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Performance Trade-Offs in IoT Enabled Drone Swarm for Amphibious Landing Operations

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Abstract—IoT enabled armed reconnaissance drones in swarms can conduct reconnaissance over large areas and launch coordinated attacks on valuable targets, which could be particularly useful in amphibious landing missions. Motivated by the rapid advance of the wireless backhaul technologies, in this work we demonstrate that the UAVs can share messages and perform cooperative beam forming for more efficient interference mitigation—a technique called Coordinate Multi-Point (CoMP) in the sky. The initial deployment of UAVs from the ground and the re-deployment of UAVs once an area is searched are also investigated for trade-offs to reduce energy costs and search time. Three strategies are compared that are scalable and decentralized, and require low computational and communication resources. Once finishing the frequency allocation, we maximize the minimum distance among subspaces spanned by codebook matrices obtained in Grassmannian subspace packing scheduling for the small unit of drone swarm. We expose our result for throughput–delay trade-off over a single-UAV-enabled network with GUs’ nominal locations and the UAV trajectories. The robustness of trade-offs is shown for the maximum transmit power and the receiver noise power as 20 dBm (0.1 W) and -110 dBm, respectively, while the channel power gain at the reference distance of 1 m is set as -50 dB. We observed that the optimized UAV trajectories are tend not only to shorten the communication distances between the UAVs and their associated GUs, but also to enlarge the separations of the two UAVs to help alleviate the co-channel interference, in the case without power control. Our outcomes encourage to solve the multi-UAV mobility prediction in a large-scale system state prediction such as Directional Airborne Network (DAN). It is observed that the UAV flies close to the two GUs by following a smooth trajectory with relatively large turning radii when $E_{\max} = 13$ kJ; whereas when E_{\max} is increased to 23 kJ, the UAV’s trajectory tends to approach that without the propulsion energy constraints. Capable of deployment from the ground, sea and air, proposed methodology of Synthetic Interference Matrix (SIM) could play a vital role in challenging missions including simultaneous and coordinated operation of a large number of drones that could prove to be very difficult to defend against.

Index Terms—Drone Swarm, Coperative Network, 5G, Amphibious Landing, Grassmannian Subspace

I. INTRODUCTION

U nmanned aerial vehicle (UAV) networks need an efficient routing scheme to form any swarming shape. Such a routing scheme exchanges the node profile information

[moving speeds, locations, quality-of-service (QoS) requirements, etc.] among UAVs to speed up the swarming process. Hierarchical routing is a classic routing with the goal to manage large-scale UAV networks and decrease routing table size in each node. It first separates the nodes into different groups based on some type of criteria such as node proximity and task synchronizations [1]. The routing process will find the group IDs to traverse each time instead of going through each individual node.

Internet routing was built in a hierarchical style. Figure 1.1 shows the multilevel Internet structure. Users or customers are first separated into different areas [called Autonomous Systems (AS)] based on their physical locations or network link states. Several network areas are connected with an Internet backbone. Those areas form one AS to several ASes can share the same upper-level backbone, which are shown as bold lines in Figure 1.1. Specific routing protocols can operate in different ASes. In Figure 1.1, there are actually three route levels, i.e., intra-area, inter-area, and inter-AS. They are responsible for transferring packets within the same area, from an area to the backbone or between different ASes (via backbone), respectively.

Here the skeleton is defined as the contour that reflects the approximate shape of the whole UAV swarm. From a geometry viewpoint, such a skeleton often represents the median axis of the entire shape. It is typically located in the core area of the network so it has the most stable routing topology. In other words, the nodes located in the skeleton do not move as much as the nodes in the marginal areas during the swarming process. A virtual backbone of the UAV network can be established by using the skeleton nodes, and a hierarchical routing topology can be formed.

Figure 1.1 also shows a general ideal of a UAV network by utilizing hierarchical routing structure. In this figure, the first-level routers (which are special UAVs located in the main skeleton sections) are located in the “trunk”. The second-level routers are located in the branches of the trunk. Other UAVs use the second-level routers to reach the first-level routers. The benefits for such a multilevel routing structure are straightforward: it is very easy to determine the communication routes by just searching the closest skeleton UAVs.

Today, UAVs are of great interest in broad areas of applications, such as military reconnaissance, firefighter operation, police pursuit and so forth. The more and more advanced

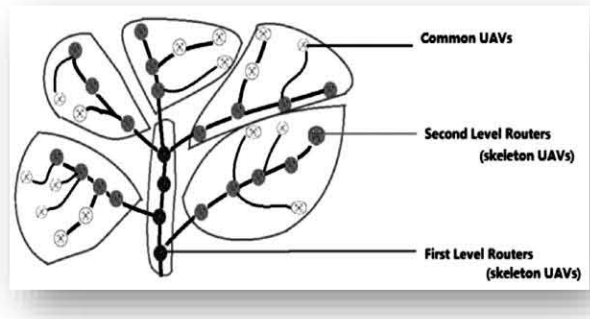


Figure 1.1 UAV network with hierarchical routing structure.

technologies enable the UAVs to perform tasks with longer distance, more accurate maneuvering, more efficient communication qualities and so forth. In this case, the U.S. Federal Aviation Administration (FAA) and the U.S. Army have issued well-built standards defining the UAV applications in detail [1, 2, 3]. Research has been done based on those regulations and standards for a more reliable and robust aerovehicle design.

Motivated by the above new and interesting trade-offs among the throughput, delay, and (propulsion) energy consumption in UAV communication and trajectory design, this work aims to provide an overview on the state-of-the-art results on them. In particular, we will focus on the use of UAVs as communication platforms (e.g., aerial BSs/relays) to serve terrestrial users, although such fundamental trade-offs also exist similarly in the other paradigm with UAVs as new aerial users to be served by the ground BSs in the cellular network.

One of the most technological difficulties lies in the topology strategies of network communications. Currently, the most common flying strategy of UAVs is the single-UAV system. The UAV is set off individually, controlled and communicated by a human through a single-phase, two-way channel. Because the single-UAV (agent [3, 4, 5]) is relatively short ranged [4, 6, 7], once the command has been issued by the controller, the drone executes and gives feedback via a wireless network. This end-to-end communication method has three possible design flaws:

- (1) the communication quality is dependent on the travel distance of the drone, where the increased distance of the UAV yields a poorer connection;
- (2) the short-range response time limits this drone from tasks that require a relatively long distance [5, 8, 9]; and
- (3) the drone is not able to respond to the change of aerial environment intelligently and give feedback in time, so that if something happened to the drone that terminated the commanding channel, the UAV-at-large might not be able to retract back to the user.

Under this circumstance, a new applicable tactic has been suggested in coping with the abovementioned disadvantages, namely multi-UAV systems. A brief comparison between single- and multi-UAV systems is illustrated in Figures 1.3 and 1.4. The search range of single-UAV forms a 2D geographical

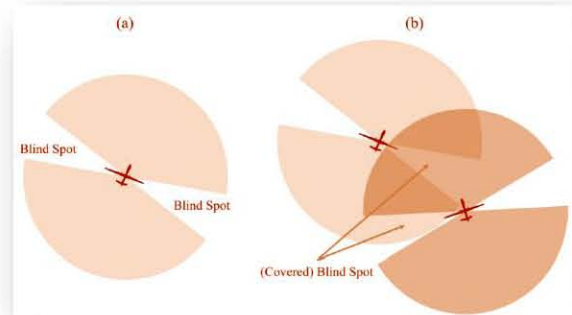


Figure 1.2 Blind spot illustration between (a) single-UAV and (b) multi-UAV systems.

map with relative coordinates x, y . Due to the limitation of its design, it is possible to leave a traceable blind spot on the map. In contrast, a multi-UAV utilizes a group of small UAVs working simultaneously on a mission such that the Field of View (FoV) formed has a depth of zero or a very limited blind spot.

From [10, 11, 12], there are many advantages of multi-UAV systems: (1) economy, (2) flexibility, (3) continuity, (4) speediness, (5) higher accuracy, (6) sustainability, and (7) ease of problem solving.

To solve this problem, Purta *et al.* suggested a multi-hop communication method, from which the movement of each agent is determined by its own assigned tasks and by the behaviors of others. The balanced icosystem rule ensures that no more than two agents will be working on the same task at once, while others in the same swarm will either be idling or working on something else [4, 13, 14]. In Lidowski *et al.* [7, 15, 16], the geographic greedy perimeter stateless routing (GPSR) is used for the UAV search mission protocol (USMP). Each agent is able to track its neighbor's location with the inner routing and conflict resolution rule designs.

This method helps avoid existing conflicts and prevent route overlying. Routing management has become a hot subject in swarm UAV maneuvering tactics, the major advantages of which are more movable and more flexible. Thus, the ground station-based control is no longer feasible due to the ranging and responding time limitations. Azeemi *et al.* [16, 17, 18, 19], suggested two possible algorithms for an ideal drone package delivering system. The task assignment is agent based instead of group based for better time-management purposes. The provided algorithms were able to achieve linear growth in package delivery with respect to time: more drones were deployed, and more tasks were done in a limited period of time. This method also can be applied to the searching missions in cases of emergency, catastrophic events and similar civil activities.

