Noise and Environmental Justice in Drone Fleet Delivery Paths: A Simulation-Based Audit and Algorithm for Fairer Impact Distribution

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***Abstract*— Despite the growing interest in the use of drone fleets for delivery of food and parcels, the negative impact of such technology is still poorly understood. In this paper we investigate the impact of such fleets in terms of noise pollution and environmental justice. We use simulation with real population data to analyze the spatial distribution of noise, and find that: 1) noise increases rapidly with fleet size; and 2) drone fleets can produce noise hotspots that extend far beyond warehouses or charging stations, at levels that lead to annoyance and interference of human activities. This, we will show, leads to concerns of fairness of noise distribution. We then propose an algorithm that successfully balances the spatial distribution of noise across the city, and discuss the limitations of such purely technical approaches. We complement the work with a discussion of environmental justice, showing how careless UAV fleet development and regulation can lead to reinforcing well-being deficiencies of poor and marginalized communities.**

I. Introduction

There has been growing interest in using Unmanned Aerial Vehicles (UAVs) for urban and rural delivery [1], [2]. UAVs can carry low weights while avoiding traffic congestion and they can deliver wherever costumers are, thus being specially suited for parcel and food delivery. Examples of such systems deployed by restaurants [1] and coffee shops already exist, while Big Tech companies such as Uber and Amazon have recently shown interest in launching food delivery services using UAV fleets. While excitement for the use of this technology is running high, the physical, social, and environmental impact of such systems in large scales is still poorly understood. Examples of potential issues and concerns include privacy intrusion [3], safety [4], and noise pollution [5]. Furthermore, and similarly to the introduction of waste management systems, transport systems and other urban technologies [6], [7], [8], these risks will not be evenly distributed across deployment areas, but correlate with social, economic, and demographic characteristics of those areas.

The goal of this paper is to estimate the impact of delivery drone fleets on urban noise, as well to anticipate issues of environmental justice [6]—in particular, issues of inequalities in the spatial distribution of noise pollution by such fleets. Intuitively, due to cities' uneven distribution of population and buying power, it is only natural that drop-off locations (and thus fleet paths) are biased towards specific parts of the city. Furthermore, distribution warehouses may make areas where they are located less attractive to live and thus lower property costs and attract specific socio-economic groups. In the other direction, poor neighborhoods are also attractive locations to build warehouses for similar reasons. Certain social groups are then more likely to be affected by noise, raising concerns of economic justice similar to those seen in waste management and transportation policies [6]. We focus on drone noise as recent research has shown that it can cause more disturbance than conventional airplane noise from a psychological perspective [9], and it is a strong contributor towards negative perception of drones [3]. We use realistic drone noise models together with simulations on real map and warehouse location data to estimate impact.

The contributions of the paper are the following:

- We develop and openly provide[1] a UAV delivery-fleet simulation system for impact assessment;
- We use drone noise models and simulation with real map and warehouse location data to characterize noise pollution and its inequalities in UAV delivery fleets;
- We propose a heuristic search-based planning algorithm for UAV-fleets, FairNoise A* (FNA*), which prioritizes traversing low-noise areas during search, thus reducing noise hotspots and balancing noise impact across cities;
- We investigate the relationship between fairness and efficiency in fairness-aware UAV-fleet planning.

II. Related work

A. UAV delivery issues

A large body of literature has been written on technical and regulatory issues of UAV delivery [10], which has called for more scientific evidence on the impact of such technology. Potential impacts are many: from energy consumption, traffic congestion, privacy intrusion and noise emission [5], to safety [4], security and others [10].

B. UAV noise modelling and perceptions

In this paper we focus on the particular aspect of noise impact. Based on noise measurement, frequency analysis, and subjective experiments, recent work has shown that drone noise can negatively impact mood and disturb communication [11], can lead to annoyance in proportion to loudness and sharpness [12], and it provokes more annoyance than ground traffic noise [13] and airplane noise [9] at the same loudness level. Other work has also studied residents' reactions to the use of UAVs in public places, showing the undesirability of drones when they stay in public areas for a long time [3].

