Delivery with UAVs: a simulated dataset via ATS

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***Abstract*—We consider a delivery food service operated by Unmanned Aerial Vehicles (UAVs). Due to the absence of a dataset on UAVs deliveries in the literature, and since it is not possible to perform real tests, we create a dataset using an open Air Traffic Simulator (ATS). Precisely, we converted a set of food deliveries operated by wheeled vehicles, proposed in the literature [1], into a set of simulated UAVs deliveries. For each delivery, we ran a UAV flight from the source to the destination. The results showed that, as expected, the UAV's course is shorter than the vehicle trajectory on the ground because the UAV follows an Euclidean path. Following that path, UAVs can be 5 to 8 times faster than wheeled vehicle, in absence of wind. Highly important, the ATS simulator allows to take care of the wind impact in a realistic way. Tailwind increases UAVs speed which becomes up to 10 times faster than the wheeled vehicles, whereas the headwind and crosswind slowdown the UAVs as the traffic slowdown the wheeled vehicles. Our work proves that air traffic simulators pave the way for realistic simulations of UAVs systems.**

***Index Terms*—Drone, Delivery Goods, Favorable winds, Simulation, Dataset, UAV.**

I. INTRODUCTION

The rise in popularity of drones or Unmanned Aerial Vehicles (UAVs) has made them a very appealing subject for different applications, like agriculture [2], environmental protection [3], video monitoring [4], localization [5], [6], and logistic [7]–[9]. In particular, deliveries with drones are potentially faster compared to standard vehicles (e.g., wheeled vehicles) because, at a suitable altitude, the drones can reach the destination by following the shortest path, that is, the line's segment that connects its position with the destination, avoiding traffic and long routes. However, the drones are limited in the flight range and in the payload weight because they are powered with battery limited in size and weight. For this reason, drones are considered suitable for the last mile deliveries of small parcels or in general for short trips. In this paper, we envision the drones as a perfect means of transportation for food deliveries. Namely, the customers usually select the food provider nearby to avoid long waiting times and thus the drone flight range results not too long. Also, quick lunch boxes, like pizzas, are well transportable by weight and bulk even by a small commercial drone.

So, for range and size, fast-food deliveries perfectly fit the drones capabilities in logistic. Moreover, food delivery is required in a burst at peak times, e.g., at dinner time, when the traffic on the roads is intense. So flying instead of driving should make the service faster because the contention on the sky-roads is not an issue yet, and also the ground-roads will be relieved by the food delivery traffic. Drones are, however, much more sensible to meteorological conditions, e.g, wind, than wheeled vehicles. To test if UAVs are a promising solution for food delivery, we need a dataset of flights of drones operating food deliveries. Since it is not yet allowed to create a test-bed that runs the service, we converted a dataset of online food deliveries [1] operated by wheeled commercial vehicles into a dataset of online food deliveries operated by UAVs by using BlueSky, an open Air Traffic Simulator (ATS) [10]. Our contributions are:

- the creation of the first, although simulated, UAV-based delivery dataset (UAV-DB) made available on GitHub GitHub;
- the evaluation of the gain in time and distance when the deliveries of [1] are operated by UAVs rather than wheeled vehicles;
- the impact of winds on drone's performances.

The rest of the paper is organized as follows. Section II presents some relevant works in the same field. Section III describes the dataset creation and simulation process. In Section IV, we evaluate our solution comparing it with a standard truck-based system, considering different wind conditions. Lastly, Section V offers conclusions.

II. THE RELATED WORK

UAVs are gaining visibility in the delivery scenario, especially recently, after the Big company of e-commerce tested UAVs in different cities and the new regulations laws from FAA just released early this year. Literature offers algorithmic solutions for several combinatorial problems, like path planning, facility location problem, vehicular salesman problem, that raise in collaborative truck-drone deliveries. An interesting survey of this area of research can be found in [11], [12].