Recently, Amazon proposed a future delivery system called Prime Air [8, 18, 20, 21], which manages short-range delivery using drones with facial and voice recognition, optical and ambient sensors, Global Position System (GPS) and other

(a)



(b)



Figure 1.3 These are (a) 3D and (b) 2D geographical maps captured by single- and multi-UAV systems, respectively. [Google Map, Municipality Park Vienna]

usable features. The task assignment is designed to be a total autonomous feedback machine so that it can automatically communicate with customers, vendors and other agents via an inner secured network. The commanding dependency from a ground station has been largely weakened due to the use of multi-layer ad hoc network architecture.

A greedy routing algorithm also is used on a variety of network graphs. It is an algorithmic paradigm that follows the problem-solving heuristic of making the locally optimal choice at each stage [9, 11, 22] with the intent of finding a global optimum. In many problems, a greedy strategy does not usually produce an optimal solution; nonetheless, a greedy heuristic may yield locally optimal solutions that approximate a globally optimal solution in a reasonable amount of time.

Despite the advantages of the proposed optimal routing algorithm, there are some non-negligible caveats with this method. First, the Open Graph Drawing Framework (OGDF)

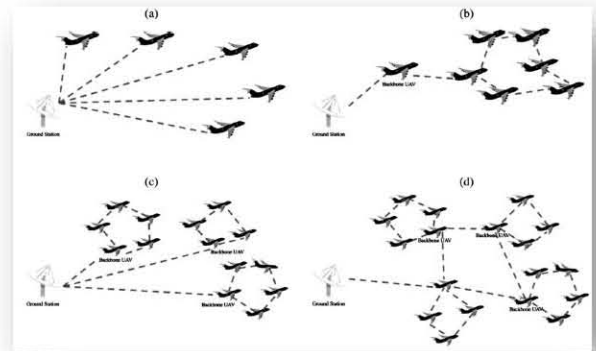


Figure 1.4 Communication architectures between UAVs and the ground station. (a) Centralized. (b) Ad hoc. (c) Multi-group. (d) Multi-layer ad hoc networks.

was considered a major code library, which has limited the system within a simulation phase [23, 24, 25]. Second, with more nodes in the system, this algorithm was overwhelmed by the random generated packages [11, 26, 27]. The performance was sabotaged by the increasing number of test nodes, which caused the entire system to be less controllable. Finally, the cost function was not taken into consideration to show if this application is economically or geographically viable.

In the last decade, during the explosive development of drones, decentralized communication architectures have been adapted to operate a one-to-many mode of operating multiple drones by providing timely air-to-air and air-to-ground information exchange [28, 29, 30, 31]. This Section presents four different architecture based on UAVs and ground stations communication as shown in Figure 1.4. Because most of the multi-UAV systems require instant communication, the communication architectures and protocols are under reformation from decade to decade. Li *et al.* introduced four major communication architectures for networking UAVs, and the topological differences are shown in Figure 1.2. The multi-layer ad hoc network works best among all four types with interchangeable network connections, and the supervising powers were distributed to the backbone UAVs such that the ground station only performs as information processing [10, 11, 12, 32]. In this way, the computation and communication loads were significantly reduced, which also facilitates a more robust and reliable ad hoc networking system.

II. UAV COMMUNICATION PROTOCOLS

In November 2017, the FAA launched a national program, namely the “Drone Integration Pilot Program,” to explore the expanded use of drones, including Beyond Visual Line of Sight (BVLoS) flights, night-time operations, and flights above people [6]. Wireless communication is an essential enabling technology of small unmanned aircraft systems (UASs) with aircraft weight less than 55 pounds (25 kg) [9, 10, 33]. On the one hand, UAVs need to exchange safety-critical information with various parties such as remote pilots, nearby aerial

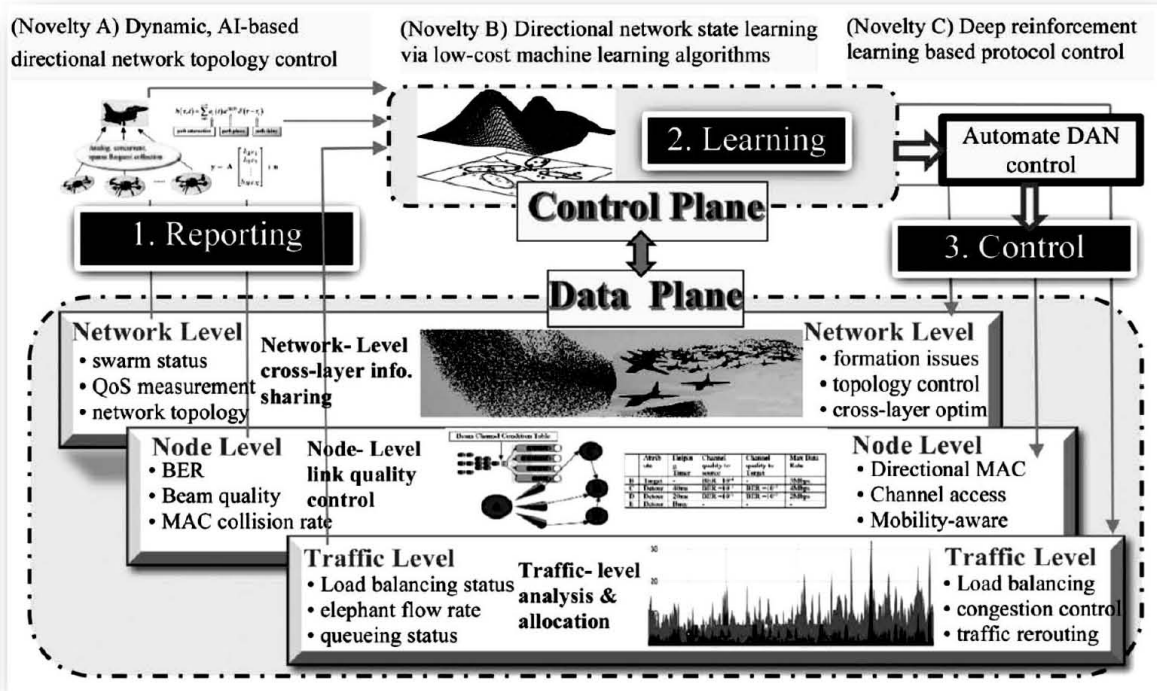


Figure 2.1 SDN-compatible intelligent directional airborne network.

vehicles, and air traffic controllers, to ensure safe, reliable, and efficient flight operation. This is commonly known as control and non-payload communication (CNPC) [11, 12, 13].

A. UAV Swarm Communication and Spectrum Requirement

Enabling reliable and secure CNPC links is a necessity for the large-scale deployment and wide usage of UAVs. The International Telecommunication Union (ITU) has classified the required CNPC to ensure safe UAV operations into three categories [11, 34, 35].

- Communication for UAV command and control: This includes the telemetry report (e.g., flight status) from the UAV to the ground pilot, the real-time telecommand signaling from ground to UAVs for non-autonomous UAVs, and regular flight command update (such as waypoint update) for (semi-) autonomous UAVs.
- Communication for air traffic control (ATC) relay: It is critical to ensure that UAVs do not cause any safety threat to traditional manned aircraft, especially for operations approaching areas with a high density of aircraft. To this end, a link between the air traffic controller and the ground control station via the UAV, called ATC relay, is required.
- Communication supporting “sense and avoid”: The ability to support “sense and avoid” ensures that the UAV maintains sufficient safety distance from nearby aerial vehicles, terrain, and obstacles.

The specific communication and spectrum requirements in general differ for CNPC and payload communications. Recently, the 3rd generation partnership project (3GPP) has

specified the communication requirements for these two types of links [2]. We use an airborne path loss model to determine the communication parameters, such as power level, queue size, sending rate, time slot length, and so forth. Moreover, we also need to achieve the end-to-end routing performance optimization by establishing a multi-hop directional data relay Cross-layer directional Medium Access Control (MAC)/ routing/ transport protocol optimization. We suggest Directional Airborne Network (DAN) plays a critical role in military applications due to its extended communication range (>1 km). Figure 2.1 illustrates our suggested architecture of SDN-based DAN with self-configurable, ML/DL-based cross-layer protocol design and real-time situation awareness. It has two novel features:

1. Three design modules between CP and DP: First, we will need practical protocols to perform “module 1 – reporting”, which aims to collect network parameters from the DAN. We suggest using compressive sampling to reduce data collection frequency while guaranteeing the data resolution and quality. Second, the “module 2 – learning” executes ML/DL algorithms to find the intrinsic network patterns and identify any abnormal events. Third, the “module 3 – control” uses the learning results to control the network protocols.
2. Three levels of network management: To manage more efficiently the directional networking protocols, the network status/operations are classified into three levels. The network level is the highest level and takes care of the entire network’s state estimation and management. For example, the CP can collect the swarming topology



Figure 2.2 Supporting UAV communications with an integrated 5G network architecture.

Source: From Zeng et al. [40].

information and adjust the routing protocol based on the new network shape. The node level focuses on the control of each individual node, such as the node mobility and directional antenna orientation changes. The traffic level aims to capture the traffic flow's distribution in the network and identify possible congestion regions and balance the elephant/mice flows' load allocation in different links.

B. Potential Existing Technologies for UAV Communications

In this work, we found that in order to support the CNPC and payload communication in multifarious UAV applications, proper wireless technologies need to be selected for achieving seamless connectivity and high reliability/throughput for both air-to-air and air-to-ground wireless communications in 3D space. Towards this end, we present four candidate communication technologies and compared next, including (i) direct link, (ii) satellite, (iii) ad-hoc network, and (iv) cellular network.

