

# Advancing Networked Airborne Computing with mmWave for Air-to-Air Communications

Haomeng Zhang<sup>1</sup>, Junfei Xie<sup>2</sup>, Yan Wan<sup>3</sup>, Shengli Fu<sup>4</sup>, and Kejie Lu<sup>5</sup>

<sup>1</sup> University of California San Diego and San Diego State University, San Diego, CA

<sup>2</sup> San Diego State University, San Diego, CA, [jxie4@sdsu.edu](mailto:jxie4@sdsu.edu)

<sup>3</sup> The University of Texas at Arlington, Arlington, TX

<sup>4</sup> University of North Texas, Denton, TX

<sup>5</sup> University of Puerto Rico at Mayagüez, Mayagüez, Puerto Rico

**Abstract.** Networked airborne computing (NAC) has witnessed a notable surge in interest over recent years. This emerging technology promises to enhance the onboard computing capabilities of Unmanned Aerial Vehicles (UAVs), potentially revolutionizing both current and future applications. Despite its promise, there are substantial challenges impeding the realization of a high-performance NAC system. Among these, reducing communication delays between UAVs is a critical issue that needs immediate attention. Traditional sub-6GHz technologies prove inadequate in meeting the low-latency requirements essential for NAC applications that involve high data traffic. A promising solution to this challenge is the adoption of millimeter wave (mmWave) frequency bands for Air-to-Air (A2A) communications, which offer a wealth of spectrum resources. However, the integration of mmWave within NAC systems remains under-explored. To bridge this gap, this paper presents a comprehensive study on the design of advanced NAC systems, integrating mmWave for A2A communications. A holistic analysis from both hardware and software perspectives is conducted, providing valuable insights that will facilitate the development of advanced NAC systems with high airborne computing performance.

**Keywords:** Millimeter Wave, Networked Airborne Computing, Air-to-Air Communication, Unmanned Aerial Vehicles

## 1 Introduction

Unmanned aerial vehicles (UAVs) have been pervasively adopted in various domains such as security and surveillance, disaster management, and precision agriculture [1]. Many of these applications involve the processing of substantial data, such as videos and images captured by onboard cameras, demanding high computational resources. The conventional approach to address this demand is to conduct computations on the ground, considering the limited payload capacity of UAVs. Nevertheless, with technological advancements, powerful yet lightweight single-board computers (SBCs) have emerged, making it possible to directly execute computation-intensive tasks onboard UAVs [2, 3]. Despite these

advancements, the computing capacity of a single UAV remains constrained. To overcome this limitation, Networked Airborne Computing (NAC) [4–7] was proposed, which explores collaboration among multiple UAVs to augment on-board computing capacity. By employing distributed computing or computation offloading techniques [7–10], UAVs can collaborate to efficiently execute computation-intensive tasks.

To achieve high-performance NAC, an imperative challenge is to minimize communication delays among UAVs. While reducing the exchanged data can mitigate delays, this approach is often infeasible for tasks that necessitate the sharing of original input data, as seen in tasks like matrix multiplication [8]. Therefore, establishing reliable and low-latency communication links among the UAVs is paramount to addressing this challenge. Current UAV platforms often rely on sub-6GHz bands, especially the 2.4GHz/5GHz Wi-Fi bands, for air-to-air (A2A) communication links [6, 11–13]. However, the achieved throughputs prove inadequate for high-data-traffic applications.

