments

This section is divided into three parts. The first part tests the proposed models on a sample network. The two models and the algorithms are implemented in GAMS [42]. In the second part, a cost-benefit analysis is presented as a criterion for decision makers to analyze their investments on aerial delivery and pickup service by drones. In the last part, computational performance of the OP model is discussed to show the benefits of using the proposed bounds discussed in Section (4.2). All experiments are made on a server running RedHat Linux 64-bit with an Intel Xeon processor and 16GB RAM.

6.1 A Numerical Example

Figure 4 is a numerical example used to illustrate the models proposed in Section 3. A real-world example is obtained based on Milam and Robertson Counties in Texas, US. There are 9 candidate sites (from C1 to C9) for centers and 40 patients (from 1 to 40) to be served by drones in the same service schedule. The candidate sites for centers are a subset of existing local medical institutes. Actual patient locations can be slightly different due to patient information confidentiality. The cost of establishing a drone center is assumed to be same for all candidate sites. Two types of drones are utilized: Type I can fly up to 32 $miles$ (=32 $minutes$), load up to 10 lbs and requires \$32 to operate per drone per flight whereas Type II has inferior specifications of 25 $miles$ (=25 $minutes$), 8 lbs and \$25, respectively.

The SP model is applied to find the optimal number of centers and their locations. The result is shown in Fig. 5, in which three sites (i.e., C1, C5 and C6) are eliminated from the candidate pool for centers. The eliminated centers are redundant and have service area that overlap with C2 and C7. The travel distance between the eliminated centers and patients who surround those centers is greater than C2 and C7. Hence, 6 out of 9 candidates are selected as the centers for serving patients.

To identify the optimal number of drones per selected center, the OP model is solved and the results are shown in Table 2. All 40 patients are assigned to 6 centers considering their locations and requested amounts. In order to satisfy all demands from the patients, the OP model determined that 19 drones are needed. The resulting drone operation cost is \$573 $(= 96 + 50 + 64 + 114 + 128 + 121)$.

Table 1 Life cycle costs of drones and centers

Cost	Description		Remark
Acquisition	Centers	c_r	Initial Investment
	Drones	c_k	Initial Investment
Operation/ Maintenance		$\alpha(c_r + c_k)$	Yearly
Labor	Direct	c_{labor}	Yearly
	Others	βc_{labor}	Yearly
Re-acquisition	Centers	r_r	Expected Life: N_1 yrs
	Drones	γc_k	Expected Life: N_2 yrs

