Optimizing a UAV-based Emergency Medical Service Network for Trauma Injury Patients*

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***Abstract*— Emergency medical service must be time sensitive. However, in many cases, satisfactory service cannot be ensured due to inconvenient logistics. For its easily deployable and widely accessible nature, unmanned aerial vehicles (UAVs) have the potential to improve the service, especially in areas that are traditionally under-served. In this paper, we develop a service network optimization problem for locating UAV bases, staffing a UAV fleet at each constructed base, and zoning demand nodes. We formulate a location-allocation optimization model with numerically simulated waiting times for the service zones as the objective. We adapt a genetic algorithm to solve the optimization model. We test our network optimization approach on instances of traumatic injury cases. By comparing our approach to a two-phase method in Boutilier et al. [1], we suggest an up to 60% reduction in mean waiting time.**

I. Introduction

After a traumatic injury, the chance of survival is higher if care is received within a shorter time interval. For many traumatic injury cases, timely delivery of medical supply leads to substantially higher survival rate. Clear evidence on 24-hour mortality reduction is associated with very short time to initial transfusion after the injury (i.e., only up to 15 minutes after the rescue of medical evacuation) [2]. Many studies have reported that more than 50% of people die within three, ten and thirty minutes after the occurrence of cases with heart stop, respiration stop, and massive bleeding, respectively [3]. As a result, in emergency medicine practice, there is the notion of "golden hour", which suggests prompt medical care and surgical treatment within an hour will have a higher chance to prevent death. However, due to traffic congestion or lack of reliable road transportation, many traumatically injured people miss the best time to be treated appropriately. Unmanned aerial vehicle (UAV) is easily deployable and independent of road conditions. Introducing UAV to emergency medical service (EMS) makes timely treatment practical, and in turn, increases survival rates for traumatically injured people.

Due to limited budget and geographical constraints, it is unrealistic to construct UAV launching stations at arbitrary locations. However, to ensure timely emergency response, every incident scene must be reached by some UAV within a reasonable threshold time interval. In this paper, we conduct a location-allocation analysis to optimize the locations of UAV stations, the number of UAVs at each station, and the demand nodes assigned to the service area of each station. Our objective is to optimally trade-off (1) the spending to ensure service capacity preparation related economic activities (e.g., station construction and maintenance, as well as UAV procurement); and (2) some service quality related measure (e.g., average time lapse from emergency notification to UAV arrival at the scene).

Our approach involves solving a location-allocation optimization problem, which is supplemented by evaluating the weighted sum of service zone specific waiting times via discrete-event simulation, all in one phase. Previously, Boutilier et al. [1] provided a two-phase approach to solve a UAV network design problem. First, UAV stations are chosen based on a set-covering method, such that all demand nodes are covered by the smallest number of stations. Second, by assuming a M/M/s queue for the service dynamics within each service zone, the number of UAVs with each station is iteratively increased until 99% of the incidents have a readily deployable UAV at their occurrences.

Many researchers have studied the facility location-allocation problem for EMS networks. For example, Fulton et al. [4] evaluated allocation rules and planning factors via Monte-Carlo method. Budge et al. [5] computed the station-specific performance measures of EMS systems for varied server workload. Bastian et al. [6] provided a decision-support methodology that assists military decision-makers with real-time coverage visualization and recommended aeromedical evacuation assets to select from for each given injury location. McLay [7] introduced the maximum expected coverage location problem with two types of servers (e.g., air and road ambulances) to increase patient survival rate.

More recent papers distinguished demands by different levels of severity or priority. For example, Fulton et al. [8] studied a stochastic optimization model to minimize the transportation time weighted by patient severity, through redistributing resources of the hospital system. McLay et al. [9] examined a way to dispatch

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heterogeneous servers to prioritized patients when dispatchers may make classification mistakes. Grannan [10] developed a binary linear programming model to optimally locate two types of air ambulances and construct catchment areas with preference lists.

The main contributions of this paper are two-fold. One, we formulate a location-allocation optimization model with simulated mean waiting time as the objective. Our model incorporates more practical relevance by considering UAV cruise range, golden-hour-survival-time threshold, time-varying arrival rates at each demand node, and service time dependent on the flight time from each demand to the UAV station assigned. Two, we conduct a case study based on the 2017 Indiana vehicular crash data. This case study verifies that our approach is superior and more practical as opposed to existing approaches in the literature through comparing it with the two-phase approach by Boutilier et al. [1].

