

UNMANNED AERIAL VEHICLES (UAV) IN CELLULAR NETWORK: APPROACH, ARCHITECTURE, AND CHALLENGES

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Abstract. *Unmanned Aerial Vehicles (UAVs) have emerged as critical components of modern cellular networks, offering potential for significantly enhancing coverage, capacity, and connectivity. This paper investigates the novel integration of UAVs into existing cellular infrastructure, presenting a comprehensive framework for their deployment and management. The study delves into the architectural complexities of UAV-cellular networks, emphasizing design considerations and technological requirements for seamless integration. Potential benefits, including rapid network deployment in remote areas, disaster recovery, and dynamic network optimization, are explored. However, the integration of UAVs also introduces challenges related to resource allocation, channel modeling, optimal placement and trajectory, and interference management. This paper provides a thorough analysis of these challenges, offering potential mitigation strategies and innovative solutions. As a contribution to future research, a novel approach is suggested for optimizing UAV placement and trajectory to enhance network coverage and efficiency in serving ground Internet of Things (IoT) devices. Through a holistic examination of UAVs in cellular networks, this study offers a comprehensive overview of approaches, architectures, challenges, and optimization techniques for effective UAV integration.*

Keywords

Autonomous Vehicle, Internet-of-Things, Cellular Network, Communication, Unmanned Aerial Vehicles.

1. Introduction

Unmanned Aerial Vehicles (UAV) utilization has surged across various fields in recent decades due to their versatility. This trend is projected to continue, driven by declining manufacturing costs and supportive government regulations worldwide [1]. Integrating UAVs with existing cellular networks offers promising opportunities. Two primary approaches emerge: UAV-assisted communication, where UAVs act as mobile communication platforms, and cellular-connected UAVs, operating as aerial users within terrestrial networks [1–4].

A key advantage of UAVs in cellular networks is their ability to dynamically optimize paths for efficient task completion [2]. Remote control and operation with virtually unlimited range are facilitated by their widespread accessibility [5]. Cellular-connected UAVs offer a flexible solution for maintaining wireless connectivity to end users and air traffic control, regardless of location [2]. However, ensuring reliable connectivity for these UAVs remains a significant challenge for current and future cellular systems [6]. In this paper, 'aerial' refers to elements operating in the air, such as UAVs or gateways, while 'air' refers to the atmosphere or the medium through which radio signals propagate.

2. Approach and Architecture

The seamless integration of UAVs into cellular networks unveils two intriguing paradigms, each delineated by the distinctive roles assumed by the UAVs. In one scenario, UAVs can operate as new aerial communication platforms extending their reach to terres-

trial users within the cellular network—a concept aptly named UAV-Assisted Cellular Communication. Meanwhile, in this equally compelling scenario, UAVs embark on autonomous missions, serving as User Equipment (UE) and accessing services from cellular Ground Base Stations (BSs). This concept is known as Cellular-connected UAVs [1, 7].

2.1. UAV-Assisted Cellular Network

UAV-Assisted cellular network, especially as aerial BSs and Mobile Edge Computing (MEC) offer enhanced coverage at reduced costs due to minimal infrastructure requirements [2]. The applications of UAVs as in UAV-assisted cellular network encompass a diverse range of scenarios, each addressing unique challenges and opportunities. UAVs acting as BSs have the capability to autonomously adjust their positions, enhancing the Quality of Experience (QoE), spectral efficiency, and coverage gains of the current terrestrial wireless communication system for users [8, 9]. In remote areas lacking ground communication infrastructure, UAVs serve as a crucial tool for cellular coverage expansion, ensuring that even in isolated regions, users can access reliable communication services. Moreover, during emergencies such as natural disasters that may disrupt ground communication infrastructure, UAVs facilitate swift service recovery, ensuring uninterrupted connectivity for emergency response efforts. In temporary hotspot areas experiencing high data traffic, UAVs play a pivotal role in offloading BS data traffic, optimizing network performance. Aerial relaying between distant ground user clusters is another valuable application, enabling efficient communication across vast and challenging terrains. Lastly, UAVs contribute to cost-effective information dissemination and data collection for Internet-of-Things (IoT), enhancing connectivity and data exchange in a variety of contexts.

The versatility of UAVs as BSs underscores their significance in addressing communication challenges and fostering connectivity in diverse scenarios [1]. Fig. 1 illustrates the architecture of UAV-Assisted Cellular Communication.

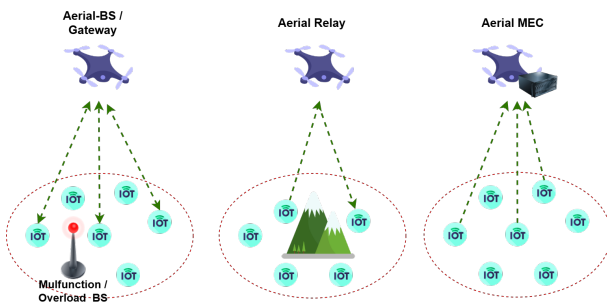


Fig. 1: UAV-Assisted Cellular Communication Architecture.

