Optimization of Drone and Truck Operations for Socially Optimal Disaster Relief Distribution

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1 INTRODUCTION

Over the past 30 years, the number of registered extreme weather events has steadily increased. In the United States, during the 1990s, there were 57 natural disasters that resulted in a total cost of \$334.1 billion. In the 2000s, this number rose to 67 disasters, with associated costs amounting to \$619.6 billion. In the 2010s, when the number of disasters nearly doubled to 131, leading to total costs of \$993.4 billion. In the past five years (2019-2023), 102 disasters have had associated costs totaling \$617.5 billion (Smith, 2020).

Traditional humanitarian logistics methods often face significant limitations in disaster-stricken areas, where infrastructure may be damaged or entirely inaccessible. In this context, the deployment of drone technology emerges as a promising advancement. Drones offer unique advantages in disaster response scenarios, including the ability to navigate difficult terrains, bypass damaged infrastructure, eliminate the risk of injuries in emergency vehicle crashes, and deliver supplies directly to isolated or hard-to-reach areas. Their use can significantly reduce the time required to deliver essential goods, thereby mitigating the immediate impacts of deprivation and aiding in quicker stabilization of affected communities.

Drone and truck hybrid operations are currently in the early research phase. The main reason for this is the advancement in drone technology over the past decade. Previously, drones were unsuitable for distributing relief supplies due to their limited battery life and load capacity. Initially, logistics companies studied drones for delivery purposes, focusing primarily on reducing logistics costs without considering the suffering of survivors in need.

A total of 37 articles published between 2016 and 2024 have been analyzed regarding the use of drones for distributing relief supplies in humanitarian logistics. Most of these articles concentrated on optimizing time or logistics costs as their objective function, while only 13% focused on social costs (i.e., accounting for both logistics and suffering costs). Additionally, only 19% of the studies examined scenarios where drones and trucks worked in synchronization. In terms of decision variables, 30% of the articles addressed resource allocation, vehicle routing, and facility location decisions.

The central research question of this study is how effectively a hybrid truck and drone system can reduce the social costs associated with distributing relief supplies after a natural disaster, and under what operational conditions this is possible. To address this question, the research introduces an optimization problem focused on the distribution of relief supplies, minimizing social costs, accounting for drones and truck synchronized operations, and simultaneously deciding the resource allocation, vehicle routing, and facility location.

2 METHODOLOGY

The proposed formulation considers an area, urban or suburban, where a sudden onset extreme disaster has stricken. Figure 1 depicts the problem conceptualization. The area has a set of distribution centers (DCs) which, right after the disaster, have available relief supplies, drones and trucks. There are groups of beneficiaries, referred to as populations, whose size (number of survivors within each population) and initial location are known. Survivors able to walk will do it inside the disaster area, seeking relief supplies. These supplies will be available to the populations at the points of distribution (PODs), and the walking inhabitants will walk towards their preferred one.

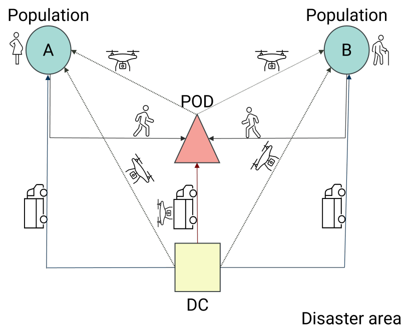


Figure 1 – *Graphic problem description.*

The formulation considers that each population can have some of their survivors stay in their initial location and not walk to any POD. Regardless of the cause, it cannot be expected that all the individuals from a population can walk to the PODs (Pérez-Guzmán, 2022). Therefore, if there are survivors staying back at their initial locations, then the aid must be delivered to them. Each POD or population is served point-to-point. There is a distribution system in place that will deliver the relief supplies from the DCs to PODs and the population. The vehicles that do the first delivery can only depart after the disaster has occurred.

Two types of survivors are considered. Populations split into two "mobility" groups: the individuals who stay and the individuals who walk. The percent for the split is known. The survivors who walk cannot stay in their initial location to receive the aid there. They will always choose to walk. The walking survivors can only receive relief supplies in the PODs. All the survivors of the same population will walk to the same POD, the population's preferred POD.

