Doctoral Thesis in Information and Communication Technology

AI Assisted Mobility Management for Cellular Connected UAVs

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Abstract

Unmanned Aerial Vehicles (UAVs) connected to cellular networks, i.e., cellular-connected UAVs, introduce unique challenges and opportunities in mobility management that distinguish them from terrestrial users. This thesis presents a comprehensive approach for optimizing UAV integration into cellular networks.

We first investigate the distinct mobility management needs for cellular-connected UAVs. Unlike terrestrial mobility management, which primarily focuses on preventing radio link failures at cell edges, UAVs experience fragmented and overlapping coverage, often with line-of-sight visibility to multiple ground base stations (BSs). Consequently, UAV mobility management must address not only link stability but also the minimization of unnecessary handovers with sustained service availability, particularly in uplink scenarios. To tackle these challenges, we propose two solutions, a model-based handover parameter optimization algorithm and a model-free deep reinforcement learning (DRL) based handover algorithm, both designed specifically for UAV mobility management. We extend the problem by integrating UAV path planning with wireless objectives, including interference management, delay reduction, and minimized handovers. This results in a joint optimization framework for UAV trajectory planning, handover management, and radio resource allocation. To solve this multi-objective problem, we develop a multi-agent DRL algorithm that combines mission-specific trajectory planning with network-driven adjustments, optimizing resource allocation and handover transitions.

Furthermore, we address mobility management in multi-connectivity scenarios where UAVs are served by clusters of distributed BSs. As UAVs move, the serving BS clusters must be dynamically reconfigured, necessitating coordinated resource allocation under stringent and time-sensitive reliability constraints. We propose a centralized, fully distributed, and hierarchical DRL-based approaches to achieve reliable connectivity, reduce power consumption, and minimize cluster reconfiguration frequency.

Lastly, to evaluate a network's capability to support range-based localization for cellular-connected UAVs, we introduce an analytical framework. This framework defines B-localizability as the probability of a UAV receiving sufficient localization signals from at least B ground BSs, meeting a specific Signal-to-Interference-plus-Noise Ratio (SINR) threshold. By incorporating UAV parameters within a three-dimensional environment, we provide insights into localizability factors such as distance distributions, path loss, interference, and SINR.

Keywords: Unmanned aerial vehicles, Reinforcement Learning, Wireless networks, Reliability, Air-to-ground channel, Mobility management, Handover

Sammanfattning

Obemannade luftfarkoster (UAV:er) som är anslutna till mobilnätverk medför unika utmaningar och möjligheter inom mobilitetshantering som skiljer sig från dem för markbundna användare. Denna avhandling presenterar ett omfattande tillvägagångssätt för att optimera UAV-integration med mobilnätverk.

Vi undersöker först de särskilda behoven av mobilitetshantering för cellulärt anslutna UAV:er. Till skillnad från mobilitetshantering för markanvändare, som främst fokuserar på att förhindra radiolänkfel vid cellkanter, upplever UAV:er fragmenterad och överlappande täckning med siktlinje till flera markbasstationer (BS:er). Därför måste mobilitetshanteringen för UAV:er inte bara hantera länkstabilitet utan även minimera onödiga överlämningar och säkerställa bibehållen tjänstetillgänglighet, särskilt i uppströmskommunikation.

För att hantera dessa utmaningar föreslår vi både modellbaserade och modellfria algoritmer specifikt utformade för UAV-mobilitetshantering. Vi utökar problemet genom att integrera UAV-ruttplanering med trådlösa mål, inklusive störningshantering, minskad fördröjning och minimerade överlämningar. Detta resulterar i en gemensam optimeringsram för UAV-ruttplanering, överlämningshantering och radioresurstilldelning. För att lösa detta multiobjektivproblem utvecklar vi en algoritm baserad på djup förstärkningsinlärning (DRL) som kombinerar uppdragsbaserad ruttplanering med nätverksdrivna justeringar, vilket optimerar resursallokering och överlämningshantering.

Vidare behandlar vi mobilitetshantering i multikonnektivitetsscenarier där UAV:er betjänas av kluster av distribuerade basstationer. När UAV:er rör sig måste de servande BS-klustren dynamiskt omkonfigureras, vilket kräver samordnad resursallokering under strikta och tidskänsliga tillförlitlighetskrav. Vi föreslår ett centraliserat, fullt distribuerat och hierarkiskt DRL-baserat tillvägagångssätt för att uppnå tillförlitlig anslutning, minska strömförbrukningen och minimera frekvensen av klusteromkonfigureringar.

Slutligen, för att utvärdera nätverkets förmåga att stödja positionsbaserad lokalisering för cellulärt anslutna UAV:er, introducerar vi en analytisk ram. Denna ram definierar B-lokaliserbarhet som sannolikheten för att en UAV tar emot tillräckliga lokaliseringssignaler från minst B markbasstationer, som uppfyller en specifik signal-till-interferens-plus-brusförhållande (SINR) tröskel. Genom att inkludera UAV-parametrar i en tredimensionell miljö tillhandahåller vi insikter om lokaliserbarhetsfaktorer som distansfördelningar, dämpning, interferens och SINR.

Keywords: Unmanned aerial vehicles, Reinforcement Learning, Wireless networks, Reliability, Air-to-ground channel, Mobility management, Handover

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Irshad Ahmad Meer,
Stockholm, Jan 2025

In Grateful Dedication to Zaina,
my Anchor in the Past and Beacon to the Future...

Contents

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List of Acronyms

A2G	Air-to-Ground
AI	Artificial Intelligence
AP	Access Point
AU	Aerial User
AOA	Angle of Arrival
BS	Base Station
CDF	Cumulative Distribution Function
CoMP	Coordinated Multi-Point
C-RAN	Centralized Radio Access Network
DA2GC	Direct Air-to-Ground Communication
DQN	Deep Q-Network
DRL	Deep Reinforcement Learning
GPS	Global Positioning System
HMADRL	Hierarchical Multi-Agent Deep Reinforcement Learning
HOM	Handover Margin
KPI	Key Performance Indicator
LOS	Line-of-Sight
MDP	Markov Decision Process
MRO	Mobility Robustness Optimization
O-RAN	Open Radio Access Network
POMDP	Partially Observable Markov Decision Process
QoS	Quality of Service
RAT	Radio Access Technology
RL	Reinforcement Learning
RRB	Resource Radio Block
RSRP	Reference Signal Received Power
RSSI	Received Signal Strength Indicator
SINR	Signal-to-Interference-plus-Noise Ratio
TTI	Time to Trigger
TOA	Time of Arrival
TDOA	Time Difference of Arrival
UAV	Unmanned Aerial Vehicle

List of Papers

1. **Paper I:** Mobility Management for Cellular-Connected UAVs: Model-Based Versus Learning-Based Approaches for Service Availability [1]
   I. A. Meer, M. Ozger, D. Schupke, and C. Cavdar
   IEEE Transactions on Network and Service Management, 2024.

2. **Paper II:** D3QN-Based Trajectory and Handover Management for UAV Co-Existing with Terrestrial Users [2]
   Y. Deng, **I. A. Meer**, S. Zhang, M. Ozger and C. Cavdar
   IEEE 21st International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt), Singapore, 2023,

3. **Paper III:** Joint Trajectory and Handover Management for UAVs Co-existing with Terrestrial Users: A Multi-Agent DRL Approach
   Y. Deng, S. Zhang, **I. A. Meer**, M. Ozger and C. Cavdar
   IEEE Transactions on Cognitive Communications and Networking (Under Major Revision)

4. **Paper IV:** Reinforcement Learning Based Dynamic Power Control for UAV Mobility Management [3]
   I. A. Meer, K. -L. Besser, M. Ozger, H. V. Poor and C. Cavdar
   IEEE Asilomar Conference on Signals, Systems, and Computers, 2023

5. **Paper V:** Learning Based Dynamic Cluster Reconfiguration for UAV Mobility Management with 3D Beamforming [4]
   I. A. Meer, K. -L. Besser, M. Ozger, D. Schupke, H. V. Poor and C. Cavdar
   IEEE International Conference on Machine Learning for Communication and Networking (ICMLCN), 2024

6. **Paper VI:** Hierarchical Multi-Agent DRL Based Dynamic Cluster Reconfiguration for UAV Mobility Management
   I. A. Meer, K. -L. Besser, M. Ozger, D. Schupke, H. V. Poor and C. Cavdar
   IEEE Transactions on Cognitive Communications and Networking (Submitted)

7. **Paper VII:** Cellular Localizability of Unmanned Aerial Vehicles [5]
   I. A. Meer, M. Ozger, and C. Cavdar
   Elsevier Vehicular Communications, Volume 44, 2023.

Other Papers

I participated in several additional projects that were not included in this thesis. However, I have listed the peer-reviewed papers resulting from these projects below for the sake of completeness.

1. Low-Latency MAC Design for Pairwise Random Networks [6]
   I. A. Meer, Woong-Hee Lee, Mustafa Ozger, Cicek Cavdar, and Ki Won Sung
   IEEE 95th Vehicular Technology Conference:(VTC2022-Spring), 2022.

Open-Source Software

- **I. A. Meer** and K.-L. Besser, "Reinforcement Learning-Based Power Allocation for UAVs with Varying Reliability Requirements," Supplementary Material, available online: , 2023.
- **I. A. Meer** and K.-L. Besser, "Learning Based Dynamic Cluster Reconfiguration for UAV Mobility Management with 3D Beamforming," Supplementary Material, available online: , 2024.

Chapter 1

Introduction

Wireless communication is rapidly advancing toward 6G and beyond, introducing new user groups and services with diverse challenges and evolving quality of service (QoS) requirements. Among these, aerial users, particularly unmanned aerial vehicles (UAVs) (or simply drones), are poised to become significant users of 6G cellular networks [7]. Integrating UAVs within the cellular infrastructure will unlock a wide range of applications, including cargo transport, surveillance, multimedia streaming, remote sensing, precision agriculture, traffic monitoring, and search and rescue operations [8]. However, these applications demand new solutions, as UAVs introduce technical challenges that differ fundamentally from those associated with terrestrial users. For instance, UAVs operate in the open air, resulting in unique air-to-ground (A2G) channel characteristics that are highly influenced by the altitude of UAVs. The UAV communication is also often asymmetric, with more data typically sent from UAVs (uplink) than received (downlink), like video from a search and rescue mission. The time-sensitive uplink data from UAV introduce new QoS requirements which are different from terrestrial users. Despite the emphasis on uplink, the downlink also remains crucial for command and control, where any disruption could severely impact mission-critical tasks. Also, when UAVs coexist with terrestrial users, their line-of-sight (LoS) connections with multiple base stations (BSs) and continuous uplink data transmissions generate significant interference for terrestrial users. Thus, potentially degrading QoS for ground users.