Some attention has received the impact of the wind on the drone flight. Authors in [13] solve what they call the Mission-Feasibility Problem (MFP), where the impact of the wind on the UAV energy consumption is considered to state the feasibility of the delivery. In [14], the authors consider a delivery system, where UAVs work in cooperation with a truck and perform the last mile of some deliveries. Precisely, on the truck route, it is proposed a way to select, in presence of wind, the take-off and the landing points of the drone to minimize the UAV's energy consumption.

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In [15], [16], the energy and the CO_2 spent by a delivery system that transports small parcels from a central depot to customers using a mixed UAVs and electric vehicles (EVs) fleet is analyzed. In those papers, the effects of environmental conditions (like wind speed and traffic conditions) on potential energy savings are estimated using a numerical energy model. According to [15], [16], in rural settings drones can help to save 5% of total energy. Under drone-favoring conditions like calm winds and heavy traffic, the energy saving potential can double. Also our paper studies a delivery system based on UAVs. However, our paper, instead of using a numerical model, to evaluate the flights uses an Air Traffic Simulator (ATS). At the best of our knowledge, our is the first paper that evaluates the UAVs on flights simulated by an ATS. This is the closest simulation to a test-bed implementation as to date it is not allowed to run UAVs flights in an inhabited city setting. Instead of comparing the energy as in [15], [16], our paper compares the distance and the time duration of real deliveries operated by wheeled vehicle available in literature [1] with the distance and the time duration of the UAVs flights simulated by ATS. Highly important, the ATS BlueSky simulator allows us to take care of the wind conditions in a realistic way.

III. Our system

In this Section, we first present our dataset, especially its composition and its origins. Then, we explain how we built it, focusing on its core assumptions and the tool we utilize for the purpose.

A. The Dataset

The first step is the creation of a UAV-based delivery dataset (i.e., UAV-DB) considering that, in the literature, there are none available. We built our own UAV-DB starting from a delivery dataset, referred from now as T-DB [1], built on real food deliveries in Bogotá. The most important columns of T-DB are described in Table I. Using BlueSky open Air Traffic Simulator (ATS) [10], with a UAV plugin built-in, we perform (by simulation) with drones the original deliveries in Bogotá. T-DB underwent a pre-processing phase: we selected the deliveries whose length (i.e., Distance_mts) is under 5 km to ensure the drone feasibility. After the pre-processing, the T-DB consisted of a total number of $\approx$ 7000 deliveries that are simulated, in the next step, to create the UAV-DB dataset to be analyzed. The simulator creates .log files as simulation output, where at a fix time step (i.e., 1 second) different values are saved for each delivery simulated. In the logs are reported, for each delivery, some UAVs parameters, such as the UAV altitude, ground speed, true airspeed, calibrated airspeed, latitude and longitude, and flown distance. We added the ***course***[1] field that stores the direction of the straight line that connects the starting point with the customer [17]. Fixed the source point $a = (lat_a, lon_a)$ and destination point $b = (lat_b, lon_b)$, the course is calculated by taking the inverse of tangent function of X and Y where X and Y are defined as follows: $X = cos(lat_b) * sin(lon_b - lon_a)$, and $Y = cos(lat_a) * sin(lat_b) - sin(lat_a) * cos(lat_b) * cos(lon_b - lon_a)$.

[1]Note that since BlueSky denotes the course as track, we use course and track interchangeably in GitHub.

TABLE I
Bogotá dataset main headers.