II. Method

A. Problem Formulation

Suppose we have a set of demand nodes $I = \{i : i = 1, \cdots, |I|\}$ (e.g., zip-code areas, each of which aggregates a set of incident sites), and a set of candidate locations for UAV launching stations $J = \{j : j = 1, \cdots, |J|\}$ (e.g., existing airports). We have three sets of decision variables: $y_j \in \{0, 1\}$ $(j \in J)$ indicating whether to construct a UAV station at location j; $u_j \in \mathbb{N}$ $(j \in J)$ specifying the number of UAVs to be stored at location j; $x_{ij} \in \{0, 1\}$ $(i \in I, j \in J)$ indicating whether demand node i is assigned to location j. For model parameters related to budgeting, we use B to denote the total budget, and f_c and f_p to denote the costs for constructing a UAV station and procuring a UAV, respectively. Finally, for each $j \in J$, we denote $W_j(x, u_j)$ to be service zone j specific mean waiting time, i.e., the mean waiting time for all the demands served by UAV station j with u_j UAV models staffed, with the demand assignment follows the binary matrix x. We formulate the optimization model as:

$$\min \quad \sum_{j:u_j>0} \left[W_j(x, u_j) \frac{\sum_{i:x_{ij}=1} \lambda(i)}{\sum_{i \in I} \lambda(i)} \right] \tag{1}$$

$$\text{s.t.} \quad \sum_{j \in J} x_{ij} = 1, \qquad \forall i \in I; \tag{2}$$

$$y_j \cdot \sum_{j \in J} u_j \geq u_j, \qquad \forall j \in J; \tag{3}$$

$$\sum_{i \in I} x_{ij} \leq y_j \cdot |I|, \qquad \forall j \in J; \tag{4}$$

$$\sum_{j \in J} y_j f_c + \sum_{j \in J} u_j f_p \leq B; \tag{5}$$

$$x_{ij}, y_j \in \{0, 1\}, u_j \in \mathbb{N}, \qquad \forall i \in I, j \in J. \tag{6}$$

In the above formulation, objective (1) aims to minimize the weighted sum of service zone specific mean waiting time. The weight associated with each constructed station is the ratio of the incident rate within the corresponding service zone to the overall incident rate. Constraints (2) imply that each demand node must be assigned to some location. Constraints (3) imply that if we plan to staff at least one UAV at some candidate location, a UAV station has to be constructed at the location. Constraints (4) imply that every demand node can be assigned to a location only if a UAV station has been constructed at the location. Constraint (5) specifies that the total spending on constructing UAV stations and purchasing UAVs cannot exceed the total budget.

To solve the optimization model, we need to further quantify have a computationally tractable functional form on the mean waiting time $W_j(x, u_j)$ for each $j \in J$, given the specification of the service zone and the number of UAVs staffed in the zone. Since we assume a general service time distribution, we resort to numerical simulation to compute $W(x, u_j)$, as detailed in the following.

B. $W_j(x, u_j)$ Estimation

A UAV-based EMS process contains six time points (Figure 1): call-in, departure from the station, arrival at the scene, departure from the scene, arrival at the station, and reset time. The time between call-in and departure from the station is response time, and the time between departure from the station (the scene) and arrival at the scene (the station) is flight time, the time between arrival at the scene and departure from the scene is on-scene time, and the time between arrival at the station and reset time is charging time and maintenance time. Thus, the service time critical to patient survival is the sum of the response letter and the outbound flight time.