The combination of these challenges, alongside the fact that cellular networks are optimized for terrestrial users, highlights the limitations of traditional network management methods for serving cellular-connected UAVs. Artificial intelligence (AI), and particularly deep reinforcement learning (DRL), offers promising solutions for real-time, adaptive optimization, enabling cellular networks to effectively manage the scalability and unpredictability of mixed aerial and terrestrial environments. Such AI-driven approaches hold the potential to empower future 6G networks to deliver the reliability, flexibility, and performance necessary for the seamless integration of cellular-connected UAVs.

A key research challenge in integrating cellular-connected UAVs is ensuring efficient mobility management. This thesis addresses the mobility management problem for cellular-connected UAVs, with particular emphasis on the challenges arising from their high mobility, the probabilistic nature of A2G channel characteristics, and the unique QoS requirements in both uplink and downlink. The first part of the thesis focuses on efficient handover management to minimize unnecessary handovers, a major challenge for UAVs, while maintaining uplink QoS requirements. Frequent handovers can disrupt time-sensitive uplink communication and critically affect the command and control link, which demands high reliability. We propose advanced handover management schemes designed to reduce unnecessary handovers without affecting the service continuity. Additionally, we integrate handover management with UAV path planning to minimize handovers, reduce interference, and minimize delay in wireless networks that serve both terrestrial and aerial users.

Next, we tackle mobility management within a cell-less network architecture featuring multi-connectivity, focusing on open issues and research gaps. One key challenge is dynamically clustering distributed BSs to form serving clusters and efficiently allocating resources within these clusters to meet the stringent downlink QoS requirements of aerial users. This challenge is further complicated when considering joint resource allocation to satisfy spatio-temporally varying QoS demands. Although multi-connectivity shows promise in enhancing QoS, particularly for reliability, it may also lead to excessive resource usage, such as increased power consumption. To address these challenges, we propose AI-based algorithms for joint clustering and resource allocation in wireless interference networks, specifically tailored for mobile aerial users with stringent and variable reliability needs. The proposed solutions are evaluated through numerical simulations, demonstrating their effectiveness in optimizing resource use while meeting high QoS demands.

Finally, we provide a foundational analysis of UAV localization using cellular networks, further contributing to the understanding and design of mobility management solutions for cellular-connected UAVs. The proposed framework provides a comprehensive evaluation of the key factors critical for enabling effective UAV localization through cellular networks. Using both analytical and numerical methods, we investigate how variables such as the number of participating BSs, signal-to-interference-plus-noise ratio (SINR) requirements, A2G channel characteristics, and network coordination influence localization performance.

The remaining part of this chapter is structured as follows. We provide the background and motivation of this thesis in Section 1.1. We elaborate on the research questions that this thesis aims to answer and provide research methodologies in Section 1.2. We provide a discussion about the sustainable goals and ethical aspects of the thesis in Section 1.3. Finally, the outline of the thesis is provided in Section 1.4.

1.1 Background and Motivation

In this section, we provide the necessary background on key technical concepts relevant to this thesis. In particular, we cover the current methods for handover procedures, the unique quality of service requirements for aerial users, the benefits and challenges of multi-connectivity, and the role of AI for network optimization. In addition, this background lays the groundwork for understanding AI-based methods in managing mobility for UAVs within cellular networks.

1.1.1 Mobility Management with Single Connectivity

Mobility management is a fundamental aspect of wireless communication networks, ensuring seamless connectivity as users move across different coverage areas [9]. It involves multiple functions, such as tracking user locations, managing connections, and optimizing resource allocation to meet the necessary QoS standards. Effective mobility management is especially important in dynamic environments, where users frequently switch between BSs.

A core component of mobility management is the handover procedure, which facilitates the transfer of a mobile user's connection from one BS to another [10,11]. This process is vital for maintaining uninterrupted service and minimizing call drop rates as users move between coverage zones. The handover procedure shifts the user's connection between a serving BS and a target BS. As illustrated in Figure 1.1, a handover request is triggered when the reference signal received power (RSRP) from the target BS exceeds that of the serving BS by a margin called the handover margin (HOM) (or A3 offset). This condition, known as the A3 event, must persist for a specified time, referred to as the time to trigger (TTT), before the handover is initiated.

The signaling procedure involved with the handover process is illustrated in Figure 1.2, between the user, serving BS, and target BS [11, 12]. The serving BS configures user measurement procedures based on roaming and access restrictions. Measurements taken by the serving BS can assist in managing the user's connection mobility. When the user's measurements satisfy the A3 event triggering condition, the A3 event is registered, starting the TTT timer. Upon expiry of the TTT timer, a measurement report is generated and sent to the serving BS. Based on the measurement report and radio resource management information, the serving BS decides whether to proceed with the handover. If the handover is approved, the serving BS issues a handover request message to the target BS, providing the information needed to prepare for the handover. The target BS performs admission control to allocate the necessary resources. If the resources are available, it sends a handover acceptance message to the source BS. The source BS then issues a handover command to the user, initiating a synchronization phase between the user and the target BS, after which the handover is completed. Once completed, the user begins transmitting data to the core network through the target BS.

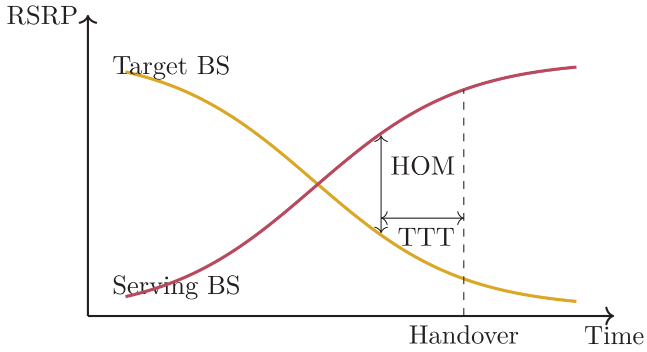

Figure 1.1: Illustration of the user's measurement report on RSRP from the serving and target BS, along with handover parameters: HOM and TTT.

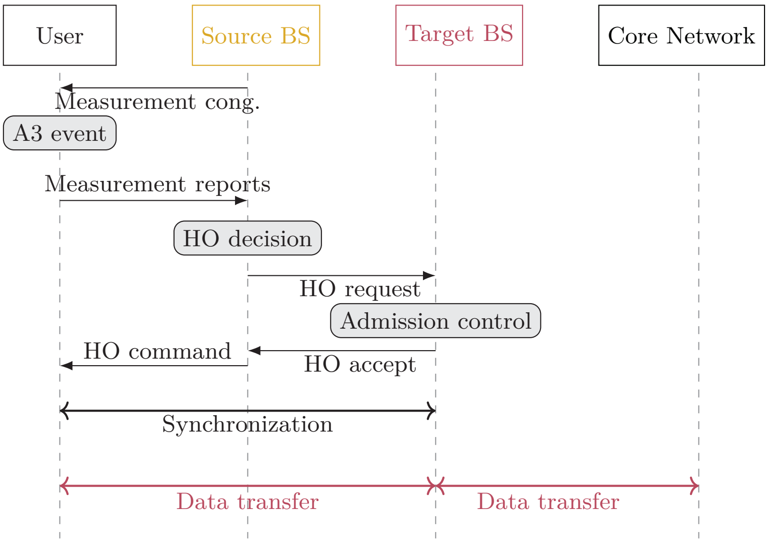

Figure 1.2: 3GPP LTE handover procedures and signaling.

In the current wireless network system, various mechanisms are implemented to enhance the handover process, including mobility robustness optimization (MRO), which optimizes the HOM and TTT parameters [13–15]. By strategically selecting these handover parameters, the system seeks to minimize handover failures and alleviate the ping-pong effect, which occurs when a user frequently switches between cells. This optimization ensures that the user is consistently connected to the BS without affecting the QoS.

1.1.2 Multi-Connectivity in Cellular Networks

In high-mobility scenarios like UAV operations, ensuring seamless handovers and reliable connections is complex due to frequent shifts in signal quality, network load, and interference. Multi-connectivity presents a powerful solution by allowing UAVs to connect to multiple, distributed BSs concurrently as they traverse coverage areas. This approach marks a significant departure from traditional mobility management, transitioning from a rigid, cell-centered handover model to a dynamic, user-centric cluster reconfiguration paradigm [16]. Consequently, the concept of network coverage has evolved to prioritize user experience, adapting network resources around the user rather than fixed cell boundaries.

In this user-centric framework, UAVs are continuously supported by clusters of distributed BSs operating on the same frequency-time resources, thereby maintaining connectivity through cooperative communication. Various advanced technologies facilitate the cooperation and clustering of BSs required for MC. Coordinated multi-point (CoMP), for instance, enables multiple BSs to coordinate their transmission and reception, reducing interference and improving signal quality for the user. Similarly, the cloud-radio access network (C-RAN) centralizes processing capabilities in the cloud, enabling efficient and dynamic coordination across BSs from a central location, which simplifies resource allocation and user management across multiple connections. Cell-free networks take this concept further by removing traditional cell boundaries, allowing the entire network of BSs to function as a unified system, providing seamless multi-BS connections as users move through the network.

1.1.3 Cellular Network-Based Localization

Since mobility management is responsible for maintaining mobile users' connections as they continue to change their location, the network must know the user locations. Cellular network-based localization can be an important alternative to global positioning system (GPS), especially in environments where GPS signals can be vulnerable to spoofing, jamming, and interception. This approach leverages the existing cellular infrastructure, allowing a target device to estimate its position by using signals from multiple BSs. Generally, the localization process involves two key stages: signal reception and position estimation.

The first stage involves the successful reception of localization signals from multiple BSs. Factors such as SINR, LoS conditions, and the spatial distribution of the BSs relative to the target affect the quality and reliability of these signals. Signal reception can be particularly challenging in cellular networks, as interference from neighboring cells and the probabilistic nature of wireless channels introduce significant variability.

Once signals from multiple BSs are received, the target's location can be estimated using range-based methods such as angle-of-arrival (AOA), time of arrival (TOA), time difference of arrival (TDOA), or received signal strength (RSS). These methods typically rely on trilateration, where each distance measurement places the target on a sphere centered on the respective BS. In a 3D environment, three BSs yield two possible location points, while a fourth BS measurement is often needed to resolve ambiguity, enabling accurate position estimation. Therefore, for unambiguous target localization, each technique needs a certain minimum number of detectable signals.

In localization, the Cramér-Rao lower bound (CRLB) is commonly used to establish a theoretical lower bound on positioning error, providing a benchmark for the best achievable accuracy under ideal conditions [17]. However, this bound assumes deterministic network conditions and ideal geometries, which are not always applicable in practical cellular environments. Consequently, performance metrics like cellular localizability, the probability that a target can receive sufficient signals from the required number of BSs, is used to assess the likelihood of feasible localization under real-world conditions, accounting for factors such as interference and channel variability.