To achieve ultra-reliable low-latency A2A communications, harnessing millimeter-wave (mmWave) frequency bands [14–17] emerges as a promising solution. Spanning frequencies from approximately 30GHz to 300GHz, these bands offer several appealing features, including exceptionally wide bandwidths, short wavelengths, and narrow beams. However, mmWave signals experience higher propagation loss, higher vulnerability to blockage, and increased difficulty in penetrating through objects, posing challenges in establishing a stable data link over long ranges when compared to sub-6 GHz signals. To tackle these challenges, the use of directional antennas or antenna arrays becomes crucial. These technologies enhance transmission gain by narrowing the beams and focusing the transmitted signal in a specific direction. However, the reduced beam width also results in a decreased coverage range. While employing a wider beam or multiple narrow beams can address this issue, shaping them onboard UAVs is challenging, due to UAVs’ size, weight, and power (SWaP) constraints. Moreover, the high mobility and the complexities of the uncertain airspace in which UAVs operate present further challenges in establishing stable mmWave A2A communications.

In this paper, we present a comprehensive study to facilitate the design of NAC systems utilizing mmWave bands for A2A communications. Specifically, we start by discussing existing survey articles on UAV communications in Sec. 2. After that, in Sec. 3, we provide an overview of NAC, delving into its advantages, applications, and challenges. Sec. 4 and Sec. 5 explore the hardware design aspects of NAC, with Sec. 4 providing insights into the overall system design and Sec. 5 focusing specifically on A2A communications. In Sec. 6, we shift our focus to the software design aspects of mmWave-based A2A communications for NAC. Finally, we conclude the paper in Sec. 7, summarizing our findings and discussing open problems and future research directions.

## 2 Related Works

In recent years, numerous survey and tutorial papers have investigated UAV communications [16, 18–23]. [18] discusses the advantages and challenges of on-demand wireless systems with low-altitude UAVs. The paper elaborates on the basic networking architecture, air-to-ground (A2G)/ground-to-air (G2A) and A2A channel characteristics, and design considerations for UAV path planning, energy-aware deployment and operation, and multiple-input multiple-output (MIMO) communications. [19] offers a comprehensive tutorial on the applications of UAVs in wireless communications, encompassing UAV aerial base stations in 5G, cellular-connected UAVs as user equipment, and flying ad-hoc networks. The challenges of wireless communication for UAVs, such as channel modeling and energy efficiency, are discussed, and various analytical and mathematical tools used in UAV wireless communications are introduced. In [20], the authors provide a comprehensive review of UAV wireless communication progress towards 5G and beyond, covering aspects such as the physical layer, network layer, and joint communication, computing, and caching. [21] explores the challenges and issues related to UAV-based Internet of Things (IoT), including UAV communication networks. [22, 23] offer exhaustive surveys of the existing papers on flying ad hoc network (FANET) routing. Additional work closely aligned with this study is presented in [16], which thoroughly surveys research on mmWave-enabled UAV communication and networking, covering topics such as antenna structure, channel modeling, UAV-connected mmWave cellular networks, and mmWave-UAV ad-hoc networks.

While these papers delve deep into the challenges of UAV communications, their main emphasis lies in utilizing UAVs as access points (APs) or relays in ad-hoc networks to serve ground users. In contrast, our focus in this paper is on the design of NAC systems with enhanced airborne computing performance through the integration of mmWave technologies, where NAC is built upon the airborne network (or FANET) with UAVs directly talking to each other via A2A links. We explore the design of NAC from both hardware and software perspectives, introducing novel aspects to the existing literature.

## 3 Networked Airborne Computing

The Networked Airborne Computing (NAC) [4–7] refers to computing in the aerial layer through the airborne network [24] that consists of multiple aerial vehicles with direct A2A communication links.

Compared to traditional ground-based computing paradigms, NAC offers numerous advantages including low latency, transportability, infrastructure-free, unmanned maneuvering, fast deployment, wide coverage and low cost [7]. Equipping UAVs with high on-board computing capabilities also allows the implementation of advanced algorithms to enhance system performance. For instance, replacing the conventional GPS system used in UAVs for localization with a real-time kinematic (RTK) system can significantly enhance the positioning accuracy from meters to centimeters [4]. Additionally, advanced control algorithms

can be applied to enhance the operational safety of the UAVs [25] and extend the communication range while increasing bandwidth between two UAVs [13].

