Opportunistic Multi-Drone Networks: Filling the Spatiotemporal Holes of Collaborative and Distributed Applications

Huber Flores

Abstract

Opportunistic networks provide the underlying foundations to enable collaborative and distributed applications close to users. These applications exploit the temporal and spatial availability of proximal devices to share the execution of different tasks ranging from sensing to networking. A key limitation of these networks is its short life span and limited coverage. In this article, we present a research vision in which spatiotemporal holes between opportunistic networks are filled through the deployment of autonomous drones acting as intelligent proxies. By doing this, it is then possible to augment the coverage of these networks as well as to improve the availability of opportunities to find collaborators. Through a rigorous analysis that considers a dataset captured by a cellular operator, we demonstrate the feasibility of the vision and highlight a road map of research challenges that have to be fulfilled to achieve it. Our results suggest that while several opportunistic networks emerge during the day in different urban locations, these networks tend to be of small size and isolated. However, by using autonomous drones to interconnect these networks, it is possible to augment the surrounding availability of proximal devices by almost 3x times.

Introduction

Opportunistic networks are formed by interconnecting devices sharing the same spatial and temporal characteristics [1, 2]. Proximal devices interconnect via short range communication networks, e.g., device-to-device (D2D); reducing the need to rely on the Internet backbone. The most common opportunistic networks exploit human mobility and personal social devices from individuals to establish networks in which devices can share distributed resources and collaborate with the execution of tasks. Different tasks can be accomplished between interconnected devices ranging from sampling data using sensors to routing network packages [3]. While disaster management and transient infrastructure are important use cases supported by these networks, emerging paradigms, such as edge intelligence [4], federated learning [5] and the Metaverse [6] can improve the performance of their applications through these networks. However, as these depend on human mobility to emerge, a key limitation is that the connectivity is intermittent and can terminate unexpectedly — even if delay-tolerant mechanisms are adopted. As a result, solutions that improve and foster larger coverage and higher availability of opportunistic networks are required.

Existing solutions have investigated the formation of opportunistic networks to enable collaborations between distributed computing, networking and sensing resources [2]. The static deployment of IoT and smart devices has been envisioned as a way to provide distributed infrastructure on the edge of the network [1]. Similar to this, cloudlets, fog solutions and frameworks to distribute tasks among multiple devices has been explored extensively [7]. A key problem with these solutions is that they require fixed deployments, which are not dense enough in the wild. In addition, there is a lack of trust towards these devices. As a result, social-aware, multi-party and security mechanisms are required to be used instead, which increases the complexity of usage. Likewise, a combination of Cloud-Edge orchestration also has been proposed to improve the continuous availability of resources. This however reduces the performance benefits of distribution and collaboration between devices. Since the uptake of autonomous drones is increasing and those are blended within urban areas, it is possible to envision them as a way to improve higher availability and coverage of opportunistic networks.

This article presents a research vision of *opportunistic multi-drone networks*. As depicted in Fig. 1, in this vision, autonomous drones that operate within urban areas are piggybacked or scheduled to act as intelligent gateways that interconnect opportunistic networks. By doing this, autonomous drones can then augment the scope of these networks and increase the opportunities of finding collaborators. Through a rigorous analysis that considers a dataset captured by a cellular operator, first, we quantify the amount of opportunistic networks that can be formed during different time intervals during a day using smartphones. With this information, we then characterize the amount of devices that can be harnessed in

1. Individual networks
2. Interconnected networks through autonomous drones.

In addition to this, we also present multiple application use cases that can benefit from this vision. We also reflect back on current state-of-the-art

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The author is with the University of Tartu, Estonia.

solutions and discuss the implications and limitations of our work.

Emerging Use Cases and Applications

Opportunistic networks are key to build the underlying infrastructure supporting collaborative and distributed applications. Below we briefly discuss representative examples of applications that benefit from improving the availability of finding collaborators in these networks.