2.2. Cellular-Connected UAV Network

UAVs also have emerged as innovative aerial UEs, operating in conjunction with terrestrial UEs within the existing cellular network infrastructure [7]. Leveraging the widespread deployment of millions of cellular BSs worldwide, the utilization of UAVs as UEs offers a cost-effective approach, eliminating the need for dedicated UAV infrastructure and resulting in significant savings in network deployment expenditures [5]. Furthermore, the ubiquitous nature of cellular networks enables remote control and piloting of cellular-connected UAVs by ground-based operators, thereby providing virtually unrestricted operational range [5]. Fig. 2 illustrates the architecture of a Cellular-Connected UAV System.

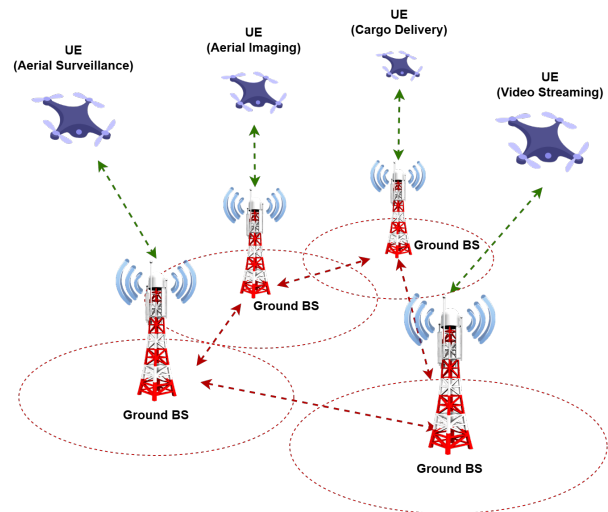


Fig. 2: Cellular - Connected UAV Architecture.

3. Open Challenges

Despite the potential benefits, the widespread integration of UAVs into cellular networks is hindered by several technical challenges [2, 5, 10]. Optimizing resource allocation for UAVs is paramount to ensure their sustained operation. Moreover, the limited endurance of current UAV technology poses a significant obstacle. Consequently, the intricate issues of placement and trajectory optimization have garnered significant attention from the research community [4, 11–17]. Nevertheless, designing optimal trajectories for UAVs requires researchers to consider various factors, including collision avoidance, terrestrial users’ demand, energy constraints, and flight duration [2, 4]. Finally, the development of effective channel models and interference management techniques for UAV-to-ground and UAV-to-BS communications remains a critical area of research for successful UAV integration into cellular networks. Table 1 and Fig. 3 summarizes the UAV in cellular network, together with its approaches, applications, and challenges.

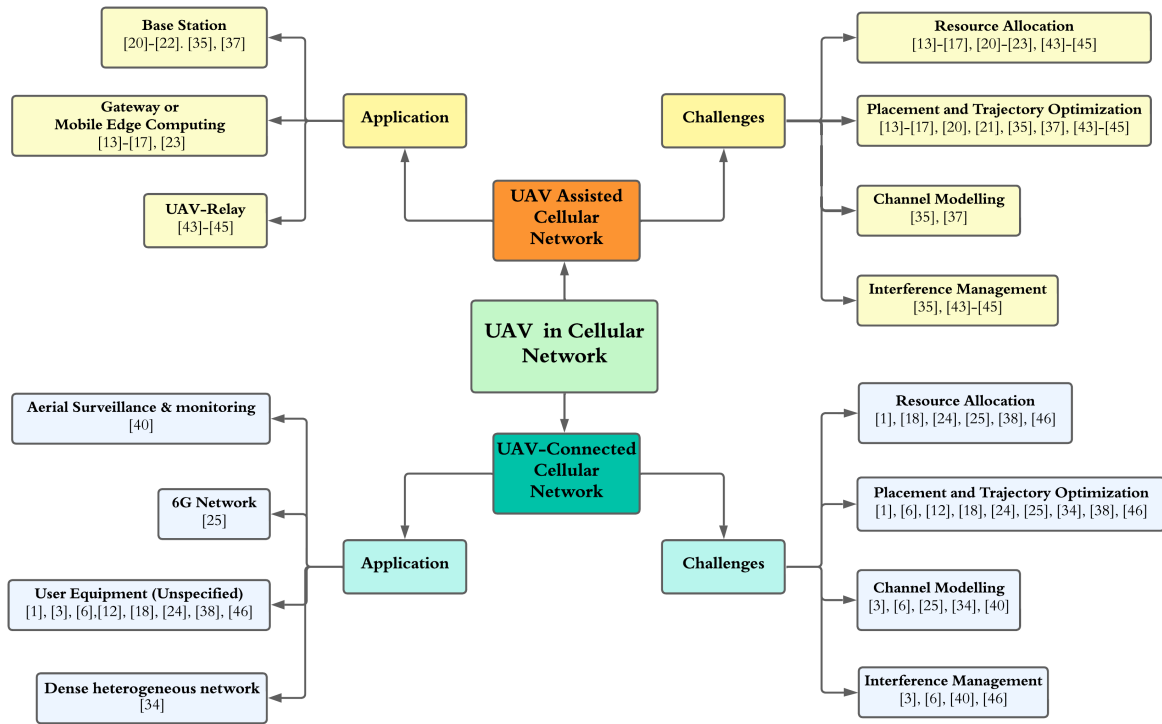


Fig. 3: Approaches, Applications, and Challenges of UAV in Cellular Network.