1.1.4 Enhanced Quality of Service Requirements

Reliability is a fundamental metric in wireless communication systems, capturing the system's ability to maintain performance standards essential for continuous and effective operation. In this thesis, reliability is defined through three primary approaches, each providing a distinct perspective on system robustness [18–21].

- **Threshold based reliability**: In conventional terms, reliability is defined by the probability that a performance metric x meets or exceeds a specified threshold $x_{\text{threshold}}$. A reliability value of 0.999 implies an outage probability $P(x < x_{\text{threshold}})$ of 10^{-3}, ensuring the system meets performance requirements 99.9% of the time. This approach is suited to applications demanding strict adherence to performance thresholds, such as service availability in data transmission for UAVs where continuous data flow is critical.

- **Probabilistic reliability bound:** In dynamic environments where system performance fluctuates, reliability can be defined as the probability that the outage probability $\epsilon = P(x < x_{\text{threshold}})$ remains below an acceptable maximum value $\epsilon_{\max}$. Here, the reliability of 0.99 indicates a 99% probability that ϵ will stay within acceptable bounds. This approach accounts for variability in conditions, offering a probabilistic assurance of stable operation.

- **Reliability via decoding error probability:** Decoding reliability is defined by the likelihood of successful message decoding. High reliability, with a decoding error probability of 10^{-3}, for example, supports data integrity and timeliness, crucial for low-latency applications. Under finite block length conditions, this metric highlights the impact of signal strength, coding, and modulation schemes on communication quality. This approach is suited for

Table 1.1: Ranges of Communication Reliability, Based on [22].

Communication Reliability	Range
Low	<99.9%
Medium	99.9% – 99.999%
High	>99.999%

downlink command and control communication, where reliable decoding is critical for ensuring responsive and safe UAV operation.

These reliability definitions collectively guide the assessment of UAV mobility management strategies within this thesis, ensuring robust connectivity and communication fidelity across diverse operational contexts. Following the categorization approach in [22], this study classifies reliability levels as low, medium, and high, as detailed in Table 1.1. Since concrete reliability requirements for specific aerial applications are still being refined, we describe them within these specified ranges.

1.1.5 Role of Artificial Intelligence

The rapid increase in wireless network demands, driven by the proliferation of connected devices and the advent of applications requiring low latency and high reliability, has significantly raised the complexity of network management and optimization. Traditional model-based and heuristic approaches to optimize wireless networks are often limited by their dependence on simplified assumptions, which fail to fully capture the dynamic, stochastic, and high-dimensional nature of real-world networks. AI, and more specifically, reinforcement learning (RL), is becoming increasingly influential in addressing these challenges by offering a data-driven approach to learn optimal policies directly from interactions with the environment [23–27].

In an RL framework, an agent learns by interacting with an environment to achieve specific goals. The agent takes actions within an environment, receives feedback in the form of rewards, and adjusts its actions over time to maximize cumulative rewards. This interaction is modeled as a Markov decision process (MDP), represented by a tuple $\langle \mathcal{S}, \mathcal{A}, P, R, \gamma \rangle$:

- $\mathcal{S}$: The set of all possible states.
- $\mathcal{A}$: The set of all possible actions.
- $P(s'|s,a)$: The transition probability function, indicating the probability of moving to state s' from state s after taking action a.
- $R(s,a)$: The reward function, which provides a reward for taking action a in state s.
- $\gamma \in [0,1]$: The discount factor, which balances immediate and future rewards.

The objective of RL is to find an optimal policy π^*, which maps states to actions, maximizing the expected cumulative reward G_t, defined as:

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}. \tag{1.1}$$

In single-agent RL, the agent learns to optimize a specific objective by interacting with the environment in isolation. This approach is often suitable for scenarios where a single control point exists, such as a single UAV managing its own mobility or a base station controlling resource allocation independently. The agent's objective is to maximize cumulative rewards, which are defined based on the optimization goals, for example, maximizing connectivity, minimizing power consumption, or reducing latency.

Single-agent RL approaches like Q-learning and deep Q-network (DQN) are commonly applied to these types of tasks. In the DQN framework, for example, the agent approximates a Q-value function to make decisions about actions based on current network states. For UAV mobility management, this might mean choosing the optimal BS and radio resource block (RRB) to maintain connectivity. The single-agent approach is effective in less complex environments or when only one decision-maker is required. However, its limitations become apparent in larger, more dynamic systems where multiple agents must interact or cooperate, such as in networks with multiple UAVs and BSs.

Multi-agent deep reinforment learning (MADRL) extends RL by enabling multiple agents to operate in the same environment, each learning and optimizing its own policy. This approach is particularly relevant in wireless networks, where various entities (e.g., UAVs, BSs, and terrestrial users) interact and must often cooperate or compete for resources. In MADRL, each agent learns from both its interactions with the environment and the actions of other agents, making it highly suitable for tasks like coordinated handovers, path optimization, joint resource allocation, and interference management in cellular networks.

Key MADRL techniques include independent Q-learning, where each agent learns independently with its Q-function, and more collaborative approaches like multi-agent deep deterministic policy gradient (MADDPG) and multi-agent proximal policy optimization (MAPPO). MADRL approaches can be cooperative, where agents work towards a shared objective, or competitive, where agents have conflicting goals. Cooperative MADRL is particularly suited for wireless networks where shared resources like bandwidth and spectrum must be efficiently allocated. Hierarchical-MADRL is another advancement, where agents are organized in a hierarchy, with higher-level agents setting overarching policies while lower-level agents make detailed, real-time adjustments.

One of the primary advantages of RL, and specifically MADRL, in wireless network optimization is its ability to operate in environments with limited or no prior knowledge, adapting to the network's intrinsic dynamics. This flexibility is valuable for managing complex interactions between different optimization variables, such as mobility, resource allocation, and interference.

However, RL-based approaches also face challenges. Single-agent RL approaches may struggle with scalability in large networks, where each decision-maker acts independently without knowledge of other agents, potentially leading to suboptimal outcomes. On the other hand, MADRL approaches require coordination among agents, which can lead to instability or slow convergence if not carefully designed, especially in high-dimensional state-action spaces. Ensuring safe and efficient exploration remains a critical concern in MADRL, as poor actions taken by one agent can disrupt network services for others.

1.2 Research Questions and Methodology

This section begins by outlining the research questions that this thesis addresses, followed by a description of the methodology employed to answer them.

1.2.1 Mobility Management and Trajectory Optimization for Cellular Connected UAVs

In current mobility management schemes, handover decisions are typically based on the relative difference in RSRP between the serving and target BS, as illustrated in Figure 1.1. However, when applied to cellular-connected UAVs, which experience LoS connections with multiple ground BSs, this approach can result in frequent, unnecessary handovers [28,29]. These excessive handovers lead to additional control signaling exchanges between the UAV and the BS, consequently filling the buffer queue and causing delays in uplink data transmission [30].

To address this issue, we propose refining the handover decision process for cellular-connected UAVs by considering not only RSRP but also the UAV's buffer queue status. For instance, a UAV with a high buffer load should prioritize handover to a stronger BS, while a UAV with minimal or no data to transmit should remain with the current BS, provided the radio link maintains an RSRP above the minimum threshold. In this direction, this thesis aims to answer the following questions:

- **RQ1.1:** How can advanced handover management schemes originally proposed for terrestrial users be adapted and optimized for cellular-connected UAVs?
- **RQ1.2:** How RL based model-free handover schemes should be designed to satisfy the uplink service level requirements for cellular-connected UAVs?

In conventional mobility management, trajectory optimization and handover decisions are often managed separately, with handover decisions driven by wireless objectives such as reducing handovers, minimizing delay, and avoiding interference, while trajectory decisions focus primarily on path optimization. However, prioritizing path planning without integrating wireless performance considerations can lead to adverse effects, including excessive handovers, increased transmission delays, and interference with terrestrial users.

To overcome these limitations, we propose a unified trajectory and handover optimization framework that combines trajectory planning, handover decision-making, and resource allocation within a network that serves both aerial and terrestrial users. This framework simultaneously considers UAV position, signal strength, network load, and interference potential, thereby balancing connectivity requirements with optimal path planning. In this direction, this thesis addresses the following key questions:

- **RQ2.1:** How to combine trajectory optimization with handover management to satisfy wireless objectives for cellular-connected UAVs?
- **RQ2.2:** How to coordinate trajectory and handover optimization for multiple cellular-connected UAVs without direct information exchange?

1.2.2 Mobility Management with Dynamic Cluster Reconfiguration for Cellular Connected UAVs

Modern communication systems must balance multiple, often conflicting objectives, such as ensuring high reliability while maintaining low transmit power. This challenge intensifies with dynamic reliability requirements that change based on system states, such as when a UAV enters a critical zone demanding highly reliable communication. Multi-connectivity, involving joint transmissions from multiple BSs, offers a potential solution to meet these demands. However, this approach can be resource-intensive, particularly in terms of total transmit power.

To address this challenge, we propose a DRL-based energy-efficient dynamic power allocation scheme that optimizes power distribution across a cluster of BSs while meeting variable QoS demands. In this direction, this thesis seeks to address the following research questions:

- **RQ3.1:** How to develop a dynamic power allocation scheme that adjusts in real-time to meet varying location-based reliability requirements?
- **RQ3.2:** To what extent the designed policy with offline training can adapt to the changing requirements?

In multi-connectivity scenarios, user mobility requires ongoing cluster reconfiguration, where the serving cluster dynamically adjusts by adding or dropping BSs to maintain optimal connectivity. Each cluster change demands joint resource allocation, which can lead to inefficient power usage and frequent reconfiguration events, especially in dense networks.

To address these challenges, we propose a joint cluster reconfiguration and energy-efficient power allocation strategy within a wireless interference network. Our approach aims to meet stringent reliability requirements, minimize power consumption, and reduce the frequency of cluster reconfigurations. Initially, we present a centralized DRL-based method to handle varying reliability demands while optimizing power usage and reconfiguration rates. To enhance scalability, we extend our solution with an H-MADRL approach, enabling more efficient and adaptable cluster management in large-scale environments. In addressing this challenge, this thesis aims to answer the following questions:

- **RQ4.1:** How to design a dynamic cluster reconfiguration algorithm to satisfy the downlink QoS requirements in multi-connectivity scenarios?
- **RQ4.2:** How to distribute the association and resource allocation decisions at different levels of the network for a scalable cluster reconfiguration?

1.2.3 Cellular Localizability of Unmanned Aerial Vehicles

Investigating the use of cellular networks to localize cellular-connected UAVs offers a promising research direction. Evaluating the network's capability for implementing range-based localization techniques requires that the target UAV receives an adequate number of usable signals. To facilitate this, a new metric is needed to quantify the probability of receiving usable signals from multiple ground BSs. Additionally, this metric must account for the dependency on the wireless channel characteristics specific to cellular-connected UAVs. In this direction, this thesis aims to answer the following research questions:

- **RQ5.1:** How can the localizability of UAVs in cellular networks and the factors influencing it be effectively modeled and analyzed?
- **RQ5.2:** How can UAV localizability be optimized across diverse wireless environment scenarios?