1) Direct Link

Due to its simplicity and low cost, the direct point-to-point communication between a UAV and its associated ground node over the unlicensed band (e.g., the Industrial Scientific Medical (ISM) 2.4 GHz band) was most commonly used for commercial UAVs in the past, where the ground node can be a joystick, remote controller, or ground station. However, it is usually limited to LoS communication, which significantly constrains its operation range and hinders its applications in complex propagation environments. For example, in urban areas, the communication can be easily blocked by, e.g., trees and high-rise buildings, which results in poor reliability and low data rate. In addition, such a simple solution is usually insecure and vulnerable to interference and jamming. Due to the above

limitations, the simple direct-link communication is not a scalable solution for supporting large-scale deployment of UAVs in the future.

2) Satellite Link

Enabling UAV communications by leveraging satellites is a viable option due to their global coverage. Specifically, satellites can help relay data communicated between widely separated UAVs and ground gateways which is particularly useful for UAVs above oceans and in remote areas where terrestrial network (WiFi or cellular) coverage is unavailable. Furthermore, satellite signals can also be used for navigation and localization of UAVs. In WRC-15, the conditional use of satellite communication frequencies in the Ku/Ka band has been approved to connect drones to satellites, and some satellite companies such as Inmarsat have launched a satellite communication service for UAVs [11, 36, 37].

3) Ad-Hoc Network

Mobile ad-hoc network (MANET) is an infrastructure-free and dynamically self-organizing network for enabling peer-to-peer communications among mobile devices such as laptops, cellphones, and walkie-talkies. Such devices usually communicate over bandwidth-constrained wireless links using, e.g., IEEE 802.11 a/b/g/n. Each device in a MANET can move randomly over time; as a result, its link conditions with other

Vehicular ad-hoc network (VANET) and flying ad-hoc network (FANET) are two applications of MANET, for supporting communications among high-mobility ground vehicles and UAVs in 2D and 3D networks, respectively [7, 25, 38].

The topology or configuration of a FANET for UAVs may take different forms, such as a mesh, ring, star, or even a straight

line, depending on the application scenario. For example, a star network topology is suitable for UAV swarm applications, for which UAVs in a swarm all communicate through a central hub UAV that is responsible for communicating with the ground stations. Although FANET is a robust and flexible architecture for supporting UAV communications in a small network, it is generally unable to provide a scalable solution for serving massive UAVs deployed in a wide area, due to the complexities and difficulties for realizing a reliable routing protocol over the whole network with dynamic and intermittent link connectivity among the flying UAVs [39, 40].

4) Cellular Network

It is evident that the aforementioned technologies generally cannot support large-scale UAV communications in a cost-effective manner. On the other hand, it is also economically nonviable to build new and dedicated ground networks for achieving this goal. As such, there has been significantly growing interest recently in leveraging the existing as well as future-generation cellular networks for enabling UAV-ground communications [17, 41, 42].

Thanks to the almost ubiquitous coverage of the cellular network worldwide as well as its high-speed optical backhaul and advanced communication technologies, both CNPC and payload communication requirements for UAVs can be potentially met, regardless of the density of UAVs as well as their distances from the corresponding ground nodes [43, 44, 45]. For example, the forthcoming fifth-generation (5G) cellular network is expected to support a peak data rate of 10 Gbps with only 1 ms round-trip latency, which in principle is adequate for high-rate and delay-sensitive UAV communication applications such as real-time video streaming and data relaying.

Despite the promising advantages of cellular-enabled UAV communications, there are still scenarios where the cellular services are unavailable, e.g., in remote areas such as sea, desert, and forest. In such scenarios, other technologies such as direct link, satellite, and FANET can be used to support UAV communications beyond the terrestrial coverage of cellular networks [46, 47]. Therefore, it is envisioned that the future wireless network for supporting large-scale UAV communications will have an integrated 3D architecture consisting of UAV-to-UAV, UAV-to-satellite, and UAV-to-ground communications, as shown in Figure 2.2, where each UAV may be enabled with one or more communication technologies to exploit the rich connectivity diversity in such a hybrid network [48].

C. Adaptive Trajectory Constraints

Besides throughput, two important factors also need to be considered in UAV communication and trajectory design, namely, delay and energy. First, to maximize throughput, each UAV should communicate with a ground user/BS when flying sufficiently close to it so as to reduce their distance and hence improve the link capacity. However, this inevitably incurs more delay in communication due to the UAV movement. Thus, there

1. Assign the mobile sensors $S = \{s_1, \dots, s_N\}$ with $s_i = (p_i, \hat{n}_i, f_i)$
2. Assign the landmarks $L = \{\ell_1, \dots, \ell_N\}$
3. Assign a partition $P = \{P_1, \dots, P_N\}$
4. Assign $\epsilon > 0$ and set $Z_i = \{s_i\}$ for $i \in \{1, \dots, N\}$
5. while $Z_i \neq \emptyset$ for some $i \in \{1, \dots, N\}$ do
6. pick s_i such that Z_i is not empty
7. pick $s_i \in Z_i$
8. for $\ell \in L_i$ do
9. if $\text{per}(s_j, \ell) < \text{per}(s_j, \ell) - \epsilon$ then
10. transfer ℓ from L_i to L_j
11. end if
12. end for
13. if one or more landmarks have been transferred then
14. $Z_i \leftarrow S \setminus \{s_i\}$
15. $Z_j \leftarrow S \setminus \{s_j\}$
16. $(p_i, \hat{n}_i) \leftarrow \text{optcov}(s_i, L_i, \Omega_i)$
17. $(p_j, \hat{n}_j) \leftarrow \text{optcov}(s_j, L_j, \Omega_j)$
18. else
19. remove
20. end if
21. end while

Figure 3.1 Generalized ALGORITHM for Discrete Lloyd Descent Drone Swarm Azeemi et al. [11]

is an interesting throughput-delay trade-off in UAV-to-ground communication [49]. Second, there also exists a new trade-off between throughput and energy in UAV-enabled communication, since the UAV generally needs to consume more propulsion energy to move closer to the ground users/BSs in order to gain higher throughput [50]. As commercial UAVs usually have limited on-board energy, more propulsion energy consumption leads to shorter endurance of UAVs, thus imposing a critical constraint on their practical applications. Last, the above two trade-offs naturally imply a delay-energy trade-off, as delay in UAV-to-ground communication can be reduced if more propulsion energy is consumed by the UAV to move faster to the ground users/BSs it is designated to communicate with.

III. DEPLOYMENT STRATEGIES

The initial deployment of UAVs from the ground and the re-deployment of UAVs once an area is searched are investigated to reduce energy costs and search time. Three strategies are compared that are scalable and decentralized, and require low computational and communication resources. The strategies exploit environment information to reduce unnecessary motion, and reduce diminishing returns and interference between UAVs:

1) Linear-temporal incremental deployment (LTID):

This strategy deploys UAVs one at a time with a fixed time interval between consecutive launches. Longer inter-launch intervals slow deployment, but decrease the number of concurrent UAVs. This reduces partial interference and unnecessary flight by exploiting environmental information acquired from the expanding network. Once a sub-area of the environment has been searched, UAV pre-deploy as explorers to new unexplored areas. Before this re-deployment

commences, there may be multiple explorers flying into this sub-area where they are not required, which is reduced with longer inter-launch intervals. Thus, LTID reduces energy consumption by reducing interference and unnecessary movement.

2) *Single incremental deployment (SID):*

This strategy is similar to LTID and deploys one UAV at a time, but waits for the previous UAV to become a beacon before launching the next. Single incremental deployment reduces unnecessary flight time because the next UAV will only deploy once the beacon network has sensed the environment and perceived if and where a new beacon is required. Thereby, explorers always fly directly to the de-sired deployment location. To implement SID, the network communicates if an explorer is flying. This can be achieved by propagating local messages across the beacon network. Beacons signal to the whole team if they perceive a flying explorer and UAVs only deploy if no signal is received. To ensure only a single UAV deploys at a time, random timeouts are used. When no flying explorer signal is present, UAVs wait a short random time period. If after this period there is no flying explorer signal, the UAV can deploy.

3) *Adaptive group size (AGS):*

This strategy adapts the density of UAVs, initially rapidly deploying UAVs, every 2–3s. Explorers measure the density of neighboring UAVs using the irrelative-positioning sensor and probabilistically land if the density is higher than a predefined threshold. This decreases the ratio of UAVs, diminishing returns and interference. UAVs which have landed launch again when there are no UAVs flying in the vicinity.

IV. RESULTS

The deployment of small cells in coverage holes can effectively reduce the penetration loss with a large amount of users. However, the small cell may produce interference to the users served by other power nodes, and simultaneously be affected by the interference from surrounding small cells and macro cells. To solve this problem, a synthetic interference matrix is utilized in resource allocation in our proposed algorithm, which is generated by the frequency and power distribution in different directions collected by the small cell. The synthetic interference matrix is extended by the spectrum sensing matrix in the system.

Figure 4.1 describes a basic model, where an integrated cell consisting of three sectors is surrounded by several power nodes. We can get the position information of all the power nodes from operator's database. In this procedure, the interferences from other eNBs and small cells are taken into account. We can fulfill the modelling adaptive interference detection and frequency angle selection scheme, which can optimally choose the frequency to use for a small cell. A detailed algorithm can be found in [15, 51].

