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A drone fleet model for last-mile distribution in disaster relief operations

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ABSTRACT

Humanitarian assistance operates under conditions characterized by the collapse of health facilities, the disruption of health systems and the breakdown of already on-going treatments in case of emergency. In addition to these circumstances, aid agencies in developing countries are often confronted with poor or non-existent infrastructure that is further disrupted in case of disasters, i.e., destroyed roads and debris-covered areas which hinder medical teams in reaching remote locations. As the supply via trucks and helicopters is not applicable in this situation, alternative means of transport have to be considered. Unmanned aerial vehicles (UAVs) are receiving increased attention by humanitarian organizations as they can help overcoming last-mile distribution problems, i.e., inaccessibility to cut-off regions. This paper considers drone applications in last-mile distribution in humanitarian logistics and presents an optimization model for the delivery of multiple packages of light-weight relief items (e.g. vaccine, water purification tablets, etc.) via drones to a certain number of remote locations within a disaster prone area. The objective of the model is to minimize the total travelling distance (or time/cost) of the drone under payload and energy constraints while recharging stations are installed to allow the extension of the operating distance of the drone. The implementation of different priority policies is discussed. The model is solved as a mixed integer linear program and illustrated numerically with different scenarios.

1. Introduction

In recent years a rising number of natural and man-made disasters have hit several regions all over the world, causing thousands of victims and long-term damage to disaster-prone locations [5]. In order to maintain live-saving operations and to cover basic needs of the suffering population it is essential to plan, implement and control an efficient flow of relief goods and information into the affected areas [20]. Humanitarian logistics, as the technical term for this process, includes the procurement, transport and warehousing of relief goods from the point of origin to the beneficiaries' location.

A number of observed disasters in recent years such as the Haitian earthquake 2011, the tsunami in the Indian Ocean 2004, flooding in India in 2013 or the Horn of Africa crisis 2011, indicate that mostly developing countries are vulnerable to natural disasters [7]. There are hundreds of more crisis that do not attract as much attention but have equally devastating impact. Urbanization, global population growth and land-shortage in developing countries increase the amount of people living in disaster-prone areas leading to even higher numbers of victims when disasters strike [9].

The impediments of humanitarian assistance in developing countries are intensified by the collapse of health facilities, the disruption of health systems and the breakdown of already on-going treatments in case of emergency. Contaminated water and poor sanitation conditions combined with low vaccination coverage often leads to water-, air- and vector borne diseases, such as diarrheal diseases, acute respiratory infections, malaria, leptospirosis, measles, dengue fever, viral hepatitis, typhoid fever, meningitis, as well as tetanus and cutaneous mucormycosis [22]. In such situations, quick response and rapid distribution of vital relief items, such as ready-to-use therapeutic food (RTUF) packages, water purification tablets, medical kits and vaccine into the affected regions could save lives and prevent or slow the spread of epidemics.

Massive problems and challenges of relief items distribution in developing countries are also associated to means of transport and transportation infrastructure. NGOs' vehicle resources in developing countries are quite limited and costly due to rising fuel consumption, maintenance and insurance. Development and emergency missions are generally conducted by aged truck fleets because of delayed vehicle replacement beyond the recommended time frame. An obsolete and poor conditioned vehicle fleet restricts loading capacities, thus leading to transport of light-weight items only. Land based motorized transport by humanitarian organizations is often limited to Sport utility vehicles (SUVs) and small trucks, because larger means of transport are not applicable under such conditions [1]. The major problem resulting from poor means of transport is the insufficient supply to rural areas because

