Drone Location and Scheduling Problems in Disaster Relief Management

Pitu Mirchandani [a,*], Monica Gentili [b], Zabih Ghelichi [b]
[a] School of Computing and Augmented Intelligence, Arizona State University, AZ, USA
pitu@asu.edu (corresponding author)
[b] Department of Industrial Engineering, University of Louisville, KY, USA
monica.gentili@louisville.edu, zabih.ghelichi@louisville.edu

December 14, 2021

Keywords: Drone logistics, Location and Scheduling, Simulation Optimization, Stochastic Optimization

1. Introduction and Motivation

A growing number of natural disasters have struck several regions around the world in the recent years, mostly related to climate and weather-related events, e.g., flooding, wildfires, and storms. For instance, the United States has experienced more than 290 major natural disasters since 1980, where millions of lives have been affected, and the damages have exceeded trillions of dollars [1]. Right after a disaster strike, immediate emergency responses are crucial to deliver urgently needed aid packages, e.g., insulin shots and blood pressure medicine, to those trapped in inaccessible regions. In such situations, transportation networks are of great importance as they provide vital platforms for rescue teams to dispatch medical and relief aid packages. However, many severe disasters commonly damage supply lines and transportation infrastructures and render people stranded without access to some urgent necessities. When land transportation modes like automobiles, trucks and trains are inoperable, at least until the road surface infrastructures are re-established again, aid delivery can resort to above ground modes.

Unmanned Aerial Vehicles (UAVs), also referred to as drones, are remote controlled flying robots that can make immediate delivery of aid packages to many cut-off regions by overcoming many difficulties of the traditional surface and air delivery modes, e.g., trucks and helicopters, face. With not being restricted to established road networks, drones are capable of delivering urgently needed aid packages in a short time. The advantages of UAV utilization go beyond merely having access to remote and hard-to-access areas: no requirement of on-board pilots, no necessity of complicated and expensive launching infrastructure, and ability of serving multiple purposes. The unique potentials of drone systems recently attracted many attentions to the application of drones for the delivery of aid items in disaster-affected areas.

Motivated by the challenges associated with the timely delivery of aid items in disaster-affected areas, this research studies the problem of drone location and scheduling problem for the delivery of aid items in cut-off regions. In this research, we first propose two alternative location optimization problems to optimally locate drone launching platforms in the disaster affected areas. A platform is a structure that provides operational support for drones from which a drone starts and ends its trips and can recharge its batteries. The first problem formulates a deterministic model for the problem of locating drone platforms in the disaster affected areas. The second problem is a stochastic variant of the drone platform location problem that assumes the set of demand locations is unknown. In this study, we also propose a simulation-based evaluation model for the problem of drone-based delivery of aid items in humanitarian logistics. The goal is to develop a simulation system that can allow us to (1) evaluate alternative solutions obtained from the platform location problems, i.e., deterministic and stochastic, and (2) improve the solutions through a simulation-optimization procedure. The simulation model is designed to capture multiple sources of variabilities such as number of demands, intervals of demand realization, flight time of the drones, and battery failure.

2. Platform Location Problems

In this section, we propose two platform location optimization models where the first model assumes the set of demand locations is definite and known beforehand, i.e., deterministic model, while the second model considers the set of demand locations is subject to uncertainty.

2.1. Deterministic Model

Given a set of candidate drone platforms and a set of demand locations, the proposed model finds the number and location of drone launching facilities – referred to as platforms – schedules drone trips and determines the assignment between drone trips and demand points. In the proposed system, aid items, e.g., food, medications, and insulin shots, are loaded into a capsule held by a drone. Drones depart from their platforms for assigned demand points. Once a drone has reached its destination, it drops off its load and returns to its platform. We assume that the drone's operational range is constrained with a maximum coverage range. We assume drones' operational range is restricted by a maximum coverage range of drones. The main problem is to concurrently decide (1) where to locate the platforms, (2) which demand points must be served from each platform, and (3) the schedule and sequence of serving demand points, so that all packages are delivered within a given time period T (e.g., one day) and the total disutility is minimized. Associated with each demand point that occurs is a utility (disutility) value that decreases (increases) with the delivery time. To address this problem, we formulated a timeslot formulation which discretize the planning period T into identical timeslot with prespecified granularity [2].