A. *Multi-Cluster Drone Swarm*

Once finishing the frequency allocation, the next task is to consider the multiuser MIMO scheduling for the small cell. The small cells and users share the same codebook to reduce system

overhead. We can obtain the codebook by Grassmannian subspace packing to maximize the minimum distance among subspaces spanned by codebook matrices. In the meantime, the users adjust to match the codebook elements and group themselves according to the channel status. Within one user group, the scheduling process is based on relative channel quality, i.e., the instantaneous channel quality condition of the subscriber divided by its current average throughput. Within one time slot, the subscriber with the largest relative channel quality is to be selected. The multiuser MIMO system can achieve throughput-fairness tradeoff by considering the relative channel quality and codebook.

To evaluate the performance of the proposed scheme above, we simulate three schemes the small cells can be deployed in contrast: the scheme with randomly distributed RBs, the scheme with RBs allocated to each user concerning the interference from macro cells, and our proposed scheme using the compressed sensing based on cylindrical antenna array.

We have developed Matlab simulation for the 5G HetNet shown in Figure. 4.1. Figure 4.2a illustrates the spectral efficiency of conventional linear precoding schemes and the proposed hybrid one under different SNR conditions. Apparently the hybrid precoding scheme has a higher spectral efficiency than the MRT precoding, and thus is more suitable for realistic mmWave system. We also simulated our proposed hybrid precoding scheme as well as the linear ZF and MRT by adopting the null-space method to mitigate inner-tier interference. As shown in Figure 4.2b, we compare these three schemes in terms of system throughput while changing the number of massive MIMO antennas at access points. Massive MIMO demonstrates a performance improvement in system throughput, as the increase of antenna number can eliminate the

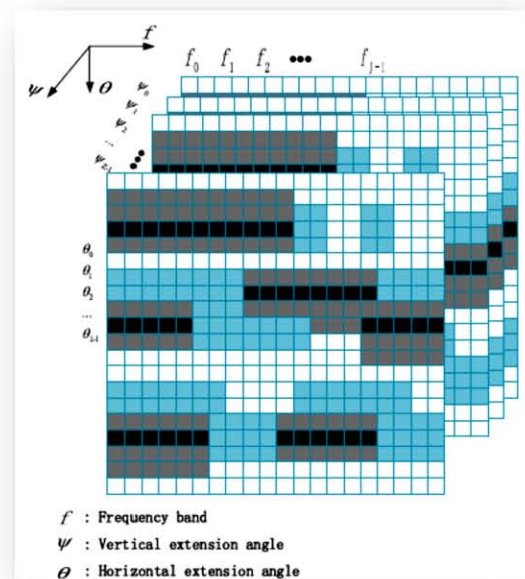


Figure. 4.1 Synthetic interference matrix—a typical set of drone

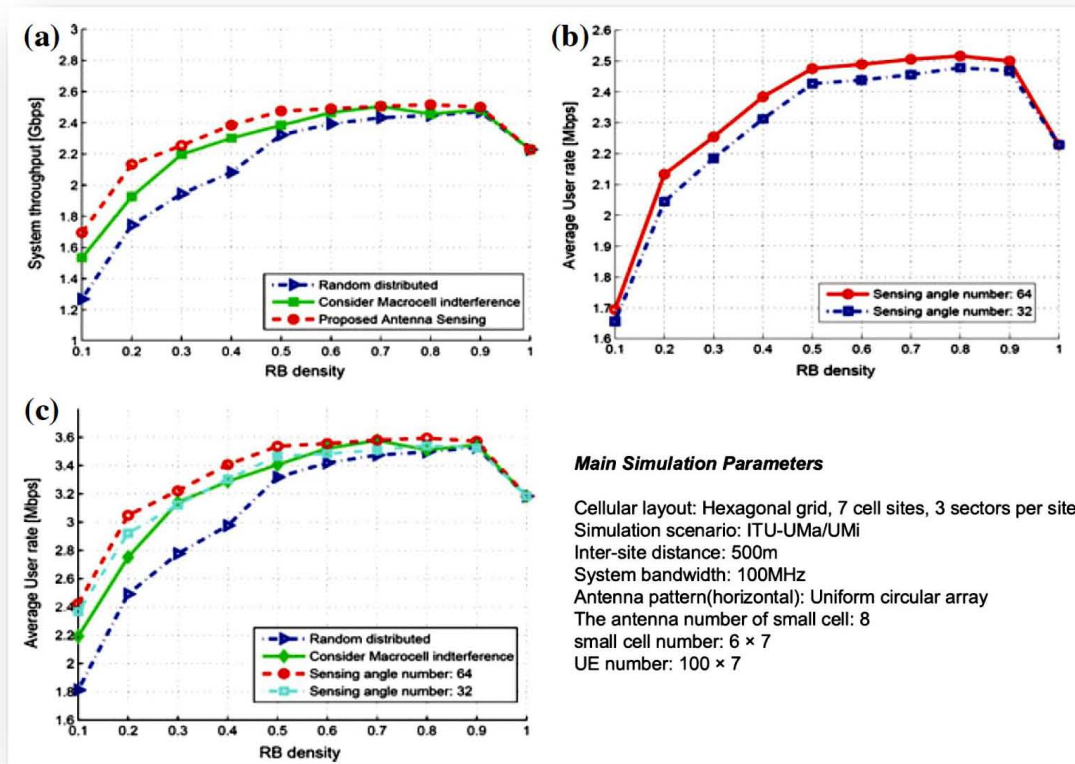


Figure 4.2 Performance evaluation. a) System throughput using different schemes. b) Average user data rate with different numbers of sensing angles. c) Average user data rate with different schemes

interference to the victim users. In addition, the null-space based hybrid precoding achieves considerable throughput gain compared to the MRT precoding when antenna number increases. Figure 4.2 overall justifies that our proposed hybrid precoding scheme is able to achieve competitive performance at lower complexity. Figure 4.2a shows that our proposed scheme can significantly enhance the overall system throughput. Furthermore, the throughputs of all three schemes tend to be similar when the density of RBs increases. This is due to the fact that larger density of RBs causes an increased probability of the inevitable interference. It also demonstrates that the increase of RBs density enhances the system throughput.

Figure 4.2b reveals that the system performance is enhanced along with the increase of sensing angles numbers in the proposed system. The system can deploy more subscribers at a single time slot when sensing with more angles. Figure 4.2c compares the average user data rate with different schemes and different sensing angle numbers. We can see the results can satisfyingly match our expectations.

B. Vulnerability to Trade-offs

In this section, we discuss aforementioned trade-offs in UAV-enabled communication and highlight the main differences with their counterparts in traditional terrestrial communication.

1) Throughput–Delay Trade-Off

The throughput–delay trade-off has been extensively studied for terrestrial wireless communications. For a basic point-to-point wireless communication link, the maximum achievable rate over fading channels, defined as the ergodic capacity, is achieved by coding over a sufficiently large number of channel coherence intervals to fully exploit the ergodicity of fading channels [6]. However, this comes at the cost of long transmission delay, which may not be tolerable for applications with stringent latency requirement. On the other hand, channel coding can be performed over each coherence interval to reduce the delay, resulting in the so-called delay-limited capacity [6]. However, the delay-limited capacity is in general smaller than the ergodic capacity for a given fading channel, and outage is usually inevitable in deep fading [6]. For general multiuser communication, the multiuser diversity gain can be attained to improve the network throughput by scheduling the user with the best channel among all users to communicate in each coherence interval, whereas this inevitably leads to more significant delay for each user as the number of users increases [6].

The above results show that there is a general throughput–delay trade-off for communication over fading channels. Moreover, it is shown in [7] that there is another trade-off between the total throughput of a mobile ad-hoc network (MANET) and the average delay tolerable by the users in the network due to the random user movement, as each user needs

to wait before communicating with each other until they become sufficiently close. By contrast, in UAV-enabled communication, channel fading is no longer a key factor contributing to the throughput–delay trade-off thanks to the LoS-dominant channels. Instead, the mobility of UAVs plays the decisive role in such a trade-off, as the UAV-to-ground LoS channels are solely determined by the distances between the UAV and ground users, which critically depend on the UAV’s location. However, in sharp contrast to the random user movement in a MANET, where the delay is random and difficult to predict [7], the delay in UAV-enabled communication can be properly controlled via a joint UAV trajectory and communication scheduling design. Moreover, another key difference lies in the time scale of the delay between the terrestrial communication and UAV-to-ground communication: in the former case, the delay is measured in terms of channel coherence time, e.g., in milliseconds, while in the latter case, the delay is mainly due to the UAV flying time (distance divided by speed), e.g., in seconds or minutes. As a result, in order to fully exploit the throughput–delay trade-off via trajectory design in UAV-enabled communication, the application needs to be more delay-tolerant as compared to that in terrestrial communication [8].

2) Throughput–Energy Trade-Off

The throughput–energy trade-off in the traditional wireless communication is fundamentally rooted in the Shannon capacity formula, which explicitly suggests that the achievable rate increases monotonically with the transmit power [6]. One useful performance metric stemming from this trade-off is “energy efficiency,” which measures the number of information bits that can be successfully communicated per unit energy consumption. If only the transmit energy is considered, it is well known that the energy efficiency monotonically increases with the decrease of the transmit rate/power [6], while if the circuit power at the transmitter is considered as well, it is shown in [9] that the energy efficiency first increases and then decreases with the transmit rate/power.