3.1. Resource Allocation

Unlike terrestrial users, UAVs face significant on-board energy limitations due to the absence of a fixed power source, coupled with the substantial energy demands of onboard processing and mechanical operations. The energy consumption for the propulsion of UAVs to remain aloft and navigate freely is typically significantly higher than the energy expended on communication, with a notable contrast between kilowatts and watts [14, 18, 19]. UAV's inability to have a constant energy source severely hampers their communication capabilities and imposes limitations on their endurance [1]. Therefore, it is crucial to prioritize resource-efficient design to enhance the longterm performance of UAVs in cellular communication.

Recent research has explored various strategies for optimizing UAV-assisted 5G networks. J. Chakareski *et al.* [20] have developed an effective optimization framework for radio resource management in a multi-tier cellular network by incorporating UAV-based aerial small cells to improve network coverage and throughput. Their findings demonstrated a substantial improvement in energy efficiency, with nearly double the efficiency achieved in certain scenarios through UAV integration. Focusing on energy-efficient data collection, M. Mozafari *et al.* [21] developed a new three-dimensional (3D) framework to optimize the deployment and movement of multiple UAVs. By minimizing the total transmit power

of IoT devices while adhering to signal-to-interference-noise ratio (SINR) constraints, their approach effectively determined UAV locations, device assignments, and optimal uplink power. In a different context, X. Guan *et al.* [22] addressed long-term average transmit power minimization of users by dynamically adjusting user association and power allocation in each time slot. Their method intelligently scheduled users to access either aerial or terrestrial BS for uplink transmission. S. Du *et al.* [23] introduced Coordinate Descent based Offloading Decision (CDOD) to address the issue of limited computing power of the UAV. Simulation results confirmed CDOD algorithm's effectiveness in various conditions. S. Chen *et al.* [14] introduced Tasks Offloading Policy Algorithm (TOPA) by comparing the Hybrid scheme (UAVs assist local edge servers to provide services to UEs) with the traditional Only fixed (The edge server is confined and handles tasks within the zone) and Only UAV (The UAVs equipped with edge servers provide computing services for UEs). Their findings indicated that the hybrid approach significantly outperformed the other two, improving task completion ratio by 35% and 75%, respectively. Collectively, these studies showcase a diverse range of strategies for resource allocation in UAV-assisted networks, addressing challenges such as energy efficiency, coverage, and task offloading.

Research on cellular-connected UAV networks has explored various optimization strategies. S. Yin *et al.* focused on maximizing downlink sum rate through

Tab. 1: Device performance with static sources.

Approach	Aim	Solution	Challenges	Ref.	Application
UAV-Assisted	Efficient coverage radius and energy efficient management	Design a resource management optimization framework by integrating UAV-based aerial small cells for network coverage	<ul style="list-style-type: none"> Resource allocation Placement and trajectory optimization 	[20]	BS
	Enable reliable uplink with minimum transmit power	Optimize 3D placement and mobility of the UAVs, device-UAV association, and power control	<ul style="list-style-type: none"> Resource allocation Placement and trajectory optimization 	[21]	BS
	Minimizing user's long-term average transmit power consumption	Optimize user association and power allocation using reinforcement learning	<ul style="list-style-type: none"> Resource allocation 	[22]	BS
	Present a 5G channel modeling scheme for UAV	Compute propagation paths in 3D urban environment using Ray tracing model	<ul style="list-style-type: none"> Placement and trajectory optimization Channel modelling 	[37]	BS
	Analyze UAV network performance with directional antennas	Proposes angle-dependent directional antennas model and analyzes system coverage performance via stochastic geometry	<ul style="list-style-type: none"> Placement and trajectory optimization Channel modelling Interference management 	[35]	BS
	Minimize network task completion time	Optimize the bandwidth, UAV transmit power, computation resource, task partition, and UAV's 3D location	<ul style="list-style-type: none"> Resource allocation Placement and trajectory optimization 	[13]	MEC
	Minimize energy consumption and delay, and improve QoS	Optimize the offloading strategy and UAV trajectory using deep deterministic policy gradient (DDPG)	<ul style="list-style-type: none"> Resource allocation Placement and trajectory optimization 	[15]	MEC
	Minimizing energy consumption while ensuring fairness and task efficiency	Optimize offloading strategy and multi-UAV 3D trajectories	<ul style="list-style-type: none"> Resource allocation Placement and trajectory optimization 	[16]	MEC
	Minimize the total UAV energy consumption	Optimize the bits allocation, time slot scheduling, power allocation, and UAV trajectory	<ul style="list-style-type: none"> Resource allocation Placement and trajectory optimization 	[17]	MEC
	Reduce MEC system cost	Propose mobile terminal task offloading strategy called Coordinate Descent based Offloading Decision (CDOD)	<ul style="list-style-type: none"> Resource allocation 	[23]	MEC
	Minimize the energy consumption of UAVs while satisfying UEs	Propose Tasks Offloading Policy Algorithm (TOPA) and Online UAVs Dispatching Base on the Shortest Distant Algorithm (ODSH) based on greedy strategy	<ul style="list-style-type: none"> Resource allocation Placement and trajectory optimization 	[14]	MEC
	Improve data rate between BS and UE by deploying multiple relaying UAVs	Design a 3D trajectory, optimal antenna directivity, and power allocation for the UAVs while keeping the interference below threshold	<ul style="list-style-type: none"> Resource allocation Placement and trajectory optimization Interference management 	[43]	UAV-Relay
	Enhance transmission reliability by relaying transmission, and reduce interference among ground users	Propose energy efficiency maximization which optimizes throughput and UAV energy consumption	<ul style="list-style-type: none"> Resource allocation Placement and trajectory optimization Interference management 	[44]	UAV-Relay
	Maximize sensor throughput	Manage the interference by optimizing the transmit power of all nodes and UAV trajectory	<ul style="list-style-type: none"> Resource allocation Placement and trajectory optimization Interference management 	[45]	UAV-Relay
	Finding optimal trajectory to optimize wireless coverage	Maximize data rate and explore DP technique to find optimum trajectory while satisfying the mission duration constraint	<ul style="list-style-type: none"> Placement and trajectory optimization 	[12]	Aerial UE (not specified)
	Optimize the UAV operation time, trajectory, transmit power and communication scheduling	Maximize data uploading throughput, subject to communication quality and UAV energy constraints	<ul style="list-style-type: none"> Resource allocation Placement and trajectory optimization 	[24]	Aerial UE (not specified)
	Minimize the energy consumption of cellular-connected UAV	Design the mission completion time, UAV trajectory, BS associations, while satisfying the communication connectivity with ground network	<ul style="list-style-type: none"> Resource allocation Placement and trajectory optimization Channel modelling 	[25]	6G Network