Headers	Description
Moment	Time of delivery. Morning, Afternoon or Noon
Name of Provider	Name of Provider
Expected Delivery Time	Expected time t reach the customer
Cost Delivery	Delivery cost for the customer
Latitude and Longitude	Starting point for the delivery
DailyTraffic	Daily traffic in colors (green, orange, red)
ClientLatitude and ClientLongitude	Customer location
Distance_mts	Distance from starting point to the customer
Time_sec	Actual time to reach the customer

The .log files are made available to the community under GitHub. The .log files created by BlueSky with different speeds of the drone and different winds are made available to the community under GitHub. A script parses the .log files and extracts information for all the simulated deliveries, and stores them in an organized manner in a .csv file, called UAV-DB. To create the UAV-DB, first of all, we create a UAV identifier for each delivery. For reducing the overhead time in simulation, we create as many UAVs as the number of deliveries and all the drones fly simultaneously. All the deliveries are performed by UAVs of type DJI Matrix 600, which is a real UAV available on the market, in principle suited for fast-food deliveries because it carries a payload up to 6 Kg and size 525 mm $\times$ 480 mm $\times$ 640 mm. According to DJI product information, DJI Matrix 600 can reach the maximum speed of 65km/h, which is approximately 20 m/s, and resists wind up to 10 m/s.

When a UAV is created, the default altitude is set to approximately 10 meters, after that the UAV has to climb to the desired altitude while moving towards the destination. Once the destination is reached, the UAV starts the descent to the ground.

BlueSky ATS follows the meteorological coordinate system for the wind and the UAV courses. Precisely, the 0 direction is when the wind blows from North to South, and the number of the directions increase clockwise. In this article, however, we refer to all (both wind and course) directions using the Cartesian coordinate system, which is more usual for us.

We consider the 4 main wind directions in the Cartesian coordinate system:

- 0 degree ($^{\circ}$) wind - the wind is blowing from West to East and has a meteorological direction of 270 degrees;
- 90 degree wind - the wind is blowing from South to North and has a meteorological direction of 180 degrees;
- 180 degree wind - the wind is blowing from East to West and has a meteorological direction of 90 degrees;
- 270 degree wind - the wind is blowing from North to South and has a meteorological direction of 0 degrees.

Moreover, we group the Cartesian directions in four sectors:

We run four different simulation scenario. Precisely, we consider two UAV speeds, $v_d = 10\mathrm{m/s}$ or $v_d = 20\mathrm{m/s}$, and two wind speeds $\omega_s = 5\mathrm{m/s}$ or $\omega_s = 10\mathrm{m/s}$.

TABLE II
GROUPING DIRECTIONS IN SECTORS.

Sector	Cartesian Coordinates °
S1	$[0, 45] \cup [315, 360]$
S2	$[45, 135]$
S3	$[135, 225]$
S4	$[225, 315]$

B. The wind effect

To understand the effect of the wind on the UAVs trajectories, let us explain the *wind triangle* rule [16], which is applied by the BlueSky ATS for steering the UAV in presence of wind. Let denote the ground UAV *course* as $\vec{c} = (c_d, g_s)$, the air UAV movement as $\vec{d} = (h, v_d)$, and the wind as $\vec{\omega} = (\omega_s, \omega_d)$. For the sake of simplicity, all the vectors are measured in Cartesian coordinate system. Then, the wind triangle ties these three vectors together as follows: $\vec{c} = \vec{\omega} + \vec{d}$. In our simulation, the wind $\omega = (\omega_d, \omega_s)$ is known in advance, whereas only the direction c_d of the course and the air speed of the drone v_d are known in advance. So, given in input c_d, v_d, ω_s, and ω_d, BlueSky ATS computes the ground-speed g_s and the direction of the UAV air movement h [18]. The former is called the tailwind/headwind effect, the latter the crosswind effect. The ground speed is computed as follows

$$g_s = v_d + \omega_s \cos(\omega_d - c_d) \tag{1}$$

The heading, instead, is given by:

$$h = c_d + \text{wca}, \tag{2}$$

where the *Wind Correction Angle* (wca) is:

$$\text{wca} = -\arcsin\left(\frac{\omega_s \sin(\omega_d - c_d)}{v_d}\right) \tag{3}$$

Note that when $\omega_s = 0$, it holds $g_s = v_d$ and $h = c_d$. When the wind speed is not null, for each delivery and at every time slot, BlueSky ATS steers the UAV using the wind triangle rule.