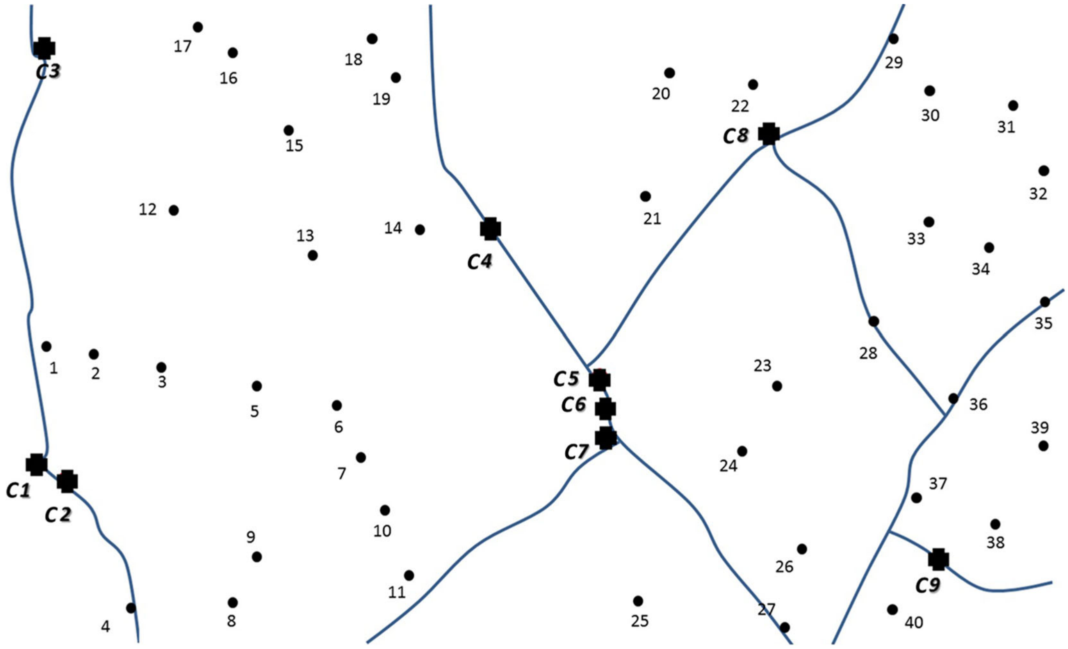

Fig. 4 Area under consideration; Milam and Robertson Counties, Texas, US

The specific routes of 19 drones for visiting 40 patients are shown in Fig. 6 (solid arrows: Type Idrones, dashed arrows: Type II drones). Some of the drones serve only one patient and other drones serve up to three patients on one flight. The number of patients being served in a path varies with the drone's specifications (i.e., loading amount and flying distance) and patient data (i.e., distances and level of demand). The patients who are covered by more than one center are assigned to only one center considering the neighboring patients and the distance between the centers and patient. Figure 7 shows the covered range (i.e., dotted circle) of each center. For example, patient 6 is covered by three centers, C2, C4 and C7. Patient

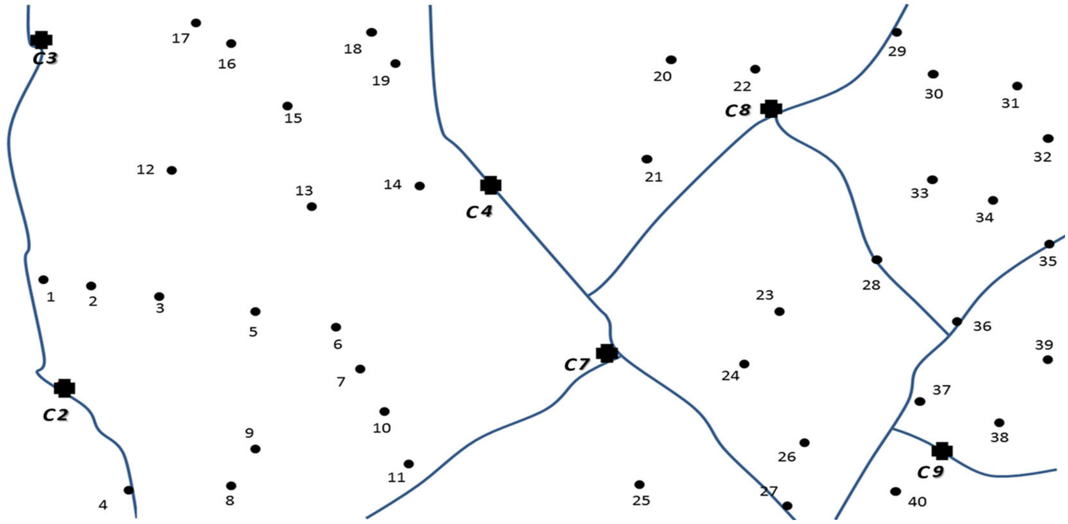

Fig. 5 The selected drone centers from the SP model

Table 2 The optimal number of drones in each center

Center	Assigned Patients	Number of Drones	Cost($)
Total	40 patients	19 (Type I : 14, Type II : 5)	573
C2	p1, p2, p3, p4, p5, p6, p8, p9	3 (Type I : 3)	96
C3	p12, p16, p17	2 (Type II : 2)	50
C4	p13, p14, p15, p18, p19	2 (Type I : 2)	64
C7	p7, p10, p11, p23, p24, p25	4 (Type I : 2, Type II : 2)	114
C8	p20, p21, p22, p29, p30, p31, p32, p33, p34	4 (Type I: 4)	128
C9	p26, p27, p28, p35, p36, p37, p38, p39, p40	4 (Type I :3, Type II : 1)	121

6 is closer to C4 than to C2 and C7. But, patient 6 is assigned to C2 because serving patient 5 and patient 6 together on the same path from C2 is the optimal route to minimize total cost (the number of drones).

6.2 Cost-Benefit Analysis

As shown in Table 3, various scenarios of parameters are presented with associated B/C ratios.

In order to measure the value of savings on driving cost (B_1), \$ $0.58/mile$ is used as the driving cost/mile based on the American Automobile Association's Driving Cost [43]. To get the support and feasibility of implementing the proposed framework (B/C ratio $\geq$ 1), the B/C ratio shows that at least 40 patients ($m \geq 40$) are sustained at every service schedule (from the 2^{nd} to 4^{th} rows in Table 3). If the number of patients in eight service schedules (N) is less than 40 patients (i.e., m $<$ 40), the longer average service distance is needed to get the value of B/C ratio of more than 1 (from the 5^{th} to 7^{th} rows in Table 3). We consider that one service schedule is left as a buffer against drone defects and unplanned delivery or pickup services and additional drones are also prepared in case as well (from the 8^{th} to 10^{th} rows in Table 3). Hence, the B/C ratio indicates that the longer average service distance is also required to get the support of implementing this scenario.