1.2.4 Research Methodology

In this section, we present our general research methodology. The research approach starts by defining a broad research area and scope. Then, a qualitative review of existing literature is done to understand the current knowledge and ongoing studies in the field. This review helps pinpoint a specific gap in the research that aligns with the initial broad questions. Throughout this process, regular checks are made to confirm that this gap is relevant and useful for practical applications. Following this, a clear system model is developed, based on realistic and practical assumptions, and is regularly reviewed along with the research gap and questions. Once the system model is in place, key performance indicators (KPIs) are established to assess the system. After that, a specific research problem is defined, with regular revisions to ensure clarity. A suitable evaluation tool is then chosen to model, analyze, and simulate the network, giving insights into system behavior and parameter effects. Based on these insights, opportunities for improvement are identified, and solutions are proposed to enhance network performance. Finally, these solutions are thoroughly tested to assess improvements and trade-offs, completing the research process.

1.3 Sustainability Aspects

This research makes significant contributions to four key United Nations Sustainable Development Goals (SDGs), namely SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action). By addressing these goals, the research emphasizes the economic, environmental, and social benefits of sustainable UAV connectivity solutions.

Economic and Environmental Sustainability

By introducing an energy-efficient, reinforcement learning-based power control framework, this thesis promotes the efficient use of radio resources for UAV integration, reducing both capital and operational expenses (CAPEX and OPEX) within UAV networks. By adapting power usage to specific reliability demands across different zones, the proposed solution minimizes energy consumption. These energy optimizations are vital for supporting SDG 7, as they align with the goal of increasing energy efficiency within the growing telecommunications industry. The decreased power consumption also contributes to SDG 13 by lowering greenhouse gas emissions, reducing the environmental footprint of UAV operations, and helping mitigate climate impacts.

Innovation and Resilient Infrastructure

This thesis contributes to SDG 9 by supporting innovation and improved infrastructure in UAV-based services, particularly in industries that rely on resilient, adaptable communications. The RL framework promotes the efficient use of existing telecommunications resources, allowing UAV systems to adapt dynamically to diverse operational conditions and meet varying QoS requirements. This adaptive approach supports infrastructure resilience by meeting demand without requiring extensive physical expansions, thus aligning with the goal of fostering innovation and sustainable industrial growth.

Social Sustainability and Urban Development

Reliable and adaptive UAV connectivity contributes to safer, more resilient urban environments, aligning with SDG 11. The proposed UAV mobility management framework enables services such as traffic monitoring, environmental surveillance, and disaster response, all of which are critical to sustainable urban living. By ensuring that UAV services can operate effectively and sustainably, cities can support smart urban infrastructure that enhances quality of life, promotes public safety, and provides equitable access to essential services. These improvements contribute to social sustainability by fostering healthier and more connected communities that can grow sustainably without compromising on resource use.

1.4 Thesis Outline

The organization of this thesis is as follows: Chapter 2 reviews the existing research and provides a discussion on the research gap in mobility management and trajectory optimization for cellular-connected UAVs. Chapter 3 reviews the literature and studies the research gap in mobility management for multi-connectivity. Chapter 4 reviews the literature and provides the research gap in the cellular localization of UAVs. Chapter 5 provides a summary of the included papers, and Chapter 6 offers concluding remarks and outlines potential future research directions. The dissertation concludes with appended papers, providing further depth and context to the studies presented.

Chapter 2

Mobility Management and Trajectory Optimization for Cellular-Connected UAVs

Mobility management for cellular-connected UAVs presents unique challenges in wireless networks due to their distinct characteristics, including 3D movement patterns, A2G channel characteristics, inconsistent cell coverage in the sky, and high mobility speeds. These challenges result in frequent handovers, increased interference, and reduced service reliability, making it essential to develop advanced strategies for seamless connectivity. To address these challenges, researchers have explored a range of approaches, from traditional threshold-based methods to advanced machine learning (ML)-driven techniques, focusing on optimizing handover decisions and enhancing network performance for UAVs.

2.1 Handover Management for Cellular-Connected UAVs

Significant advancements have been achieved in aerial communications, encompassing both low-altitude UAVs and high-altitude platforms such as airplanes [31–40]. Building on these developments, recent research has prioritized the integration of UAVs into cellular networks. Cellular-connected UAVs enable high-speed, low-latency, and reliable communication, facilitating wide-area connectivity and enhancing beyond visual LoS operations [41–45]. However, UAVs face unique challenges compared to ground users due to differences in propagation conditions and network design.

Key challenges arise from the dominance of LoS links for UAVs, which, while offering favorable propagation conditions, also result in significant inter-cell interference. For example, UAVs at higher altitudes often experience reduced SINR due to strong LoS-interfering signals from neighboring BSs. Measurements show that UAVs at 150 meters altitude can suffer a SINR degradation of up to 7 dB compared to ground users [43]. This interference is compounded by the down-tilt of BS antennas, which primarily serve UAVs through their weaker side-lobes, further reducing coverage and connectivity [44]. Simulation results confirm that high-altitude UAVs are more vulnerable to interference, limiting their performance compared to ground users [42, 43].

The authors in [45] investigate the impact of altitude on UAV handover frequency, highlighting the challenges posed by aerial mobility in LTE-A networks. The study presents experimental measurements of cell selection and handover in a suburban environment, revealing a significant increase in handover frequency as the flight altitude rises. For instance, a UAV flying at a typical altitude of 150 meters undergoes approximately five cell changes per minute, compared to only one change for ground users moving at the same speed. This disparity is attributed to differences in cell selection criteria between ground and aerial devices, driven by the broader LoS connectivity experienced by UAVs. The findings underscore the need for revised handover techniques tailored to UAV operations and emphasize the importance of considering aerial devices in the planning and optimization of 5G and 6G radio access networks.

Although these studies demonstrate the feasibility of connecting UAVs to cellular networks, they do not propose new solutions to address the challenges. UAVs at higher altitudes struggle with LoS interference, reduced antenna gains, frequent handovers, and increased handover failures, highlighting the need for tailored approaches to improve their connectivity and performance.

Recent advancements in handover management for cellular-connected UAVs can be broadly classified into three categories: (1) threshold-based methods, (2) MRO-driven approaches, and (3) learning-based solutions tailored to address the unique challenges and requirements of UAVs. For a comprehensive understanding, we summarize the main contributions of recent works in Table 2.1, which compares handover methodologies, optimization parameters, and the primary performance indicators addressed in these studies. This comparative analysis provides insights into the evolution of mobility management strategies for cellular-connected UAVs, identifying gaps and opportunities for further research.

Traditional Threshold-Based Approaches

Conventional mobility management methods for UAVs primarily rely on threshold-based techniques, where handover decisions are triggered by fixed criteria such as RSRP or SINR, alongside predefined values for HOM and TTT. Numerous studies [46–51] have explored various threshold-based schemes to improve UAV connectivity and mitigate the challenges associated with high mobility in aerial environments.

For instance, [46] proposes a route-aware handover mechanism that leverages pre-configured UAV flight paths to make handover decisions based on SINR. This approach reduces unnecessary handovers, minimizes handover failures, and eliminates ping-pong effects in some scenarios, achieving a reduction in handover rates as compared to conventional methods. Similarly, [47] employs a probabilistic, distance-

Table 2.1: Mobility Management Schemes Proposed for Cellular-connected UAVs.

	Contribution	**Handover (HO) methodology**	**HO decision parameters**	**Main KPIs**
Threshold based UAV mobility management	[46]-Route-aware handover for UAVs based on measurements	Threshold based	SINR	HO rate, Ping-Pong rate
	[47]-3D random waypoint mobility model based handover decision for the UAVs served by coordinated multi-point (CoMP) transmissions	Probabilistic distance based	Distance	Coverage probability, HO rate
	[48]-Study the effect of 3D beamforming and antenna topology on the UAV HO management	A3 event with fixed HOM and TTT	RSRP	HO rate
	[49]-Performance analysis on the current cellular network support for the mobility of the cellular-connected UAVs	A3 event with fixed HOM and TTT	RSRP	RLF, number of HOs
	[50]-Down-tilt angle tuning using RL algorithm (or measurements) for improving the data rate and reducing the number of HO	A3 events with fixed HOM and TTT	RSRP	Average number of HOs, user data rate
	[51]-RL-based speed optimization for connectivity, handover, and energy balance	Strongest BS association	RSRP	HO rate, discontinuity
MRO	[52]-DQN-based HO parameter optimization based on the quality of experience (QoE) for the terrestrial users	A3 event with MRO	QoE and RSRP	QoE, number of HOs
	[53]-Q-Learning based HO parameter optimization for the flying UAV BSs to enhance the sum capacity of served users	A3 event with MRO	Sum capacity and RSRP	User data rate, number of HOs
	[15]-HO parameter optimization based on the load-balancing in the serving and neighboring cells	A3 event with MRO	Cell load and RSRP	cell load
Learning based UAV mobility management	[54]-DQN-based mobility management scheme that maximizes the overall data throughput while keeping the rate of handovers manageable	DQN based policy	SINR	Coverage, Probability of association
	[55]-RL-based HO management to reduce the number of HOs while maintaining reliable connectivity	Q-table based policy	RSRP	RSRP, number of HOs
	[56]-RL-based HO management for selecting the strongest access beam to maximize the throughput in a 5G cellular network	Q-table based policy	RSRP	RSRP
	[57]-RL-based HO management scheme for UAVs to jointly optimize communications delay, interference, and number of handovers over cellular networks	DQN based policy	Interference, delay	Number of HO, delay, interference
	[58]-DQN-based HO management to achieve a tradeoff between signal strength and handover frequency	DQN based policy	RSRP	RSSI, number of HOs

based handover decision framework using a 3D random waypoint mobility model. The study highlights how coordinated multi-point transmission can improve UAV coverage probability, addressing the impact of UAV altitude and vertical movements on handover rates.

Further exploration of handover dynamics in 3D environments is presented in [48], which examines the influence of 3D beamforming and mmWave communication on UAV mobility. Through a realistic case study of a 5G deployment, the study emphasizes the challenges of frequent handovers and the importance of optimizing antenna configurations to support high-speed UAVs. On a broader scale, [49] highlights the mobility challenges faced by cellular-connected UAVs, such as increased radio link failures and frequent handovers at higher altitudes. The authors suggest potential enhancements, including adaptive mobility support, to improve performance in aerial environments.

To address these challenges, advanced techniques have been proposed. [50] introduces a RL-based downtilt optimization mechanism to dynamically adjust BS antenna angles. This method improves signal quality for UAVs while maintaining throughput for ground users, resulting in reduced handovers and enhanced connectivity. Additionally, [51] develops a learning-based multi-armed bandit (MAB) algorithm that optimizes UAV speed to balance connectivity time, handover rates, and energy consumption. The approach demonstrates significant improvements in reducing the handover rate compared to non-adaptive strategies.