The proposed formulation is a facility location and vehicle routing problem with drones and social costs. It is defined in a graph $G = (N, A)$. N is the node set, containing the depot nodes (DCs), the destination nodes that represent the populations (L), and the points of distribution (PODs). $A = \{(i, j)|i, j \in N, i \neq j\}$ is the arc set. A set of trucks K, a set of drones D, and the available relief supplies are initially located at the DCs. The PODs serve as docking hubs, i. e. as a transfer station for drones, since it has turned out to be a preferable way in the drone delivery industry (Wang & Sheu, 2019).

A drone can be loaded with up to L^D weight units of customer parcels. Trucks are considered to have infinite carrying capacity, as it is a common assumption in humanitarian logistics (Chung *et al.*, 2020). The maximum flying duration of a drone is T^D, according to the specifications of the DJI FlyCart 30 drone (DJI, 2024). A population or POD can be served by more than one vehicle. To serve populations or PODs, all vehicles need to start from the DCs, noting that a drone can be carried by a truck to a POD, and then fly independently to a population. If a population or POD is within the flying range of a drone, the drone can serve it independently. It is assumed that there are enough drones and trucks in the DC (a common assumption in disaster relief literature (Chung *et al.*, 2020)). The time of swapping the battery and the time of loading a drone are assumed to be zero, as they do not have a significant impact on the total cost. Trucks are modeled to follow Manhattan trajectories, as they have to use the available roads to reach their destination, whereas drones follow Euclidean trajectories. The populations are considered destinations, so vehicles cannot travel from one population to another.

The objective is to minimize the social cost that consists of the summations of logistic and suffering costs. The logistic costs include the transportation cost of trucks and drones. The suffering costs include the deprivation costs (Holguín-Veras *et al.*, 2013) and the walking costs. Only one delivery is considered. Therefore, the deprivation cost function considers the time it takes for the last mobility group of each population to receive the relief supplies.

2.1 Problem Formulation

The described problem leads to a complex optimization model consisting of 10 sets, 24 parameter types, 23 variable types with up to four indexes, and 50 constraint sets. The social costs objective function is defined as

$$\min \quad Z_{fix} + Z_{var} + Z_{depr} + Z_{walk} \tag{1}$$

where Z_{fix} and Z_{var} denote the logistic and Z_{depr} and Z_{walk} the suffering costs, determined by:

$$Z_{fix} \geq C^P \left|P\right| + C_D^P P_D \tag{2}$$

$$Z_{var} \geq C^T \sum_{(i,j)\in A} \sum_{k\in K} t_{ij}^T \left(x_{ijk} + u_{ijk}\right) + C^D \sum_{(i,j)\in A} \sum_{d\in D} t_{ij}^D y_{ijd} \tag{3}$$

$$Z_{depr} \geq \sum_{l\in L} \Gamma_l \tag{4}$$

$$Z_{walk} \geq \sum_{l\in L} P_{l,o} v_l g_l r_l, \quad \forall o = 2 \tag{5}$$

Constraint 2 represents the cost of opening and operating the PODs. C^P is the fixed cost of opening a POD, $|P|$ refers to the number of opened PODs, C_D^P is a parameter that quantifies the additional cost incurred when a drone operates in a POD, and P_D represents the number of PODs visited by drones. Constraint 3 denotes the transportation costs for both trucks and drones. The parameters C^T and C^D define the value of time for trucks and drones, respectively. The variables t_{ij}^T and t_{ij}^D account for the travel times for each arc for trucks and drones. x_{ijk} is a binary variable representing if the truck k is traveling independently through the arc (i, j), u_{ijk} represents if the truck is traveling through the arc carrying drones, and y_{ijd} represents if a drone is flying independently through the arc. Constraint 4 denotes the deprivation costs of the populations. It is based on the deprivation cost function defined in equation 6.

$$\gamma(\cdot) \to \mathbb{R}^+, \gamma_{l,o}(\delta_{l,o}) = \beta_{l,o}^1 e^{\beta_{l,o}^2 \delta_{l,o}} \tag{6}$$