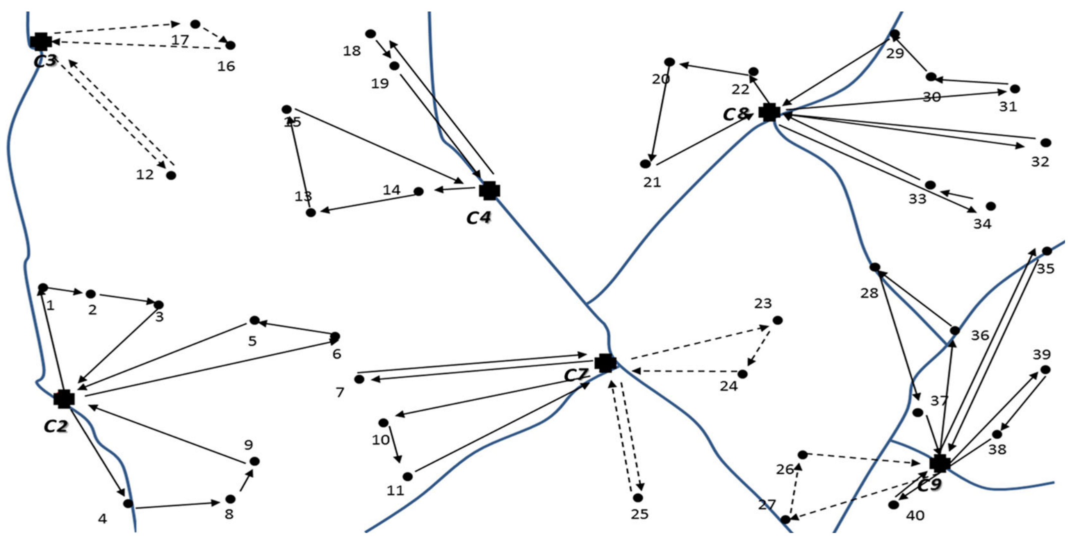

Fig. 6 The assignment of drones to patients: solid arrows for Type I drones and dashed arrows for Type II drones

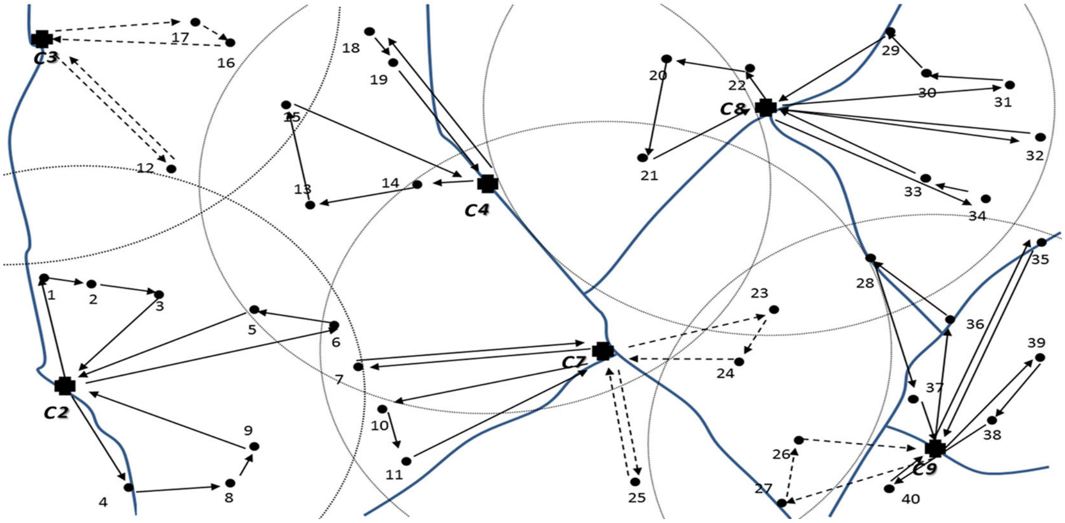

Fig. 7 Covered areas by 6 centers

6.3 Computational Performance

This section presents the computational performance of the bounds generation methods (i.e., Partition method and LR algorithm) proposed in Section 4.2. For the subgradient algorithm, the value of θ is in the range of 1 to 4 (i.e., $\theta \in [1, 4]$) and the stopping criteria (convergence) is less than 1% (i.e., $\epsilon = 0.01$). The two OP models (with and without the bound generation methods) are executed with a stopping criterion of 5% gap which is calculated as $100 \times \frac{Upper Bound - Lower Bound}{Upper Bound}$.