2.2. Stochastic Model

In this section, we extend a stochastic model to address the problem of locating drone platform in disaster affected areas. The model seeks to attain timely delivery of aid packages to disaster-affected regions via a fleet of drones when the set of demand locations is unknown. While the deterministic model assumes all the demand locations are known beforehand, a major realistic challenge for this problem is the consideration that the set of demand locations is initially unknown. The main problem is to locate a set of drone platforms such that with a specified probability α (a percentile level), the maximum total disutility under all realizations of the set of demand locations is minimized, in other words the value of the α percentile of the disutility distribution is minimized. In this study, we use the term *combination* to refer to a set of drone platforms. Therefore, among all possible combinations of drone platforms, the goal is to select the combination whose disutility distribution has the minimum α percentile. In this problem situation, the set of demand points is subject to uncertainty, and the uncertainty set is comprised of a collection of scenarios. We develop a Chance Constrained Programming (CCP) formulation to find the (optimum) platform combination whose disutility distribution has the minimum α percentile. To obtain the disutility distribution, we adopted the aforementioned deterministic timeslot formulation which essentially schedules and sequences a set of trips for the given fleet of drones so that the disutility is minimized [2].

The proposed stochastic optimization formulation comprises multiple complexities and is computationally tedious. We propose a multi-stage algorithmic solution approach to efficiently address these complexities. The first stage applies a set of criteria to filter out a collection of the preferable candidates of platform combinations with a prespecified size. An example of such a criterion is *coverage extent* which measures the total number of demand locations that a combination of drone platforms can cover for a given maximum coverage range. The second stage derives disutility distributions for each set of candidate combination of platforms by solving a drone scheduling problem for each possible scenario of a set of demand locations. In this stage, we need to solve the scheduling model for every pair of platform combinations and scenarios. Owing to the large number of iterations and the NP-hard nature of the drone scheduling problem, we develop a heuristic greedy algorithm to mitigate the computation efforts for solving larger instances of the problem [3]. The last stage employs the properties of a Sample Average Approximation (SAA) method and CCP formulation to select the combination of platforms that produces the minimum α percentile [4].

3. Simulation-based Performance Evaluation Model

In this simulation-based performance evaluator, we assume a set of drone platforms have already been located from which the drone fleet must serve the unknown demand locations. This decisions for locating these drone platforms are obtained through solving the deterministic or stochastic location optimization models. After the disaster strikes, the rescue team receives new information within variable time intervals. This information includes *(i)* the number of new demands and *(ii)* their corresponding coordinates in the disaster-affected area. Upon receiving the information, a scheduling model finds an optimum schedule and assigns a set of ordered trips to each drone. Then, the simulation model simulates the drone flights considering the dynamics and variabilities of the real-world environment, such as variable travel time, service times, and battery failure. Then, after some random time interval such δ, a set of information, including the information about the new demands, previously received demands, and the current state of the drones in the system, will be fed to the system, and the scheduling model will update drone schedules. And the process will be continued and repeated until a stop condition, e.g., operational time, is met (see Figure 1). The proposed simulation model captures the variations in different system parameters including (1) *Interval of updating the system* after receiving new information, (2) *demand parameters*: the demand rate and their spatial distribution (locations), (3) *service time parameters*: travel times, setup and loading times, payload drop-off times and repair times, and (4) *drone energy level:* battery's energy is impacted and requires battery change/recharging while flying. We employ the simulation model to evaluate the performance of alternative solutions obtained from the platform location models and improve them through a simulation-optimization procedure.