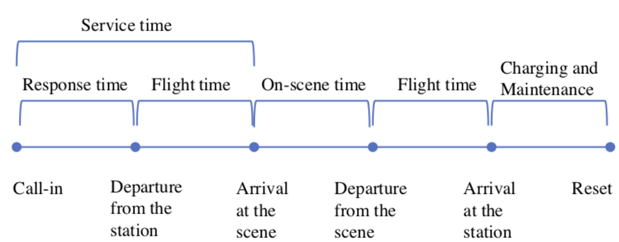


Fig. 1. An Illustration of UAV-based EMS Process

For the optimization, we compute the mean waiting time for the service requests that occur in the service zone of station j over a time period $[0, T)$ (e.g., one year) with n_j replications. We denote I_j as the set of demand nodes served by UAV station j, and u_j as the number of UAVs to be staffed at the station. We denote $t_f(i, j)$ as the one-way flight time from j to i (or from i to j). We denote $\lambda_i(t)$ as the arrival rate function for each $i \in I_j$ at time t, and denote $\lambda_i^\star$ as the maximum arrival rate for $i \in I_j$ within the time interval (i.e., $\max_{t\in[0,T]} \lambda_i(t)$). To track the scheduled time for each of the u_j UAVs throughout the time interval, we introduce $s_1, \cdots, s_{u_j}$ and initialize each of them as 0. We consider the warm-up period as the time interval influenced by the initial condition when all of the UAVs are idle and no demand is generated. Regarding the warm-up period ends when there is a demand having nonzero response time, we set a binary variable $\texttt{Flag} \in \{0, 1\}$ to represent if the system has passed (1) or remains (0) in the warm-up period.

For each replication, we generate arrival events based on two periodic Poisson processes, and assign the corresponding demands to the idle UAVs by a first-come-first-serve principle. That is, we sort arrival events by their arrival times in ascending order, assign an idle UAV to the earliest arrived but unserved event, and adjust each UAV's completion time accordingly.

Algorithm 1: Generating waiting time $W_j(x, u_j)$

```
for n=1:n_j do
    (Generate two-periodic Poisson processes);
    for i ∈ I_j do
        Set t = 0;
        while t ≤ T do
            Set U_1 = U_2 = 1;
            while U_2 ≥ λ_i(t)/λ_i^* do
                Generate U_1, U_2 ~ Uniform(0,1)
                  independently;
                t = t − log U_1/λ_i^*;
            end
            Add (i,t) into list L;
        end
        Remove the last added (i,t) in L;
    end
    (Assign the generated events to idle UAVs with FCFS);
    Sort the tuples in L with increasing arrival time;
    Denote the k-th tuple in L as L(k), denote the first and the
      second elements of L(k) as L(k)_1 and L(k)_2;
    Flag = 0;
    W_j^n = 0;
    s_1 = s_2 = ··· = s_{u_j} = 0;
    for k ∈ 1 : |L| do
        Search the earliest completed server
          s_r ∈ arg min_{r∈{1,···,u_j}} {s_1, s_2, ··· , s_{u_j}};
        Generate a random time a representing the on-scene
          time and the charging and maintenance time;
        Update s_r ∈ max{s_r, L(k)_2} + 2t_f(L(k)_1, j) + 2a;
        if L(k)_2 > s_r then
            Flag = 1;
        end
        if Flag = 1 then
            W_j^n = W_j^n + (L(k)_2 − s_r)^+ + t_f(L(k)_1, j);
        end
    end
    W_j^n = W_j^n/|L|;
end
W_j(x, u_j) = Σ_{n=1}^{n_j} W_j^n/n_j;
```

C. Genetic Algorithm

Overall, the genetic algorithm consists of six parts: random initialization, parent selection, crossover, mutation, survivor selection, and termination checking. The sketch of the overall genetic algorithm is shown in `Algorithm 2`.

We define (x, u) as our chromosome, where $x \in \{0, 1\}^{|I|\times|J|}$ and $u \in \mathbb{N}^{|J|}$. Namely, each chromosome is a solution consisting of the binary assignment matrix for every demand node and the number of UAVs staffed at every station. We use the objective function (1) as the fitness function $\texttt{get\_fitness}(x, u)$ directly.

We denote a fixed number (N) as the population size in each generation of chromosomes. We apply crossover to generate two children from two parents, where the two parents are chosen if they have the smallest fitness function values in the current generation. The two children chromosomes are modified by the mutation step, (in which the mutation number M represents the level of mutation) and compared with the N chromosomes in the current generation with their fitness function values. The worst two chromosomes are discarded and the rest N chromosomes constitute the next generation.