C. Technical methods for UAVs

Multiple algorithms have been proposed to improve the efficiency of drone fleets, from path planners taking into account drone traffic [14], to optimizers for deciding the location of recharging stations [15]. Some methods have

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[1] https://github.com/martimbrandao/icra2023-drone-noise

also been proposed to tackle UAV noise: through the use of propeller control [16], hardware design [17] and path planning methods as well [18], [4]. Regarding path planning methods, examples of work that is most related to this paper include pilot assistance systems that optimize landing trajectories [18], and risk-minimization path planners that take into account human safety, property damage, and noise impact risks [4]. This paper also proposes a method to minimize noise harm, but with the important distinction that we focus not on minimizing *total noise* but *inequalities in spatial distribution* of noise—thus innovately considering aspects of fairness.

D. Fairness in robotics and robot paths

Issues of fairness in robotics have been anticipated by multiple researchers recently [19], [20], [21]. For example, [19] shows how issues of bias may take place in robotics applications such as policing and patrolling, autonomous vehicle crash optimization, and medical robot resource allocations. Some researchers [20] have anticipated issues of bias in social navigation (e.g. proxemics) in cleaning, guidance and caregiving robots; while others [21], [22] have focused on rescue and disaster response robots. Similarly to recent "fair" navigation [21] and coverage [22] work, in this paper we use simulation of envisioned robot systems and real census data to anticipate issues of fairness in robot applications. Instead of disaster response, however, here we focus on an application with mundane everyday impact—delivery fleets.

E. Environmental justice

Our focus on fairness is inspired by the body of literature on "environmental justice" [6]. Work in environmental justice has shown that urban policy decisions often lead to unequal spatial distributions of environmental harms. For example, waste dumping and bad air quality are often concentrated on poor neighborhoods [6], and transportation policies often reinforce inequalities of opportunities along economic and racial factors [7], [6]. Similarly, studies have shown that aviation often has a strong noise pollution impact on already-marginalized ethnic communities [8]. The problem is not that policies target low-income and racial-minority neighborhoods on purpose, but that inequalities along these axes exist in housing markets, population distribution, and the organization of institutions—which then lead to correlations between harm and socio-economic attributes [6].

This paper is motivated by similar concerns. The premise is that just like waste management sites and pollutive industries are are often placed in cheaper land that is close to low-income residential areas (or often cause a shift in the socio-economic makeup of those areas)—similar phenomena could happen with warehouses, distribution centers, and noise of drone delivery fleets. We therefore focus on anticipating such issues in drone delivery fleets, in order to promote better design and regulation of such systems in the future.

III. Methodology

A. Noise model

Similarly to recent studies on the impact of drones [5], in this paper we assume drones are omnidirectional point sources of sound. Thus, we can use the inverse square law to estimate noise level L_2 in dB at a location on the ground, given the distance to the drone h_2 and a known noise level L_1 at distance h_1:

$$L_2 = L_1 - \left| 10\log_{10}\left(\left(\frac{h_2}{h_1}\right)^2\right)\right|. \tag{1}$$

As in [5], and consistent with the median value over multiple low-weight UAV products in [23], we assume that drones will produce a noise of L_1 =90dB at h_1 =1m distance. Therefore, to estimate noise at a given location in the map $\mathbf{x}_m = (x_m, y_m, z_m)$, let the noise contribution of drone i be

$$L_i(\mathbf{x}_m) = 90 - \left|10\log_{10}\left(||\mathbf{x}_m - \mathbf{x}_i||^2\right)\right|, \tag{2}$$

where $\mathbf{x}_i = (x_i, y_i, z_i)$ is the location of drone i. Then, assuming noise level is logarithmic with the number of drones [5], the noise level at $\mathbf{x}_m$ accounting for N drones is:

$$L(\mathbf{x}_m) = 10\log_{10}\left(\sum_{i=1}^{N} 10^{\frac{L_i(\mathbf{x}_m)}{10}}\right). \tag{3}$$

This model assumes the city is a free field with no obstructions or boundaries on the map. Thus, similarly to other studies [5], we ignore sound reflection and baffle.