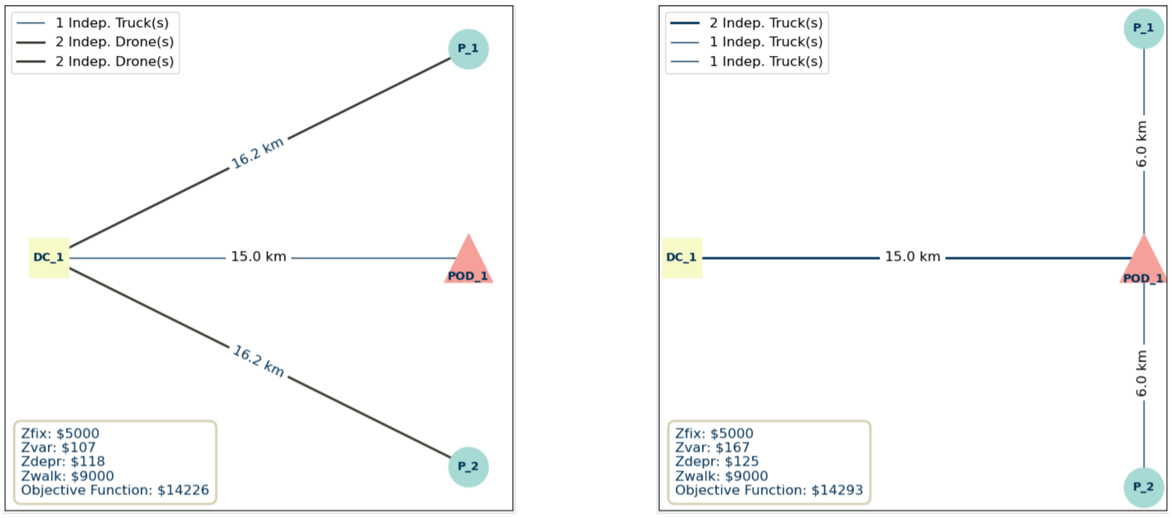
$\beta_{l,o}^1$ and $\beta_{l,o}^1$ are parameters that reflect the vulnerability of each population and mobility group, whereas $\delta_{l,o}$ refers to the deprivation time of population l. Once the deprivation cost is computed for each individual, equation 7 aggregates it to the entire population with size $P_{l,o}$.

$$\Gamma(\cdot) \to \mathbb{R}^+, \Gamma_l = \sum_{o\in O} P_{l,o} \gamma_{l,o}(\delta_{l,o}) \tag{7}$$

Constraint 5, defines the walking costs. The variable r_l accounts for the walking time of the population until the last survivor reaches the chosen POD. The parameter g_l represents the walking cost per unit of distance and v_l the walking speed of the survivors in population l.

3 RESULTS

Numerical experiments were implemented in Python and solved with Gurobi API and the Gurobi 11.0.1 solver. The objectives of the experiments are to test the ability of the formulation to produce sensible results and assess the effects of changes in the characteristics of the problem. The experiments performed included (1) comparing a hybrid fleet of trucks and drones with a truck-only fleet, (2) varying the distance between the DC and populations, (3) varying the cost of installing PODs visited by drones, (4) varying the cost of walking, and (5), varying the number of survivors in the populations. The base problem consists of 200 survivors per population, two populations 15 kilometers apart, and the relief supplies received by the survivors are 2 liters of water. Figure 2 shows the result of the experiment of comparing a hybrid fleet of trucks and drones with a truck-only fleet.



(a) *Hybrid Model.* (b) *Truck-Only Model.*

Figure 2 – *Comparison between the hybrid model and model without drones.*

In the hybrid case (shown in Figure 2a), the results obtained included four drones flying independently from the DC, with two of them flying to each one of the two populations to deliver to the staying survivors. One truck travels independently to the POD to supply walking survivors. The POD is located in the middle point of the segment formed by the two populations. In the trucks-only case (shown in Figure 2b), two trucks travel from the DC to the POD, delivering relief supplies for the walking survivors. Each one of them then departs to each of the populations to provide the staying survivors with the supplies. As a result, the variable costs increase by 57% in the truck-only case, going from $107 to $167, as the trucks have a transportation cost due to lower speeds and longer distances. Deprivation costs increase too, from $118 to $125, as the trucks take more time to provide the staying survivors with relief supplies.

4 DISCUSSION

As proven by the increased number of extreme weather events happening during the last years and the issues that traditional response logistics present, including not considering survivors' movement and road accessibility, there is a need for humanitarian applications of drones. Throughout a series of numerical experiments, this research shows the conditions and various scenarios under which a hybrid truck and drone model can minimize social costs. Additional findings include that drones and trucks complement each other. While trucks lead to higher costs they are necessary due to their carrying capacity and ability to travel long distances, and drones decrease social costs when the distance and carrying necessities are suitable for them.

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