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mid- and long distances cannot be overcome and product markets are not reachable for humanitarian organizations [18]. In addition to these conditions, aid agencies are often confronted with poor or inexistant infrastructure. Road surface quality in developing countries is further characterized by low percentages of paved roads and narrow road widths. Geographical characteristics, e.g. geographically dispersed islands or adverse terrain, represent additional impediments to the already challenging situation [17]. In the event of a disaster, the already poor conditions are further disrupted, as roads are flooded or blocked, small bridges are collapsed and land sections are covered with debris [15]. Under these conditions roads are impassable and many locations are completely unreachable by land based transportation means. Subsequently, last-mile distribution of relief items proves to be extremely difficult by means of traditional transport systems. Air cargo via helicopters is often also not applicable due to the lack of trained pilots as well as helicopters and land-based personnel in the disaster region. Bringing such human and material resources from outside to disaster locations is costly and often takes too much time when time pressure to provide aid is extremely high. Consequently, the call for developing alternative means of transport and the integration of innovative technologies in last-mile distribution is given. Practitioners as well as scientific communities state that there has to be more governmental support to design, develop and analyze methods, systems and innovations for potential applications in disaster response. Advanced technologies that are already in use within the commercial context have to be tested for their applicability in humanitarian logistics [26]. In this regard, unmanned aerial vehicles (UAVs), commonly referred to as drones, can provide solutions to the problems associated to current last-mile ground transportation. They seem to offer the potentials to save time and costs compared to traditional means of transport and make relief items supply to cut-off regions possible in the first place [31].

Drones are autonomous or teleoperated flying machines that do not require constant user control [12]. Drone applications have mainly been considered in the commercial supply chain context, focusing on the applications in cargo delivery, mapping, target covering and surveillance (see,e.g. [11,8,28,30,25]). In this respect, optimization models consider drones in combination with other means of transport. Numerous large companies, such as Amazon, DHL or Google [11,25] already show interest in drone applications for parcel delivery in urban areas.

Currently available cargo drones include fixed-wing, rotor and hybrid models, each of them with different specifications, capacities and drop-off systems. State of the art drones can deliver products with a maximum payload between 0.5 kg and 2.5 kg [14]. Conventional drones use batteries to operate their engines and need to be recharged after they run out of power. Recharging stations can be installed within existing infrastructure in advance to a disaster or can immediately be deployed in the response phase using mobile base stations, e.g. trucks or SUVs. This strategy has been tested by the Austrian Red Cross in cooperation with Land Rover in a project called “Hero”. Here, a Land Rover Discovery is used as a commando vehicle for drones, where take-off, landing and recharging during an ongoing operation is possible. Energy–aware drone routing problems are considered in [8,11,28] where the energy consumption of the drone is assumed to depend on one or more of the flight related parameters; payload, speed, distance and altitude. A drone routing model that integrates recharge stations in the context of surveillance is presented in [30].

Recently, the humanitarian community also became aware of the benefits of drone usage, as they can support emergency operations along the entire disaster management cycle, i.e. mitigation, preparedness, response and recovery stages [21]. Drones in humanitarian logistics can assist in emergency response mapping, damage assessment, cargo delivery and search and rescue (SAR) missions during the preparedness and immediate response phases [6]. Fire detection, imagery collection, monitoring and path planning also are among the most common drone applications to date (see, e.g. [16,23,10,3,8]). In the context of last-mile distribution, they offer great potentials to overcome the problem of inaccessibility to remote locations for providing basic emergency items to beneficiaries. In these situations drones offer the advantages to traverse heavy terrain, blocked streets, destroyed bridges

Table 1
Overview about scenario settings.

Scenario	*M* (in packages)	*E* (in kJ)
1	8	200
2	4	200
3	8	100
4	8	60

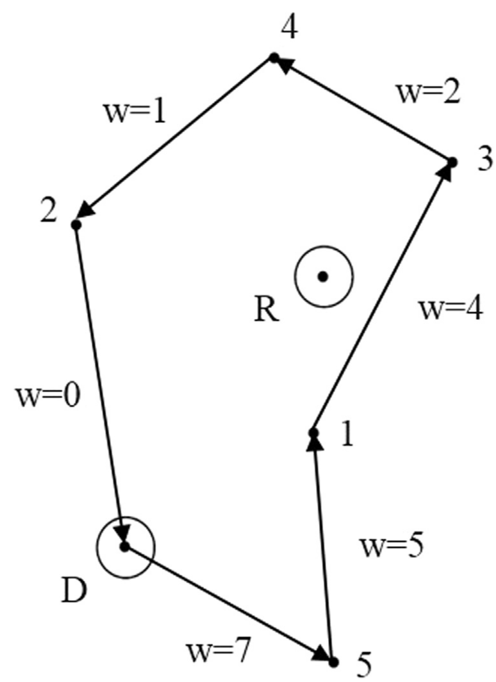

Fig. 1. Scenario 1.