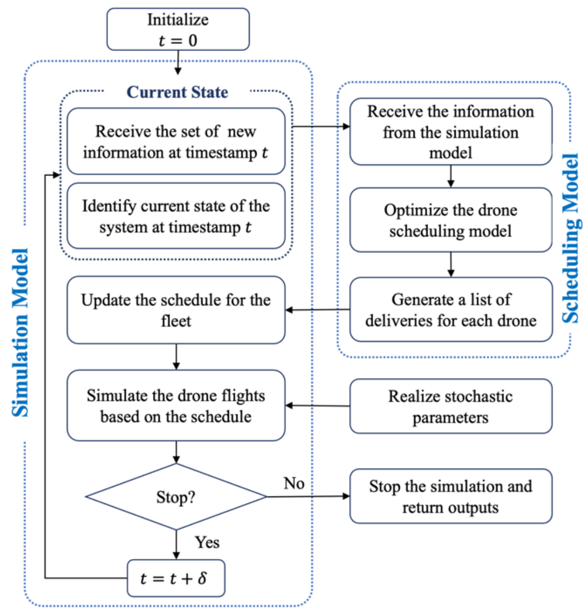

Figure 1. Simulation Model

4. Simulation-Optimization Procedure

In this section, we employ the proposed simulation model to improve the solutions obtained from the platform location optimization models through a simulation-optimization procedure. The procedure starts with finding an optimum solution to the platform location problems. Let λ_m^* the set of optimum platform locations when m drone platforms are selected in a platform location model, e.g., deterministic model. Now, we perform a set of analytical studies by evaluating the k-opt neighbors to λ_m^*. A k-opt neighbor to the optimum solution with m platforms is a list of m locations which differs from λ_m^* in k elements. By

λ_m^i, we denote the i^{th} neighbor in k-opt neighborhood of λ_m^*. Once we have explored the neighborhood to λ_m^* and identified a set of neighbors, we run the simulation model for λ_m^* and all the identified neighbors λ_m^i. Given a set of performance criteria, e.g., waiting time per demand and percentage of served demands, if there exists an alternative solution, i.e., neighbors, such λ_m^j which can outperform the optimum solution λ_m^* in terms of all the performance criteria, then we can substitute the optimum solution λ_m^* with λ_m^j and repeat the procedure. If there are multiple such solutions that outperform λ_m^* , we can choose one of the randomly or optimize a weighted summation of measures.

Simulation-Optimization procedure	
1.	Solve the platform location problem by using an optimization model
2.	Find the optimum set of platforms λ_m^*
3.	Explore the k-opt neighborhood of λ_m^*
4.	Run the proposed simulation model for λ_m^* and its neighbors λ_m^i
5.	Evaluate the performance of each solution based on a set of measures
6.	Identify neighbors λ_m^j that outperforms λ_m^* in terms of all measure (if there exists any)
7.	$\lambda_m^* = \lambda_m^j$
8.	Repeat steps 2 to 6 until stop.

5. Preliminary Results

Considering a case study of central Florida discussed in Gentili et al. [2] with 25 candidate drone platform and 100 demand locations, we solved the platform location problem by using the proposed deterministic and stochastic models where the set of optimum locations with m drone platfroms are denote by λ_m^* (deterministic) and γ_m^* (stochastic), respectively. We first employed the simulation model to evaluate the performance of the alternative solutions λ_m^* and γ_m^* for differnet range of demand values. We observed that when a large number of demands appear in the realization, the solution of the deterministic model outperforms the stochastic one. On the other hand, we can observe that the only case where the solution from the stochastic model outperforms the deterministic models is when there are a small number of platforms to locate, i.e., $m = 8$, and a small number of potential demand locations. In another set of experiments, we used the proposed simulation-optimization procudere as to improve the obtained solutions from the deterministic and stochastic models. We observed that a simple 1-opt neighborhood search could improve the obtained results in all aspects. For example, for the deterministic model when $m = 8$, we could identify 4 nieghbor that outpeforms the optimum solution λ_8^*. We also observed that with lower number of available platforms, i.e., $m = 8$, the difference between the optimum solution and its better neighbors is more significant. However, as the number of platforms increases, this difference becomes smaller.

6. References

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