Since we compute the fitness function values for each chromosome in a generation, we stop generating new generations once the best fitness function value has not been improved for C generations. The counter for that is recorded by $\texttt{counter}$, which is initialized as 0.

Algorithm 2: Genetic Algorithm sketch for (x, u)

```
Random initialization;
counter = 0;
while counter < C do
    Parent Selection;
    Crossover and Mutation to generate Child_1, and Child_2;
    if get_fitness(Child_1) and
      get_fitness(Child_2) are both greater or equal to
      the current minimum value then
        counter = counter + 1;
    end
    Rank the fitness values of the elements in population set
      and Child_1, Child_2;
    Remove the worst two elements and form the updated
      population set;
end
Calculate f_B = min_{k=1,···,N} get_fitness(x^k, u^k) with
  the current population {(x^1, u^1), ··· , (x^N, u^N)};
Return f_B and its corresponding (x^k, u^k)
```

1) Random initialization: In this step, we initialize the population of N chromosomes. To generate one chromosome (x^k, u^k), we first decide the number of stations s (a randomly chosen positive integer no greater than $B/(f_c + f_p)$), and generate the number of UAVs at each selected location until the total cost of constructing UAV stations and procuring UAV models does not exceed the budget B. Once we generate the vector u^k, where each element represents the number of UAVs placed at each candidate station, we assign each demand node to the nearest constructed station and determine the assignment matrix x^k for the k^{th} chromosome.

2) Parent selection: In this step, we apply the Roulette Wheel Selection scheme by assigning prob-

Algorithm 3: Random initialization

Output: N Chromosomes: $(x^1, u^1), \cdots, (x^N, u^N)$;
for $k = 1 : N$ **do**
  Randomly choose $s \in \mathbb{Z}^+ \cap [1, B/(f_c + f_p)]$;
  Randomly choose s facilities, and denote the facilities as $j_1, \cdots, j_s$;
  Let $\hat{B} = 2 \cdot B$;
  while $\hat{B} \geq B$ **do**
    Randomly choose $u_j \in \mathbb{Z}_+$ for each $j \in \{j_1, \cdots, j_s\}$;
    Let $u_{j'} = 0$ for all $j' \in J \backslash \{j_1, \cdots, j_s\}$;
    $\hat{B} = s \cdot f_c + \sum_{j \in \{j_1, \cdots, j_s\}} u_j f_p$
  end
  for $i \in I$ **do**
    Find the facility $j \in \{j_1, \cdots, j_s\}$ such that $t_f(i,j) \in \min_{j \in \{j_1, \cdots, j_s\}} t_f(i,j)$;
    Let $x_{ij}^k = 1$, and $x_{ij'}^k = 0$ for all $j' \in J \backslash \{j\}$;
  end
end

abilities to the N generated chromosomes based on their fitness function values. Since we aim to minimize the fitness value, the higher the value, the lower the probability assigned to the chromosome to be chosen as a parent. Therefore, we use the reciprocal of the fitness value to decide the proportion of the probability for each chromosome.

Algorithm 4: Parent selection

Output: Two chromosomes: Parent_1 and Parent_2;
Calculate $f_B = \min_{k=1,\cdots,N} \texttt{get\_fitness}(x^k, u^k)$;
$S = \sum_{k=1}^{N} 1/\texttt{get\_fitness}(x^k, u^k)$;
Generate a random number P between 0 and S;
Starting from the top of the population, keep adding the fitness values to the partial sum P, until $P > S$;
The individual for which P exceeds S is the chosen individual Parent_1;
Repeat the previous steps to get Parent_2 ;

3) Crossover and Mutation: For crossover, we apply uniform crossover to generate $u^{\text{Child\_1}}$ and $u^{\text{Child\_2}}$, the numbers of staffed UAVs for Child_1 and Child_2. For each candidate station, these two numbers inherit those of Parent_1 and Parent_2. Which one inherits which is determined randomly with even probability.

For mutation, instead of assigning all demand nodes to their nearest constructed facilities, we randomly pick M demand nodes and assign them to all constructed facilities with certain probabilities, which are inversely proportional to the flight times.