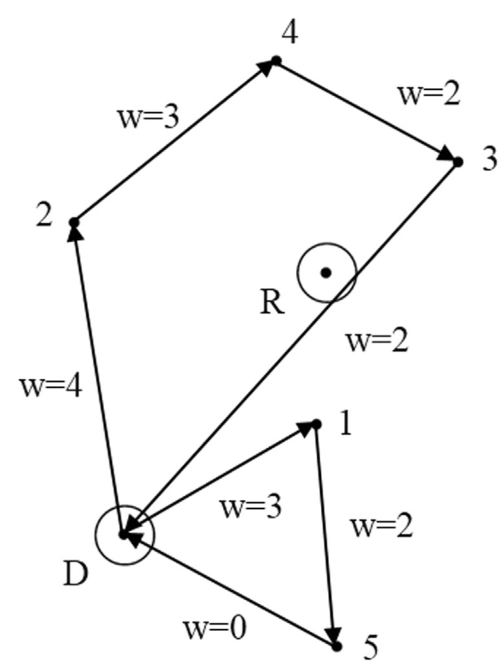

Fig. 2. Scenario 2.

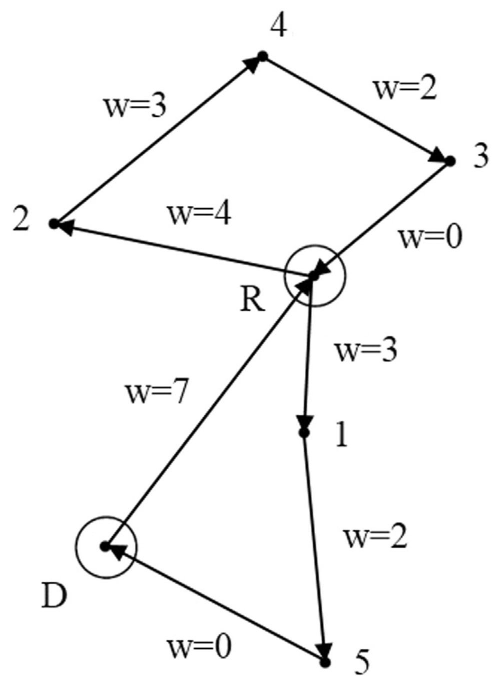

Fig. 3. Scenario 3.

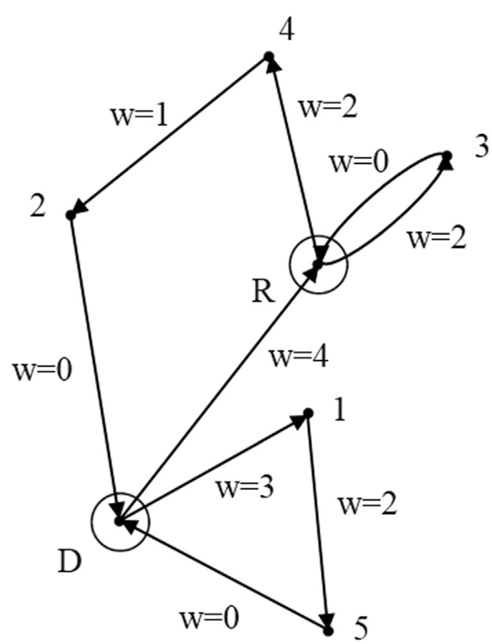

Fig. 4. Scenario 4.

and flooded infrastructure in disaster scenarios. The advantages of drone supply of life-saving commodities such as blood products, vaccine or pharmaceutical products, to critical access hospitals [27,13] have been tested in multiple field projects. A number of humanitarian organizations are currently testing the potential of drones to deliver essential humanitarian supplies to persons in difficult-to-access areas [2]. In Papua New Guinea, tuberculosis infected people that were cut off the outside world due to heavy rainfalls were supplied with medical treatment by means of UAVs [19].