Table III shows the simulation of 4 different UAV courses with $c_d = \{0°, 90°, 180°, 270°\}$. The source and the destination are at distance approximately 10Km on the ground. The UAV air speed is set to $v_d = 20$ m/s. The wind direction is $\omega_d = 90°$.Table III compares the distance traversed log_dist and the duration of the flight log_time when the wind speed is $\omega_s = 15\text{m/s}$ with the distance $log\_dist\_no\_w$ and the time $log\_t\_no\_w$ in the case without wind (i.e., $\omega_s = 0\text{m/s}$). All the data with prefix 'log' are extracted from the simulation .log files. Table III reports also the ground speed g_s when $\omega_s = 15\text{m/s}$ and the $g_s\_no\_w$ when $\omega_s = 0\text{m/s}$, computed according to Eq. 1. The heading and wca in Table III are the values initially computed by BlueSky, according to Eqs. 2 and 3, to steer the UAV when $\omega_s = 15\text{m/s}$. They are then recomputed at regular interval of time by BlueSky until the destination is not reached.

It is evident the impact of the wind from the example reported in Table III. When $\omega_s = 0$, the distance traversed and the duration time of the flight is the same for all the four course directions. Moreover, $v_d = g_s = 20$. When $\omega_s = 15\text{m/s}$, the log_dist varies with c_d because the UAV heading is recomputed from time to time to steer the UAV towards the course. The effect of the wind is even more evident looking at the log_time column. It decreases under the tailwind effect (i.e., $c_d = 90$, $g_s = 35\text{m/s}$), increases under the headwind effect (i.e., $c_d = 270$, $g_s = 5\text{m/s}$), and is the same under the crosswind (i.e., $c_d = 0, 180$ and $g_s = 20\text{m/s}$). It is important to note that when $\omega_s = 15m/s$ and $g_s = 20m/s$, the duration time of the flight is greater than that when $\omega_s = 0m/s$ and $g_s = 20m/s$. Although there is a strict correlation between the g_s and the duration of the flight, the duration of the flight cannot be simply computed by dividing the traversed distance by the ground speed. This observation reinforces the importance of evaluating the distance traversed and the duration time of the flight by an ATS simulator rather than via analytical models.

C. UAV-DB Deliveries Distribution

The sources (restaurants) and destinations (clients) of UAV-DB deliveries are illustrated in Fig. 2, where the background map is taken directly from the DJI site [19]. In Fig. 2, the airport in red is a strict "no-fly-zone"; from there, two gray zones expand in opposing directions. In the gray zones flights are restricted below 150 meters. Since in our system the flight altitude is set at 100 meters, all deliveries are feasible in the gray zone. In the map, we have also plotted the closest 150+ meters buildings (9 in total); as we can observe from the Fig. 2, most of those reside on the edge of the "altitude-restricted-zone", therefore, we can ignore them. Roughly speaking, because we can easily change the flight altitude on-demand before each delivery, we can avoid all crashes between UAVs and with buildings. This solution also reduce the overall complexity of the UAV delivery system.

IV. Evaluation

In this Section, we will analyze the average traversed distances and duration time of the simulated flights, without and with wind, stored in the UAV-DB. The touchstone for comparing the UAV performances will be the average distance and time travelled by the wheeled vehicle extracted from T-DB, respectively, shown in Fig. 1a and 1b. We grouped the deliveries into 4 different groups based on the vehicle delivery distance: (i) under 1km, (ii) from 1km to 2km, (iii) between 3km to 4km, and (iv) from 4km to 5km. Then, we reordered the deliveries in each distance group according their course sectors S1, S2, S3, and S4, in Table II. Notice that some sectors are void.