The advantages of NAC extend beyond current UAV applications, encompassing drone light shows, precision agriculture, packet delivery, and land surveying, while also opening avenues for new possibilities. For instance, with enhanced situational awareness, UAVs equipped with advanced on-board computing capabilities are poised to play a crucial role in shaping the next generation air transportation systems. Moreover, these UAVs are also expected to integrate seamlessly into the multi-access edge computing (MEC) systems, providing computing services to ground users or serving as relays to assist MEC applications [26]. They will also be pivotal in IoT, facilitating the collection, processing, and distributions of sensing data.

Despite the compelling advantages of NAC, research in this field is still in its infancy, and realizing its full potential entails overcoming numerous daunting challenges. Building upon the airborne network, one of the primary challenges faced by NAC is A2A communication, as the overall NAC performance is constrained by delays in A2A communication. Hence, establishing reliable and low-latency A2A links is crucial for unleashing the full capabilities of NAC and achieving high-performance airborne computing. MmWave technologies [16] offer a potential solution, as we will explore in-depth later in this paper. Nevertheless, the application of mmWave for A2A communications necessitates tackling not only hardware design challenges to meet UAVs' SWaP constraints, but also software design challenges arising from the directional nature of mmWave beams and the unique characteristics of UAVs. These characteristics include 1) high 3-D mobility, which can cause frequent network topology changes, link failures, data losses, and task interruptions; 2) complicated environmental uncertainties such as convective weather and other vehicles, which will modulate UAV dynamics and disturb A2A communications; and 3) strict safety requirements on aerial maneuvers, necessitating UAV operations to adhere to mechanical and aerodynamic constraints.

## 4 Hardware Design: Overall System

Designing a UAV platform with advanced networked airborne computing capabilities entails consideration across five core hardware units including the 1) airframe unit; 2) computing unit; 3) communication and networking unit; 4) control unit; and 5) power source and distribution unit. Next, we discuss the design of each unit.

The *airframe unit* serves the purpose of lifting and mobility, encompassing the frame, motors, propellers, and electronic speed controllers. There are two main types of airframes, fixed-wing and multirotors. In the context of NAC, multirotors are considered more suitable due to their salient capabilities including the ability to hover statically in the air, ease of operation, and ability to operate in controlled indoor environments that is especially beneficial for early development and testing [4].

The *computing unit* is responsible for on-board processing and data storage. The selection of SBCs for this unit needs to consider various factors, including the processing and storage capacity, power consumption, dimension, weight, availability of community support, open-access design documentation and configuration toolboxes, and application needs. A thorough comparison of the state-of-the-art SBCs and the selection guidelines are provided in [2].

The *communication and networking unit* facilitates A2G/G2A, and A2A communications. The A2G link can be used to transmit application data or UAV state information and the G2A link can be used to transmit control or other information from the ground station to the UAV. They can be established using Commercial Off-The-Shelf (COTS) Wi-Fi Access Point [13] or COTS telemetry modules [5]. The A2A communications are for data exchanges among the UAVs, which are further discussed in the following section. There are some other wireless links that need to be established, such as the flight control signal link between the remote controller and the UAV, GPS signal link to receive location information when flying outdoor, as well as the link that connects the computing hardware to the UAV.

The *control unit* is responsible for the mobility control of the UAV. There are numerous flight controllers available on the market. Among them, Pixhawk [27] is one of the most popular choices. It supports open-source flight control software including PX4 [28] and ArduPilot [29], offering a considerable degree of customization. In addition to UAV mobility control, when directional antennas are employed to improve A2A communications, it is essential to also implement effective antenna direction control algorithms to ensure robust communication among UAVs [13].