While these threshold-based methods provide valuable improvements, they often rely on fixed parameters such as HOM and TTT, limiting their adaptability to dynamic network conditions. This underscores the need for more flexible and scalable mobility management solutions to support the growing demands of UAV connectivity in cellular networks.

Mobility Robustness Optimization (MRO)

MRO has traditionally focused on terrestrial users, with optimization of handover parameters such as HOM and TTT aimed at enhancing network metrics [13, 14, 59–61]. Recent advancements in this field have refined handover parameter optimization to improve KPIs such as Quality of Experience (QoE), sum capacity, and cell load [15, 52, 53]. These efforts align closely with our objective of developing a model-based approach to enhance service availability. These methods often rely on heuristic tuning or analytical models to manage the trade-offs among key handover-related performance indicators.

For example, [52] introduces a QoE-aware MRO algorithm that dynamically tunes handover parameters on a per-adjacency basis to enhance both handover success rates and user QoE. Unlike traditional methods focused solely on reducing handover failures, this approach considers diverse mobile services and user expectations, demonstrating significant improvements in user QoE while increasing the overall percentage of successful handovers in a multi-service LTE scenario.

Expanding MRO to aerial contexts, [53] addresses the challenges of handover for flying BSs (FlyBSs) by employing Q-learning to optimize the HOM of static BSs. The algorithm balances the trade-off between user capacity and handover costs, achieving an increase in the sum capacity of users served by FlyBSs and a reduction in handover occurrences compared to state-of-the-art methods. This highlights the potential of RL techniques to enhance mobility management for aerial nodes.

In another approach, [15] focuses on load-aware MRO, incorporating cell load conditions into handover decisions. By adjusting handover parameters, the proposed load-balancing algorithm redistributes traffic from overloaded cells to neighboring cells with available capacity, improving user satisfaction and network efficiency. Simulations show that this method can dynamically adapt to changing network conditions, ensuring an optimal balance between cell loads without degrading overall network performance.

While these approaches demonstrate the potential of MRO in improving mobility management, their focus has largely been on terrestrial users or UAVs as BSs rather than as mobile aerial users, leaving significant room for the development of MRO schemes specifically tailored to the unique mobility challenges of UAVs.

Learning-Based Approaches

The advent of ML, particularly RL, has introduced transformative paradigms for mobility management in wireless networks. By leveraging data-driven techniques, RL enables dynamic optimization of handover decisions, adapting to network conditions and user behavior in real-time. Recent research highlights the potential of RL-based schemes in enhancing mobility management for UAVs [54–58, 62–64].

In [54], a DQN-based handover policy is proposed to optimize handover rate and user throughput, demonstrating significant improvements in network efficiency. The learned policies enable UAVs to intelligently associate with BSs by leveraging information about signal strength, BSs location, and building topology. This study also evaluates the impact of UAV height, building density, and handover-induced throughput loss, providing a comprehensive analysis of its effectiveness in urban environments.

Similarly, [55] employs Q-learning to balance the trade-off between minimizing handover frequency and maximizing signal quality. The framework is tailored to the dynamic nature of UAVs and achieves a significant reduction in handover frequency compared to traditional schemes relying on the strongest cell connection while maintaining consistent connectivity and mobility support. However, this work assumes the UAV acts as a BS serving terrestrial users, limiting its direct applicability to mobility scenarios where UAVs are clients.

The authors in [56] utilize Q-table-based policies to select the strongest access beam based on RSRP. This work incorporates centralized training with decentralized execution, optimizing handover decisions by considering channel conditions, causal association information, and both transmission and overhead energy costs.

The proposed algorithm achieves significant energy savings and reduces overhead in dense network scenarios.

Addressing uplink interference caused by UAVs, [57] develops an RL-based handover scheme that jointly optimizes communication delay, interference levels, and the number of handovers. Analytical models for communication delay and interference are derived, and an optimization problem for handover and radio resource management (H-RRM) is formulated. Transforming this problem into a machine learning framework, a DRL solution is proposed. Simulation results reveal the influence of UAV speed, altitude, and interference tolerance on optimal H-RRM policies. Heatmaps of handover decisions underscore the need to revise legacy handover schemes and redefine cell boundaries for UAVs in the sky.

The authors in [62] investigate handover management for small-scale systems with dynamic mobility, focusing on a single UAV following predetermined paths. They propose a DQN-based approach to optimize BS associations and resource block allocations, aiming to minimize the weighted sum of transmission delay, interference, and handover occurrences for the UAV. Simulation results demonstrate that their framework reduces handovers while maintaining robust connectivity, with a slight compromise in signal strength compared to always connecting to the strongest BS.

In a proactive approach, [58] employs DQN to balance signal strength and handover frequency, ensuring stable and efficient connectivity. Using a proximal policy optimization algorithm, with UAV state inputs and a reward function based on received signal strength indicator (RSSI), the framework dynamically optimizes handover decisions. Evaluated in a 3D-emulated UAV mobility environment, the proposed method demonstrates a reduction in unnecessary handovers compared to greedy and Q-learning-based methods.

Hybrid ML approaches have also shown promise. In [63, 64], the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is combined with Q-learning to enhance energy efficiency while reducing unnecessary handovers in fixed-trajectory scenarios. Similarly, [65] introduces a DRL framework for energy-efficient handover decision-making in heterogeneous networks. This framework incorporates causal association information and centralized training with decentralized execution to balance energy consumption and overhead costs. Results demonstrate significant improvements over contemporary mechanisms, especially in scenarios with high handover energy overheads.

Research Gap: The studies discussed above introduce advanced handover management schemes tailored to the unique characteristics of UAVs. However, none of these approaches, whether model-based or learning-based, consider service availability as a critical metric. With UAVs increasingly relying on uplink data-driven applications, integrating service availability into handover decisions is becoming essential. While current methods prioritize metrics such as signal strength and handover rate, these metrics alone do not adequately account for the impact of buffer conditions on overall QoS. This omission creates a significant gap between theoretical advancements and practical requirements, particularly in scenarios demanding high uplink service reliability.

This thesis, through **Paper I**, addresses this gap by incorporating service availability as a core consideration in handover decision-making. By integrating UAV buffer queue states into the process, we aim to ensure not only robust connectivity but also reliable and efficient uplink data delivery. We propose handover management solutions within both model-based and learning-based frameworks for cellular-connected UAVs. However, the proposed schemes have been evaluated using UAVs with predefined trajectories with a limited number of BSs. Future work can focus on testing these schemes with realistic UAV flight paths to enhance their applicability.

2.2 Communication-Aware Trajectory Optimization for Cellular-Connected UAVs

To enable the seamless integration of UAVs into cellular networks, effective collaborative mechanisms for managing interference and handovers are essential. Research in this area has predominantly focused on two key aspects: optimization of handovers and radio resource allocation and communication-aware trajectory planning. However, most existing studies treat these aspects as separate optimization challenges. Having discussed the literature on handover optimization techniques in Section 2.1, we now shift our focus to presenting relevant research on trajectory optimization.

Communication-aware trajectory planning aims to dynamically adjust UAV flight paths to ensure mission completion while maintaining the required communication quality. This involves designing UAV trajectories based on factors such as shadowing effects and coverage overlaps among BSs, thereby avoiding connectivity gaps, reducing unnecessary handovers, and mitigating interference. This approach has garnered significant attention [66–71] due to its ability to leverage the inherent maneuverability of UAVs.

For example, [66] addresses a trajectory optimization problem for a cellular-connected UAV tasked with flying from an initial to a final location while maintaining reliable communication with ground BSs. The objective is to minimize the mission completion time while ensuring a minimum signal-to-noise ratio (SNR) throughout the UAV's journey. The study tackles the non-convex optimization problem by leveraging graph theory and convex optimization techniques to develop efficient algorithms capable of producing high-quality approximate solutions. These methods provide a flexible tradeoff between computational complexity and performance, with solutions that closely approach the optimal trajectory. Numerical results demonstrate the proposed methods' effectiveness, outperforming benchmark schemes in both performance and efficiency.

The authors in [67] optimize the trajectory of a UAV to maximize its transmission rate while minimizing co-channel interference to terrestrial users. They investigate two scenarios: a quasi-stationary UAV, where its 3D placement and power control are optimized to maximize the rate while meeting interference constraints, and a mobile UAV, where its trajectory and power control are jointly optimized. The study ensures the interference at primary receivers stays below a predefined threshold, termed interference temperature. Numerical results show that in the quasi-stationary case, the UAV achieves optimal performance at minimum altitude, while in the mobile case, it adjusts its altitude and horizontal trajectory dynamically to enhance communication performance.

In [68], the authors enhance the throughput of terrestrial users by optimizing the trajectory of a UAV that functions as a relay to extend the coverage of BSs. Their approach leverages fine-grained LoS information to determine the optimal UAV position, rather than relying solely on statistical air-to-ground channel models. The proposed algorithm efficiently identifies the best UAV position to maximize end-to-end throughput, even in complex terrain. Numerical results show that in dense urban environments, the UAV-aided system nearly doubles the capacity compared to direct BS-to-user links.

In [69], the authors investigate the trade-off between operational time and throughput for a UAV acting as an aerial relay. They propose the use of landing spots to allow the UAV to rest and recharge, extending its operational lifetime while moderately impacting throughput. A dynamic programming approach is developed to optimize the UAV's trajectory with landing spot integration.

Research efforts have expanded to the coordination of multiple UAVs, as explored in [70,71]. In [70], DQN are employed to optimize the trajectories of multiple UAVs, enhancing the SINR while mitigating mutual interference. Meanwhile, [71] utilizes DRL with echo state networks (ESN) to jointly optimize UAV trajectories, BS associations, and power allocations. This approach minimizes transmission delay, generated interference, and operational time for UAVs. However, [71] highlights the practical challenge of requiring constant action broadcasting among UAVs due to their limited communication capabilities and privacy concerns, which complicates real-world implementation.

Handover Management for Interference Management

Handover management is another approach for addressing the intense interference caused by UAVs to terrestrial UEs [72–75]. This approach optimizes system-level resource allocation for multiple UAVs by coordinating their BS associations and radio resource block (RRB) allocations, aiming to facilitate smooth handovers and reduce generated interference.

In [72], field measurements reveal that UAVs generate up to 7.7 dB more uplink interference than terrestrial UEs within a 15 km radius due to their elevated positions and wider LoS coverage. To address this, two mitigation strategies are evaluated: controlling the UAV's cruising height and employing directional transmissions. The latter proves more effective by reducing interference without compromising uplink power.