Few papers have been published focusing on drone delivery in emergency situations, mainly concentrating on the combination of drones and alternative means of transport. Such models are proposed by Mosterman et al. [24], Scott and Scott [29] and Chowdhury et al. [4] where most of the proposed models are formulated as mixed integer linear programs (MILP) with the objective to minimize the overall mission time, cost, distance or the number of used UAVs. The potentials of UAVs in supplying remote locations in developing countries and their positive impact on relief chain performance remain therefore, relatively unexplored. In order to shed more light on this emerging topic, this paper aims at developing a mathematical model for the optimization of drone delivery in last-mile distribution of emergency items considering technical specifications of drones and disaster specific circumstances. In particular, the proposed model considers the drone energy consumption as a function of payload and flight mode and takes disaster specific circumstances into consideration. The model considers the possibility for drones to stop at recharging stations in mission for recharging the battery which makes travelling back to the base station for the recharging unnecessary and extends the operation distance of the drone. Considering these details in the optimization model enables us to generate realistic solutions, thus bringing value to existing literature on drone delivery in humanitarian logistics.

The rest of the paper is organized as follows. First, we introduce notations along with the assumptions and build our optimization model for drone delivery. Then, we present numerical examples to illustrate the use of the model and show the effect of payload and energy constraints on the optimal solution of the problem. A short discussion and outlook to future research conclude the paper.

2. Methodology and model formulation

Deriving from the previous discussed last–mile distribution challenges in developing countries, we consider the problem of supplying multiple packages of light–weight relief items to remote locations using a single or a fleet of drones (UAVs) with identical characteristics. The drones depart form a unique base station (depot) with a fully charged battery and may stop for recharging at additional available recharge stations if necessary. The relief packages are only available at the depot. Each drone can carry a maximum number M of relief packages while E is the maximum amount of energy supplied by a fully charged battery.

We now define the remaining sets, variables and constants and build our mathematical model.

2.1. Sets

In our model we distinguish three different sets of geographical locations. The first one is D which represents the depot. As we assume that drones are initially located at a single base station, D is a singleton set. Demand locations are included in set P which is further partitioned into priority subsets according to a given number of priority levels (say, 3 levels). Therefore, P_1 represents the set of the highest priority demand locations, P_2 the set of middle priority and P_3 the set of the lowest priority locations. Finally, recharge stations are represented in set R. Let $V = D \cup P \cup R$ be the set of all locations in the system.

We can construct a graph where the nodes are the elements of V and the arcs represent the possible moves. When it is possible for a drone to move from any location to any other location, the graph is complete.

2.2. Variables

For setting up the objective function and model constraints we are in need of defining three different variables. The first variable x_{ij} is used to describe the number of times the drone moves from location i to location j. The level of energy in the battery when the drone is about to leave location i to j is represented by e_{ij}. We use w_{ij} to denote the number of packages carried by the drone when it leaves location i to j.

2.3. Constants

We assume that demand is only present at locations P and not at the depot D and recharging stations R. Let d_i be the demand at location i,

$i \in P_1 \cup P_2 \cup P_3$. We assume that demand at each location $i \in P$ does not exceed the maximum payload of a drone ($d_i \leq M, \forall\, i \in P$). The energy function (Eq. (1)) describes the amount of energy used by the drone to move from location i to j with payload w_{ij}. We denote this amount by $R_{ij}(w)$ and calculate it as follows:

$$R_{ij}(w) = \gamma_0 + \gamma w_{ij} + \delta_{ij}(\rho_0 + \rho w_{ij}), \tag{1}$$

where,

γ_0	Energy needed for takeoff and landing for an empty drone.
γ	Additional energy amount needed for takeoff and landing with an additional package.
ρ_0	Energy to fly one distance unit for an empty drone.
ρ	Additional energy amount needed to fly one distance unit with one package.
δ_{ij}	Distance between locations i and j, $i, j \in V$.

2.4. Objective

The objective of the model is to minimize a cost function f which may represent the total travelling distance, total travelling time or total travelling costs (financial) of the drone(s):

$$min\, f_\alpha(x, w, e). \tag{2}$$

where α is a vector of coefficients of the cost function elements. To simplify, we assume that f is a linear function with respect to the variables x, w and e. An objective function is given in the linear form:

$$min \sum_{i,j \in V} \alpha_{ij} x_{ij}, \tag{3}$$

where α_{ij}, $ij \in V$ are coefficients that express the cost (e.g. financial, time, distance, energy) of drone moving between each couple of locations. For instance, to minimize the total distance traveled by the drone we would take the following:

$$\alpha_{ij} = \delta_{ij}. \tag{4}$$

2.5. Constraints

2.5.1. Degree constraints

We assume that each demand location in P is visited exactly once by only one drone (Eq. (5)).