In UAV-enabled communication, the propulsion energy (usually in the order of kilowatts (kW)) required to maintain the UAVs airborne and support their high mobility is generally orders of magnitude higher than the transmit and circuit energy for communication (usually in the order of watts (W) or even smaller). As a result, the effect of propulsion energy on the UAV trajectory is the dominant factor determining the throughput–energy trade-off in UAV-enabled communication. For example, to enhance the throughput, each UAV needs to fly over a longer distance with a faster speed so that it can reach each of its served ground users as close as possible and stay near them as long as possible, given a finite flight duration, in order to exploit better LoS channels with them. Moreover, each UAV may also need to adjust its altitude and/or make sharp turns to avoid blockages in the directions of its served ground users. All these can lead to more significant propulsion energy consumption. As a result, for UAV-enabled communication, the energy efficiency is more appropriately defined in terms of information bits per joule (J) of propulsion energy, rather than

that of transmit/circuit energy in traditional wireless communication. Such a new metric has a high practical significance, as it indicates the maximum number of information bits that can be communicated with a finite amount of the UAV’s on-board energy.

3) Delay–Energy Trade-Off

As discussed in the above two subsections, the throughput–delay and throughput–energy trade-offs in UAV-enabled communication exhibit interesting new aspects compared to their traditional counterparts in terrestrial communication. As a result, their corresponding delay–energy trade-offs are also drastically different due to the new UAV trajectory design and the high UAV propulsion energy consumption. For example, to reduce the delay in movement and transmission, each UAV should fly between its served ground users with its maximum speed, but remain at its minimum speed (e.g., hovering) when serving them in its proximity, both resulting in more propulsion energy consumption in general.

In the following two sections, we will focus on examining the throughput–delay and throughput–energy trade-offs, respectively. Since the delay–energy trade-off becomes straightforward given the above two trade-offs, it is omitted for brevity. We will provide concrete examples to illustrate them more clearly, provide overviews on their state-of-the-art results, and also point out promising directions for future research.

C. Vulnerability to Throughput–Delay Trade-Off

In this section, we investigate the joint UAV trajectory and communication design to characterize the throughput–delay trade-off. Specifically, we first consider a simple setup with one UAV serving two ground users (GUs) to draw useful insights. Then, we extend our study to the general case with multiple UAVs serving multiple GUs, followed by further discussions on related/ future work.

1) Single-UAV-Enabled Wireless Network

We consider a UAV-enabled downlink communication system where one UAV is employed to serve two GUs in a finite period of T seconds. The UAV is assumed to fly at a constant altitude of H in meters with the maximum allowable speed denoted by V_{\max} in meters per second (m s^{-1}). The air-to-ground channels from the UAV to the GUs are assumed to be dominated by the LoS links. As such, it is preferable to let the UAV fly as low as possible in order to reduce the signal path loss with the GUs. However, the minimum value of H is practically limited for terrain or building avoidance. The two GUs are assumed to be quasi-stationary with a distance of D meters between their nominal locations, where we assume that their maximum movement distances from their respective nominal locations within the given period T are negligible compared to D and the UAV altitude H ; thus, their effects on the corresponding LoS channel gains are ignored. We consider that the UAV communicates with GUs via time-division multiple access (TDMA), i.e., only one GU is scheduled for communication at any time instant. To serve GUs continuously

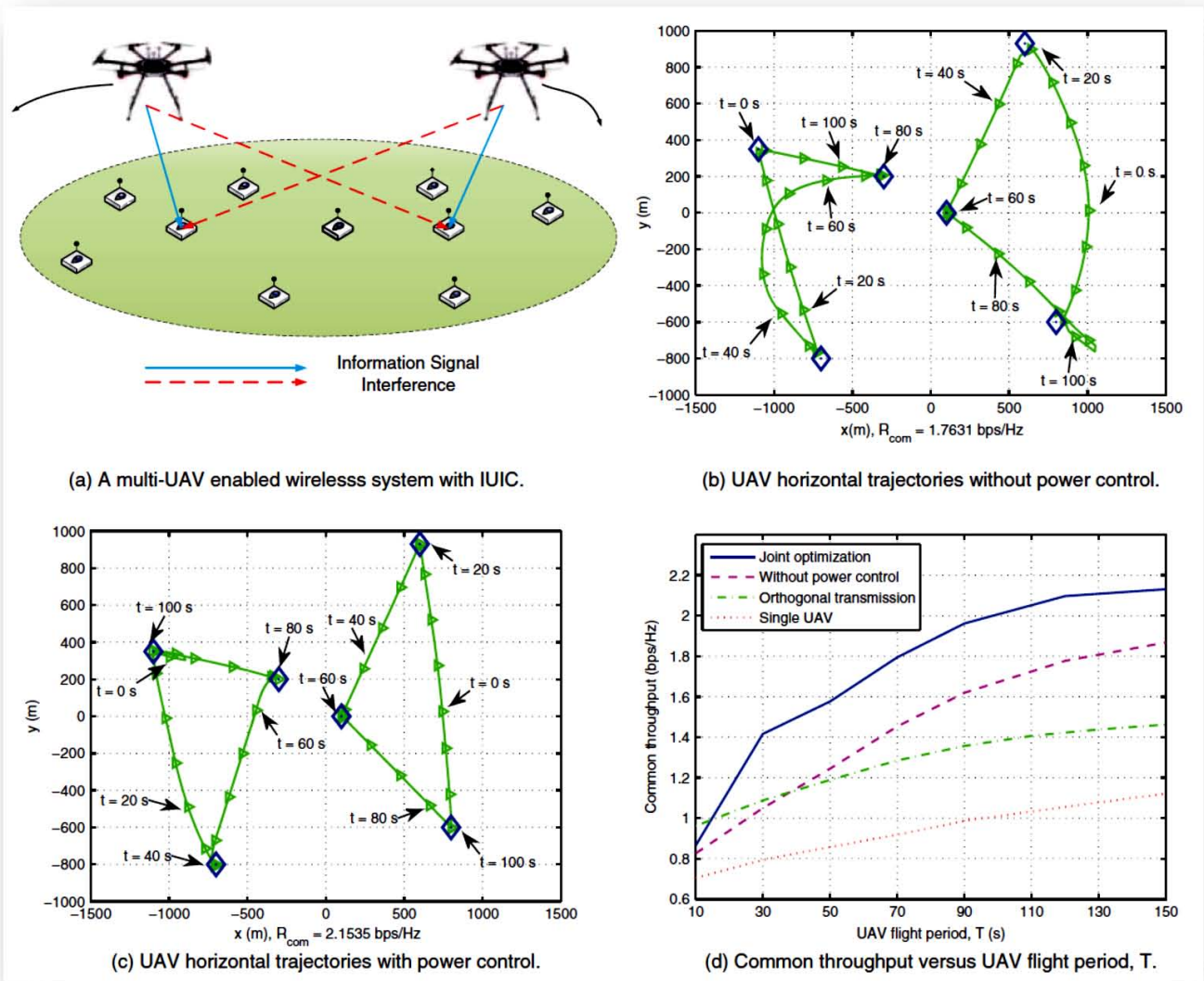


Figure 4.3 Throughput–delay trade-off for a multi-UAV-enabled wireless system with IUI. The GUs’ nominal locations are marked by ‘ \diamond ’s and the UAV trajectories are marked by ‘ \triangleright ’s. The simulation parameters are set to be the same as those in Figure 4.2. The user common throughput is denoted by R_{com} in bps/Hz.

in a periodic manner, we assume that the UAV needs to return to its initial location by the end of each flight period T while the initial location can be optimized for maximizing the throughput. To ensure fairness among GUs, we aim to maximize the common (minimum) throughput among the GUs via jointly optimizing the UAV trajectory and communication scheduling. The UAV’s optimal trajectories projected onto the ground plane under different flight periods, T . It is observed that, as T increases, the UAV tends to fly closer to the two GUs, while when T is sufficiently large (e.g., $T = 100$ s), the UAV flies between the two GUs with its maximum speed to save more time for hovering right above each of them to maintain the best channel for communication.

Furthermore, at any time instant, to maximize the throughput, the GU that is closer to the UAV (thus with a better channel) is scheduled for communication, while the other GU has to wait until the UAV flies closer to it again. As such, each GU will

experience awaiting time of $T/2$ for communicating with the UAV periodically. We illustrated the user scheduling and plotted over time. It is observed that a larger T leads to a longer waiting time for each GU.