B. Fleet deployment simulation

Let $S = \{1, ..., m\} \times \{1, ..., n\}$ be the space of discretized locations on a map. We model a robot delivery fleet as a set of warehouse locations W, a set of drones D, and a set of order requests R. Each warehouse $w \in W$ is a location in S. Each drone $d \in D$ is a tuple $d = (w_d, f_d, x_d, r_d)$ of the warehouse it belongs to $w_d \in W$, a Boolean variable specifying whether the drone is free (i.e. not flying) f_d, the drone's current location $x_d \in S$, and the currently assigned order request $r_d \in R \cup \emptyset$. Each request $r \in R$ is a tuple of two locations (x_b, x_c)—a business location (e.g. a restaurant) and a costumer location (e.g. a customer's home). During simulation, whenever a drone is free it is assigned an order: which requires the drone to travel to the business to pick up the order, then travel to the consumer to deliver it, and finally return to its warehouse to recharge batteries. We assume immediate battery recharges (e.g. by battery swapping), and thus when a drone becomes free it is immediately assigned one of the remaining order requests to be fulfilled. We further assume drones do not collide even if they are on the same coordinates. This is a reasonable assumption due to the large area associated with each coordinate and the possibility to use slight height variations for each drone to avoid collision. If a drone is busy then we compute its path as the shortest path connecting the points x_w, x_b, x_c, x_w using a sequence of A* queries with distance as cost. We assume customer and business locations follow the same distribution as population density, and thus generate business and consumer locations randomly according to population density obtained from census data.

To estimate noise pollution of a fleet, we simulate the execution of order assignments and flying paths of the fleet. At each iteration, we compute the location of each drone and use these locations to compute the noise that is heard across the whole city using eq. (3). We use a noise map $\mu : S \mapsto \mathbb{R}$, where each cell $\mu(x)$, $x \in S$, keeps track of the average noise that is heard in that location throughout the simulation period. We call $\mu(x)$ the "average regional noise" at x.

Algorithm 1 Fleet Simulator Pseudo-code

```
1:  input: S, W, D, R
2:  μ ← INITIALIZE_NOISE_MAP(S)
3:  while R not empty do
4:      UPDATE_NOISE_MAP(μ, D)
5:      for each free drone d ∈ D : f_d = 1 do
6:          r_d ← RANDOM_PICK(R); R ← R \ r_d
7:          f_d ← 0
8:      for each busy drone d ∈ D : f_d = 0 do
9:          p ← A*(d) or p ← FairNoiseA*(d, μ)
10:         x_d ← p[1]
11:         if length(p) = 1 then
12:             f_d ← 1
13: output: μ
```

Algorithm 1 shows simple pseudo-code for the simulator. Basically, at each simulation step the algorithm starts by updating the noise map (using equation (3)) given the drones' current locations. Then, the algorithm assigns order requests to free drones and updates their state. Finally, the simulator computes (or re-computes) the shortest-path (line 9) to connect each drone's current location to the remaining locations it needs to visit (business, customer, and warehouse). Our baseline method uses A* with distance as cost, and thus in fact would not need to re-compute it at each iteration, as paths are constant. Re-computation becomes useful in our fairness-aware algorithm, which we will explain in Section III-D. Lines 11-12 serve to identify when a drone has completed its order request and has returned to its warehouse.

C. *Equity and fairness*

Due to the non-uniform distribution of population—and thus the locations for pickup and delivery—paths taken by drones will also be biased towards flying over specific areas of the city related to population distribution. Furthermore, even when warehouses are not located in the center of the region that they serve, drones will be more likely to pass through areas that need to be crossed often (e.g. the geometrical center of the city). Therefore, we expect μ to be far from uniform, and assume that hotspots and inequalities in the distribution of noise pollution will be deemed unfair by society and the people living in high-impact areas.