A. UAV-based delivery in absence of wind

In absence of wind, Fig. 4a reports on the y-axis the actual distance covered by the UAV preserving on the x-axis the grouping of Fig. 1 (that is, the delivery are gouped according to the distance traversed by the wheeled vehicle). It is evident that the UAV average distance is always smaller than that of the ground vehicle. Specifically, the deliveries in S2 and

TABLE III
UAV SPEED $v_d = 20\text{m/s}$, WIND SPEED $\omega_s = 15\text{m/s}$, WIND DIR $\omega_d = 90°$ degree

c_d (°)	g_s (m/s)	g_s_no_w (m/s)	log_time (s)	log_time_no_w (s)	heading (°)	wca (°)	log_dist (m)	log_dist_no_w (m)
0	20.0	20.0	994	548.0	41.4	-48.6	9992.333	9864.524
90	35.0	20.0	308	548.0	180.0	-0.0	10074.524	9864.524
180	20.0	20.0	994	548.0	-41.4	48.6	9992.333	9864.524
270	5.0	20.0	3280	548.0	-0.0	-0.0	9899.774	9864.524

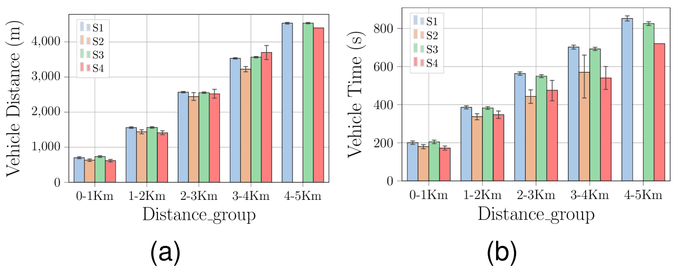


Fig. 1. Vehicle deliveries grouped by distance and sectors.

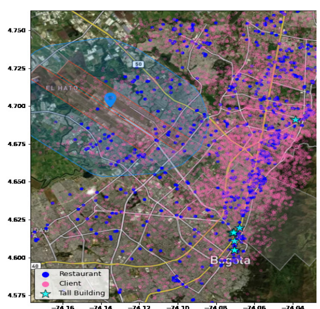


Fig. 2. UAV-DB deliveries distribution in Bogotá.

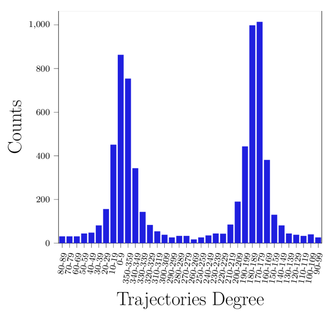


Fig. 3. Number of trajectory occurence every 10 degree.

S4 cover a distance that is always slightly less than 500m independently of the distance covered by the ground vehicle. Hence, we observe that to serve the deliveries in S2 and S4, the UAV trajectories are much shorter than those of the ground vehicles. To better quantify the gain of the UAV's journey, for each delivery, we compute the ratio between the distance traveled by the ground vehicle and the distance covered by the UAV. We then plot in Fig 4b the average of the delivery ratios along with the confidence interval at 95% level. Note that the confidence interval is larger for the deliveries in $S2$ and $S4$ than for those in $S1$ and $S3$ because much less deliveries fall in the $S2 \cup S4$, as depicted in Fig. 3. All the directions in Fig. 3 are reported in the Cartesian Coordinate system. The distance ratio in Fig. 4b is constant, equal to 1,5-2, and independent from the distance in S1 and S3. We deduce that the ratio 1,5 in S1 and S3 is the scaling factor to convert the UAV distance (Euclidean distance) into the vehicle distance in downtown Bogotá. Instead, in S2 and S4, the ratio between UAV trajectories and vehicle trajectories in Fig. 4b is higher than 4 and increases up to 10 for the deliveries between 3-5 km. In order to explain this behavior, recall that the drone follows a straight line between the source and the destination, while the ground vehicle must follow the road map. The largest distance gain in S2 and S4 can be explained by the fact that the wheeled vehicles follow longest paths perhaps due to the presence of orographic obstacles (parks, lake) as shown in the map of Bogotá reported in Fig. 2. Such obstacles are easily ignored by the UAVs. This could also be the reason restaurants do not have many clients in S2 and S4, as reported in Fig. 3.