III. Case Study: network design for Indiana vehicular crashes

We apply the proposed method to optimally design a UAV network for emergency services due to severe vehicular crash accidents from the State of Indiana. We assume each zip-code area in Indiana to be a demand node (959 zip-codes in IN in total [11]), and each existing airport in IN as a candidate location of UAV launching station (99 airports in total [12]). We assume the price of a UAV model is \$30,000. The UAV model is able to fly continuously at most 30 minutes. Since a UAV landing pad does not cost too much, we only consider the venue rental, for which we consider different annual rental cost of \$50,000, \$100,000, \$200,000 as the choices for the construction cost.

Algorithm 5: Crossover: uniform crossover

for $j \in J$ **do**
  Generate $a \sim \text{Uniform}(0,1)$;
  if $a < 0.5$ **then**
    $u_j^{\text{Child\_1}} = u_j^{\text{Parent\_1}}$; $u_j^{\text{Child\_2}} = u_j^{\text{Parent\_2}}$;
  else
    $u_j^{\text{Child\_1}} = u_j^{\text{Parent\_2}}$; $u_j^{\text{Child\_2}} = u_j^{\text{Parent\_1}}$;
  end
end
for $i \in I$ **do**
  Find the facility $j \in \{j : u_j^{\text{Child\_1}} > 0\}$ such that $t_f(i,j) \in \min_{j \in \{j : u_j^{\text{Child\_1}} > 0\}} t_f(i,j)$;
  Let $x_{ij}^{\text{Child\_1}} = 1$, and $x_{ij'}^{\text{Child\_1}} = 0$ for all $j' \in J/j$;
  Find the facility $j \in \{j : u_j^{\text{Child\_2}} > 0\}$ such that $t_f(i,j) \in \min_{j \in \{j : u_j^{\text{Child\_1}} > 0\}} t_f(i,j)$;
  Let $x_{ij}^{\text{Child\_2}} = 1$, and $x_{ij'}^{\text{Child\_2}} = 0$ for all $j' \in J/j$;
end

Algorithm 6: Mutations with level M

for Child $\in$ {Child_1 *and* Child_2} **do**
  Randomly choose M demand nodes from I, and denote them as $i_1, \cdots, i_M$;
  for $i \in \{i_1, \cdots, i_M\}$ **do**
    Choose a facility j in $\{j : y_j^{\text{Child}} > 0\}$, each facility is chosen with probability $(1/t_f(i,j))/\sum_{i \in \{i_1, \cdots, i_M\}} (1/t_f(i,j))$;
    Let $x_{ij}^{\text{Child}} = 1$, and $x_{ij'}^{\text{Child}} = 0$ for all $j' \in J \backslash \{j\}$;
  end
end

The 2017 Indiana vehicular crash accident data [13] have the records of 761149 accidents. Among the 741149 records, 629636 contains the latitude and longitude information for the crash spots. Among the 629636 records, 40872 contain a description indicating the most severe injury to the person involved in the accident. Among the 40872 records, 1871 indicate severed injury (severed, severe bleeding, internal, severe burn). We thus use the proportion of severe injury, i.e., $1871/40872$ to approximate that the annual number of severe injury accidents as $1871/40872 \cdot 629636 \approx 28823$.

For each zip-code i, we denote the number of accidents occurred from 8 am to 8 pm (8 pm to 8 am) as $\texttt{count}_d(i)$ ($\texttt{count}_n(i)$). Then we set the daytime (nighttime) arrival rates of severely injured accidents at node i to be

$$\lambda_d(i) = \frac{\texttt{count}_d(i)}{\sum_{i \in I}(\texttt{count}_d(i) + \texttt{count}_n(i))} \cdot \frac{28823}{365 \cdot 12},$$
$$\lambda_n(i) = \frac{\texttt{count}_n(i)}{\sum_{i \in I}(\texttt{count}_d(i) + \texttt{count}_n(i))} \cdot \frac{28823}{365 \cdot 12}.$$

For on-scene time as well as charging and maintenance time, we assume they take around 0.5 – 1.5 minutes each. For each accident, we assume that either time does not differ between the two periods during a day. We denote the time for each period as a, which is generated as a random number between 0.5-1.5 minutes.

We use the two-phase approach, a method introduced by [1] as the baseline to compare with in terms of different UAV station construction costs. In the following, we first describe the two-phase approach and then report the comparison results.