To handle both uplink and downlink interference, [73] introduces centralized and decentralized inter-cell interference coordination (ICIC) algorithms. These algorithms jointly optimize BS associations and power allocation across multiple RRBs. The centralized method focuses on a global optimization to maximize the uplink sum-rate, while the decentralized approach distributes the decision-making process among BSs to improve scalability. Simulation results show that these techniques can mitigate interference, preserving terrestrial UE performance and maintaining UAV connectivity even in worst-case scenarios.

In [74], the interference challenges in both uplink and downlink scenarios are tackled by leveraging UAV sensing capabilities and power control strategies. By exploiting the LoS connectivity of UAVs and inactive BSs, the study proposes methods to actively mitigate interference and enhance spectral efficiency. These solutions extend coverage and address the limitations of conventional terrestrial interference mitigation techniques.

Finally, [75] proposes a cooperative interference cancellation (CIC) approach that utilizes the LoS connectivity between UAVs and distant idle BSs. By coordinating with these idle BSs, UAVs can cancel out interference at the source, effectively improving spectrum efficiency and reducing both aerial-to-ground and ground-to-ground interference. This technique is particularly effective in dense network scenarios where UAV interference impacts a larger number of BSs and terrestrial users.

Research Gap: The existing body of research predominantly treats UAV trajectory design and handover management as independent optimization challenges, overlooking their critical inter-dependencies. This fragmented approach limits the potential for achieving optimal outcomes, as it fails to exploit the synergies between these areas. Furthermore, while multi-UAV coordination has been studied, it often simplifies the problem by relying on assumptions such as global state availability or continuous action broadcasting, both of which are impractical due to communication bottlenecks and scalability constraints.

This thesis, through **Paper III**, bridges these gaps by addressing trajectory design and handover management in an integrated manner, specifically within the context of multiple UAVs operating cooperatively without sharing direct information. The work focuses on minimizing KPI: delay, interference, and handovers, within a multi-agent cooperative game framework. This approach accounts for the complex interactions among UAVs, tackling challenges such as the scalability of coordination, the anticipation of other UAVs' policies, and the mitigation of co-channel interference and resource conflicts. By addressing these challenges, this research aims to advance the state-of-the-art in UAV mobility management and provide practical solutions for scalable and efficient UAV integration.

Chapter 3

Mobility Management for Multi-connectivity

The mobility management strategies discussed earlier, including threshold-based approaches [46–51], mobility robustness optimization (MRO)-based techniques [15, 52, 53], and learning-based solutions [54–58, 62–64], primarily focus on addressing challenges for aerial users with single connectivity. However, mobility management for aerial users leveraging multi-connectivity in mobile networks represents a relatively new and underexplored research area. This thesis investigates mobility management strategies designed for aerial users served through multi-connectivity and presents relevant contributions in this context.

3.1 Mobility Management with Dynamic Cluster Reconfiguration for Cellular Connected UAVs

In multi-connectivity scenarios, users are typically served by clusters of distributed multiple candidate BSs. Efficiently managing these clusters in dynamic mobility conditions presents a significant challenge. Previous studies have explored multi-connectivity and mobility management in such scenarios but are primarily focused on terrestrial users with non-stringent reliability requirements [76–80]. These studies often employ cell-free massive MIMO (CF-mMIMO) networks for multi-connectivity, where scalability is increasingly recognized as a critical requirement [81].

For instance, the authors in [78] examine the coupling between CF-mMIMO networks operating at millimeter-wave (mmWave) frequencies and user mobility. Their work introduces a mmWave channel model that accounts for user mobility and channel aging effects. Three beamforming techniques and a dynamic user association rule are proposed for updating BS clusters in a mobile environment. Numerical results demonstrate the effectiveness of these methods in improving network performance for the proposed mmWave scenarios.

Similarly, the study in [79] analyzes user mobility in CF-mMIMO networks under imperfect channel state information (CSI) and pilot training. Distributed algorithms for joint pilot assignment and cluster formation are proposed to reduce BS and pilot changes while maintaining low computational complexity. Simulation results highlight the efficiency of these methods in optimizing spectral efficiency and reducing pilot reassignments, particularly in ultra-dense and highly loaded network scenarios.

The scalability of CF-mMIMO networks in mobile environments is further addressed in [80]. This study derives cluster and BS handover rates for scalable CF-mMIMO networks and provides closed-form approximations for analyzing mobility-aware throughput. Results reveal trade-offs in spectral efficiency (SE) across varying mobility levels. While scalable CF-mMIMO maintains advantages for high-percentile users in dense networks with low control delays, the study also identifies degraded median SE as a limitation under moderate to high mobility scenarios.

The authors in [82] address the challenges of managing BS clusters in mobile environments by introducing a realistic model for the temporal evolution of channels. They propose two clustering and handover strategies: a fixed clustering approach that updates clusters when a threshold is exceeded and an opportunistic strategy that incrementally adds BSs as users move. Furthermore, their integration of these strategies with the open-radio access network (O-RAN) architecture demonstrates practical feasibility, leveraging open interfaces for network-wide control. However, the fixed clustering method significantly increases signaling overhead and requires frequent cluster reconfiguration whenever a user is added or removed.

Learning-based approaches have shown significant potential in multi-connectivity scenarios. For example, the authors in [83] propose a hybrid DRL model that combines deep deterministic policy gradient (DDPG) and deep double Q-network (DDQN) to design beamforming vectors for dynamic BS clustering in a cell-free network serving terrestrial users. The study demonstrates considerable improvements in rate performance compared to static clustering and exhaustive search methods. However, this method focuses on terrestrial users and does not consider varying or stringent reliability constraints.

Matching theory has also been utilized to optimize clustering and resource allocation in multi-connectivity scenarios. The authors in [84] introduce a matching theory-based algorithm combined with a novel scheduler to guarantee stringent reliability requirements in multi-cellular systems. While this approach achieves significant reliability and throughput improvements, it relies on static snapshot models and does not address the dynamic nature of mobility. Similarly, the study in [85] employs many-to-many swap-matching theory to address dynamic resource cooperation in fully-decoupled radio access networks (FD-RAN). While their framework improves spectral efficiency in downlink scenarios, it also operates under static clustering assumptions, limiting its applicability in highly dynamic mobility environments.

Hierarchical deep reinforcement learning (HDRL) has emerged as an effective approach for addressing complex optimization problems by decomposing them into smaller, hierarchically structured subproblems [86, 87]. In [86], HDRL is applied to multi-drone trajectory planning and resource allocation. The proposed framework decomposes the problem into two hierarchical subproblems: (1) global trajectory planning for high-mobility users using a multi-agent DRL algorithm and (2) local resource allocation using a DDPG-based approach. This decomposition enables efficient optimization compared to non-learning-based methods.

Similarly, [87] leverages HDRL to solve the joint problem of radio access technology (RAT) assignment and power allocation in heterogeneous networks. Their proposed DeepRAT model decomposes the problem into two stages: a single-agent DQN algorithm for RAT-ED assignment and a multi-agent DDPG algorithm for power allocation. This hierarchical structure facilitates adaptability to abrupt changes, such as device mobility, and demonstrates superior network utility compared to heuristic methods.

More recently, the study in [88] extends HDRL to address handover management and power allocation for terrestrial users in FD-RAN. Their framework decomposes the problem into two layers: a double deep Q-network (DDQN) for optimizing multi-connectivity BS cooperation sets and a transformer-assisted soft actor-critic (TSAC) algorithm for fine-grained link power control. The method minimizes long-term discrepancies between user rate demands and actual serving rates, ensuring seamless connectivity and improved service quality. However, it does not consider stringent reliability requirements, particularly in the finite block-length regime, which are critical for emerging applications such as UAV communications and ultra-reliable low-latency services.

Table 3.1 highlights the existing studies on mobility management solutions for multi-connectivity with focus on various aspects, including user mobility in CF-mMIMO networks and dynamic BS clustering. These studies highlight both the strengths and limitations of current approaches, particularly in addressing challenges related to aerial users and multi-connectivity scenarios.

Research Gap: While existing studies have made progresss in addressing mobility challenges in CF-mMIMO networks and dynamic BS clustering, they predominantly focus on terrestrial users or rely on static clustering assumptions, limiting their applicability in highly dynamic scenarios. Moreover, these approaches often fall short of addressing the spatio-temporally varying reliability requirements in a wireless interference network. To the best of our knowledge, there is limited research focusing on energy- efficient mobility management solutions that meet stringent reliability requirements in the finite block-length regime for aerial users with multi-connectivity configuration in mobile networks.

This thesis, through **Papers IV, V, and VI**, addresses some of these gaps by proposing novel mobility management strategies for aerial users served via multi-connectivity. Specifically, Paper IV introduces a dynamic power control scheme to satisfy spatio-temporally varying reliability requirements in a non-interference network. Paper V extends this by developing a dynamic cluster reconfiguration and power allocation algorithm tailored for interference networks with similar reliability demands. Paper VI further advances the field by addressing stringent reliability requirements in the finite block-length regime through joint cluster reconfiguration and power allocation. These strategies collectively tackle the challenges of ensuring seamless connectivity, optimizing resource allocation, and delivering reliable service in dynamic and complex mobility scenarios.

Table 3.1: Summary of Key Studies on Dynamic Cluster Reconfiguration

Ref.	Key Focus	Strengths	Limitations
[78]	Coupling between CF-mMIMO at mmWave frequencies and user mobility	Improves network performance in mmWave mobility scenarios	Focuses on terrestrial users; does not address UAV-specific challenges
[79]	User mobility in CF-mMIMO networks under imperfect CSI and pilot training	Reduces BS and pilot reassignments; computationally efficient	Primarily for ultra-dense terrestrial networks
[80]	Scalability of CF-mMIMO networks in dynamic mobility scenarios	Closed-form approximations for mobility-aware throughput	Degraded median SE in moderate to high mobility scenarios
[82]	Realistic BS clustering and handover strategies for dynamic environments	Practical integration with O-RAN architecture	Increased signaling overhead; frequent reconfiguration
[83]	Hybrid DRL for dynamic BS clustering in cell-free networks	Significant rate performance improvement via DRL optimization	Does not address aerial user challenges (mobility, reliability)
[84]	Matching theory for reliability in multi-cellular systems	Enhanced reliability and throughput via novel scheduler	Static snapshot model; not dynamic
[85]	Many-to-many swap-matching for dynamic resource cooperation	Improves spectral efficiency in downlink scenarios	Limited applicability in highly dynamic mobility scenarios
[86]	HDRL for multi-drone trajectory planning and resource allocation	Efficient optimization through hierarchical problem decomposition	Focuses on multi-drone systems; not UAV-specific challenges
[87]	HDRL for RAT assignment and power allocation in heterogeneous networks	Adaptability to dynamic environments; superior network utility	Not designed for stringent reliability in UAV communications
[88]	HDRL for handover management and power allocation in FD-RAN	Minimizes long-term rate discrepancies; ensures seamless connectivity	Does not address finite blocklength reliability requirements

Chapter 4

Cellular Localizability of Unmanned Aerial Vehicles

Reliable localization of UAVs without GPS remains a critical challenge, especially in environments where GPS signals are weak, obstructed, or deliberately jammed, such as urban canyons, dense forests, or indoor spaces. This limitation has driven extensive research into alternative localization methods. Visual-based localization techniques, such as visual odometry [89,90] and simultaneous localization and mapping [91–93], have demonstrated notable success by utilizing camera-based inputs to map environments while estimating UAV position. These methods are often enhanced by integrating data from stereo cameras, inertial measurement units (IMUs), and altimeters to address challenges such as scale ambiguity and estimation errors [94]. Despite their effectiveness, these approaches require sophisticated sensors and computationally intensive algorithms, which can be impractical for small UAV platforms with limited power and processing capacity [94].