In this paper we will quantify unfairness of spatial noise distribution by the standard deviation of regional noise values (i.e. how much variance exists in the amount of noise that is heard locally):

$$\sigma = \sqrt{\frac{1}{|S|}\sum_{x\in S}(\mu(x) - \overline{\mu})^2}, \tag{4}$$

where

$$\overline{\mu} = \frac{1}{|S|}\sum_{x\in S}\mu(x). \tag{5}$$

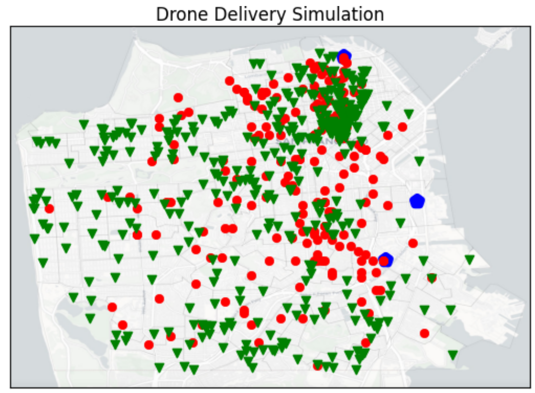

Fig. 1. Map with warehouse locations (blue pentagons), orders (green triangles), and drones (red circles).

D. *FairNoiseA**

To decrease the inequality of the distribution of city noise, we propose a path-planning algorithm that explicitly takes this inequality into account—we will call it FairNoiseA*. In Algorithm 1, FairNoiseA* replaces A* in line 9. The idea of the algorithm is to dynamically update the drones' paths at each simulation step, using an updated map μ of the average city noise collected so far. FairNoiseA* will compute paths that visit the businesses, customers, and warehouses in short distances while at the same time privileging paths that move over areas with lower average noise. To do this, we again use A* search to compute paths but where the cost of transitioning from a cell x_d to its neighbor x_n is now related to the average noise of the region surrounding the neighbor:

$$\mathrm{cost}(x_n) = \alpha.||x_d - x_n|| + \mu(x_n)^P, \tag{6}$$

where P is a parameter to control the degree of importance of noise relative to distance, and α is a scaling parameter (set to $\alpha = L_1$ in our experiments). The larger the value of P, the more likely drones will be to choose paths along low average noise cells. For $P = 0$ the algorithm becomes agnostic to noise distribution, as in Section III-B.

IV. Results

A. *Setup*

We conducted a series of experiments to estimate the spatial distribution of noise in drone fleets. In all experiments we assumed drones travel at a constant height of 100m and speed of 22m/s. We considered noise under 45dB to be harmless, and over 45dB to be equally undesirable by the whole population. This is based on studies [24] where 45dB is considered to provoke interference and annoyance, and may add noise to that typically heard at night in urban areas. Averages of 70dB provoke hearing loss over time [24], though as we will see the fleets do not reach such amount of noise.

Fig. 1 shows the map of the considered city—San Francisco. We chose San Francisco for experiments due to its vibrant tech sector and frequent testing of new products, thus being a likely city for actual deployment. The figure shows delivery UAVs as red dots, drone waypoints (i.e. consumers and businesses) as green triangles, and warehouses as blue pentagons. We used

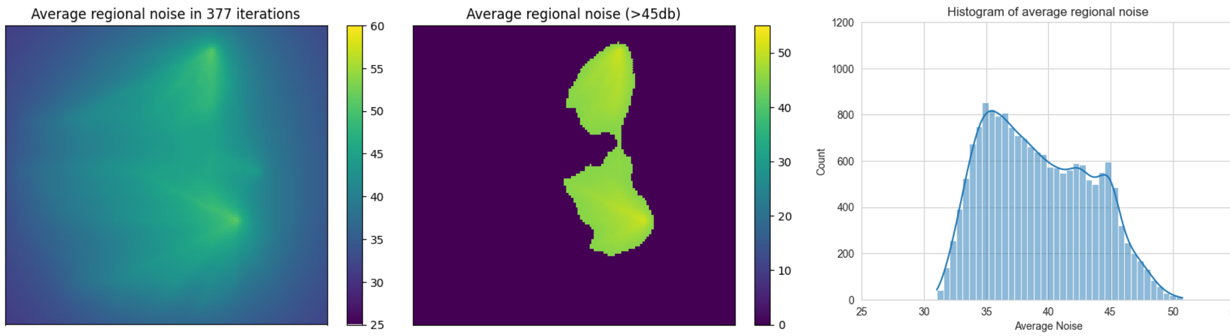

Fig. 2. Average regional noise (400 drones delivering a total of 1469 packages per hour).