UAV-Connected	Maximize signal for UAV-UE communication to improve the cellular communication links performance	Develop framework using CoMP by studying the effect of distance, UAV altitude, and UAV-UE speed on the performance	<ul style="list-style-type: none"> • Placement and trajectory optimization • Channel modelling • Interference management 	[6]	Aerial UE (not specified)
	Minimize mission completion time of UAV under connectivity constraint	Propose an iterative trajectory optimizing algorithm based on geometric planning	<ul style="list-style-type: none"> • Resource allocation • Placement and trajectory optimization 	[38]	Aerial UE (not specified)
	Minimize mission completion time of UAV	Optimize the trajectory, subject to a quality-of-connectivity specified by a minimum receive SNR	<ul style="list-style-type: none"> • Resource allocation • Placement and trajectory optimization 	[1]	Aerial UE (not specified)
	Maximizing the energy efficiency of UAV under trajectory constraint	Optimize the UAV's trajectory considering communication throughput and UAV's energy consumption	<ul style="list-style-type: none"> • Resource allocation • Placement and trajectory optimization 	[18]	Aerial UE (not specified)
	Analyze the BS performance for the downlink transmission	Derive coverage probability and achievable throughput performance model	<ul style="list-style-type: none"> • Resource allocation • Placement and trajectory optimization • Interference management 	[46]	Aerial UE (not specified)
	Improve network performance for UAV and ground users	Develop network-based solutions based on UAV altitude and antenna configuration	<ul style="list-style-type: none"> • Placement and trajectory optimization • Channel modelling 	[34]	dense heterogeneous network
	Mitigate the uplink interference for a cellular network with coexisting UAV and ground UEs	Apply NOMA technique for the uplink communication	<ul style="list-style-type: none"> • Channel modelling • Interference management 	[40]	Surveillance and monitoring
	Ensure the efficient coexistence between ground and aerial UEs	Optimize the UAV's uplink cell associations and power allocations over multiple resource blocks	<ul style="list-style-type: none"> • Channel modelling • Interference management 	[3]	Aerial UE (not specified)

simultaneously optimizing resource allocation using Frequency Division Multiple Access (FDMA) and placement of UAV BS. Their findings revealed that the relationship between energy, communication resources, and interference is complex, and adding more UAVs does not always improve performance. Recognizing the limited onboard energy of UAVs and the additional propulsion energy required for movement [18,19], C. Zhen *et al.* [24] proposed methods to maximize uplink data uploading throughput while adhering to energy budget and cellular connectivity. In a complementary effort, C. Zhan *et al.* [25] introduce a novel design framework aimed at minimizing energy consumption in UAV system within the context of a 6G network. This approach involves the optimization of mission completion time, BS associations, and UAV trajectory. In summary, these studies emphasize the intricate challenges of resource allocation in cellular-connected UAV networks. Balancing downlink performance, uplink throughput, and energy efficiency requires nuanced approaches to address the unique characteristics of UAV-based systems.

3.2. Channel Modelling

Anticipating the influence of UAV altitude, antenna movement, and shadowing on network is crucial in channel modelling [2]. Recent research into UAV communication propagation characteristics demonstrate that the correlation between altitude and link quality can be accurately represented by integrating path loss and fading effects associated with Line-of-Sight (LoS) and Non-

Line-of-Sight (NLoS) links. Parameters in this model may fluctuate as the UAV's altitude varies [26,27].