Traditional methods like the extended Kalman filter (EKF) also play a significant role in UAV localization. EKF-based approaches fuse data from various sensors, including IMUs and inter-UAV distance measurements, to provide robust positioning in GPS-denied scenarios [95, 96]. For example, EKF has been used successfully with two-way time-of-flight ultra-wideband transceivers to achieve accurate localization in indoor environments [96]. However, these methods are highly dependent on precise sensor calibration and availability, which can limit scalability [95, 96].

Recent innovations include ultraviolet light-emitting diodes for navigation [97], cooperative localization among UAVs using anchor nodes [98], and radar-based systems [99]. Additionally, radio frequency (RF) signal tracking using specialized ground-based sensors has been proposed [100]. However, these methods often require additional hardware and specialized setups, making them a costly solution for large-scale UAV deployments.

Radio-based localization presents an attractive alternative by leveraging the analysis of RF signal characteristics. Among these, RF fingerprinting has emerged as a promising technique, utilizing unique signal features from imperfections in RF components to identify and localize devices [101]. While RF fingerprinting can function without specialized sensors, its accuracy is often compromised in multipath-rich environments, such as indoor settings with high fading, where signal interference and hardware variability affect reliability [102]. More recent advances include packet-based localization methods, which estimate UAV positions using data transmitted within communication networks. Techniques such as AOA, TOA, and TDOA enable precise positioning without requiring additional infrastructure [103, 104].

In the field of range-based localization, techniques such as TOA and TDOA present effective alternatives for UAV positioning [105]. These methods can be combined with RF and vision-based systems to form hybrid approaches, enhancing localization reliability in GPS-denied environments. Such hybrid systems are crucial for UAV applications like search and rescue operations, infrastructure inspections, and environmental monitoring.

Range-based localization typically involves two main steps: first, acquiring a sufficient number of decodable signals at the target, and second, employing signal processing techniques to accurately determine the target's location. The existing body of research in this area largely concentrates on refining these signal processing methodologies to achieve precise 3D localization, often under the assumption of ideal channel conditions. For example, studies such as [106–108] propose advanced 3D location estimators based on metrics like RSS and AOA. These works have significantly advanced target localization capabilities within wireless sensor networks (WSNs).

The authors in [106] address both noncooperative and cooperative localization problems in 3D WSNs under scenarios of known and unknown sensor transmit power. By employing a hybrid system that fuses distance and angle measurements derived from RSS and AOA information, they propose a novel nonconvex estimator based on the least squares criterion. Their approach tightly approximates the maximum likelihood estimator for scenarios with small noise. For noncooperative localization, they reformulate the problem into a generalized trust region subproblem framework, while for cooperative localization, they apply semidefinite programming relaxation techniques to transform the problem into a convex form. The simulation results highlight the robustness of these estimators against uncertainties in transmit power and their exceptional performance compared to existing methods.

Similarly, [107] explores RSS-based techniques for both 3D receiver navigation and source localization, focusing on practical scenarios where sensor measurements are biased due to design imperfections or environmental factors. Unlike traditional methods that assume bias-free measurements, this work introduces united-RSS (URSS) and differential-RSS (DRSS) approaches to address biases. URSS jointly estimates the location and sensor bias, while DRSS eliminates the effect of bias to estimate location. These methods leverage semidefinite programming and constrained least squares to avoid the nonconvexity challenges of maximum likelihood estimation. Numerical evaluations demonstrate the necessity of accounting for sensor bias in RSS-based localization and the superior accuracy of the proposed methods.

In [108], the authors also tackle 3D localization in noncooperative and cooperative WSNs, integrating RSS and AOA measurements. They develop a nonconvex least squares estimator that approximates the maximum-likelihood estimator under small noise conditions. For non-cooperative scenarios, the problem is reformulated using a generalized trust region subproblem framework, whereas cooperative localization benefits from a semidefinite programming relaxation for convex reformulation. The study emphasizes that the proposed estimators are robust to uncertainties in transmit power and outperform existing approaches across all considered settings.

Despite these advancements, most studies assume the availability of sufficient decodable localization signals under ideal conditions, such as perfect LoS communication and minimal interference. However, these assumptions are often impractical in real-world scenarios. In actual wireless networks, localization accuracy is significantly influenced by challenges such as multipath effects, non-LoS propagation, and interference, which can degrade performance and reliability. Therefore, to achieve precise localization, it is crucial to determine the capacity of the wireless network to provide the required number of decodable signals to the target. This metric is referred to as the localizability of the network. When the wireless network used for localization is a cellular network, the focus shifts specifically to cellular-localizability, which quantifies the network's ability to support accurate positioning within the cellular infrastructure.

Cellular networks have been extensively investigated for localization, with studies proposing various frameworks to enhance precision [109]. For instance, [110] establishes a novel framework for improving UAV localization by jointly utilizing multiple RSS measurements from multiple BSs and trajectory points. The authors propose a joint maximum likelihood (ML) method that integrates trajectory information and multi-BS measurements to significantly enhance location accuracy. To address the complexity of the joint ML method, two low-complexity localization approaches are introduced: the LCSL-BST method, which calculates the UAV position by fixing a BS and exploiting trajectory information, and the LCSL-TBS method, which reverses the order. Simulation results demonstrate that the joint ML method achieves the CRLB, offering substantial improvements over conventional ML techniques that lack trajectory knowledge. These methods highlight the potential of leveraging trajectory information to enhance cellular localization performance.

The concept of cellular localizability, particularly for UAVs, has seen limited exploration in the literature. Authors in [111] analyze terrestrial user devices localization performance using stochastic geometry. They model BS locations as a Poisson Point Process (PPP), enabling analytical derivations of key performance metrics across varying BS geometries. The study focuses on the probability of detecting a minimum number of BSs, a crucial metric for achieving satisfactory localization performance, regardless of the specific localization technique (e.g., TOA, TDOA, AOA). To mitigate excessive interference, the framework incorporates BS coordination and frequency reuse, analytically quantifying the performance gains. While this work provides valuable insights into terrestrial localization, its assumptions regarding random BS distributions and the absence of UAV-specific challenges limit its direct applicability to aerial scenarios.

Similarly, [112] examines cellular-network-based positioning for narrow-band Internet of Things (NB-IoT) devices, emphasizing their reliance on terrestrial cellular networks for localization in GPS-denied environments. The authors develop a probabilistic model to analyze positioning performance by considering the distance distribution between the target device and surrounding evolved Node Bs (eNBs). This model accounts for network randomness, propagation effects, and interference, offering insights into how system parameters and participating eNBs impact positioning accuracy. While the study provides a robust framework for ground-based localization, it does not address the complexities of 3D localization required for UAVs, such as accounting for altitude, A2G channel dynamics, and the varying densities of eNBs in different aerial environments.

Addressing the challenges of UAV localization in realistic 3D communication environments requires the development of advanced frameworks that account for the unique dynamics of UAV mobility and the stochastic nature of cellular networks. While works like [113] have begun exploring UAV localizability by incorporating A2G channel characteristics and network dynamics, the study lacks detailed statistical characterizations of critical parameters such as path loss, received power, and SINR.

Research Gap: Existing studies have made significant strides in enhancing localization techniques; however, many are tailored to terrestrial scenarios or rely on deterministic assumptions that do not fully capture the complexities faced by UAVs. For instance, UAV-specific factors such as altitude, A2G channel variability, interference from neighboring BSs, and LoS links with multiple BSs are often overlooked.

This thesis, though **Paper VII**, addresses critical gaps in UAV localization by introducing a comprehensive analytical framework for cellular-localizability, rigorously modeling the stochastic behavior of cellular networks, and capturing key parameters such as path loss, received signal strength, interference, and SINR. The framework serves as a practical tool for network designers, offering insights into how factors like environment, BS density, and UAV altitude impact localizability. This thesis also identifies strategies to enhance localizability, such as processing gain, inter-BS coordination, and optimizing UAV operations. While the analysis simplifies interference control and uses a snapshot approach, it effectively captures the influence of interference and sets the stage for future research leveraging time-series data to improve the localization of moving UAVs in dynamic scenarios.

Chapter 5

Summary of Papers and own Contributions

Positioning our studies within the context of existing research and guided by the research questions posed, the key contributions of this thesis are outlined as follows.

5.1 Mobility Management and Trajectory Optimization for Cellular Connected UAVs

This section presents our contributions to single-connectivity UAV mobility management and trajectory optimization, which balances service availability, interference, delay and handover efficiency through model-based and learning-based solutions.

- **Service Availability-Centric Handover Optimization:** We begin by modeling the service availability for the cellular-connected UAVs. Based on the model, we propose a model-based MRO method that dynamically tunes handover parameters, specifically the HOM and TTT. The optimization of the handover parameters relies on both signal strength and the buffer queue status of the UAV, allowing handover decisions to adapt to real-time connectivity and service availability demands. This method effectively minimizes unnecessary handovers while maintaining consistent service availability. In parallel, we introduce a model-free approach based on DQN, which take the association and resource allocation decisions based on UAV movement patterns, A2G channel conditions, and UAV buffer status. This model-free strategy ensures high connectivity with minimal handovers and service disruption, making it well-suited for UAVs in rapidly changing environments. Both model-based and model-free handover optimization techniques demonstrate improved performance compared to the legacy approach with fixed handover parameters.

- **Paper I: I. A. Meer**, M. Ozger, D. Schupke, and C. Cavdar, "Mobility Management for Cellular-Connected UAVs: Model-Based Versus Learning-Based Approaches for Service Availability", IEEE Transactions on Network and Service Management, 2024.

Division of work: The proposal for service availability-oriented mobility management, including both the model-based and model-free approaches, originated from the doctoral candidate and the supervisors. The doctoral candidate implemented the algorithmic solutions, conducted simulations, and analyzed results for the UAV mobility management framework, supported by collaborators in validating the simulation environment and interpreting results.