A. The two-phase approach

The two-phase approach first determines the location of each UAV station by a set-covering method, by which all of the demand nodes are covered by the smallest number of UAV stations. Secondly, by iteratively increasing the number of UAVs in each service zone until 99% of the accidents has an available service UAV on average, the number of UAVs staffed at each station is thus determined.

Given the maximum distance reachable for a UAV (i.e., maximal flight time of 30 minutes with maximum cruising speed of 70 km/h) and the geography data for the 959 zip-code areas and 99 airports in Indiana, we perform the set-covering step by solving the following optimization problem.

$$\begin{aligned}
\min \quad & \sum_{j \in J} y_j \\
\text{s.t.} \quad & \sum_{j \in J} x_{ij} = 1, \qquad \forall i \in I \\
& x_{ij} \cdot t_f(i,j) \leq 0.5, \qquad \forall i \in I, \quad \forall j \in J \\
& \sum_{i \in I} x_{ij} \leq y_j \cdot |I|, \qquad \forall j \in J \\
& x_{ij}, y_j \in \{0,1\}, \qquad \forall i \in I, j \in J
\end{aligned}$$

With the provided data, the set-covering step outputs five UAV locations. They are Skylane Airport, Shelbyville Municipal Airport, Hendricks County Airport-Gordon Graham Field, Smith Field Airport, and Porter County Regional Airport.

We determine the five service zones by assigning each of the 959 zip-code areas to the closest station among the five selected airport locations as above. For each service zone, we sum the day-time arrival rate and night-time arrival rate as its total arrival rate:

$$\lambda_j = \sum_{i \in I_j} (\lambda_d(i) + \lambda_n(i)).$$

We assume the mean service time for each service zone is the weighted service time (consisting of round flight time, on-scene time, as well as charging and maintenance time). The mean service time in service zone j is considered as

$$\mu_j = \sum_{i \in I_j} \frac{\texttt{count}_d(i) + \texttt{count}_n(i)}{\sum_{i \in I_j} \texttt{count}_d(i) + \texttt{count}_n(i)} \cdot 2 \cdot (a + t_f(i,j)).$$

By applying steady-state equations (Kleinrock 1975), we reach the UAV numbers staffed for each of the five airports: Skylane Airport would be staffed with 7 UAVs, Shelbyville Municipal Airport, 10, Hendricks County Airport-Gordon Graham Field, 9, Smith Field Airport 8, and Porter County Regional Airport 7. The mean waiting time for the network design based on the two-phase approach is 14.8 minutes.

Given the results from the two-phase approach, we compare its mean waiting time with that of the proposed method, under different UAV station construction cost: \$50,000, \$100,000, \$200,000. Mores specifically to make the comparison fair, we compute the total cost for the two-phase approach with each construction cost level, determine the corresponding budgets (i.e., B) for the proposed approach, and compare the mean waiting times and waiting-time distributions.