Metaverse applications: AR/VR applications provide the basis for a Metaverse [6]. These applications are resource intensive and individual devices drain their batteries when running them continuously, e.g., video rendering. Distributed and collaborative processing can facilitate reducing the complexity of executing these applications as well as minimizing the need of relying on remote infrastructure. For instance, image processing applications can speed up 2x and more when using additional devices to execute them [2, 5]. By using autonomous drones to reach other opportunistic networks, there is a larger amount of opportunities to interconnect devices in proximity, such that Metaverse applications can sustain longer through low-latency infrastructure available in their surroundings.

Vehicular services: Advancements in autonomous cars are quickly hampered by the large amount of computation required to analyze the data produced by the vehicles, e.g., autonomous cars generate in average 5T of data per hour [8]. While 6G networks are envisioned to accelerate data transferred, distributed computation in the surrounding of vehicles is also required to reduce the computational latency of data processing. Autonomous drones can exploit surrounding infrastructure to pre-process large amounts of data asynchronously, such that pre-computed functionality is available to vehicles. For instance, pedestrian counting is necessary to regulate car speed in a location and this can be fetched by surrounding vehicles from autonomous drones.

Edge intelligence: Distributed AI services in proximity to end devices require a robust low-latency network to ensure continuous connectivity between devices deployed on the edge [4]. Autonomous drones acting as gateways to interconnect transient networks can improve the availability of devices. Besides this, autonomous drones can facilitate the training and execution of AI models by acting as coordinators. In this manner, autonomous drones can help in acquiring data contributions to train models by selecting the most suitable devices.

Challenges and Opportunities

Autonomous drones are rapidly automating several activities performed by humans, e.g., grocery and delivery. As their adoption increases, these autonomous devices are starting to have their own mobility patterns and emerging routes, which can be exploited for establishing and interconnecting opportunistic networks. This section starts by reflecting on current state-of-the-art methods and solutions, and then presents the challenges and opportunities to enable multi-drone support for opportunistic networks.

Multi-drone capacity planning: Autonomous drones have designated routes to move across different locations. These routes can be exploited; such that autonomous drones can become intelligent gateways to interconnect different opportunistic networks [1]. Indeed, even if autonomous drones are in constant movement, their operations within specific locations can be scheduled to move in and out based on their available number, e.g., drone churn. A key challenge is to have stable availability of autonomous drones to maintain continuous and consistent communications between interconnected opportunistic networks. The stable availability of autonomous drones as gateways can aid in preserving network functions active, such that it is easy to find collaborators for users. To estimate optimally the amount of autonomous drones that are required to interconnect different networks, it is necessary to apply capacity planning techniques that consider different factors [9], such as type of drone, operational time, surrounding infrastructure and expected workload to mention some. While over-provisioning of autonomous drones in area can also support continuous communication, the number of drones allowed in an area is commonly restricted such that human-perception of the surrounding is not perturbed. This is another challenge surrounding the deployment of autonomous drones in the wild.