The existing cellular network was originally developed to cater users located at ground level or within indoor environments [26]. Ground-to-air communication differs substantially from traditional ground-to-ground links, mainly due to the notable correlation between channel characteristics and flying altitude. Specifically, UAVs operating at higher altitudes experience restricted coverage and connectivity due to lower antenna gains [6,28–31]. While antennas are crucial for signal reception and coverage expansion [32]. However, in a cellular network, the BSs' antennas are commonly oriented downward to the centre of their ground coverage area [33]. This downward tilt is employed to facilitate downlink transmission for cellular users [3,25,34]. This results in UAV being served by the antenna sidelobes, reducing the received signal strength [29]. Furthermore, most existing research on UAV networks predominantly utilizes omni-directional antenna patterns, leading to overlapping coverage areas and causing significant co-channel interference. This interference arises particularly due to the prevalence of airto-ground LoS channels [35]. Therefore, the modelling and analysis of BS cooperation for cellular-connected UAV networks emerge as significant areas of interest. Hence, J. Peng *et al.* [35] introduce an angle-dependent directional antennas model and conduct an analysis of system coverage performance using stochastic geometry.

Z. Wang and J.Zheng in [29] developed a performance model to examine the downlink transmission

performance of a UAV with BS cooperation, focusing on achievable throughput and coverage probability. These performance models are invaluable in providing theoretical guidance for formulating BS cooperation strategies.

3.3. Optimal Placement and Trajectory

Optimizing UAV trajectories demands careful consideration of collision avoidance, meeting user demands, conserving energy, and ensuring efficient flight times [2,4]. While traditional UAV coverage models focus on two-dimensional (2D) planes, the 3D nature of UAV flight necessitates a more comprehensive approach to accurately represent interference patterns [36].

Research has explored various aspects of UAV trajectory optimization. D. S. Lakew *et al.* [4] offer a comprehensive survey on optimization of 3D UAV placement and trajectories within UAV-assisted cellular network. M. M. U. Chowdhury *et al.* [12] address the critical task of optimizing UAV trajectories to enhance the wireless coverage of a terrestrial cellular network. They formulate an optimization problem focused on maximizing the proportional-fair (PF) data rate of the cellular network. Utilizing the dynamic programming (DP) technique, they seek the optimal UAV trajectory while adhering to the constraints imposed by the mission duration. In their subsequent work presented in [11], Chowdhury *et al.* extend their approach by incorporating backhaul constraints and the 3D antenna radiation pattern of macro cell BSs in a downlink cellular network. Assuming a uniform distribution of UE and macro cell BS locations across the network, they formulate a time-constrained 3D trajectory optimization problem. DP is utilized to generate optimal approximate paths, revealing that the proposed 3D optimal paths result in significantly enhanced network performance compared to trajectories with fixed UAV altitudes. F. M. Altheeb *et al.* [37] utilized a ray tracing model to calculate propagation paths within 3D outdoor urban environment. Additionally, Y. Xu *et al.* in [13] optimized 3D location deployment of UAVs to ensure efficient task completion. Their optimization process involved carefully considering and balancing multiple factors, including communication bandwidth, UAV transmit power, computation resources, task partitioning, and the strategic placement of UAVs in the 3D space. In another study on optimizing the trajectory while minimizing the energy consumption, Y. Gan *et al.* [15] employ DDPG to obtain the optimal trajectory UAVs while simultaneously minimizing total energy consumption and delay. Furthermore, in an enhanced version of the DDPG algorithm, Y. He *et al.* [16] focus on optimizing the 3D trajectory of multiple UAVs considering ground devices that select the target UAV for task

computation. This research proposes a UAV-assisted offloading system that optimizes resource allocation and device selection. UAV trajectories are represented as a series of location updates, and a multi-agent deep deterministic policy gradient (MADDPG) algorithm is used to determine the optimal UAV movements and device associations. This approach effectively addresses the complex interactions between multiple UAVs and ground devices, leading to optimized task offloading and efficient resource allocation. T. Zhang *et al.* [17] focused on energy minimization by strategically optimizing computation bit allocation, power allocation, time slot scheduling, and trajectory optimization. The trajectory design considers the constraints on the UAV's mobility, such as maximum speed and initial or final location. The UAV served ground devices using orthogonal frequency-division (OFDM). These research findings emphasize the crucial role of strategic positioning and path planning in UAV-assisted cellular networks, demonstrating the possibility of significant enhancements in performance.