Finally, the achievable common throughput in bits per second per Hertz (bps/Hz) versus T . Note that the throughput upper bound is obtained by ignoring the time spent on traveling between the two GUs, which holds when T goes to infinity. In addition, the throughput of a static UAV is obtained by fixing the UAV at the middle location between the two GUs at all times. One can observe that, compared to the case of a static UAV, the common throughput can be significantly improved as T increases with a mobile UAV. However, such a throughput gain is at the cost of increasing the user delay (or larger T), which thus reveals a new throughput–delay trade-off in UAV-

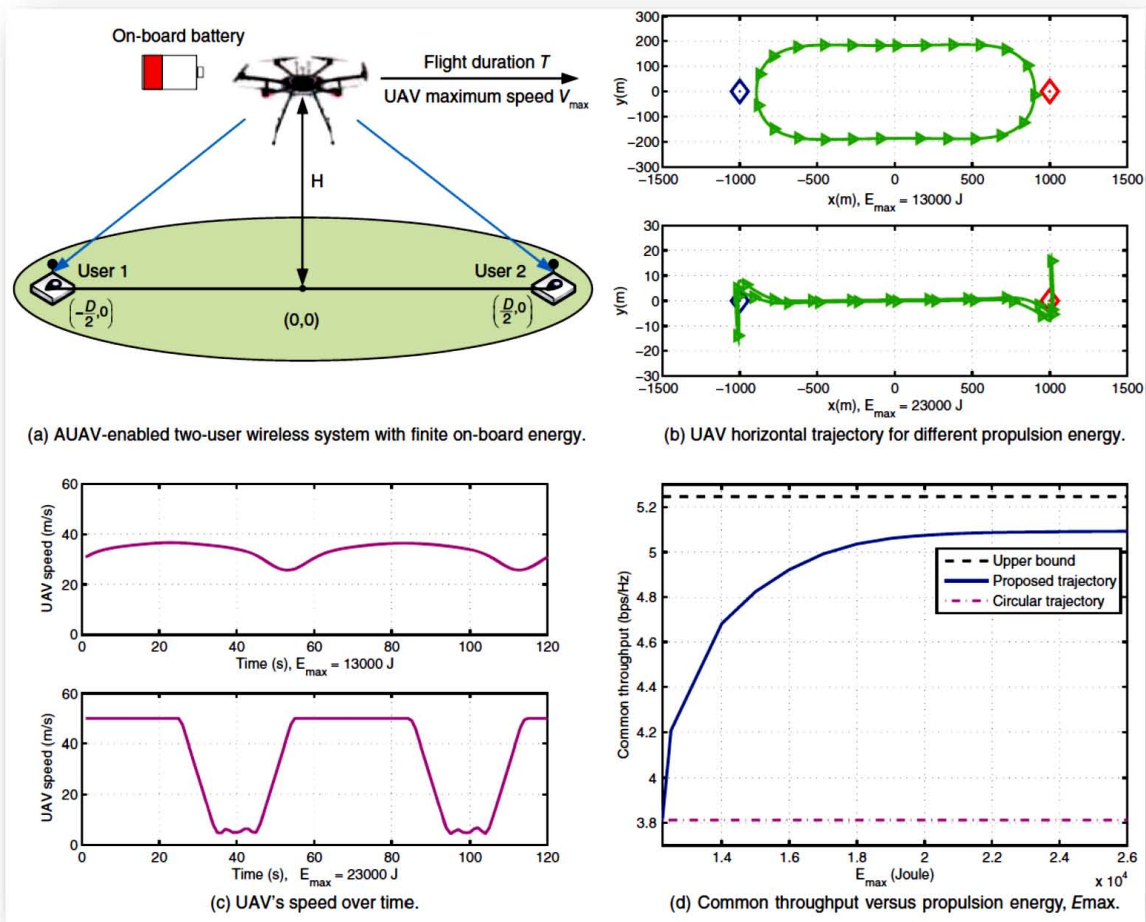


Figure 4.4 Throughput–energy trade-off for a single-UAV-enabled network with two GUs. The GUs' nominal locations are marked by ' \diamond 's and the UAV trajectories are marked by ' \triangleright 's. For the propulsion power consumption model in [10], the constants c_1 and c_2 are set as 9.26×10^{-4} and 2250, respectively. The simulation parameters are set as follows: $V_{\max} = 50 \text{ m s}^{-1}$, $V_{\min} = 5 \text{ m s}^{-1}$, $a_{\max} = 5 \text{ m s}^{-2}$, and $T = 120 \text{ s}$. Other parameters are set to be the same as those in Section III

enabled wireless network.

2) Multi-UAV-Enabled Wireless Network

The use of multiple UAVs for cooperatively serving the GUs is an effective solution to improve the throughput–delay trade-off over the single-UAV-enabled network, by dividing the GUs into smaller-size groups, each served by one of the UAVs. To demonstrate this, we consider a multi-UAV-enabled downlink transmission system as shown in Figure 4.3(a), where two UAVs are employed to serve a group of K GUs in a finite period of duration T . To achieve high spectral efficiency, we consider a spectrum sharing system, where the UAVs share the same frequency band for communication and each of the UAVs serves its associated GUs via the periodic TDMA. As such, each GU suffers from severe interference from other non-associated UAVs due to the LoS channel, which needs to be effectively mitigated by employing inter-UAV interference coordination (IUI) via jointly designing the UAV trajectories, transmit power and user associations.

We aim here to maximize the common throughput of all GUs

with optimally designed IUI. However, this problem is a non-convex optimization problem involving infinite variables due to the continuous UAV trajectory. To tackle this problem, we first apply time discretization to divide the UAV flight period into a finite number of equal-time slots, each with a nominal location of the UAV. Then, we apply the block coordinate descent (BCD) and successive convex approximation (SCA) optimization techniques to obtain a suboptimal solution to the IUI design [10]. As an initial UAV trajectory is needed for our algorithm, we adopt a simple and yet practical circular UAV trajectory for initialization [10]. For the purpose of illustration, we consider a setup with $K = 6$ GUs. Specifically, we show the optimized UAV trajectories without and with power control in Figure 4.3(b) and (c), respectively, for $T = 120 \text{ s}$. In the former case, both UAVs transmit with their maximum power at all times. It is observed from Figure 4.3(b) that the optimized UAV trajectories tend not only to shorten the communication distances between the UAVs and their associated GUs (e.g., from $t = 0$ to $t = 20 \text{ s}$), but also to enlarge the separations of the two UAVs to help alleviate the co-channel interference (e.g.,

from $t = 40$ s to $t = 60$ s), in the case without power control. However, at certain pairs of UAV locations, enlarging the UAVs' separation is achieved at the cost of compromising direct link gains, especially when the UAVs are flying on their ways to serve two GUs (e.g., the two nearby GUs around the center in Figure 4.3(b)) that are close to each other.

In contrast, for the case with power control, it is observed from Figure 4.3(c) that the optimized UAV trajectories do not tend to compromise the direct link gains in return for large distance separation. This is because power control can help avoid strong interference even when the two UAVs have to be close to each other (e.g., when serving the two nearby GUs around the center).

As a result, the common throughput is substantially improved over the case without power control, as shown in Figure 4.3(d). In addition, an orthogonal UAV transmission scheme is adopted for comparison where the two UAVs take turns to transmit information to serve GUs over orthogonal time slots, and the system is then interference-free. One can observe that, for short flying time T , which implies limited UAV flying ranges, the orthogonal transmission even achieves higher throughput than those non-orthogonal schemes, since the latter suffers from severe interference between the UAVs. However, as T increases, the proposed joint design significantly outperforms the orthogonal transmission, since the UAVs' trajectories can be more flexibly designed to enlarge the inter-UAV distance such that the spectrum can be better reused by the two UAVs with small interference. Finally, it is also observed that the user throughput in the multi-UAV network is significantly improved over the single-UAV network at the same delay, thus verifying the improved throughput–delay trade-off via effective multi-UAV cooperation with optimized IUC.

D. Vulnerability to Throughput–Energy Trade-Off

In this section, we investigate further the throughput–energy trade-off in UAV-enabled communication and trajectory design. First, we discuss the energy consumption models of UAVs. Then, we revisit the single-UAV-enabled system described by taking into account the UAV's propulsion energy consumption, followed by discussions on other related work and future research directions.

1) UAV Propulsion Energy Consumption Model

Fixed-wing and rotary-wing UAVs are the two main types of UAVs that have been widely used in practice. Both of them possess respective unique sets of advantages and limitations that render them more or less suitable for different applications. To investigate the throughput–energy trade-off in UAV-enabled communication, the UAV's propulsion energy consumption needs to be properly modeled first. Towards this end, two analytical propulsion power models have been presented for fixed-wing and rotary-wing UAVs in [11] and [10], respectively. In general, the propulsion power required for the UAV depends on its velocity (including both the flying speed and direction) as well as the acceleration. In Figure 4.5, the typical propulsion power consumption versus the UAV's

flying speed is illustrated for both fixed-wing and rotary-wing UAVs. In both cases, it is observed that, as the UAV's flying speed increases, the corresponding propulsion power required first decreases and then increases, which implies that flying at too high or too low speeds is not energy-efficient. Furthermore, flying at a very low speed is extremely energy-consuming and even impossible for fixed-wing UAVs in practice, which renders them very difficult to hover over a small geographical area to serve GUs, while this is not an issue for rotary-wing UAVs. However, rotary-wing UAVs suffer from consuming excessive propulsion power when the UAV's flying speed is very high, which makes them inefficient for tasks over a wide geographical area. In practice, fixed-wing and rotary-wing UAVs can be both leveraged simultaneously to enhance the communication efficiency.

For example, a promising UAV-enabled networking architecture is to deploy rotary-wing UAV-enabled BSs hovering at well-selected locations for establishing signal hotspots and at the same time to dispatch fixed-wing UAV-enabled BSs flying around periodically for wider coverage and higher throughput.

2) Energy-Constrained Trajectory Optimization

As shown in Figure 4.4(a), we consider the same UAV-enabled two-user system for a given UAV flight period T where the UAV has a limited on-board energy, and thus the maximum propulsion energy that can be consumed during this period is denoted by E_{\max} . For the purpose of exposition, we consider a fixed-wing UAV with the minimum speed and maximum acceleration denoted by V_{\min} in m s^{-1} and a \max in m s^{-2} , respectively. Similarly, we consider the common throughput maximization for the two GUs via jointly optimizing the UAV trajectory as well as the user scheduling, and subject to the new UAV's total energy constraint and the mobility constraints (on its speed and acceleration).