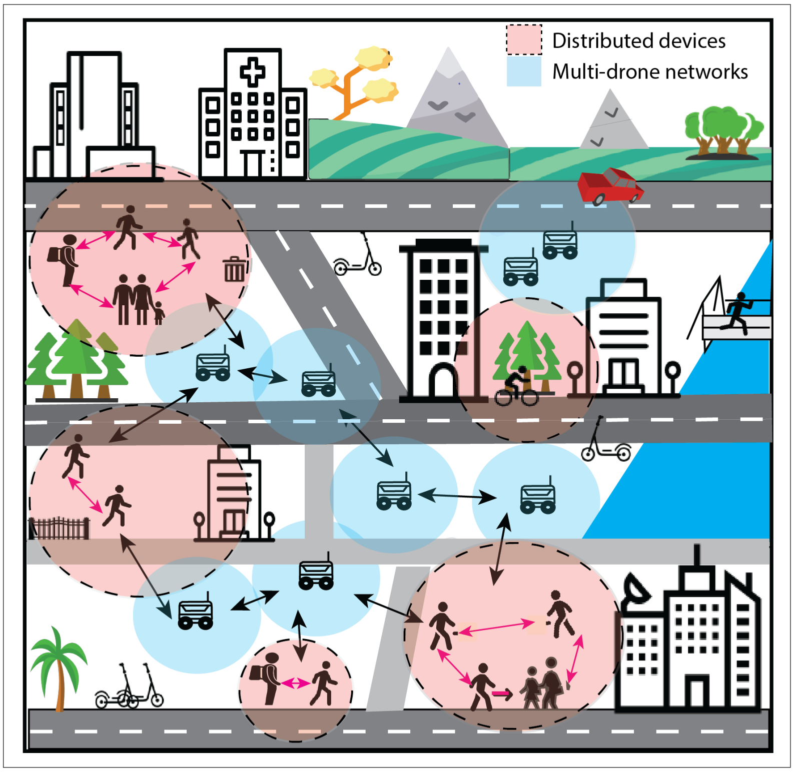

FIGURE 1. Our vision of opportunistic multi-drone networks – Isolated networks are interconnected through autonomous drones acting as intelligent proxies.

Swarm and network intelligence: Besides having awareness about their surroundings and contexts, autonomous drones are also expected to work as a collective swarm that further optimizes network service provisioning [10]. For instance, when transferring low priority packages, to save energy, some drones may prefer to offload data to proximal 5G stations rather than rely on device-to-device communications. Another example is to regulate the formation of opportunistic networks through autonomous drones. Here, autonomous

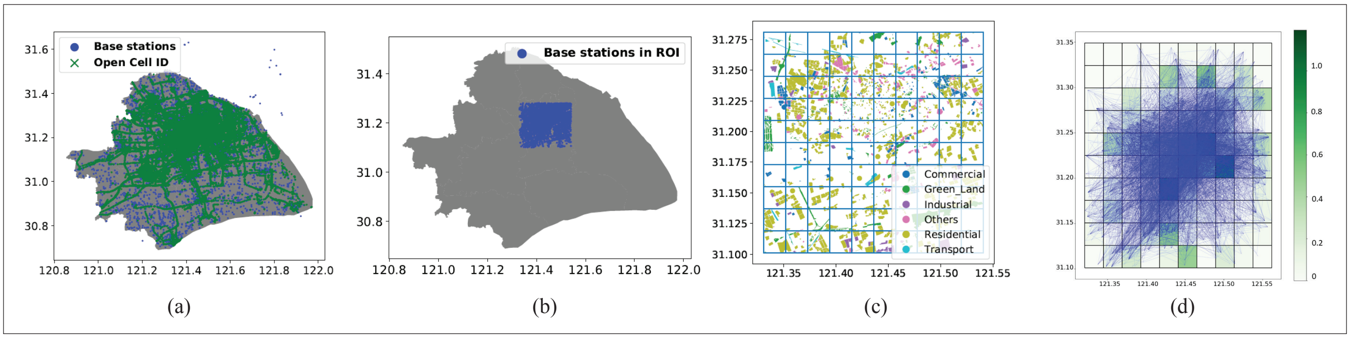

FIGURE 2. Dataset pre-processing and preparation; a) dataset validation with urban locations; b) region of interest (ROI) selected for the analysis; c) types of locations in the ROI and d) mobility of users obtained from the dataset.

drones can coordinate the use of opportunistic networks for certain tasks, e.g., distributed and collaborative computing for rending videos or processing large amounts of distributed data. The use of advanced machine learning opens a plethora of opportunities for swarm optimization. A key challenge is to have representative and large enough data that can model the coordination between autonomous drones. In addition to this, autonomous drones are also expected to adopt resilient typologies, in which multi-paths are always available even in the present of drone failures. Multi-paths are especially important for multiverse-like applications (AR/VR) [3].

Security and privacy-preserving mechanisms: Autonomous drones can become a source for attacks and threats for users transferring data [11]. This is specially problematic for opportunistic networks harnessing computing power for edge applications and intelligence [12]. Indeed, compromised autonomous drones can be easily utilized to perform attacks over model and data of applications, e.g., data poisoning and model evasion. As a result, autonomous drones require to be authenticated before forming part of the network. Thus, a key challenge is to make autonomous drones trustworthy. Notice that other infrastructure like cloudlets and edge servers suffer the same problem. To overcome the issue, deployment of these technologies is typically powered by well-known providers, such that the trust of users in using them increases. Naturally, attackers can also impersonate service providers to steal personal information or digital entities. As a result, privacy preserving methods need to ensure no sensitive data is transmitted to this type of infrastructure.