To ensure reliable coverage for cellular-connected UAVs, C. Zhan *et al.* [25], proposed a strategy that considers mission completion time, UAV trajectory, and maintains reliable communication with the ground cellular network during UAV flight to reduce energy consumption. Expanding on this, R. Amer *et al.* [6] conducted a comprehensive analysis of the impact of various system parameters on overall performance in cellular-connected UAV networks. These parameters included collaboration distance, UAV-UE altitude, and UAV-UE speed. This indepth investigation provides valuable insights into the factors influencing the performance of such networks. The high mobility of UAVs compared to terrestrial vehicles or UEs leads in rapid signal strength degradation and increased handover probability, as discussed in [10]. To address these challenges, D. Yang *et al.* [38] proposed an iterative trajectory optimization algorithm that minimizes mission completion time while maintaining connectivity requirements. This algorithm focuses on finding the shortest flight path with rapid convergence and minimal computational complexity. S. Zhang *et al.* [1] explored the use of Uplink Non-Orthogonal Multiple Access (NOMA) to minimize UAV mission completion time while adhering to connectivity constraints and ensuring adequate signal-to-noise (SNR) ratio for the ground BS-UAV link. N. Senadhira *et al.* [39] further contribute to this field by studying the trajectory model for NOMA-assisted cellular-connected UAVs. NOMA, unlike conventional orthogonal multiple access, efficiently serves multiple users within the same resource block, thereby optimizing resource utilization [40,41]. The study reveals that the minimum height of the aerial UE influenced by its distance from the BS as it moves along the given trajectory, emphasizing the critical need to accurately model aerial UE trajectories in cellular-connected UAV sys-

tems. Collectively, these studies offer a comprehensive exploration of various crucial aspects for optimizing the performance of cellular-connected UAVs.

3.4. Interference Management

Ensuring efficient coexistence between the ground network and UAV presents a significant challenge, primarily attributed to the pronounced aerial-ground interference [5, 40]. The LoS conditions present both advantages and drawbacks in cellular network [3, 38, 40, 42]. While LoS can improve signal quality, it also introduces challenges such as interference and reduced antenna performance at higher altitudes [6]. Additionally, they are subjected to severe uplink or downlink interference [3, 40], thus necessitating advanced intercell interference coordination (ICIC) techniques. Conversely, the LoS channel enables UAVs to connect with multiple BSs, leading to inter-cell interference [30], but also resulting in higher macro-diversity gain.

Researchers have explored various techniques to mitigate interference in UAV-assisted networks. A. Rahmati *et al.* [43], leverage the mobility of UAVs to mitigate unintentional interference by optimizing antenna directivity. W. Wang *et al.* [44] proposed a relaying-based approach to improve data transmission reliability and alleviate interference among ground users. Additionally, S. Zhang *et al.* [45] managed interference by optimizing transmit power of all communication nodes and planning the trajectory of UAVs. These studies collectively demonstrate various strategies for interference management in UAV-assisted communication systems. Whether through leveraging mobility features, implementing relaying assistance, or optimizing transmit power and trajectory planning, these approaches effectively address interference challenges, leading to improved network reliability and performance.

R. Amer *et al.* [6] introduced a coordinated multi-point (CoMP) transmissions to support cellular-connected UAVs, along with a novel mobility model adept at capturing the 3D movements of UAV-UEs, effectively mitigating interferences in cellular-connected UAV scenarios. Additionally, W. Mei *et al.* [40], employed the NOMA technique for uplink communication from a UAV to cellular BSs. This is implemented within spectrum sharing with existing ground users, specifically addressing the challenges posed by severe uplink interference. In summary, these studies highlight inventive methods in handling interference for cellular-connected UAVs. Whether utilizing CoMP transmissions or employing NOMA techniques, these approaches play a crucial role in alleviating interference challenges and enhancing the overall reliability of UAV communication in cellular networks.

4. UAV as Aerial Gateway (AG) Placement and Trajectory Optimization

The synergy between placement and trajectory optimization for UAVs as aerial gateways (AG) stands at the forefront of innovation, addressing the rapid demand for efficient connectivity, particularly in the context of the IoT. AGs play a vital role in optimizing the performance of IoT devices by serving as agile and adaptable hubs. The strategic placement of AGs, coupled with 3D trajectory optimization, facilitates the seamless integration of IoT devices into the broader network. AGs introduce unique aerial coverage and interference challenges that limit network connectivity. One viable approach to overcome these challenges is to characterize and visualize the aerial coverage in 3D for optimum placement and trajectory. It allows for a comprehensive visualization of the 3D space that aids in assessing the coverage provided by individual AGs, enabling the identification of optimal locations for deployment to maximize overall coverage in a given area. By incorporating 3D coverage visualization, AGs operators can identify obstacles and terrain variations within the coverage area. This information is crucial for determining optimal placement, ensuring that AGs are deployed in locations that minimize interference and maximize the efficiency of data acquisition or communication tasks.

Fig. 4 shows the AG can adjust its path both horizontally or vertically to avoid the obstacles or reduce the interference to maintain SINR quality to the serving BS. The AG can detect a low received signal strength indicator (RSSI) or poor SINR value in a particular area by combining these metrics with 3D coverage data. It can identify potential obstacles or interference sources that may be blocking the signal using 3D coverage data.

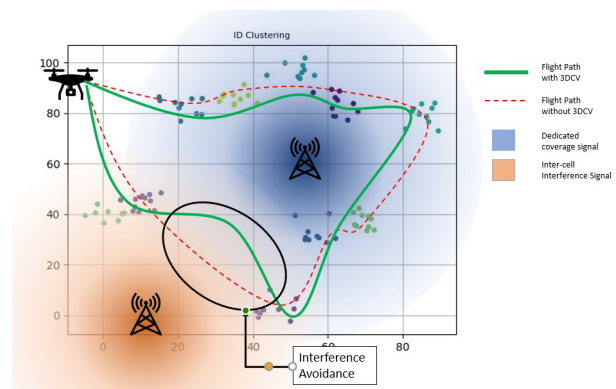


Fig. 4: Expected Flight Path Optimization Based on 3D Coverage.