The *power source and distribution unit* provides power supply to other units. Small UAVs are usually powered by batteries [13]. Nevertheless, due to small payload, battery-powered UAVs are limited in flight time, typically less than 30min. Various efforts have been made to extend the flight time, such as using hybrid power sources [30] or leveraging wireless power transfer techniques [31]. In NAC systems, the majority of the energy is consumed by UAV propulsions. Nonetheless, substantial power is also consumed by computing and communication processes, which should also be considered in power management.

If UAVs are designed for autonomous outdoor flight, it's essential to also include the localization unit. Conventional GPS modules, commonly used for UAV localization, prove insufficient for applications demanding precise adherence to pre-planned trajectories with deviation errors below centimeters, such as drone light shows. This issue can be resolved using the RTK technique [5].

In our previous work [5], we presented an initial design of the NAC hardware platform, incorporating RTK for localization and a COTS Wi-Fi router for A2A communications. Real flight tests revealed that A2A communication delays emerged as a bottleneck for distributed computing tasks requiring exchanges of substantial data, impeding the attainment of high airborne computing performance. In the following section, we delve into the hardware design for A2A communications.

**Table 1.** Potential mmWave devices for A2A communication

| Antennas                     | Brand    | Dimensions<br>(mm)          | Weight<br>(kg) | Max.<br>bitrate<br>(Gbps) | Max.<br>No.<br>clients<br>supported | Coverage<br>(km) | Max.<br>power<br>consump.<br>(W) |
|------------------------------|----------|-----------------------------|----------------|---------------------------|-------------------------------------|------------------|----------------------------------|
| wAP60G AP<br>and wAP60Gx3 AP | Mikrotik | $185 \times 85 \times 30$   | 0.6            | 2                         | 8                                   | 0.2              | 5                                |
| RBLHGG-60ad                  | Mikrotik | $\phi 391 \times 222$       | 2.28           | 2                         | 8                                   | 0.8              | 5                                |
| Wave AP                      | Ubiquiti | $212 \times 205 \times 187$ | 2.3            | 5.4                       | 15                                  | 5                | 24                               |
| airFiber 60                  | Ubiquiti | $413 \times 413 \times 320$ | 1.8            | 1.9                       | -                                   | 2                | 11                               |
| Wave Nano                    | Ubiquiti | $\phi 256.5 \times 113.5$   | 0.932          | 2                         | 15                                  | 5                | 20                               |

## 5 Hardware Design: A2A Communications

### 5.1 Sub-6GHz-based A2A Communications

Current investigations into A2A communications primarily rely on numerical models [32, 33] and employ sub-6GHz technologies with omni-directional antennas [11]. While this simplifies NAC hardware design, flight tests in [5] show that sub-6GHz technologies are inadequate for high-load NAC tasks. Specifically, the NAC platform proposed in [5], which employs 2.4GHz TP-Link Wi-Fi routers, achieves an A2A throughput of 100Mbps at a distance of 30m but fails to establish a reliable connection beyond 48m. Utilizing 5GHz Ubiquiti Nano-station Loco M5 directional antennas, the aerial communication system introduced in [12, 13, 34] enhances the throughput and communication range, achieving 48Mbps at 300m and 2Mbps at 5km [34]. However, the attained throughput remains insufficient, as demonstrated in [5].

### 5.2 MmWave-based A2A Communications

To enable high-rate transmission between UAVs, researchers have started to explore mmWave bands, which offer ample spectrum resources. Nevertheless, the distinctive characteristics of UAVs and the directional nature of mmWave beams pose substantial challenges in establishing and maintaining A2A links. Currently, research in this domain is in its early stages, primarily characterized by theoretical analyses and simulation-based approaches. Only a few studies have progressed to constructing UAV hardware testbeds for the practical implementation of mmWave-based A2A communications. A notable example is found in [35], where a self-organizing network of UAVs utilizing mmWave technology was designed. This network utilizes MikroTik WAP 60G [36] 60GHz radios, powered by the Qualcomm QCA6335 chipset with 32 phased array antenna, to establish 60GHz mmWave links between UAVs. Each link can support up to 2.3Gbps bitrate. The network management algorithm, which jointly optimizes UAV deployments and traffic routing across the UAV network, operates on an Amazon Web Service instance. Control commands generated by this algorithm are sent to each UAV via the LTE interface of a smartphone, which is connected