Recurring issues: Battery life of autonomous drones is a recurring problem that prevents long term usage of the technology. As autonomous drones acquire more sophisticated autonomy, the demand for heavy processing increases, resulting in short life span of batteries. Thus, a key challenge is energy consumption and optimization of tasks of autonomous drones. Anchor stations to re-charge autonomous drones periodically have been proposed to overcome this problem. Other solutions rely on the use of solar panels and harvesting energy mechanisms [13], e.g., wind and tidal. Power-based wireless solutions are becoming a reality and can be also envisioned to aid in overcoming this issue. Charging times can potentially be piggybacked to easily interconnect opportunistic networks. Besides this, other recurring issues are the augmentation of autonomous drones with plug and play components [9], and the robust training of models to support different autonomous functionalities, e.g., navigation. Another key issue to overcome is related to the interoperability between autonomous drones and other devices. This can be addressed by adopting well-known standards to route information, e.g., forwarding protocols; and state-of-the-art algorithms to disseminate data, e.g., epidemic protocols.

The Experiment

The potential of the proposed vision is demonstrated through the rigorous analysis of a mobile operator dataset. We rely on this dataset to quantify the amount of opportunistic networks that emerge during a day on an hourly basis. With this information, we then analyze how autonomous drones acting as intelligent gateways can fill the gaps between individual opportunistic networks to interconnect them. Lastly, as users look for collaborators, we quantify the augmented amount of collaborators that is available through interconnected opportunistic networks. In the following, a detail description of the experiment is provided.

Dataset and preparation: The dataset contains real-world crowd-sensed measurements of app usage and mobility patterns, depicting real world situations. The dataset is anonymized and gathers data over the period (August 21, 2017) for 24 hrs from a cellular operator in Shanghai. The dataset was released in Applens workshop in 2019. As our goal is to identify crowded areas where opportunistic networks can be established, the dataset captures suitable insights about human mobility and behavior. The dataset contains information from users connecting to base stations as a consequence of calls, messaging, and data transfer activities associated with mobile application usage. Each sample contains the device identifier, the start and end time of a session to the level of seconds, the amount of data exchanged during the session (in bytes), the identifier of the base station that handles the connection, and the GPS coordinates of the base station. The dataset comprises information from 998 unique devices and 7663 base stations. The IDs of devices are anonymised to guarantee the privacy of users.

Pre-processing: Before our analysis, we validate the base stations in our data using the Opencellid database.[1]. The Opencellid project is the largest collaborative open-data repository worldwide of GPS positions of cell towers. The project aims to offer GSM localisation from data gathered from various sources, including mobile apps and

[1] https://opencellid.org/

network providers. Figure 2a shows the base stations (using blue dots) and Opencellid database (using green dots). From Fig. 2a, it can be clearly observed that not all base stations in the dataset are overlaying geographically over the Opencellid dataset. To make a proper matching between these two datasets, we used radial distance to overlay the GPS coordinates of our operator dataset. In particular, we used a maximum 500-meter radial distance to verify and calibrate base station location. The resulting dataset contains 8,248,775 samples from 826 devices and 4011 base stations.

Region of Interest: Our analysis focuses on the most dense area in the dataset as it captures better human mobility in different urban scenarios. We focus our analysis on the 20 km^2 area (**R**egion **O**f **I**nterest — ROI) with the highest density of base stations located in the northeast part of the city (Fig. 2b), which allow us to evaluate data gathering over various spatiotemporal levels. The selected area contains 3,425,014 samples from 548 devices and 1198 base stations.

Methodology: Before quantifying opportunistic networks, we first model the mobility of individuals users. We rely on grid-like structure that overlaps the ROI to analyze the mobility of all the users available in that location. Figure 2c clearly illustrates the grid overlapping the ROI. Our grid structure consists of 100 cells and each cell represents a region containing a set of base stations in which devices connect to. By looking at devices connecting to the same base station during a specific interval of time, it is possible to identify devices that are at one-hop distance between each other. This is important to quantify the amount of devices that can interconnect together in an opportunistic network. In addition to this, we also built the trajectories of individual users. These trajectories depict user mobility as transitions between cells. With this information, it is then possible to analyze the multiple opportunistic networks that are formed by different combination of users as they encountered each other.