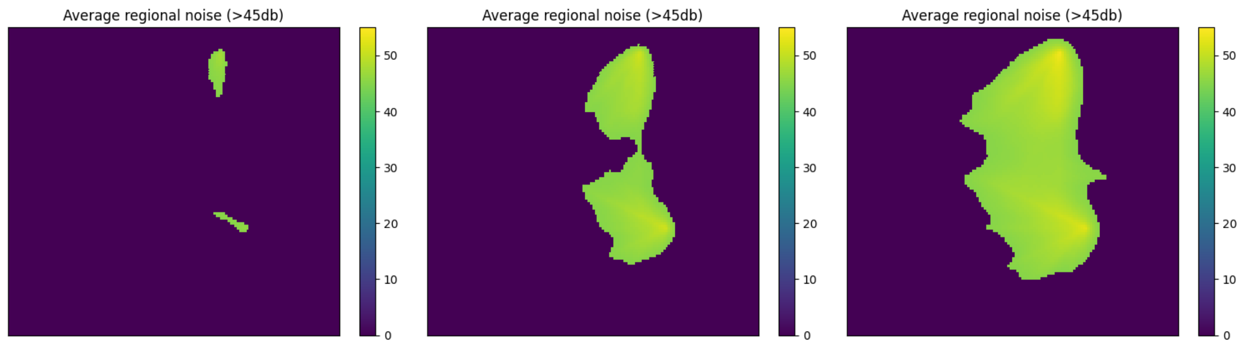

Fig. 3. Average regional noise. From left to right: 200, 400, 800 drones (delivering 741, 1469, 2956 packages per hour).

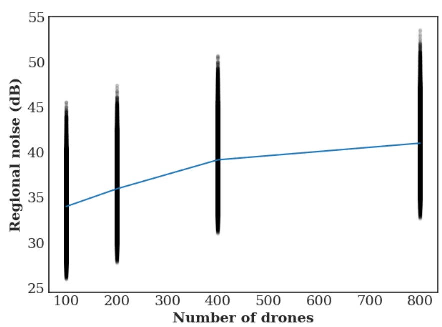

Fig. 4. Average regional noise as a function of the number of drones in the air (related to number of orders per hour). Black dots represent values at specific locations in the map, while the blue line represent the average.

real coordinates of two Amazon warehouses and a FedEx shipping center in San Francisco as warehouse locations. Uber Eats completes at least 10000 orders per day [25], which corresponds to 400 orders per hour assuming a uniform distribution, or considerably larger during lunch and dinner peaks assuming a more realistic distribution. We thus assumed the delivery fleet needs to fulfil orders in the range of 400-3000 per hour (requiring 100-800 drones in our simulations). The noise map was discretized with cells of 100m by 100m. We used the OpportunityAtlas website[2] to obtain data of population density, based on which we uniformly biased orders towards highly populated areas. Experiments were conducted on a 2.3 GHz Quad-Core Intel Core i5 with 16GB RAM. Code is publicly available (URL in Section I).

[2]https://www.opportunityatlas.org

B. Noise pollution simulation

Fig. 2 shows the results of simulating a drone fleet of 400 drones delivering 800 packages over a period of 1960 seconds (on average 1469 orders per hour). The whole simulation took 82 minutes to complete without parallelization. The figure shows the average noise across the whole city (average noise heard at each location throughout the 1960 seconds), as well as the average undesirable noise (noise over 45dB) and the histogram of average regional noise. The histogram shows the distribution of average noise values across the whole city, meaning that average noise can vary between 30 and 51dB, depending on where you live. The figure shows that, predictably, areas around two of three warehouses are frequently visited by UAVs because UAVs always start and finish orders from a warehouse and need to return to warehouses for inspection and recharging. However, they do not limit themselves to a circle around the warehouse but extend in the direction of the geometrical center of the city and of highly populated areas. The figure also shows that these areas are large and reach an average noise of around 50dB. Furthermore, 10.5% of the city experienced over 45dB average noise.