to a SBC mounted on the UAV. The DJI Matrice 600 Pro serves as the airframe to carry the necessary communication, computation, and control units. In another notable work [37], an empirical propagation loss model for 60GHz mmWave-enabled A2A communications in ad hoc networks is presented. To validate the proposed model, a hardware testbed that consists of two DJI M600 UAVs was built. Each UAV carries an Intel NUC computer for flight control and a Facebook Terragraph mmWave radio, configured as a channel sounder, for A2A communications.

### 5.3 Comparison of Potential MmWave Devices for A2A Communication

With the advancement of mmWave phased array technology, an increasing number of user-friendly mmWave devices have become available in the market. However, most of these devices have not yet been examined for their suitability in A2A communications. To facilitate the hardware design for mmWave-based A2A communication, we next examine six state-of-the-art commercial 60GHz mmWave devices, each with the potential for use in A2A communications. Their key characteristics are summarized in Table 1.

**Mikrotik wAP60G AP and wAP60Gx3 AP** The wAP60G AP [36] is an integrated 60GHz wireless access point (AP) device capable of establishing point-to-point and point-to-multipoint high-speed wireless links, reaching bitrates of up to 2Gbps. The wAP60G AP version [36] features a single phased array, while the wAP60Gx3 AP version [38] features 3 phased arrays. Both versions support up to eight simultaneous clients at a distance of 200m, with dimensions of  $185 \times 85 \times 30$ mm and a weight of 600g. Their maximum power consumption is 5W.

**Mikrotik RBLHGG-60ad** The RBLHGG-60ad [39] is a 60GHz customer premise equipment (CPE) unit that can connect to a 60GHz AP over long distances. When paired with a 60GHz AP device like the wAP60G AP or wAP60Gx3 AP, it can create a cost-effective point-to-multipoint wireless link with an aggregated bitrate of up to 2Gbps. A single 60GHz AP can connect to as many as eight of these CPE units, supporting distances up to 800m in point-to-multipoint mode and up to 1500m in point-to-point mode. The dimensions of this device are  $\phi 391 \times 222$ mm, it weighs 2.28 kg, and its maximum power consumption is 5W. The device is built in with the 60GHz 802.11ad wireless networking standard.

**Ubiquiti Wave AP** The Wave AP [40], a 60GHz AP device, supports both point-to-point and point-to-multipoint wireless connections. It is capable of delivering a bitrate of up to 5.4Gbps with a  $30^\circ$  sector coverage. Additionally, the device is equipped with an integrated backup radio operating at 5GHz, which can achieve over 800Mbps. This AP can connect up to 15 clients. The dimensions

of the device are  $212 \times 205 \times 187$ mm, and it weighs 2.3kg. The maximum power consumption is 24W. Notably, the device’s backup 5GHz radio is built in with the 802.11ax (Wi-Fi 6) wireless networking standard.

**Ubiquiti airFiber 60** The AirFiber 60 [39], a 60GHz point-to-point radio system, features a 5GHz backup ratio. When connected with an AP, it can establish a 60GHz link spanning up to 2km, offering a maximum bitrate of 1.9GHz. Its dimensions are  $413 \times 413 \times 320$ mm, and it has a weight of 1.8kg. The maximum power consumption is 11W.

**Ubiquiti Wave Nano** The Wave Nano [41] is a 60 GHz point-to-multipoint station, also equipped with a 5GHz backup radio. It can establish 2Gbps links with an effective range of 5km when paired with an AP. Its long-range variant can extend the range to 8km. Compact in design, its dimensions are  $\phi 256.5 \times 113.5$ mm, and it weighs 932g. However, its maximum power consumption reaches 20W.