In Figure 4.4(b), we plot the UAV's optimized trajectories under different constraints on the propulsion energy. It is observed that the UAV flies close to the two GUs by following a smooth trajectory with relatively large turning radii when $E_{\max} = 13$ kJ; whereas when E_{\max} is increased to 23 kJ, the UAV's trajectory tends to approach that without the propulsion energy constraint shown in Figure 4.3(b). This is because, in the latter case, sharp turning in the flight direction to quickly shorten the UAV–GU distance requires more propulsion energy consumption.

Furthermore, the UAV's flying speeds over time in the above two cases are illustrated in Figure 4.4(c). It is observed that, in the first case, the UAV's flying speed does not vary much around 30 m s^{-1} during the total period due to the limited propulsion energy; while in the latter case, with more available energy, the UAV first flies at the maximum speed (50 m s^{-1}) to get close to each of the GUs and then hovers around the GU at the minimum speed (5 m s^{-1}), so as to maximize the throughput.

Finally, the achievable throughput versus the propulsion energy is plotted in Figure 4.4(d). The throughput upper bound is obtained by ignoring the propulsion energy constraint, which is the same as that in Figure 4.3(d) under the same T . The

throughput lower bound is achieved by the initial circular trajectory [12] with the UAV's speed equal to 30ms^{-1} . One can observe that the common throughput can be significantly improved at the cost of more propulsion energy consumption. In particular, as the propulsion energy increases, the common throughput first increases rapidly and then approaches a constant that is strictly lower than the throughput upper bound. This is because, in addition to the propulsion energy constraint, the practically achievable throughput is also subjected to the UAV's mobility constraints on the minimum speed and maximum acceleration.

V. CONCLUSION

In this work we presented several state-of-the-art spatio-temporal trade-offs prediction models and particularly explored the use of DNNs in a large-scale system state prediction such as Directional Airborne Network (DAN). Those methods also could be employed to solve the multi-UAV mobility prediction problem. Several strategies and evaluation metrics were discussed that can be used to implement a DNN in the UAV domain. DAN plays a critical role in military applications due to its extended communication range (>1 km). Besides orthogonal multiple access schemes such as TDMA considered for multiuser communications, non-orthogonal multiple access schemes based on Superposition Coding (SC) or dirty paper coding can be jointly designed with the UAV trajectory to further improve the throughput–delay trade-off and achieve the capacity limits of UAV-enabled wireless networks. For example, a two-user broadcast channel (BC) is also studied in, where it is shown that a simple and practical “Hover–Fly–Hover” (HFH) trajectory with SC achieves the capacity region. However, whether similar results hold for a UAV-enabled BC with more than two users or other multiuser channel models still remains an open problem that is worth investigating in future work.

Furthermore, in our study above, the user delay is roughly measured in terms of the UAV flight period. However, the delay requirements in 5G networks may vary dramatically in time scale, from milliseconds (e.g., for online gaming/video streaming) to seconds or even minutes (e.g., for large file sharing/sensor data collection). Thus, how to model such heterogeneous delay requirements and design the joint UAV trajectory and communication resource allocation to efficiently meet them is also an important problem for future research. For the multi-UAV-enabled network, we propose the IUIIC as an effective technique to mitigate the strong LoS interference by exploiting the coordinated multi-UAV trajectory design. Alternatively, motivated by the rapid advance of the wireless backhaul technologies, the UAVs can share messages and perform cooperative beam forming for more efficient interference mitigation—a technique called Coordinate Multi-Point (CoMP) in the sky. It is worth noting that the methodology for designing the optimal UAV trajectories for CoMP is generally different from that for IUIIC. For example, to maximize the cooperative beam forming gain in CoMP, it may be desirable to let some UAVs form a fleet to serve the GUs along the same trajectory, while this is apparently undesired in

the IUIIC case due to the inter-UAV interference. Another important issue worthy of further investigation is how to dynamically adjust the UAV trajectories according to the GUs' movements to improve their throughput and/or delay performances. The throughput–energy trade-off can be further extended by taking the GUs' energy consumption into account, e.g., in the application of UAV-enabled data collection in IoT networks. Since IoT devices are generally of low power and limited battery life, how to prolong their lifetime is critical for the sustainability and proliferation of future IoT ecosystem.

Thanks to the controllable mobility, a UAV-enabled mobile data collector can move sufficiently close to the IoT devices, such as sensors or tags, to collect their data with minimum transmit energy. However, this will incur more propulsion energy consumption of UAVs, which implies an interesting new perspective in the throughput–energy trade-off in UAV-enabled communication. On the other hand, the UAVs' energy supply can also be provisioned by means of other technologies such as solar energy harvesting and laser-beamed wireless power transfer by ground chargers. However, these technologies generally bring new design considerations that need to be further studied. For example, for solar-powered UAVs, while increasing the flying altitude will lead to higher path loss, it helps harvest more solar energy to support more flexible trajectory design to adapt to the GUs' dynamic locations and communication requirements. As such, the throughput–energy trade-off in UAV-enabled communication needs to be revised with carefully designed altitude control. Furthermore, in the case of multiple UAVs cooperatively serving the GUs, besides their communication cooperation through IUIIC or CoMP, the design of multi-UAV trajectories also needs to consider their individual energy availability. For example, the propulsion energy consumptions of different UAVs should be balanced via cooperative trajectory design to maximize their endurance from a UAV network lifetime maximization perspective.

It is worth pointing out that, besides the three trade-offs considered in this work, there exist other important design considerations in UAV-enabled communication, which have not been fully explored yet and thus require further investigations. These may include, for example, the deployment cost of mobile UAVs, their wireless backhaul constraints, as well as the severe air-to-ground interference issue due to the LoS-dominant channels. For example, using multiple collaborative UAVs, each equipped with multiple antennas/full-duplex functionality, can largely improve the system throughput and/or reduce the user delay, while the system complexity and cost are also inevitably increased, which leads to the complexity/cost–throughput/delay trade-off.

On the other hand, the UAV-to-ground LoS channel model is only appropriate for rural or suburban areas or when the UAV altitude is sufficiently high. However, for other cases, such as in urban environments, other air-to-ground channel models, such as probabilistic LoS model and Ricean fading model, are more suitable. It is worth noting that such non-LoS channel models may have significant impacts on the optimal UAV trajectory design in UAV-enabled wireless networks. For

instance, lowering the UAV's flying altitude under the probabilistic LoS channel model generally decreases the probability of having LoS links with GUs, while it is always beneficial under the LoS model. As a result, a more complex 3D trajectory optimization problem (as compared to the 2D design in our typical scenario under the LoS model) needs to be investigated. Moreover, although the presence of LoS links makes the UAVs well suitable for 5G technologies such as millimeter wave (mmWave) and massive multiple input–multiple output (M-MIMO) communications, the severe air-to-ground interference issue and 3D mobility-induced Doppler Effect deserve more investigations in the future.