$$\sum_{i \in V/\{j\}} x_{ij} = 1,\ j \in P. \tag{5}$$

A drone can visit recharging stations and depots as many times as necessary, i.e. when the drone battery is empty or for loading of relief items. However, in–degree must be equal to out–degree for all nodes (Eq. (6)).

$$\sum_{i \in V/\{j\}} x_{ij} = \sum_{i \in V/\{j\}} x_{ji},\ j \in V. \tag{6}$$

At least one drone is used for supplying relief packages to locations in P. Therefore the number of drone moves x_{ij} between the depot D and demand locations P or recharging stations R has to be greater than 0. We put,

$$\sum_{j \in V/D} x_{ij} > 0,\ i \in D. \tag{7}$$

2.5.2. Demand constraints

For energy saving purposes, the drone does not need to carry the maximum payload at each route. We impose that the drone returns empty to the depot (Eq. (8)) and calculate backwards the required number of items for each location. If the drone moves from i to j, then the difference between the payload (at arrival then departure) is equal to the demand at location i (Eq. (9)) except for recharge stations (Eq. (10)). Obviously, the payload on any route cannot exceed the maximum payload of the drone (Eq. (11)).

$$\sum_j w_{ji} = 0,\ i \in D, \tag{8}$$

$$\sum_j w_{ji} - \sum_j w_{ij} = d_i,\ \ i \in P, \tag{9}$$

$$\sum_j w_{ji} - \sum_j w_{ij} = 0,\ \ i \in R, \tag{10}$$

$$w_{ij} \leq M x_{ij},\ \ i, j \in V. \tag{11}$$

2.5.3. Energy constraints

We assume that the drone battery is always fully charged when the drone leaves the depot or a recharging station to another location (Eq. (12)). Obviously, the level of energy in the battery is always lower or equal to the maximum energy level E (Eq. (13)). Eq. (14) gives the energy balance, i.e., amount of energy consumed to move from any location to location i in P. The energy level in the battery when the drone is about to leave location i must be sufficient to reach its next destination (Eq. (15)).

$$e_{ij} = E x_{ij},\ \ i \in D \cup R, j \in V/\{i\}, \tag{12}$$

$$e_{ij} \leq E x_{ij},\ \ i \in P, j \in V/\{i\}, \tag{13}$$

$$\sum_{j \in V/\{i\}} e_{ji} - \sum_{j \in V/\{i\}} e_{ij} = \sum_{j \in V/\{i\}} (\gamma_0 x_{ji} + \gamma w_{ji} + \delta_{ji}(\rho_0 x_{ji} + \rho w_{ji})),\ \ i \in P, \tag{14}$$

$$e_{ij} \geq \gamma_0 x_{ij} + \gamma w_{ij} + \delta_{ij}(\rho_0 x_{ij} + \rho w_{ij}),\ \ i \in V,\ \ j \in V/\{i\}. \tag{15}$$

2.5.4. Priority constraints

Priority in the context of humanitarian logistics plays an important role, as emergency locations in the field can be differently impacted by a disaster. In this regard, it is important to prioritize certain locations and to provide aid to the people that are in highest need first. For instance, in the case of the outbreak of a waterborne epidemics, fast and targeted intervention is required in order to save lives and limit or slow the spread of the disease. Hence, outbreak locations are served with the highest priority level while any other areas connected via watercourse to the infected locations must receive high attention (priority level 2). The remaining locations are considered at priority level 3. Obviously, it is possible to define more or less than 3 priority levels.

There are different approaches to define priority classes and to set priority rules in the optimization model depending on the real situation. We distinguish the following priority rules:

2.5.4.1. Relative priority. Lower priority locations can be served in the same route with higher priority locations if this is optimal. A simple procedure to execute the solution of the above optimization problem according to this priority rule is as follows:

(1) All routes containing nodes with high priority (P_1) are executed first.
(2) Routes containing nodes with medium priority (P_2) are executed next.
(3) The remaining routes containing only low priority locations (P_3) are executed last.

