MIKE: Task Scheduling for UAV-based Parcel Delivery

Extended Abstract

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ABSTRACT

Unmanned aerial vehicle (UAV) networks represent an ecological alternative to truck-based delivery systems, especially in urban areas prone to traffic congestion. In this paper, we formalize MIKE as the problem of assigning deliveries to a fleet of drones to minimize the time makespan. We solve this problem with a polynomial-time algorithm, P&D, which outperforms other state-of-the-art solutions.

KEYWORDS

Drone delivery; network of drones; task scheduling; autonomous route-planning; sustainable delivery system

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1 INTRODUCTION

Parcel delivery has become a critical factor in the satisfaction of e-commerce customers. Customers are interested in fast and cheap deliveries and are increasingly aware of the need for sustainable delivery systems. Drone delivery is already a reality in several cities worldwide, where big e-commerce and shipping companies use drones for deliveries of several kinds of goods (e.g., [2, 8, 16, 17]), suggesting that delivery systems will increasingly include drones. The need for more efficient and low-emission delivery systems motivates the design and adoption of a distributed, autonomous and resilient system, leveraging a fleet of UAVs and a set of service stations providing parcel storage and battery replacement. Nevertheless, this goal comes with several challenges. Some authors have studied how no-fly zones, obstacles and weather conditions affect the design of delivery routes of drones in both urban and rural environments (see e.g. [9, 14, 19]). Some works focus on a single drone that has to carry out single [19] or multiple deliveries [11]. Other works specialize in medical [6, 18] or food [13, 15] delivery. Several works focus on multi-agent systems based on drones [3, 10, 12, 20]. Differently from these solutions, we envision a delivery system where drones rely on a decentralized infrastructure composed of several service stations that provide both parcel storage and battery replacement. We formalize this problem with MIKE (MInimum maKEspan), a MILP that minimizes the time makespan. We solve MIKE with a polynomial-time algorithm, P&D (Partition&Deliver), and extend it to a dynamic scenario to adaptively cope with changes due to weather conditions and battery failures.

2 PROBLEM FORMULATION

We consider a set of service stations S equipped with fully charged batteries for replacement. P is the set of deliveries. Each delivery $p \in P$ is characterized by the parcel's weight and the departure and arrival stations $d(p), a(p) \in S$. We consider a homogeneous fleet U of drones with batteries of capacity B that fly at speed v. Each drone $u \in U$ departs from a home station $h(u) \in S$. We build a *transport graph* T whose nodes are the stations S. Two stations are linked in T if a drone can move from one station to another with a full battery. We model the energy consumption rate of a drone's battery based on the distance and the carried payload. Each T's edge is labelled with the time required to move between its two adjacent nodes. A central unit is responsible for orchestrating drones and instructing them to carry out all the deliveries while minimizing the *makespan*, i.e. when the last parcel is delivered. We formalize this as a scheduling problem, where deliveries are assigned to drones. We call this problem MIKE and formalize it as follows:

$$\min \gamma \tag{1a}$$
$$s.t.\ \gamma > \textstyle\sum_{i=1,\dots,|P|} \tau_u(i) \quad \forall u \in U \tag{1b}$$
$$\chi_u(p_0^u, 0) = 1, \quad \forall u \in U \tag{1c}$$
$$\textstyle\sum_{u \in U} \sum_{i=0,\dots,|P|} \chi_u(p, i) = 1, \quad \forall p \in \mathcal{P} \tag{1d}$$
$$\textstyle\sum_{p \in \mathcal{P}} \chi_u(p, i) \le 1, \quad \forall u \in U, i \in \{0, \dots |P|\} \tag{1e}$$
$$\textstyle\sum_{p \in \mathcal{P}} \chi_u(p, i) \le \sum_{p \in \mathcal{P}} \chi_u(p, i-1), \ \forall u \in U, i \in \{0, \dots, |P|\} \tag{1f}$$
$$\chi_u(p, i) \in \{0, 1\}, \forall u \in U, p \in \mathcal{P} = P \cup \{p_0^u, \forall u \in U\}, i = \{0, \dots, |P|\} \tag{1g}$$

We call $t_u = \langle p_1, \dots, p_{k_u} \rangle$ the sequence of delivery tasks assigned to drone u, where $p_i \in P$ $i > 0$. p_0^u represents a fictitious delivery

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with $d(p_0^u) = a(p_0^u) = h(u)$. $\tau_u(i)$ is the time required by drone u for i−th delivery (i.e., for moving from $a(t_u(i-1))$ to $d(t_u(i))$ and from $d(t_u(i))$ to $a(t_u(i))$ along the shortest paths in T with battery capacity constraints). $\chi_u(p,i)$ is 1 if $t_u(i) = p$, i.e., if delivery p is the i−th task of drone u, and 0 otherwise. Eq. 1c constrains each drone u to begin its route from its home station. By Eq. 1d, each delivery has to be assigned to exactly one drone, and each task can involve at most one delivery (Eq. 1e). Eq. 1f forces tasks to be assigned to each drone one after the other. Notice that from the resulting χ_u we can derive t_u by defining $t_u(i) = p$ if $\chi_u(p,i) = 1$. The number of delivery tasks assigned to drone u (k_u), is the last index i in χ_u such that $\exists p \in P : \chi(p,i) = 1$. It is easy to prove that MiKe is NP-hard by reducing a generic instance of the job scheduling on identical parallel machines problem to MiKe where jobs are deliveries and machines are drones. Because of its complexity, in the next section, we describe a polynomial time algorithm to solve MiKe, called P&D.