REFERENCES

- [1] U.S. United States Department of Defense, "Environmental engineering considerations and laboratory tests," Department of Defense, MIL-STD-810F, 2000.
- [2] U.S. Department of Defense, "Requirements for the control of electromagnetic interference characteristics of subsystems and equipment," MIL-STD-461G, 2007.
- [3] R. Purta, S. Nagrecha, and G. Madey, "Multi-hop communications in a swarm of UAVs," *Proceedings of the 2013 Agent-Directed Simulation Symposium*, Society for Computer Simulation International, vol. 1, pp. 5–13, 2013.
- [4] A. Agogino, C. Parker, and K. Tumer, "Evolving large scale UAV communication systems," *Proceedings of the 2012 14th Annual Conference on Genetic and Evolutionary Computation*, vol. 9, pp. 1023–1030, 2012.
- [5] M. Tareque, M. Hossain, and M. Atiquzzaman, "On the routing in flying ad hoc networks," *Proceedings of the 2015 Federated Conference on Computer Science and Information Systems (FedCSIS)*, vol. 5, pp. 1–9, 2015.
- [6] M. Chen and J. Macdonald, "Optimal routing algorithm in swarm robotic systems," *Course for the Department of Computer Sciences, California Institute of Technology*, vol. 5, no. 1, pp. 1–8, 2014.
- [7] R. Lidowski, B. Mullins, and R. Baldwin, "A novel communications protocol using geographic routing for swarming uavs performing a search mission," *2009 IEEE International Conference on Pervasive Computing and Communications*, vol. 4, pp. 1–7, 2009.
- [8] Amazon, "Amazon Prime Air," <https://www.amazon.com/Amazon-Prime-Air/b?node=8037720011>, 2016.
- [9] P. Black, "Greedy algorithm," <https://xlinux.nist.gov/dads/HTML/greedyalgo.html>, in *Dictionary of Algorithms and Data Structures* [online], 2005. Accessed March 2021.
- [10] J. Li, Y. Zhou, and L. Lamont, "Communication architectures and protocols for networking unmanned aerial vehicles," *2013 -IEEE Globecom Workshops (GC Wkshps)*, 2013.
- [11] N. Z. Azeemi, "Cooperative Trajectory and Launch Power Optimization of UAV Deployed in Cross-Platform Battlefields," *International Association of Engineers, Engineering Letters*, Volume 29, Issue 1, pp. 57-68, May 2021, ISSN: 1816-093X, 1816-0948
- [12] N. Z. Azeemi, O. Al-Basheer, G. Al-Utaibi, "Zero Down Time—Smart Data Guard for Collaborative Enterprise Dataware Systems," *Journal of Theoretical and Applied Information Technology*, Aug-Sep 2020, 31st August 2020. Vol 98. No16, pp. 3282-3293. (e-ISSN 1817-3195, p-ISSN 1992-8645)
- [13] N. Z. Azeemi, G. Al-Utaibi, O. Al-Basheer, "Customer-in-Loop Adaptive Supply Chain Migration Model to Enable IoT", *International Journal of Innovative Technology and Exploring Engineering*, ISSN: 2278-3075, Volume-9 Issue-6, pp. 1755-1762, April 2020.
- [14] N. Z. Azeemi, N. U. Saquib, E. Ahmed, "On-Chip Laser Probe Fabrication for Trace and Cross Triggered Scanning (T&CTS) in Optical Microscopy," in *Journal of Theoretical and Applied Information Technology*, Vol. 99, No. 04, pp. 797-811, Feb 28th, 2021, (e-ISSN 1817-3195, p-ISSN 1992-8645)
- [15] N. Z. Azeemi, "Compiler Directed Battery-Aware Implementation of Mobile Applications", *2006 International Conference on Emerging Technologies*, Year: 2006 Pages: 251 - 256, DOI: 10.1109/ICET.2006.335979
- [16] Naeem Zafar Azeemi, "Multicriteria Energy Efficient Source Code Compilation for Dependable Embedded Applications", *2006 Innovations in Information Technology Year: 2006*, Pages: 1 - 5, DOI: 10.1109/INNOVATIONS.2006.301963
- [17] N. Z. Azeemi; A. Hameed; I. Ali; T. Rasool, "Ultra Wide Band Radar Based Tamper-Resistant Clinical Asset Tracking System (ATS)", *2008 Cairo International Biomedical Engineering Conference Year: 2008* Pages: 1 - 4, DOI: 10.1109/CIBEC.2008.4786102
- [18] N. Z. Azeemi, Z. Hayat, G. Al-Utaibi, O. Al-Basheer, "Hybrid Data Protection Framework to Enhance A2O Functionality in Production Database Virtualization", *International Journal of Recent Technology and Engineering*, Volume-8 Issue-6, pp. 5691-5697, Mar. 2020.
- [19] Naeem Zafar Azeemi, "Exploiting Parallelism for Energy Efficient Source Code High Performance Computing", *2006 IEEE International Conference on Industrial Technology*, Year: 2006 Pages: 2741 - 2746, DOI: 10.1109/ICIT.2006.372685
- [20] Naeem Zafar Azeemi, "Handling Architecture-Application Dynamic Behavior in Set-top Box Applications", *2006 International Conference on Information and Automation*, Year: 2006 Pages: 195 - 200, DOI: 10.1109/ICINFA.2006.374111
- [21] FAA (2018). UAS Integration Pilot Program Resources. https://www.faa.gov/uas/programs_partnerships/integration_pilot_program/ (accessed 18 February 2021).
- [22] FAA (2016). Summary of small unmanned aircraft rule. https://www.faa.gov/uas/media/Part_107_Summary.pdf (accessed 18 February 2021).
- [23] ITU (2009). Characteristics of unmanned aircraft systems and spectrum requirements to support their safe operation in non-segregated airspace. *ITU Tech. Rep. M.2171*.
- [24] 3GPP TR 36.777 (2017). Technical specification group radio access network: study on enhanced LTE support for aerial vehicles, v.15.0.0.
- [25] Inmarsat (2017). Launch of Inmarsat Swift Broadband unmanned aerial vehicle service to provide operational capability boost. <https://www.inmarsat.com/press-release/launch-inmarsat-swiftbroadband-unmanned-aerial-vehicle-service-provide-operationalcapability-boost/> (accessed 18 February 2021).
- [26] I. Bekmezci, O. K. Sahingoz, and S. Temel (2013). Flying ad-hoc networks (FANETs): a survey. *Ad Hoc Networks*, 11 (3): 1254–1270.
- [27] Y. Zeng, J. Lyu, and R. Zhang (2019). Cellular-connected UAV: potentials, challenges and promising technologies. *IEEE Wireless Commun.* 26 (1): 120–127.
- [28] Y. Chen, S. Zhang, S. Xu, and G. Y. Li (2011). Fundamental trade-offs on green wireless networks. *IEEE Commun. Mag.* 49 (6): 30–37.
- [29] Carlos J Bernardos, Antonio De La Oliva, Pablo Serrano, Albert Banchs, Luis M Contreras, Hao Jin, and Juan Carlos Zúñiga. An Architecture for Software Defined Wireless Networking. *IEEE Wireless Communications*, 21 (3): 52–61, June 2014.
- [30] C. Bettstetter. Smooth is better than sharp: a random mobility model for simulation of wireless networks. In *ACM International Workshop on Modeling, Analysis and Simulation of Wireless and Mobile Systems*, Rome, Italy, July 2001.
- [31] C. Bettstetter, H. Hartenstein, and X. Pérez-costa. Stochastic properties of the random waypoint mobility model. *Wireless Networks*, 10: 555–567, 2004.
- [32] J. Boudec and M. Vojnovic. Perfect simulation and stationarity of a class of mobility models. Technical report, Technical Report IC/2004/59, 2004.
- [33] Salvatore Costanzo, Laura Galluccio, Giacomo Morabito, and Sergio Palazzo. Software defined wireless networks: Unbridling sdns. In *Software Defined Networking (EWSN)*, 2012 European Workshop on, pages 1–6. IEEE, 2012.
- [34] Evan T Dill, Kelly J Hayhurst, Steven D Young, and Anthony J Narkawicz. UAS hazard mitigation through assured compliance with conformance criteria. In *AIAA Information Systems-AIAA Infotech@ Aerospace*, pages 1218–1218. 2018.
- [35] Edward Falcov. Use of self-organizing airborne networks to monitor commercial aircraft globally. Working Paper WP10, multidisciplinary meeting on global tracking, 2014.
- [36] Pingzhi Fan, Jing Zhao, and I Chih-Lin. 5g high mobility wireless communications: Challenges and solutions. *China Communications*, 13 (2): 1–13, 2016.
- [37] Scott Xiang Fang, Siu O'Young, and Luc Rolland. Development of small uas beyond-visual-line-of-sight (bvlos) flight operations: System requirements and procedures. *Drones*, 2 (2): 13, 2018.

- [38] R. Ghanta and S. Suresh. Influence of mobility models on the performance of routing protocols in ad-hoc wireless networks. *IEEE 59th Vehicular Technology Conference*, pages 2185–2189, 2004.
- [39] B. Gloss, M. Scharf, and D. Neubauer. A more realistic random direction mobility model. In *4th Management Committee Meeting*, Würzburg, Germany, October 2005.
- [40] R. A. Guérin. Channel occupancy time distribution in a cellular radio system. *IEEE Transactions on Vehicular Technology*, 35 (3): 89–99, August 1987.
- [41] Lav Gupta, Raj Jain, and Gabor Vaszkun. Survey of important issues in uav communication networks. *IEEE Communications Surveys & Tutorials*, 18 (2): 1123–1152, Second Quarter 2015.
- [42] Tanzeena Haque and Nael Abu-Ghazaleh. Wireless software defined networking: A survey and taxonomy. *IEEE Communications Surveys & Tutorials*, 18 (4): 2713–2737, Fourth Quarter 2016.
- [43] J. P. Helferty. Improved tracking of maneuvering targets: the use of turn-rate distributions for acceleration modeling. *Proceedings of the IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, pages 515–520, October 1994.
- [44] E. Hyttiä, P. Lassila, and J. Virtamo. Spatial node distribution of the random waypoint mobility model with applications. *IEEE Transactions on mobile computing*, 5 (6): 680–694, June 2006.
- [45] ASTM International. Committee f38 on unmanned aircraft systems, 2019. URL <https://www.astm.org/COMMIT/SUBCOMMIT/F38.htm>.
- [46] Tyler Reid. Orbital Diversity for Global Navigation Satellite Systems, PhD Dissertation. PhD thesis, 2017.
- [47] Tyler GR Reid, Andrew M Neish, Todd Walter, and Per K Enge. Broadband LEO constellations for navigation. *Navigation: Journal of The Institute of Navigation*, 65 (2): 205–220, 2018.
- [48] Deepshikha Shukla. Controlling drones and uavs: Advancements in wireless technologies. *Electronics For You*, pages 70–71, December 2018.
- [49] R. A. Singer. Estimating optimal tracking filter performance for manned maneuvering targets. *IEEE Trans. Aerospace and Electronic Systems*, AES-6: 473–383, 1970.
- [50] Alexander Solodov, Adam Williams, Sara Al Hanaei, and Braden Goddard. Analyzing the threat of unmanned aerial vehicles (uav) to nuclear facilities. *Security Journal*, 31 (1): 305–324, 2018.
- [51] Keshav Sood, Shui Yu, and Yong Xiang. Software-defined wireless networking opportunities and challenges for internet-of-things: A review. *IEEE Internet of Things Journal*, 3 (4): 453–463, 2016.



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