Our grid-like structure uses 100 cells for the grid as it provides an optimal cell area to merge base stations while retaining enough descriptive information to differentiate multiple regions. Each cell depicts an area of 2 km^2. Our grid is placed on the ROI as it represents the busiest part of the city, hence more descriptive patterns that capture human mobility can be discovered. To avoid abnormal trajectories that depict very short or long mobility patterns, the dataset is pruned down further. The pruning is done by removing all connectivity sessions below the 10th percentile or above the 90th percentile. To estimate sessions of users, we model sessions on hourly basis intervals. An example to illustrate this, it's a session of a device connecting to the base station B1. Assuming that the device starts its session at 09:20 AM and ends at 10:10 AM, this leads to two sessions in our analysis, one at 9:00 AM and another at 10:00 AM. Moreover, multiple sessions that are identified during the same hour are combined. For instance, a device connecting to base station B2 with a starting session at 09:30 AM and ending at 09:40 AM; and then a subsequent session of the same device starting at 09:45 AM and ending at 09:55 AM, leads to one session at 9:00 AM. After applying this final data pruning and refining, our dataset contains 1,655,271 samples for 512 devices with 1,171 base stations.

Land usage mapping: Lastly, to have an intuitive view of human behavior and patterns in the city, we also identify land uses and locations in the ROI. We rely on general areas (Residential, Commercial, Green land, Industrial, Transport and Others) that are inherent in any urban structural planning of a city. The land use is extracted using OpenStreetMap. The selected areas, include: *commercial* areas representing all the offices, shopping centres, warehouses, or retail stores; the *residential* areas depicting all the residential sites like buildings, and private houses; the *green land* depicting all the available forests, nature reserves and public parks; the *industrial* areas representing all the sites that are used for industrial development and the *transport* area representing the sites that users use to commute using bus or train. Another reason to choose these areas is that they are representative examples of locations that people encounter as part of everyday routines on a daily basis. For example, commercial and industrial areas expose working hours' patterns, a train and bus stations describe users' transportation mobility, and residential areas describes habitual housing patterns. Figure 2d shows the trajectories that can be calculated from all the 512 users in our dataset and consider the mobility of users for the whole day. The intensity of the cell color quantifies the amount of users available in that cell, where white color is the lowest and darker (green) color the highest.

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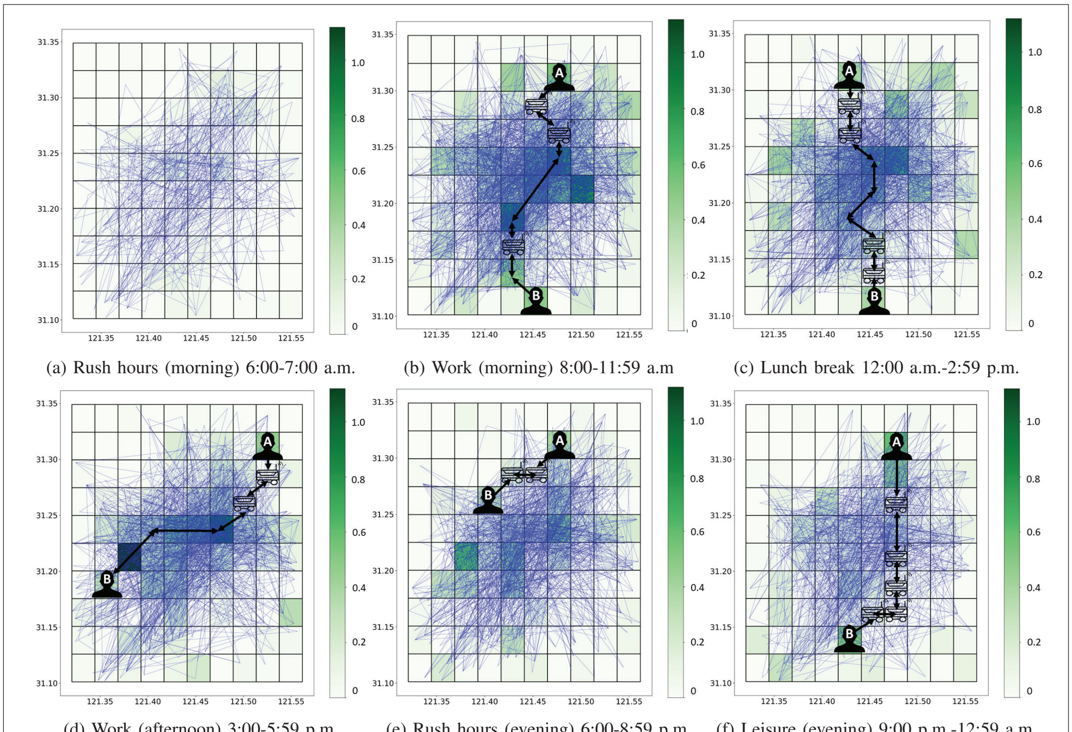
Evaluation and Results