We have noticed that the distances traversed by the UAV when it moves at 20m/s (Fig. 4) are slightly longer than those traversed when the drone moves at 10m/s (Fig. 5). So a slower UAV traverses shorter courses than a fast one. This is probably due to the fact that the course can be approximated smoothly when UAV goes slow.

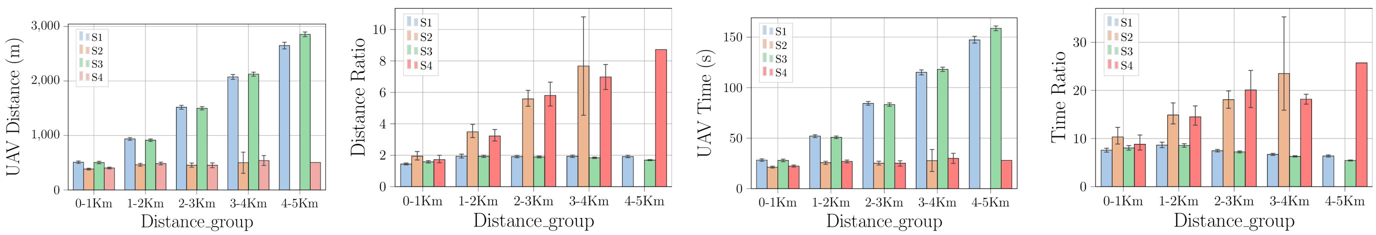
Regarding the flight duration in Fig. 4c in absence of wind, the duration of the UAV journeys is entirely consistent with the fact that in the simulation the drone speed is fixed to 20 m/s. As said, comparing the duration of the vehicle's trajectories with their average length, we derive that the vehicle moves at the speed of 5 m/s (or 18 Km/h) in S1 and S3 and 6.5 m/s in S2 and S4. These wheeled vehicle speeds, although so moderate, are realistic when the wheeled vehicle travels in a big city, with multiple intersections, often controlled by traffic lights. In order to evaluate the gain in time using the drone, again, for each delivery, we calculate the ratio between the vehicle-trip duration and the UAV-trip. Then, we plot in Fig. 4d and 5d the average value of the ratios along with the confidence interval at 95% level when the drone moves at 20 m/s or 10 m/s, respectively.

The high observed gain in time is easily justified when one considers that the speed of the drone is at least 3 times that of the vehicle and the distance traveled by the drone is 2 to 10 times shorter than that of the vehicle. Again we notice a much larger confidence interval for the sectors $S2$ and $S4$ than $S1$ and $S3$.

Our analysis confirms that, using UAVs in absence of wind, food deliveries via UAVs are significantly faster than those made by wheeled vehicles in a large city such as Bogotá.