In this way, routes containing the highest priority locations may also contain nodes with lower priorities but the value of objective function is not changed. It is also possible to implement relative priority rules using time windows by imposing narrow time windows for the highest priority nodes and wider or no time windows for the lowest priority locations.

2.5.4.2. Absolute priority. Following the absolute priority rule, locations with higher priority must be served before any other locations. A strict implementation of this rule is achieved by decomposing the problem according to the number of priority classes, i.e., we solve the problem with only nodes of the same priority level in P each time. Therefore, we attach an extra index $k \in \{1, 2, 3\}$ to the variables x, w and e representing the priority level and add the constraint:

$$\sum_{j \in V/\{i\}} x_{ijk} = 0, \;\; i \in P/P_k, \; k \in \{1, 2, 3\}. \tag{16}$$

The drone has to return to the depot after serving all locations with high priority even if extra capacity is left.

3. Numerical examples

In this section, we provide numerical examples to illustrate the use of our optimization model. They are solved on a personal computer with a 3.3 GHz CPU and a 4.00 GB memory space. The optimization engine used to solve the MILP is GAMS (General Algebraic Modeling System). In all of the examples, there is 1 depot, 1 recharging station and 5 demand locations. Demand at these locations is characterized as follows: at location 1 the demand is 1 package, at location 2 the demand is also 1 package, at location 3 the demand is 2 packages, at location 4 the demand is 1 package and at location 5 the demand is 2 packages. Initially, the drone is located at the depot as a starting point for the delivery process. In total, we computed 4 different scenarios, with varying payload capacity M and maximum energy level E of the drone (Table 1). For transporting relief packages we assume a conventional rotor-drone. The objective in all 4 scenarios is to minimize the total distance traveled by the drone. Thus we can set the objective function to:

$$min \sum_{i,j \in V} \delta_{ij} x_{ij}. \tag{17}$$

Since the model is convex, we can guarantee global optima. In the following we discuss the result of each scenario in order to generate more insights into the optimization model.

In Scenario 1, the optimal solution (Fig. 1) consists of only one route. Indeed, the maximum payload of the drone is greater than the total demand of all the locations and the energy supplied by the battery is enough for the drone to carry out the mission without needing to recharge.

In Scenario 2, we assume that the maximum payload of the drone is $M = 4$. Consequently, two routes are necessary to supply all the locations (Fig. 2). Recharging the battery remains unnecessary.

In scenario 3, we use a drone with a maximum payload of 8 packages but a restricted battery level. According to the optimal solution, the drone departs from the depot with sufficient payload to serve all the demand locations (Fig. 3). The operating distance of the drone is extended by the recharging station. The drone stops to recharge the battery and continues the mission to serve remote locations.

Finally, we assume in Scenario 4 that the used drone has a maximum payload of 8 packages and an even lower battery capacity (Fig. 4). The drone needs to recharge its battery three time (once at the depot, and twice at the recharge station). As shown in this example, it is sometimes optimal to return to the depot for recharging.

The above examples show how the energy consumption function of the drone can affect the optimal solution of the proposed routing problem. Additionally, the implementation of the recharge stations can influence the feasibility of the problem, i.e., some locations may be very far apart that it is not possible to serve them directly from the depot.

4. Concluding remarks

Relief items distribution to remote locations in disaster affected areas poses several challenges for humanitarian organizations, especially in developing countries, where the infrastructure is non-existant or, at best, poor in normal situations and is disrupted when disasters strike. Drone technology for emergency items delivery solves the problem of inaccessibility to cut-off regions where land-based transportation and air cargo is not applicable anymore. However, the current drone technology has several limitations such as limited payload and operations range due to energy constraints.

This paper explores the application of drones for last-mile distribution of relief packages in the immediate response to disasters. We proposed a mathematical model to optimize the delivery process under realistic constraints. It takes into consideration the limitations of the drone in terms of energy and payload and incorporates specific features such as the implementation of recharge stations in order to extend the operations range. The definition of priority classes and the incorporation of priority rules in the model have been discussed. The proposed model can be extended in many directions to take into account the real life constraints and the characteristics of the drones based on the available technology. In particular, hybrid systems that combine various transportation means such as trucks, SUVs and drones are of interest.

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