Quantifying Opportunistic Networks

Analysis: Our goal is to identify the amount of opportunistic networks that emerge at different times during the day in different (cell) locations in our ROI. After that, autonomous drones are deployed in locations to interconnect isolated opportunistic networks to augment their coverage. To perform this, it is first necessary to define a human daily routine. This is important to identify opportunistic devices that can be harnessed together. As a result, we selected a human routine that divides the day into 8 intervals. This routine is selected from [2] and depicts a fine-grained level of human activities that can be realistically performed during the day by individuals. Routines with low amount of time intervals are not selected as it is difficult to observe clear mobility patterns between time periods. Likewise, routines with higher amount of intervals do not depict an average human routine. Our selected routine divides the day into fairly intuitive intervals, including, Rest (early morning) 1:00 a.m. to 5:59 a.m.; Rush hours (morning) 6:00 a.m. to 7:59 a.m.; Work (morning) 8:00 a.m. to 11:59 a.m.; Lunch break 12:00 p.m. to 2:59 p.m.; Work (afternoon) 3:00 p.m. to 5:59 p.m.; Rush hours (evening) 6:00 p.m. to 8:59 p.m.; and Leisure (evening) 9:00 p.m. to 12:59 a.m.

Results: Figure 3 shows the results. The interval Rest (early morning) is not presented as the amount of possible opportunistic networks to be formed is low. This is reasonable as this time depicts sleeping patterns of users, providing low opportunities for the execution of collaborative and distributed tasks. Previous research has also

Here, cells with darker (green) colors depict higher concentration of users while lighter (green) tonalities depict a few or none users (white).



(a) Rush hours (morning) 6:00-7:00 a.m. (b) Work (morning) 8:00-11:59 a.m (c) Lunch break 12:00 a.m.-2:59 p.m. (d) Work (afternoon) 3:00-5:59 p.m. (e) Rush hours (evening) 6:00-8:59 p.m. (f) Leisure (evening) 9:00 p.m.-12:59 a.m.

FIGURE 3. Opportunistic networks that emerge at different locations during different times of the day; and tentative deployments of autonomous drones that can be used to interconnect opportunistic networks: a) rush hours (morning) 6:00–7:00 am; b) work (morning) 8:00–11:59 am; c) lunch break 12:00 am–2:59 pm; b) work (afternoon) 3:00–5:59 pm; e) rush hours (evening) 6:00–8:59 pm; f) leisure (evening) 9:00 pm–12:59 am.

reported low human mobility within this time intervals [14]. To identify the opportunistic networks, we quantify the amount of users connecting to base stations within a cell. Devices in the same cell can form opportunistic networks easily by interconnecting to each other using short range communications or by connecting to the same base station [2]. Here, cells with darker (green) colors depict higher concentration of users while lighter (green) tonalities depict a few or none users (white). In addition, we also construct trajectories from individual mobility traces for each user (blue lines). The key insight of these trajectories is to show that even though there are moving users through cells, there is not enough time for devices to collaborate [2]. Overall, from Fig. 3, it is possible to observe a different number of networks during different time intervals. It is possible to observe higher number of networks emerging during Work and Lunch hours (Fig. 3b, c and d). Moreover, despite users moving between cells, we can also observe time intervals of activities where a low amount of networks can be formed (Fig. 3a and f). This indicates that devices are moving around, but there is not enough time to establish meaningful collaborations between them as connectivity is intermittent and encounter between devices spontaneous. All in all, while our results suggest that several opportunistic networks can be discovered, these networks are isolated from other networks. Interconnecting these networks can potentially improve the availability of distributed resources, and enable a large variety of collaborative applications [5], reducing the need to rely on the main Internet backbone infrastructure to access the resources.