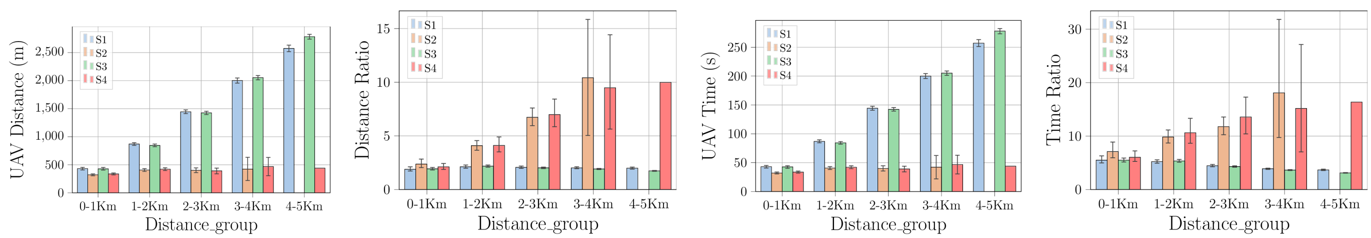
B. The wind impact

In this Section we analyze the four wind scenarios described in Section III-A, and to better understand how the wind influences the flight of a UAV, we keep the delivery grouped based on their course. For each delivery course (i.e., trajectory direction between source and destination), we expect to see the effect of a favorable wind (i.e., wind with the same direction of the UAV course), not favorable wind (i.e., a wind with a direction opposite to the course), and lateral wind that partially affects the UAV.



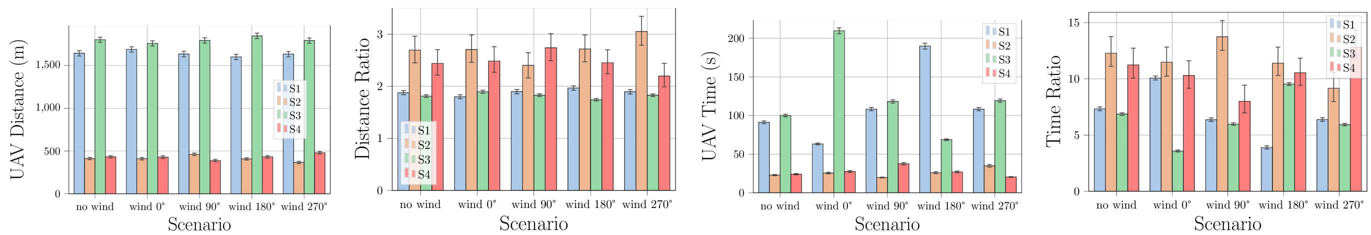
(a) (b) (c) (d)

Fig. 4. Absence of Wind: UAV moving at 20 m/s at altitude 100 m. Distance and time performance.



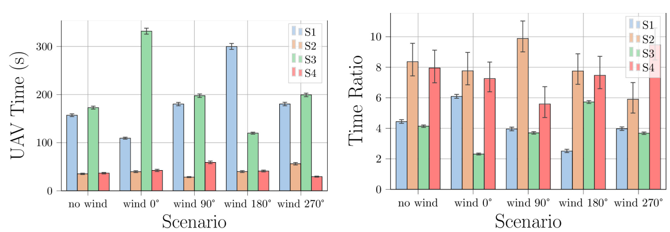
(a) (b) (c) (d)

Fig. 5. Absence of Wind: UAV moving at 10 m/s at altitude 100 m. Distance and time performance.



(a) (b) (c) (d)

Fig. 6. In presence of wind: UAV moving at 20 m/s at altitude 100 m, and wind speed 10 m/s. Distance and time performance.



(a) (b)

Fig. 7. In presence of wind: UAV moving at 10 m/s at altitude 100 m, and wind speed 5 m/s. Time performance.

In the following, we abandon distance grouping and analyze the effect of wind on deliveries grouped only by courses. Since the effect of the wind depends on the trajectory course, we first count the occurrences of the courses (see Fig. 3) in each sector. This will help us to interpret the results on the sectors. In our analysis, both the drone trajectories (a.k.a. courses) and the wind are reported in the Cartesian coordinate system.

In UAV-DB, the deliveries are not evenly distributed among the sectors: there are many more deliveries in S1 and S3 than in S2 and S4. Moreover, in S1 and S3, the (Cartesian) course 0° and 180° dominate. We then expect that the wind directions 0° and 180° [2] have more impact that the other wind scenarios.