4.1. Key Performance Metrics for AG Placement and Trajectory Optimization

To measure the effectiveness of 3D coverage visualization in addressing aerial coverage and interference challenges, several key performances need to be evaluated.

One critical metric is coverage optimization, which focuses on maximizing the area covered by AGs within a given 3D space. With 3D utilization, operators can assess the coverage provided by individual AGs and identify optimal deployment locations. This ensures that the maximum area is covered while accounting for the unique obstacles present in aerial environments, such as buildings or terrain variations.

Another important metric is SINR, it is a vital measure of signal quality and network reliability. By analyzing 3D coverage data and adjusting the flight paths, it helps AGs in avoiding obstacles and interference sources. As a result, AGs can maintain a higher SINR, ensuring better communication performance across the coverage area.

Energy efficiency is also a central consideration in UAV-based networks. By leveraging 3D coverage visualization, AGs can optimize their trajectories to minimize unnecessary movements, which, in turn, reduces energy consumption. This optimization leads to longer flight durations and more efficient use of AG resources, a crucial factor in ensuring the sustainability of UAV-assisted networks.

Finally, the system monitors the RSSI to detect areas with poor signal quality. AGs can then adjust their flight paths to improve signal strength in these areas, enhancing connectivity for ground IoT devices.

4.2. Channel Modelling for AG Communication

Accurate channel modelling is a critical aspect of UAV-assisted cellular network design, as it directly affects the reliability of signal strength estimation and optimization strategies. Traditional models such as Free Space Path Loss (FSPL) provide a simplified approach based solely on the distance between transmitter and receiver. FSPL is expressed as in Eq. (1)

$$FSPL = 20 \log_{10}(f) + 20 \log_{10}(d) + 32.44 \quad (1)$$

While FSPL is computationally efficient and useful for initial approximations, it is inadequate for scenarios involving complex terrain.

The Irregular Terrain Model (ITM), also known as the Longley-Rice model, offers a more robust and realistic

representation of radio propagation in such environments. Unlike models based only on distance, ITM uses elevation data and calculates both line-of-sight and diffraction losses along the path. The ITM model is expressed in Eq. (2)

$$L_{ITM} = FSPL + EnvFactor + DiffractionLoss \quad (2)$$

To validate the accuracy of the model, field measurements has been conducted to measure the path loss from a UAV deployed in a suburban environment. The measured signal strength values were then compared against both FSPL and ITM-based predictions. The results as in Figure 5 revealed a significant discrepancy between FSPL estimates and observed values. ITM predictions were much closer to the observed values.

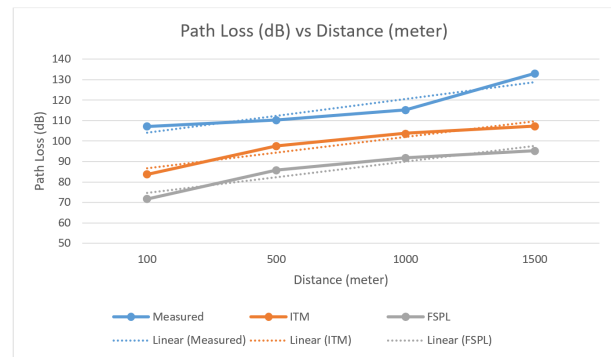


Fig. 5: Path Loss Analysis: Measured vs. ITM vs. FSPL Models.

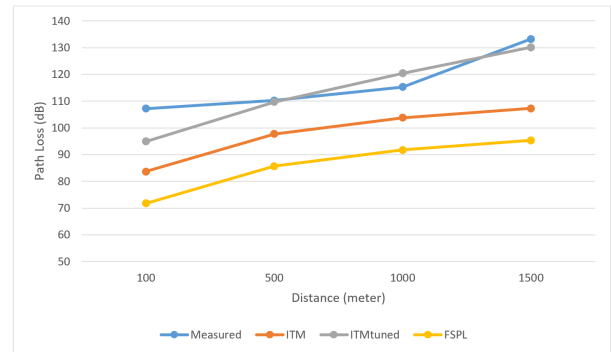


Fig. 6: Improving Model Accuracy: ITMTuned vs Measured vs. ITM vs. FSPL Models.

To bridge the gap between the ITM and the measured values, a correction factor (CF) in Eq. (3) was introduced to the new tuned ITM formula (ITM_{Tuned}) as expressed in Eq. (4). The result is portrayed in Figure 6.

$$CF(d) = (-0.01183 * d) + 24.7075 \quad (3)$$

$$ITM_{tuned} = 20 \log_{10}(f) + 20 \log_{10}(d) + 32.44 + 6 + ((-0.01183 * d) + 24.7075) \quad (4)$$

By applying the adjustment, the ITM_{Tuned} showed improved alignment with the measured values. For example, at 1000 meters, the ITM_{Tuned} predicted a path loss of 120.44 dB, significantly narrowing the differences. Integrating ITM_{Tuned} into the interference-aware SINR framework Eq. (5) allows for enhanced UAV placement and path planning under realistic channel conditions.