We also ran a simulation with 200 and 800 drones (741 and 2956 orders per hour respectively). We show these results in Fig. 3, where we can see that the areas subject to undesirable noise increase rapidly with the number of drones and orders. The proportion of the city experiencing over 45dB increases from 0.8% with 200 drones, to 10.5% with 400 drones, and 21.6% with 800 drones. This relationship between noise and the number of drones is also shown as a curve on Fig. 4.

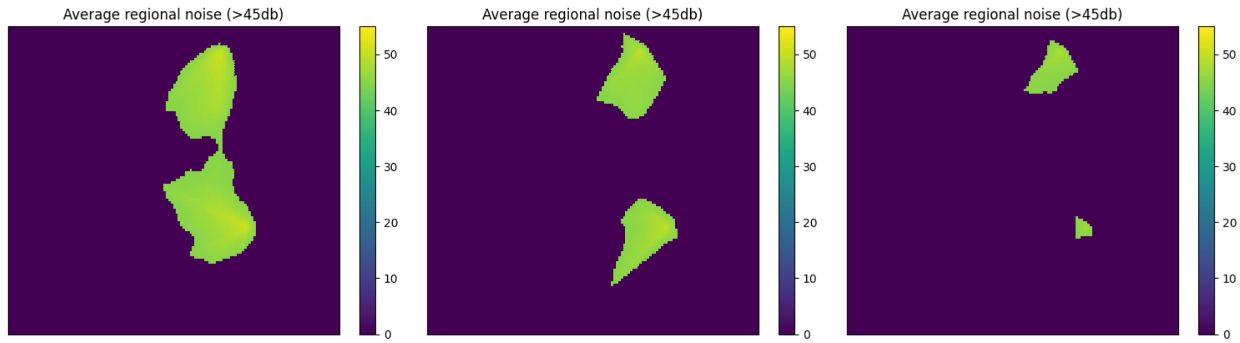

Fig. 5. Average regional noise with fairness-aware planner FNA* (P=0, P=2, P=5).

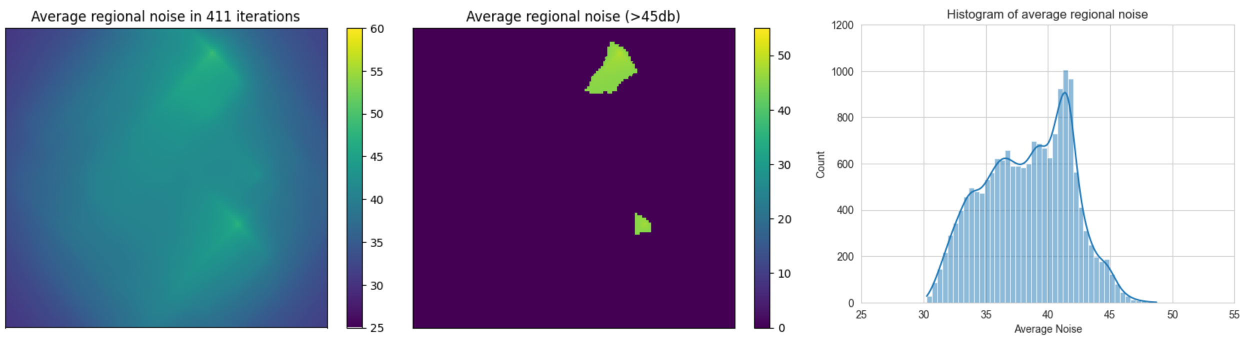

Fig. 6. Average regional noise with fairness-aware planner FNA* using P=5 (to compare against Fig. 2)

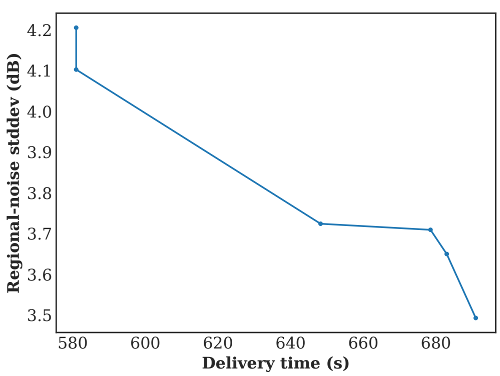

Fig. 7. Trade-off between efficiency and fairness.