In assessing the six mmWave devices, the Ubiquiti Wave AP stands out for its superior communication performance, offering the highest bitrate at 5.4Gbps, the ability to support the most clients, and the greatest coverage range. However, it is also the heaviest and most power-hungry among the compared devices, making it less suitable for small UAVs with limited payload and battery capacity. On the other hand, the Mikrotik wAP60G AP and wAP60Gx3 AP are remarkable for their compact size and energy efficiency. Being the most lightweight with the lowest power consumption, they become a practical choice for A2A communications, as evidenced in [35]. Their primary shortcoming is a limited coverage range. For applications requiring long-range communications, the Ubiquiti Wave Nano might be a more suitable option, offering a long range of 5km and a manageable weight of under 1kg. Nevertheless, its considerable power consumption necessitates a thoughtfully designed power management unit to maximize battery life efficiently.

## 6 Software Design for mmWave-NAC

Integrating mmWave technologies to enhance the NAC performance requires tackling various software design challenges. In this section, we delve into three critical issues that have garnered attention in the literature, including neighbor discovery, routing, and resource allocation. The involvement of machine learning (ML) in addressing these challenges is also discussed.

### 6.1 Neighbor Discovery

Neighbor discovery is a crucial mechanism for establishing and maintaining connectivity in a network, which aims to identify nearby devices for potential communications. In mmWave-NAC networks, neighbor discovery can be



time-consuming due to the need for 3D-space scanning to identify neighboring UAVs, differing from ground-based 2D networks. Moreover, the directionality of mmWave beams can lead to issues such as the misalignment problem, as well as deafness and hidden terminals [42].

Neighbor discovery can be conducted deterministically through steering beams in a predefined pattern [43] or probabilistically through randomly selecting directions for beam steering [44, 45]. The deterministic methods typically offer assured success in neighbor discovery, whereas probabilistic methods have a shorter discovery time. While neighbor discovery is a well-explored problem, most approaches are designed for 2D scenes and cannot be readily extended to 3D UAV networks. A notable work addressing mmWave-based UAV networks with 3D mobility is found in [46], which introduces a two-way handshaking discovery algorithm. This algorithm achieves a reduced spatial scanning time through cross-layer optimization and a shorter neighbor discovery time by using multiple reply channels. Another two-way handshaking algorithm for 3D UAV networks is presented in [47]. However, it is not tailored for mmWave communications, and it assumes that the receive antennas are omnidirectional.

## 6.2 Routing

To execute an NAC application such as data distribution in IoT, data may need to be transmitted from one UAV to another UAV or the ground station multiple hops away. Designing an effective routing algorithm is crucial to ensure that UAVs successfully deliver the data through a feasible path while satisfying the application's QoS requirements. Nevertheless, designing routing algorithms for mmWave-NAC networks is more challenging than in traditional ground-based networks. As UAVs have limited onboard resources, the routing algorithm should be both time- and energy-efficient. Additionally, it must account for link and topology changes caused by UAVs' 3D mobility. Environmental uncertainties further complicate the problem, emphasizing the importance of finding a reliable path resilient to these uncertainties. Furthermore, the adoption of mmWave technologies makes it essential to consider mmWave-associated characteristics, such as mmWave beam steering, channel conditions, and potential interferences from other sources.

Various routing algorithms have been proposed for UAV networks, which can be broadly classified into four categories: topology-based, geographic, hybrid, and bio-inspired (see detailed discussions in [16]). Among them, bio-inspired routing algorithms, such as bee colony and ant colony algorithms [48–50], are gaining popularity in UAV networks for their promising performance in handling dynamic network topologies. However, their relatively high computational complexity is a notable drawback. While the computing resources onboard UAVs in NAC networks may be adequate to efficiently run these algorithms, and distributed computing strategies could potentially further accelerate computation, further investigation is required in this direction.