Filling the Holes

Opportunities to users: Besides Fig. 3 showing the results of quantified opportunistic networks, we also include in the figure how these networks can be interconnected and what are the benefits of doing this. Thus, we next show how the interconnecting of opportunistic networks can improve the opportunities to establish collaborations between users. We ranked all the cells in our ROI based on two factors,

1. Total amount of users in that cell
2. Adjacent number of users in neighbor cells.

From this list of candidate networks, two users (user A and user B) are selected and evaluated in different situations. The selection criteria is that a user should belong to an opportunistic network ranked in the 50th percentile; each user is chosen randomly from the list of candidate networks, and the two users cannot belong to the same network. This ensures that users can be conceptually treated as workers [15], such that workers are required to establish collaborators to perform a task and do not engage into collaborators from networks that are very sparse and highly volatile, e.g., very oscillating churn rate. Notice that other situations for augmenting opportunistic networks could be adopted, however, we focus on situations that make it feasible and reasonable to establish collaboration between devices. Indeed, in these situations, the churn of devices is stable enough to guarantee that users will benefit from collaborating rather than deplete their resources from non-beneficial collaborations [2].

Network model and assumptions: After selecting the users in the opportunistic networks, we next illustrate how the amount of collaboration opportunities can be augmented by using autonomous drones as proxy to interconnect isolated networks. To make our results intuitive to understand, we proceed to interconnect the previous selected users A and B. We assume that networks with large concentrations of devices in adjacent cells can interconnect automatically, while cells with fewer or none (white and lighter-green backgrounds) require the deployment of autonomous drones. In addition, we also highlight stable paths that are created by exploiting cells with denser (darker-green) amount of devices to intercommunicate users A and B. Notice that other paths and networks can be considered, however, other paths may be less stable or require more jumps to establish intercommunication, making the network paths more difficult to follow.

Results: Figure 3 overlaps the deployment of autonomous drones required to interconnect users A and B in different networks as well as highlights the communication path between them. From the figure, we can observe that the deployment of autonomous drones can augment the amount of opportunities to find collaborators for individual users. Table 1 quantifies the number of devices that are accessible for each user A and B in their respective surrounding area (within the same cell), and adjacent cells as these devices can be accessed by any device in the opportunistic network. In parallel to this, by using autonomous drones as intelligent gateways, it is also possible to observe the amount of devices that are in reach when interconnecting different networks (Path A-B). Here, we can observe that the deployment of an autonomous drone facilitates the access to other devices in more distant cells. Our results suggest that the amount of devices in average increases 3x times when interconnecting networks using autonomous drones. For instance, during Lunch break for User A and B, the number of devices in average increases from 97 to 352, suggesting that a higher amount of devices can be considered as underlying infrastructure of collaborative and distributed applications. Despite this, Fig. 3 also shows that there are several locations (cells) with fewer number of devices. For instance, Figure 3a and 3f shows the locations with the less concentration of devices. In this case, the deployment of autonomous drones can be used instead for caching content and assignation of training tasks that are asynchronously delivered to users rather than enabling synchronous execution of distributed and collaborative applications [5].

Discussion

Multi-drone deployment size: In our analysis, the area of each cell in reality depicts a 2 km squared area in the ROI. A deployment of autonomous drones is required in each cell to enable gateway connectivity services that interconnect the opportunistic networks. The amount of autonomous drones required in each cell can be selected based on a large spectrum of aspects, such as drone modality (aerial, aquatic, land), drone capacity (resource payload), connectivity range, drone stationary time, battery life, and amount of users in the location to mention some. While our results demonstrate the potential of using autonomous drones for interconnecting networks, further modelling and analysis of the problem using multiple parameters is required to select the optimal deployment of autonomous drones in complex urban contexts. Our previous work [9] explores this selection simply by using the amount of users available in a location as a single parameter.