C. Fairness-aware planner

We then ran simulations on the same 400-drone scenario, using our noise-distribution fairness-aware planner FairNoiseA*. Fig. 5 shows the map of undesirable noise obtained by executing our planner, for P parameters equal to 0, 2, 5 (where 0 is equivalent to no fairness consideration). The figure shows that our planner is able to considerably reduce the portion of the city exposed to undesirable noise, from 10.5% of the city to 1.7%. With P=5, these areas become tightly concentrated around the warehouses.

The algorithm achieves low concentration of noise by deviating drones' paths from each other, at the expense of increasing trajectory lengths and thus delivery times. Therefore, there is a trade-off between efficiency (average delivery times) and noise-exposure fairness (standard deviation of the regional noise). We show this trade-off in Fig. 7, where each point corresponds to a different value of P. The figure shows that to decrease standard deviation from 4.2 to 3.5dB (17% decrease), orders will on average have to be delivered 17% slower (from 580 to 690 seconds).

Fig. 6 further details the results obtained with P=5. The figure (left side), when compared to Fig. 2 (left side) shows that straight-line paths towards population-density hotspots become less common, and instead noise is more scattered. Furthermore, the histogram shows that noise is mostly kept below 45dB (except for a small tail corresponding to the warehouses), and does not reach 50dB. The histogram also shows that the peak of noise distribution gets shifted from 35dB to 42dB. This is due to the longer paths of drones and an increase in visits to low-visited areas.

V. Discussion of societal consequences

The simulation results we obtained show that not considering spatial noise distribution inequalities when planning paths for drone delivery fleets can lead to problematic consequences. In particular, drone delivery fleets will create hotspots of undesirable noise which extend well beyond the warehouses and towards high-population-density areas.

Our results also show that accounting for noise distribution in path planning can decrease the extent of noise hotspots around warehouses, at the expense of slightly longer delivery times (though arguably still acceptable from consumer perspectives, at 11 minutes average in San Francisco).

Another important observation from our modelling and simulation results is that delivery fleet noise increases rapidly with the number of drones. This points to a limit of drones per geographical area after which it becomes impossible to contain high-noise areas and thus impossible not to affect the quality of life of neighborhoods located around warehouses. These areas are also potentially correlated with typical socio-economic inequalities in urban areas that force poor communities to live in undesirable environmental conditions [6]. Such inequality could penalize already marginalized communities, as repeatedly happens with urban policies of waste management and transportation [6], [7], [8]. Urban planning, policy making, and regulation should thus intervene to avoid such situations.

One limitation of our modelling approach includes the lack of modelling of take-off and landing, which would further raise the average levels of noise observed in the present paper—and thus further aggregate the issues discussed.

VI. Conclusions

In this paper we proposed a system to simulate the impact of drone delivery fleets in terms of noise pollution. We used accepted models of sound propagation, together with real data on drone noise levels, population density, and warehouse locations, to simulate noise impact on the city of San Francisco. Our results show that drone delivery fleets can lead to noise hotspots that extend far beyond warehouses, at levels that lead to annoyance and interference of human activities. This distribution of noise is uneven and concentrated in areas around warehouses, high population-density areas, and the city's geographical center. Our results also show that this noise increases rapidly with the size of the fleet.

We then introduced a fleet-planning method that takes the spatial distribution of noise into account. We showed that this method can balance the level of noise across the city, and reduce the extend of undesirable noise hotspots considerably to narrow areas around warehouses. This comes at the cost of a decrease in delivery speed and a slight increase of city-wide noise (though below assumed interference thresholds). We discussed societal consequences and framed the discussion through the lens of environmental justice.

Important future research directions include the study of how increasing or spreading out warehouses would affect noise distributions; a comparison of impact on urban, suburban, and rural areas; better modeling of order locations to account for buying power; and the involvement of stakeholders such as city planners, companies, residents, and health agencies in finetuning models and requirements. Some technical improvements can also be explored, such as better trajectory profile modelling in terms of height, speed, and acceleration, the inclusion of noise frequencies, as well planning algorithms with longer horizons and joint warehouse assignments.

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