Although routing in UAV networks has been extensively researched, the integration of mmWave technologies presents new, underexplored challenges. For in-

stance, the directionality of mmWave beams and the limited number of mmWave radios that a UAV can carry necessitates efficient management of mmWave link activations among UAVs. This directly impacts the determination of data transfer paths. A recent study [51] addresses the optimal network topology formation problem for mmWave-based UAV networks. This study introduced a generative adversarial network (GAN)-based approach to find the optimal network topology that maximizes the total throughput. Once the network topology is determined, some of the traditional routing algorithms can be applied. Nevertheless, this GAN-based approach requires full knowledge of the UAV network and has a high computational complexity. Its ability to handle rapid network changes also remains unexplored.

### 6.3 Resource Allocation

Effective allocation of resources, such as time, space, frequency, and power, is essential for optimizing network performance. The directionality of mmWave beams allows for the enhancement of network capacity through spatial reuse for concurrent transmissions. However, fully harnessing the power of spatial reuse introduces new challenges in resource allocation. Other features of mmWave-NAC, such as dynamically evolving network topologies, fluctuating link states, 3D mobility, and time-consuming beam alignment, also present unique challenges.

Although resource allocation has been well studied in the realm of mmWave communications, existing approaches, like those described in IEEE 802.11aj [52] and IEEE 802.11ay [53], primarily rely on 2D models and assume low node mobility. Hence, they may not be suitable for UAV networks. There have been some studies on mmWave-based UAV networks, but most of them focus on scenarios where UAVs function as base stations, providing communication services to ground users [54, 55]. The primary goal of these studies is to enhance downlink performance. For instance, [54] considered a scenario where a single UAV equipped with an antenna array is deployed to serve multiple ground users via mmWave bands. The study formulates a nonconvex optimization problem aimed at maximizing downlink coverage, through optimizing user-subcarrier association and the transmit power of subcarriers. In [55], a two-layer UAV network was designed to serve ground users. This network comprises multiple low-altitude UAVs operating in sub-6GHz bands to serve ground users, and a high-altitude UAV using mmWave bands as a hub for wireless backhaul of the low-altitude UAVs. In this study, the authors aim to maximize user connectivity and network throughput by jointly optimizing the UAV deployment, power control, channel allocation, and rate control.

Research on resource allocation for mmWave-based UAV networks with A2A communications is scarce. A notable contribution to this field is found in [56], which focuses on enhancing network capacity while considering QoS requirements, fairness, and link priority. This resource allocation problem is formulated as a mixed integer non-linear programming problem, with antenna boresight, slot allocation, and transmit power as decision variables to be optimized. To solve

this problem, a Lagrangian dual theory-based method and a heuristic approach are proposed.

#### 6.4 Machine Learning

In recent years, ML has gained growing popularity within the wireless communication domain, primarily owing to its exceptional data interpretation capabilities. It has demonstrated promising potential in resolving challenges related to neighbor discovery, routing, and resource allocation [57–63]. For instance, [58] investigated the use of reinforcement learning (RL) to improve the efficiency of neighbor discovery for ad hoc networks using directional antennas. Four RL algorithms, including Q-Learning, SARSA,  $Q(\lambda)$ , and SARSA( $\lambda$ ) were evaluated in terms of their neighbor discovery time and ratio. Simulation results reveal that neighbor discovery based on Q-Learning achieves the highest efficiency.