4.3. Mathematical Model for AG Placement and Trajectory Optimization

To effectively optimize the performance of UAVs within a cellular network, a mathematical model that captures key performance metrics such as Signal-to-Interference-plus-Noise Ratio (SINR), coverage area, and energy consumption is essential. In this study, we propose a model focusing on 3D trajectory and placement optimization of UAVs acting as Aerial Gateways (AGs).

Figure 7 illustrates a scenario where each AG communicates with a dedicated base station (BSS) while experiencing interference from neighbouring base stations (BSI).

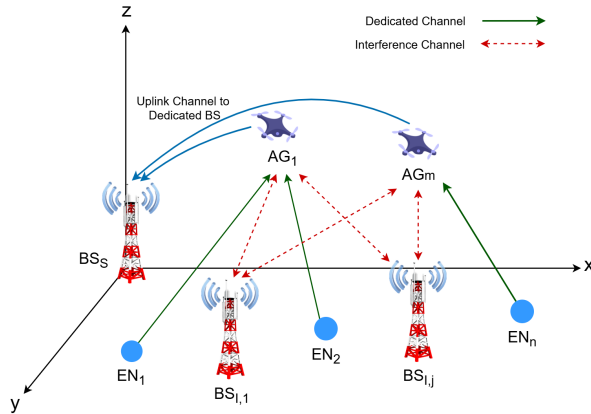


Fig. 7: System Architecture for UAV as AG.

The SINR model used in this study accounts for interference from neighboring base stations to provide a realistic estimation of uplink quality for AGs. The goal is to maximize the SINR between each AG and its BSS, while minimizing interference caused by BSI. This is achieved by optimizing both transmission power and spatial placement of AGs in 3D space. The total SINR across all AGs is defined in equation (2)

$$SINR_{m,BSS} = \frac{\frac{Power_{m,BSS}}{L_{ITM_{m,BSS}}(d)}}{\sum_{j \in BSI} \frac{Power_{m,j}}{L_{ITM_{m,j}}(d)} + N_o} \quad (5)$$

Where $m \in AG$ denotes each Aerial Gateway, BSS is the set of base stations dedicated to AGs, BSI is the set of interfering base stations, $Power_{m,BSS}$ is the

transmit power from AG to its serving BS, $L_{ITM_{m,BSS}}$ is the effective channel gain from AG to its serving BS, $Power_{m,j}$ and $L_{ITM_{m,j}}$ denote the interference power and channel gain from interfering BS and N_o is the thermal noise. The overall objective becomes:

$$\max_{m \in AG} \sum SINR_{m,BSS} \quad (6)$$

With constraint of $E_{total} \leq E_{max}$ to ensure flight feasibility, and $Coverage \leq \tau$ to maintain the quality-of-service for ground devices.

This formulation captures the need to optimize AG placement in a way that maximizes signal quality to serving BSs while minimizing the impact of co-channel interference. This model is critical for planning real-world UAV deployments where shared spectrum and dense BS deployments can significantly degrade performance if not accounted for.

5. Expected Impact and Theoretical Implications

As this paper presents a conceptual and mathematical framework, simulation and field validation are proposed as future steps. However, based on theoretical modeling and the design assumptions described in 5.1 and 5.2, the proposed approach offers several potential benefits.

The SINR-based optimization model is expected to enhance signal quality and provide more uniform coverage for ground IoT devices. By carefully optimizing UAV placement and trajectory, it is theoretically possible to maintain robust communication links between AGs and BSs, reducing packet loss and improving data throughput.

Furthermore, by explicitly modeling the interference from surrounding base stations, the framework provides AGs with the ability to identify and avoid high-interference regions. This adaptability can improve communication stability and reduce retransmission rates.

The energy-aware design of the model enables AGs to operate within defined energy constraints by balancing propulsion and communication demands. This is especially important for AGs with limited battery capacity, as it can extend mission duration and operational coverage while ensuring successful data transmission.

Although numerical results are not presented in this concept paper, the framework offers a promising theoretical foundation for further development. The model can be applied in various practical contexts including remote area monitoring, smart city deployments, and disaster response scenarios, where adaptive, interference-aware AG deployment is essential.

6. Conclusion

The integration of UAVs within cellular networks represents a groundbreaking frontier in the realm of telecommunications and aerial technologies. As explored in this article, the unique capabilities of UAVs can change the way we understand and deploy cellular infrastructures, particularly in areas that are geographically challenging or require rapid deployment. The approach to integrating UAVs into cellular networks has been carefully examined, highlighting the architectural intricacies that must be considered to ensure seamless integration and optimal performance. Mathematical models for SINR and energy consumption has been derived, and a multi-AG optimization framework to mitigate interference from neighboring base stations has been introduced. The proposed model is especially relevant in environments where UAV performance is highly sensitive to interference.

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Author Contributions

N. S. A. I. wrote the manuscript and designed the figures. N. S. A. I. and F. A. S. developed the theoretical framework and contributed to the final version of the manuscript. F. A. S. supervised the project.

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