Routine (activities)	User A	User B	Path (A-B)
Work (morning)	130	118	369
Lunch break	100	95	352
Work (afternoon)	116	78	366
Rush hours (evening)	93	80	240
Leisure (evening)	151	136	252
Total	**118**	**101.4**	**315.8**

TABLE 1. Number of distributed devices that are available in individual and interconnected networks.

Re-designing urban areas: Currently, urban areas are not designed for the easy integration of autonomous drones. Existing solutions operate in sidewalks or within specific locations, e.g., University campus. Moreover, certain modalities of autonomous drones are also preferable for operating in specific areas. For instance, autonomous ground drones are preferable for operating in urban areas when compared with aerial drones as ground drones produce less noise. As the deployment of drone technology increases, it is possible that cities may re-design urban spaces to blend their deployments more transparently. This implies that in future city designs, it is easy to exploit autonomous drones in our surroundings, e.g., in a bus stop and metro.

Stakeholders: Service and content providers would be the main stakeholders of our solution. Similarly, vendor of apps can lease autonomous drones to support the performance of their applications. For instance, Pokemon Go and Metaverse apps. Governmental institutions and municipalities would also be interested in maintaining ready-to-use communication infrastructure for disaster management powered by autonomous drones.

Room for improvement: While our work uses a grid-like method with cells of fixed dimensions for mobility analysis between areas, we are interested in exploring whether optimal selection of autonomous drones is possible when considering different area sizes (smaller cells). Besides this, we are also interested in mapping better the land usage of a city to a specific modality of autonomous drone. For instance, in a park area with a lake, underwater drones could be a more energy-efficient option to interconnect networks as the underwater drone can float on the surface. In parallel to this, we are also interested in verifying our results further with datasets from other cities. It is possible that different cities have slightly different urban structure characteristics, suggesting that the use of autonomous drones may not be possible to be piggybacked transparently in some cases, requiring instead, dedicated autonomous drones for performing network routing and forwarding tasks in a specific location.

Data collection at scale: Our work demonstrates that a deployment of multiple autonomous drones can be exploited to fill the gaps between networks, supporting better collaborative and distributed applications. While autonomous drones to deliver services on the edge have been envi-

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sioned in the art [9], autonomous drones can also be utilized to support a variety of data collection applications. For instance, crowdsensing and crowdsourcing methods could be initiated by an autonomous drone instead of a central server. The collected data can then be transmitted asynchronously between autonomous drones until reaching its destination. At the same time, autonomous drones can be used to cache data. This cached data can be delivered in other locations to bootstrap the performance of smartphone and wearable applications.

Micro-mobility infrastructure: Another type of smart infrastructure that can be exploited to interconnect opportunistic networks is micro-mobility one. Micro-mobility vehicles, e.g., scooters and bicycles; can integrate packet forwarding interfaces to disseminate network data. Moreover, micro-mobility infrastructure inherently follows human mobility patterns, making it more suitable to interconnect opportunistic networks. Micro-mobility may provide better area coverage and more adaptability and flexibility to different cities with different urban structure characteristics. Naturally, a combination of multiple solutions (micro-mobility vehicles and autonomous drones) can provide more robust performance of the gateways and better coverage at city-scale.

Summary and Conclusions

In this article, a research vision of opportunistic multi-drone networks is presented. This vision builds on the idea of using autonomous drones to improve the coverage and the process of finding collaborators in opportunistic networks. Through a rigorous analysis that consider a dataset captured by a cellular operator, the feasibility of the vision is demonstrated. Our results suggest that autonomous drones can fill the holes between individual networks to overcome their limited coverage and short life span. By doing so, our findings also indicate that it is possible to augment the surrounding availability of proximal devices up to 3x times. Our work paves the way towards new solutions that can advance further the usage of opportunistic networks to support emerging application domains, such as the Metaverse and edge intelligence.

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Biographies

Huber Flores (huber.flores@ut.ee) is an Associate Professor at the University of Tartu. Research: Distributed, mobile and pervasive computing systems.