- **Joint Optimization of Trajectory Design and Handover Management:** Building on the model-free approach for handover management, the second contribution in this thesis addresses the joint optimization of UAV trajectory design and handover management to minimize the weighted sum of three KPIs: delay, uplink interference, and handover frequency. Leveraging the unique LoS connectivity of UAVs with multiple BSs, we propose a dueling double DQN (D3QN) based single agent algorithm and MADRL framework-based multi-agent QMIX algorithm. These approaches integrate mission-based trajectory optimization with network-driven trajectory adjustments, ensuring efficient resource allocation and informed handover decisions. The algorithms optimize the UAV's trajectory to bypass overlapping coverage areas, reducing handovers and interference while managing radio resources efficiently. Results show that the proposed approaches reduce handovers and interference with minimal impact on transmission delay compared to the benchmark scheme.

  - **Paper II:** Y. Deng, **I. A. Meer**, S. Zhang, M. Ozger and C. Cavdar, "D3QN-Based Trajectory and Handover Management for UAV Co-Existing with Terrestrial Users", IEEE WiOpt, 2023.
  - **Paper III:** Y. Deng, S. Zhang, **I. A. Meer**, M. Ozger and C. Cavdar, "Joint Trajectory and Handover Management for UAVs Co-existing with Terrestrial Users: A Multi-Agent DRL Approach", IEEE Transactions on Cognitive Communications and Networking (Submitted)

As Paper III is the extended journal version of Paper II, only Paper III has been included in this thesis.

Division of work: The doctoral candidate collaborated closely with the lead author, making substantial contributions to problem formulation, solution design, and developing the initial code base that served as a foundation for subsequent enhancements. The lead author, an MSc thesis student with the doctoral candidate as co-supervisor, focused on implementing the system model, obtaining results, and drafting the paper. Additionally, the doctoral candidate played an active role in drafting the initial manuscript and refining it to align with the study's objectives. The collaborators contributed with the KPI modeling, system model development, result evaluations, and final review of the papers.

5.2 Mobility Management with Dynamic Cluster Reconfiguration for Cellular Connected UAVs

In this section, we provide the contribution of this thesis toward the mobility management of aerial users served through multi-connectivity. These contributions include a range of RL-based approaches for optimizing power allocation and clustering, specifically designed to manage UAV mobility while addressing stringent, spatio-temporally varying reliability requirements in a wireless interference network.

- **Dynamic Power Allocation Scheme:** Our first contribution introduces a RL-based dynamic cluster reconfiguration and power allocation scheme aimed at minimizing the total transmit power across all BSs while maintaining an outage probability below a tolerated threshold. This threshold varies based on the UAV's operational context, such as entering a critical zone that requires high reliability. This approach dynamically adjusts power levels to conserve energy while meeting the UAV's reliability needs in a non-interference network.

  – **Paper IV: I. A. Meer**, K. -L. Besser, M. Ozger, H. V. Poor and C. Cavdar, "Reinforcement Learning Based Dynamic Power Control for UAV Mobility Management", IEEE Asilomar Conference on Signals, Systems, and Computers, 2023

  Division of work: The concept of adaptive power control for time varying reliability requirements through RL was developed by the doctoral candidate and the supervisor. Co-authors contributed to formulating the problem model, selecting RL algorithms, and refining simulation parameters. The doctoral candidate implemented the SAC-based solution, performed simulations, and conducted the primary analysis, while collaborators provided insights on interpreting results and validating the algorithm's performance under realistic conditions.

- **Dynamic Clustering and Power Allocation with Masked Soft Actor-Critic:** Our next contribution uses a masked soft actor-critic algorithm to manage dynamic clustering and power allocation jointly in an interference network. The UAVs are served using non-orthogonal multiple access, with BSs capable of 3D beamforming to limit interference. This model minimizes power usage and reduces the frequency of cluster reconfigurations, adapting to the changing reliability requirements of UAVs. The model is tailored for wireless interference networks where UAVs are supported by clusters of BSs, efficiently balancing reliability and energy efficiency.

- **Paper V: I. A. Meer**, K. -L. Besser, M. Ozger, D. Schupke, H. V. Poor and C. Cavdar, "Learning-Based Dynamic Cluster Reconfiguration for UAV Mobility Management with 3D Beamforming", IEEE International Conference on Machine Learning for Communication and Networking (ICMLCN), 2024

Division of work: The doctoral candidate developed the SAC algorithm with action masking, and conducted all simulation experiments. The collaborators contributed to formulating the problem requirements, evaluating reliability thresholds, and validating the algorithm's performance in dynamic network scenarios.

- **Hierarchical Multi-Agent DRL Framework for Dynamic Cluster Reconfiguration:** Our final contribution in multi-connectivity presents a scalable and efficient framework for dynamic clustering and power allocation with stringent reliability requirements in an interference network. The stringent reliability requirements are model in the finite block-length regime. To address this, we propose a H-MADRL framework that optimizes clustering and power allocation in real-time. This framework leverages a high-level agent in the edge cloud to manage optimal clustering policies, while low-level agents at each BS handle power allocation. Using an action-observation transition-driven algorithm, the low-level agents incorporate clustering actions from the high-level agent into their local observations, allowing for coordinated power management. This distributed framework matches the performance of centralized approaches but scales more effectively, as demonstrated by the numerical results.

  - **Paper VI: I. A. Meer**, K. -L. Besser, M. Ozger, D. Schupke, H. V. Poor and C. Cavdar, "Hierarchical Multi-Agent DRL Based Dynamic Cluster Reconfiguration for UAV Mobility Management", IEEE Transactions on Cognitive Communications and Networking (Submitted)

  Division of work: The doctoral candidate led the design and implementation of the hierarchical framework, developed and trained the DRL models, and conducted all simulation tests. The collaborators assisted in refining the clustering strategy, evaluating UAV reliability needs, and validating the simulation outcomes.

5.3 Cellular Localizability of Unmanned Aerial Vehicles

In this section, we provide the contribution of this thesis towards cellular localization of the UAV.

- **Localizability of Unmanned Aerial Vehicles:** We introduce an analytical framework for B-localizability of UAVs, representing the probability of successfully receiving localization signals above a specific SINR threshold from at least B ground BSs. This framework provides a comprehensive view of factors like the target UAV's distance distributions, path loss, interference, and received SINR by incorporating UAV-related parameters within a 3D environment. Our simulations examine how localizability is influenced by key factors such as the number of participating BSs, required SINR levels, air-to-ground channel characteristics, and network coordination, which are found to be critical to UAV localizability. We also formulate an optimization problem to maximize localizability performance and analyze how different altitude scenarios affect localizability outcomes.
  - **Paper VII: I. A. Meer**, M. Ozger, and C. Cavdar, "Cellular Localizability of Unmanned Aerial Vehicles". Elsevier Vehicular Communications, Volume 44, 2023.

Division of Work: The doctoral candidate developed the analytical framework, conducted simulations, and formulated the optimization problem. Collaborators contributed to defining key system parameters and validating simulation environments, ensuring model accuracy for various scenarios and BS deployment densities.

5.4 Open-Source Software

The results presented in Papers IV–VII were generated using a framework developed as part of the work described in Section 5.2. The source code for this framework, along with the scripts used to produce the published results in Papers IV and V, is publicly available online. The source code for Paper VII will be released upon the publication of the paper.

- **I. A. Meer** and K.-L. Besser, "Reinforcement Learning-Based Power Allocation for UAVs with Varying Reliability Requirements," Supplementary Material, available online: , 2023.
- **I. A. Meer** and K.-L. Besser, "Learning Based Dynamic Cluster Reconfiguration for UAV Mobility Management with 3D Beamforming," Supplementary Material, available online: , 2024.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

This thesis has investigated several critical aspects of mobility management for cellular-connected UAVs, addressing a range of research questions that highlight the unique challenges posed by UAV integration into existing cellular networks. Through a combination of model-based and reinforcement learning (RL)-based approaches, we have developed solutions aimed at improving handover efficiency, optimizing trajectory, enhancing power control, and increasing localizability in scenarios that involve both terrestrial and aerial users.

In response to the limitations of traditional handover schemes, which often rely solely on signal strength metrics, this thesis demonstrates that integrating additional metrics, such as buffer queue status, significantly improves handover decision accuracy for UAVs. This approach mitigates unnecessary handovers by allowing the UAV to make context-aware decisions, ultimately enhancing service continuity and reducing uplink transmission delays.

This thesis further extended mobility management by integrating trajectory planning and resource allocation, providing a unified framework that adapts UAV paths based on network dynamics and connectivity requirements. By adopting a Double Dueling DQN model for single-UAV scenarios and QMIX for multi-UAV scenarios, we were able to balance connectivity needs with efficient path planning, minimizing handovers and interference. This work highlights the trade-offs between optimizing different KPIs such as delay, interference, and handover frequency, providing insights into achieving an effective balance between mission objectives and wireless performance.

In multi-connectivity settings, we addressed the inefficiencies arising from static, worst-case power allocation. Through our adaptive power control algorithm, which adjusts power distribution based on zone-specific reliability requirements, we demonstrated substantial improvements in energy efficiency without compromising connectivity. This dynamic approach ensures that network resources are allocated more effectively, addressing varying QoS demands in real time.

Finally, we explored the localizability of UAVs within cellular networks, establishing a metric to quantify the probability of receiving sufficient localization signals. This analysis emphasized the impact of UAV altitude, base station (BS) distribution, and channel conditions on localization accuracy. Our findings indicate that cellular networks can indeed support effective UAV localization, provided that network coordination and resource allocation are optimized.

In conclusion, this thesis has provided a comprehensive set of frameworks and algorithms that address the critical requirements for UAV mobility management in cellular networks. These contributions offer practical solutions to the challenges of UAV connectivity and pave the way for more advanced and reliable integration of UAVs into future cellular networks.

6.2 Future Work

This thesis primarily addresses the mobility management problem within a single edge cloud service area, where it is assumed that the serving BSs can be coordinated at the edge cloud. A natural extension of this work is to consider handover management across multiple edge cloud regions, enabling more robust connectivity for UAVs as they transition between service areas. Additionally, while machine learning algorithms have shown great promise in mobility management, their black-box nature can limit insights into the factors driving specific handover decisions, which is essential for enhancing system interpretability and trust.

- **Mobility Management Between Edge Clouds in Multi-connectivity Environments:** As UAVs traverse multiple edge cloud regions in a multi-connectivity scenario, seamless handover management across these boundaries becomes essential. Future research can explore distributed handover management strategies and cross-edge-cloud coordination to maintain connectivity while minimizing latency and service interruptions. Investigating hierarchical architectures that balance local decision-making at the edge with global coordination could improve scalability and network resource efficiency.

- **Explainable AI for Handover Management:** Integrating Explainable AI (XAI) techniques can provide transparency and insights into the decision-making process of AI-driven handover management for cellular-connected UAVs. By employing XAI, researchers can analyze and visualize the rationale behind handover decisions, thereby enhancing interpretability and fostering trust among network stakeholders. Future work can focus on identifying key features influencing handover decisions, creating interpretable models, and developing visualization tools that facilitate intuitive understanding of AI actions.

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