Figure 8 shows the progression of convergence of the model as a function of time. The result is based on a test case with 2 centers and 12 patients. Dashed lines represent the OP model without the bound generation methods, while solid lines are associated with having the bound generation methods in the model. Both cases (with and without the bound generation methods) showed a quick convergence

Table 3 B/C ratio with varying conditions

c_k($M)	b_1($)	N	m	Benefit($M)	Cost($M)	B/C	Remark
0.18	18	8	40	3.704	3.672	1.0089	
			39	3.612	3.672	0.9837	Number of Patients
			38	3.519	3.672	0.9585	
0.18	19	8	38	3.592	3.672	0.9784	
	20			3.666	3.672	0.9984	Avg. Distance
	21			3.739	3.672	1.0184	
0.24	22	7	40	3.511	3.711	0.9463	Avg. Distance with
	24			3.646	3.711	0.9827	additional drones and
	25			3.714	3.711	1.0009	reduced service schedules

c_r(Center) = \$12 M, c_{labor} = \$1.536 M, b_2(Copay) = \$30, $N_1 = 20$ yrs, $N_2 = 2$ yrs, $\alpha = \beta = 0.1$, $\gamma = 1$, and $i\% = 0.01$

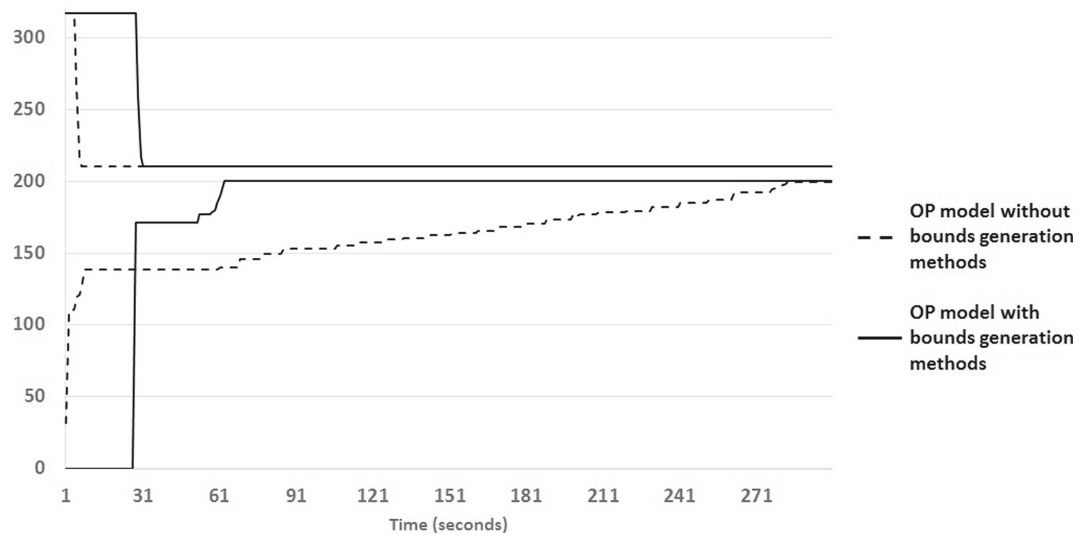

Fig. 8 Objective value vs. CPU time on a test case

of the upper bounds within 30 seconds. But, a big difference was observed on the convergence of the lower bound between these two approaches. The OP model displayed a substantial speed gain when the bounds were provided as compared to the slower convergence without the bounds. Overall, the OP model satisfied the stopping criterion in 63 seconds (4.8% gap) when the bound generation methods were used, but it took almost four times longer without the bounds (5% gap). As a result, the OP model found the solution about 5 times faster when the bound generation methods were used on this particular example.

7 Conclusion

In this paper, a new approach for healthcare delivery service was introduced to alleviate healthcare disparities in rural areas using an aerial delivery and pickup method. This new model was used for reducing the out-of-pocket expenses of patients with chronic diseases, thus enhancing the healthcare environments of rural areas, improving the quality of healthcare service, and reducing the burden of limited caregivers. To achieve these purposes, two planning methods were presented: first, the SP determined the location and number of centers that covered all patients and also eliminating redundant and infeasible candidate sites. Second, the OP found the optimal number of drones in each center, considering all schedules in a given area. The cost-benefit analysis method was introduced as a decision-making criterion for stakeholders. It was implemented using different cost and benefit values as the criteria for deciding this project. Finally, the computational analysis was conducted to compare the performance of the problem using the Partition method and LR algorithm which produced better performance than the model without these components.

An extension of this work may include variable flight times that are associated with a different battery consumption rate according to the loaded amounts and travel distances. Priority can be assigned to the model in delivery routing and scheduling.

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