ML has also been adopted to solve dynamic routing [59, 60] and resource allocation [61–63] problems in UAV networks. For instance, deep RL was applied in [60] for link maintenance in FANETs with unknown topological changes. The proposed RL algorithm adaptively adjusts the link maintenance cycle and is compatible with all active routing protocols. [61] explored deep Q-learning for resource allocation in static multi-UAV-assisted cellular networks. The objective is to maximize the overall downlink system throughput via the joint design of UAV deployment, user association, and transmit beamforming at the UAVs. Numerical results show that the proposed algorithm can improve network performance by up to 70%. Unlike [61], [62] considers mobile UAV-assisted networks where UAVs move to serve multiple ground users. A clustering-aided RL algorithm was proposed to maximize the total channel capacity by jointly optimizing user association, UAV trajectory design, and power control. In [63], UAV-assisted cellular networks operating in mmWave bands were explored. This study delves into the use of deep learning techniques to optimize the system utility across all users through intelligently managing UAV trajectories, user association, and energy scheduling.

### 7 Conclusion and Open Issues

In this paper, we conducted a systematic investigation into the design of NAC systems, with a focus on integrating mmWave technologies to enhance airborne computing performance. Specifically, we first explored the system design from the hardware perspective, addressing both the overall system architecture and specific considerations for A2A communications. Guidelines for the design of each key hardware unit were provided, followed by discussions on potential A2A communication techniques, along with a comparative analysis of state-of-the-art commercial mmWave devices suitable for A2A communication. The provided insights facilitate the practical implementation of mmWave in NAC systems. To fully unleash the power of mmWave-based A2A communications, we further examined system design from the software perspective, concentrating on three

critical design issues including neighbor discovery, routing, and resource allocation. How ML can be harnessed to augment these aspects was also discussed.

In addition to the aforementioned design issues, there are still numerous open issues that have not been well addressed. Next, we discuss a few of them.

### 7.1 Robust Connectivity Under High Mobility and Environmental Uncertainties

Different from ground-based networks, where antennas remain static and encounter minimal environmental uncertainties, NAC systems are highly mobile, operating in a complex 3D airspace with various environmental uncertainties. These uncertainties and high UAV mobility pose great challenges to the stability of A2A links and network connectivity, directly impacting airborne computing performance. Although coded computation techniques [7, 8] could alleviate the impact of uncertain stragglers (nodes that are slow in computing or fail to return results), how to establish a stable link, which links to activate, and how to maintain robust connectivity are crucial issues that need to be addressed for robust airborne computing under uncertainties. There have been some preliminary efforts on the deployment of robust mmWave networks operating in mobile and dynamic environments. For instance, [64] investigated the use of ambient environmental information, such as reflectors, blockers, and the positioning of APs and clients, to enhance link quality. [65] explored an array of phased arrays architecture to simultaneously improve mmWave coverage and link quality. [66] developed beam tracking techniques to stabilize connections between ground stations and moving vehicles. Despite these advancements, the scenarios where both AP and client are highly mobile are less explored and demand further investigation.

### 7.2 Joint Computation Offloading, Routing, and Resource Allocation

In NAC systems, UAVs collaboratively perform computation tasks. These tasks may be offloaded either fully or partially from one UAV (or ground station) to one or multiple other UAVs within the network. The offloading decisions, including task partitioning and the selection of offloaders, are closely correlated with routing and resource allocation. Communication delay between the offloader and offloaders, as well as the resources allocated for UAVs engaged in computations, both influence the offloading decisions. The joint optimization of computation offloading, routing, and resource allocation to enhance the overall performance of mmWave-based NAC systems is a significant yet under-researched challenge that requires further exploration.

### 7.3 UAV and Task Heterogeneity

NAC networks may consist of UAVs equipped with different hardware modules for computing, communication, and networking. Conventional network manage-

ment solutions that assume homogeneous devices may not work or yield suboptimal performance. Moreover, NAC tasks can vary significantly in their requirements for the type and quantity of resources, as well as in their QoS requirements such as computation delay, reliability, and throughput. The heterogeneity in both UAV capabilities and task requirements calls for adaptive approaches that are capable of efficiently coordinating resources across different UAVs to accommodate and balance the varied demands of each task. Advanced techniques, such as software-defined networking [67], which enables centralized network control, and ML [57], hold great potential to effectively tackle these challenges.

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