B. Comparison with different UAV launching station construction costs

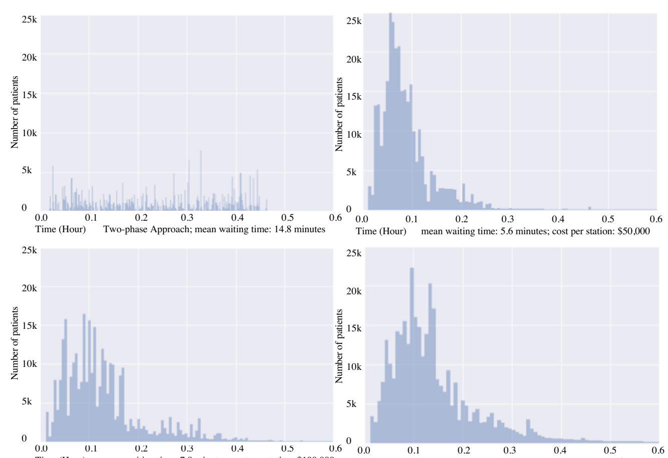
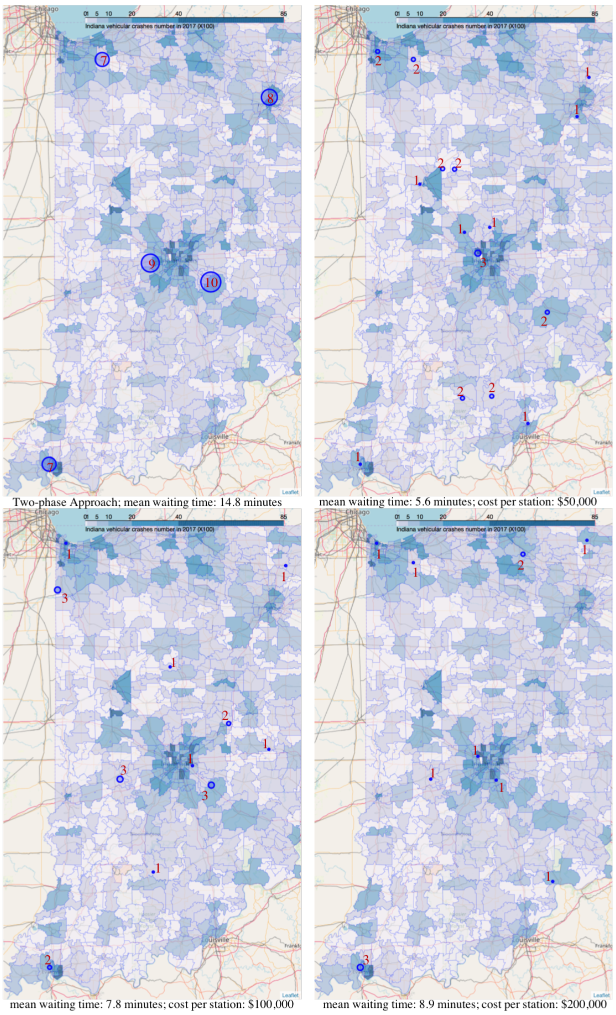


Fig. 2. Waiting time distribution comparison

From the results in Table I, we can see an increasing trend of the mean waiting time with increased UAV station construction cost. It is intuitive since the higher the station cost is, the less flexibility of UAV station numbers to choose from under a fixed amount of budget. From Figure 2, we find the waiting-time distribution is moved to the left as opposed to the one generated with the two-phase approach. This suggests reduced waiting time and thus improved emergency response. Further, based on the network designs presented in Figure 3, we see more scattered UAV station locations coupled with uniformly reduced number of UAVs at each station. Based on the comparisons, we conclude that our proposed method is superior to the existing ones.



Two-phase Approach; mean waiting time: 14.8 minutes

mean waiting time: 5.6 minutes; cost per station: $50,000

mean waiting time: 7.8 minutes; cost per station: $100,000

mean waiting time: 8.9 minutes; cost per station: $200,000

Fig. 3. Network design comparison

IV. Conclusions and Future Research

In this work, we formulate a location-allocation optimization model with mean waiting time as the objective. Our model incorporates more practical relevance by considering UAV cruise range, golden-hour-survival-time threshold, time-varying arrival rates at each demand node. We conduct a real-world case study based on the 2017 Indiana vehicular crash data. Our results verifies that our proposed approach is superior and more practical as opposed to existing approaches in the literature.

In the future, we plan to more realistically incorporate the flight-time simulation beyond of merely considering distance-based flight time. We will incorporate several aerodynamic parameters, and thus the uncertainty in the flight time will likely increase, which requires better design of a simulation-based discrete optimization method. We also plan to relax the Poisson arrival assumption. However, with increased computational complexity, we will seek meaningful approximations as the objective for the already computationally expensive location-allocation optimization model. Finally, we will consider multi-objective optimization to better trade-off the service of certain quality and the spending for maintaining such quality level.

Station cost Total budget	(Total UAV and station numbers) mean waiting time Two-phase approach	 The proposed method
$50K $1480K	5 stations, 41 UAVs 14.8 minutes	15 stations, 24 UAVs 5.6 minutes
$100K $1730K	5 stations, 41 UAVs 14.8 minutes	11 stations, 19 UAVs 7.8 minutes
$200K $2230K	5 stations, 41 UAVs 14.8 minutes	9 stations, 12 UAVs 8.9 minutes

TABLE I

Staffing and mean waiting time results comparison

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