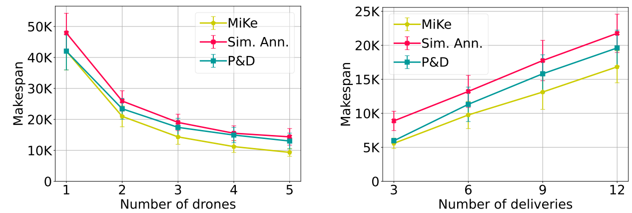
3 ALGORITHMIC FRAMEWORK

To solve MiKe, we propose P&D, an algorithmic framework divided into two phases: 1) *Delivery partition* and 2) *Delivery scheduling and drone assignment*. This procedure is applied to the delivery graph, a structure that encapsulates the time for travelling from a delivery's arrival station to another delivery's departure point.

Delivery Graph. We call *delivery graph* the bi-directed complete graph $D = (P, E_D)$, whose nodes are the set of deliveries P, and E_D is the set of edges, $|E_D| = |P|(|P|-1)$. For each sorted couple of deliveries p_1, p_2, the direct edge (p_1, p_2) exists; its weight is the time required to travel from the arrival station of p_1 to the departure station of p_2 through the shortest path in T without parcel plus the time for carrying out delivery p_2. Notice that edge weights are generally not symmetric, i.e., $w(p_1,p_2) \neq w(p_2,p_1)$.

P&D Algorithm. The first phase of P&D consists of partitioning the deliveries into $|U|$ disjoint sets $P_1, \ldots, P_{|U|}$ so that the workload is as balanced as possible. We do it with a greedy approach. For each obtained set of deliveries P_i, we build a reduced delivery graph D_i, and we run an approximate algorithm for the asymmetric Traveller Salesman Problem (aTSP) on each D_i. We highlight that solving MiKe is equivalent to finding the shortest Hamiltonian path (SHPP) on each delivery graph D_i. Nevertheless, it is easy to prove that we can obtain a valid solution to SHPP by solving aTSP on D_i where we add a 0-weight edge between D_i's nodes and the initial fictitious delivery p_0^u of a drone u, representing its home station and having zero-time cost. Finally, we want to find the best way to assign each drone u a sequence of deliveries P_i. An assignment is better than another if it results in a smaller makespan. We assign the partition with the highest delivery time to a drone u such that $SHPP_{i,u}$ has minimal makespan, where $SHPP_{i,u}$ is the solution obtained by the aTSP after removing the fictitious delivery p_0^u.

Autonomous path re-planning. Once P&D is completed, each drone u begins its mission following the sequence of deliveries t_u assigned to it. We assume that each drone has a sensor that can track sizable changes in the energy consumption rate, which defines drones' maximum flight distance. Such alterations can happen due to changes in the weather conditions or battery capacity [1]. If such changes are detected, the drone recomputes the shortest paths based on the new parameters and the updated vision of T.



(a) $P = 10$ **(b)** $U = 3$

Figure 1: Makespan evaluation

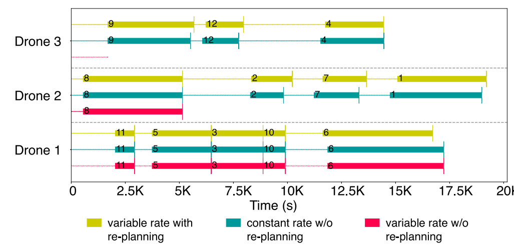


Figure 2: Deliveries w/o α variations and w/o path rerouting.

4 PERFORMANCE EVALUATION

We consider an area of $(60 \times 60)\ km^2$ where the stations S are deployed randomly. We set the drone speed v to $5\frac{m}{s}$ [4]. In the experiments of Fig. 1a, we deploy 50 stations and 10 deliveries to be carried out by a variable number of drones. The results achieved by P&D are very close to MiKe's (implemented by the Gurobi optimizer [7]), with the optimality gap between 1.12 and 1.38. In Fig. 1b, three drones must carry out a variable number of deliveries. The optimality gap spans between 1.16 and 1.36. Simulated Annealing is the method proposed in [5] for delivery assignment to drones. Then, we evaluate the adaptability of drones to online changes in the energy consumption rate, α. Fig. 2 shows the scheduling of deliveries. We compare three scenarios: constant α without re-planning, variable α with re-planning, and variable α without re-planning. Bars represent the time steps in which drones are busy carrying out a delivery, whilst the thinner lines represent the periods that the drone is travelling from $a(p_i)$ to $d(p_{i+1})$. If drones implement the base approach without re-planning, they do not adapt their routes, which may no longer be optimal, as in the case of delivery 6 for drone 1. If α increases and drones do not route re-planning, they fail to carry out all the deliveries, as for all deliveries assigned to drone 3 and deliveries 2, 7 and 1 assigned to drone 2.

5 CONCLUSIONS

In this paper, we formalize MiKe, the problem of minimizing the time makespan of deliveries carried out by a fleet of drones. We provide a MILP formulation that minimizes the delivery completion time under energy constraints. As MiKe is NP-hard, we design P&D, a heuristic algorithm that employs a top-down approach to solve MiKe. We also consider alterations in drones' mobility due to changes in the energy consumption rate and battery availability.

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