Fig. 6 describes how the 4 wind scenarios (Cartesian wind directions 0°, 90°, 180°, and 270°) impact the time and the distance traveled by the UAV when the UAV moves at 20m/s and the wind speed is 10m/s. We also report in Fig. 6 (leftmost bars) the results in absence of wind as a baseline. The 4 wind scenarios have minimum impact on the distance, as shown in Fig. 6a, 6b, and confirmed by the examples in Table III.

The effect of the tailwind and headwind on the time of the flight is, instead, strong. As regards the flight time (see Fig. 6c and 6d), when the wind blows at 0 °, the flight time for the deliveries whose course fall in Sector S1 significantly decreases, while the flight time for the deliveries whose courses fall in Sector S3 increases. Namely, as explained in Section III-B, the deliveries with course 0 in S1 have the wind in favor and their ground speed increases, while the ground speed decreases when the wind is against as for the trajectories with course 180 in S3. With respect to the baseline, S3 loses more than S1 wins. The deliveries in S3 move at an average speed of about 8 m/s (the UAV speed decreases by 12 m/s),

[2]The direction of the wind is reported in the Cartesian coordinate system.

while those in S1 at an average speed of 27 m/s (the UAV speed increases 7m/s). The increase and decrease are different because the effect on the ground speed is weighted by the number of courses in the different directions (see Fig 3). With the wind at 180 °, the results are opposed as expected. The deliveries in S3 have tailwind and they take less time than in the scenario with no wind, while those in S1 take a longer time because they experience headwind. The wind is in favor of the course dominant in S3 and against the course dominant in S1. On average the speed in S3 is 28 m/s, while in S1 is 8.5 m/s.

Under the wind 0 and wind 180 scenario, S2 and S4 don't change much from the baseline. The directions in S2 and S4 are subject to a crosswind and the impact is minimal.

Under the wind 90 and 270 scenarios, the courses with wind in favor fall, respectively, in $S2$ and $S4$. However, the impact of the tailwind is moderate with respect to the speedup achieved with wind 0 and 180 on $S1$ and $S3$ because there are fewer deliveries in S2 and S4. The time flight for the deliveries in S1 and S3 which experience crosswind does not differ much from the baseline although many deliveries belong to S1 and S3. So we deduce that the impact of the crosswind remains minimal and not comparable in strength with the impact of the tailwind or headwind.

Fig. 7 reports how the wind affects the time of the flight if the UAV moves at 10m/s and the wind speed is 5m/s. We do not report the distance performance because we have already seen that the wind speed impacts it in a minimal way. Fig. 7 presents the same trends as the time performance in Fig. 6 both qualitatively and quantitatively. The time ratio in Fig. 7b degrades with respect that in Fig. 6d, but it is worthy to note that it remains well above the half of Fig. 6d Our analysis confirms the results in Table III: the food delivery time changes considerably when the wind is factored in. Especially, when the course c_d is opposite to the wind direction or completely in favor.

V. Conclusions

We created the first UAV-based delivery dataset, obtained by simulating a real truck dataset in Bogotá. Our preliminary dataset shows that the drone is definitely faster than the truck both in the city and in the suburbs. So we believe it is worthy to explore the use of this means of transportation.

Next, we found that with a favorable wind the drone and wind speed almost add up, while headwinds can slow down the drone. The impact of wind on the flight duration is definitely crucial for deriving the expected delivery time to the customer. Therefore, the wind cannot be ignored devising a delivery system based on drones. Finally, the UAV speed impacts all the aspects of the flight: time, duration, and effect of the wind. It is then crucial to better understand the UAV speed role for implementing a UAV food delivery system. Although these early results are very interesting, more work is required on the following aspects that are currently not covered by the simulator: (i) the energy consumed of the drone, (ii) the impact of the payload on all the aspects of the flight, and (iii) the no-fly zones.

Beyond the delivery food system, this preliminary study offers also interesting research sparks, like the possibility of obtaining information on the overflown territory from the superimposition of information deduced from different means of transport.

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