Enhancing the Performance of UAV Communications in Cellular Networks

Hamed Hellaoui
Enhancing the Performance of UAV Communications in Cellular Networks

Hamed Hellaoui

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Abstract
The use of cellular networks as a communication infrastructure for Unmanned Aerial Vehicles (UAVs) has become the current trend. This would mainly enable beyond visual line-of-sight applications and allow UAVs to benefit from the latest evolutions achieved in cellular networks. Despite the advantages that cellular networks can bring to UAVs, several issues still need to be addressed. Indeed, cellular networks are deployed to serve ground user equipment (UEs), whereas UAVs’ aerial communications are characterized by different channel conditions. Field evaluations have shown that flying UAVs can experience poor link quality, or even negatively affect ground communication. In addition, UAV applications can be deployed in a challenging environment characterized by different types of QoS (Quality of Services). For instance, UAVs can be deployed to provide network connectivity to ground devices, whereas each one of the latter requires sending two types of traffic with different QoS, at the same time. Furthermore, the consideration of cellular networks for UAVs can bring more opportunities that merit to be explored to enhance the communications, mainly in terms of taking advantage of the presence of several UAVs and Mobile Network Operators (MNOs).

The main objective of the dissertation is to contribute to enhancing the performance of UAV communications in cellular networks. The contributions of this dissertation can be divided into six categories. First, as aerial communication presents different channel conditions, we are interested in modeling UAV communications in cellular networks and deriving expressions that define the performance indicators. All the contributions build from these expressions, and target performing network optimization to enhance UAV communications in cellular networks. Second, we consider a cellular network deployed to serve both UEs and UAVs, and we investigate their co-existence by enhancing their underlying performances. Next, we focus on supporting the co-existence of several QoS types in UAV communications. To this end, we consider the scenario where UAVs are deployed to provide network connectivity to ground devices, where each one of the latter requires two different QoS types. In the fourth and the fifth categories, we focus on new opportunities that cellular networks can bring to UAV communications. In particular, we investigate the possibility of taking advantage of the presence of several UAVs and MNOs in a way to enhance the performance of UAV communications. Finally, we explore the use of machine learning in order to enable fast optimization and enhance the performance of UAV communications.

All the contributions of this dissertation have been validated with a series of performance evaluations.

Keywords Unmanned Aerial Vehicles, Wireless Networks, Radio Resource Allocation.
This thesis was conducted at the Department of Communication and Networking (ComNet), School of Electrical Engineering (ELEC) of Aalto University.

I would like to deeply thank Prof. Tarik Taleb and Prof. Jukka Manner for supervising this thesis and accompanying me throughout this road.

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Helsinki, September 7, 2022
Hamed Hellaoui
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List of Publications

This dissertation consists of an overview of the following publications, which are referred to in the text by their roman numerals.


IV H. Hellaoui, A. Chelli, M. Bagaa, T. Taleb, “Efficient steering mechanism for mobile network-enabled uavs,” In 2019 IEEE Global Communications Conference (GLOBECOM), Waikoloa, HI, USA, pp. 1-6, Dec 2019.


Author’s Contributions

Publication I: “Towards Mitigating the Impact of UAVs on Cellular Communications”

The author edited the paper, implemented the solution and evaluated the results. Dr. Chelli proposed the communication model, assisted in defining the problem and revised the paper. Dr. Bagaa assisted in defining the problem and the contribution, and also revised the manuscript. Pr. Taleb supervised the process and reviewed the paper.

Publication II: “Aerial control system for spectrum efficiency in UAV-to-cellular communications”

The author edited the paper, implemented part of the solution and discussed the associated results. M. Bekkouche implemented part of the solution and edited the associated evaluation. Dr. Bagaa advised on the main contributions of the paper and revised the manuscript. Pr. Taleb supervised the process and reviewed the paper.

Publication III: “Towards efficient control of mobile network-enabled UAVs”

The author proposed the contribution, edited the paper, proposed the communication model (considering the same channel conditions as in publication II), implemented the solution and evaluated the results. Dr. Chelli validated the communication model, assisted in defining the problem and the contribution of the paper, and also revised the manuscript. Dr. Bagaa advised on using graph theory for the optimization, assisted in defining
the contribution and revised the paper. Pr. Pätzold revised the paper. Pr. Taleb supervised the process and reviewed the paper.

**Publication IV: “Efficient steering mechanism for mobile network-enabled uavs”**

The author proposed the contribution, edited the paper, implemented the solution and evaluated the results. Dr. Chelli verified the communication model, assisted in defining the problem and the contribution, and also revised the paper. Dr. Bagaa assisted in defining the game-based solution and revised the manuscript. Pr. Taleb supervised the process and reviewed the paper.

**Publication V: “UAV communication strategies in the next generation of mobile networks”**

The author proposed the contribution, edited the paper, implemented the solution and evaluated the results. Dr. Challi proposed the communication model, assisted in defining the problem and the contribution of the paper, and also revised the manuscript. Dr. Bagaa assisted in defining the optimization problem and revised the manuscript. Pr. Taleb supervised the process and reviewed the paper.

**Publication VI: “Joint Sub-Carrier and Power Allocation for Efficient Communication of Cellular UAVs”**

This journal is an extension of publication III. The author proposed the contribution, edited the paper, implemented the solution and evaluated the results. Dr. Bagaa assisted in defining game-based solution and revised the manuscript. Dr. Chelli validated the communication model, assisted in defining the contributions and revised the paper. Pr. Taleb supervised the process and reviewed the paper.

**Publication VII: “On Supporting Multi-Services in UAV-Enabled Aerial Communication for the Internet of Things”**

This journal is an extension of the publication V. The author proposed the
contribution, edited the paper, implemented the solution and evaluated the results. Dr. Bagaa assisted in defining the optimization problem and the contribution, and also revised the paper. Dr. Chelli validated the communication model, assisted in defining the solution and the iterative process, and also revised the manuscript. Pr. Taleb supervised the process and reviewed the paper.

**Publication VIII: “Towards using Deep Reinforcement Learning for Connection Steering in Cellular UAVs”**

The author proposed the contribution, edited the paper, implemented the solution and evaluated the results. Dr. Yang revised the paper. Pr. Taleb supervised the process and reviewed the paper.
# List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full Form</th>
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<tbody>
<tr>
<td>3GPP</td>
<td>3rd Generation Partnership Project</td>
</tr>
<tr>
<td>5G</td>
<td>5th Generation of mobile networks</td>
</tr>
<tr>
<td>A2C</td>
<td>Advantage Actor Critic</td>
</tr>
<tr>
<td>ACS</td>
<td>Aerial Control System</td>
</tr>
<tr>
<td>ARQ</td>
<td>Automatic Repeat Request</td>
</tr>
<tr>
<td>BS</td>
<td>Base Station</td>
</tr>
<tr>
<td>BVLOS</td>
<td>Beyond Visual Line-of-Sight</td>
</tr>
<tr>
<td>C2</td>
<td>Command and Control</td>
</tr>
<tr>
<td>CH</td>
<td>Cluster Head</td>
</tr>
<tr>
<td>ComNet</td>
<td>department of Communications and Networking</td>
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<tr>
<td>DL</td>
<td>Downlink</td>
</tr>
<tr>
<td>DRL</td>
<td>Deep Reinforcement Learning</td>
</tr>
<tr>
<td>DQN</td>
<td>Deep Q-Learning</td>
</tr>
<tr>
<td>eMBB</td>
<td>enhanced Mobile Broadband</td>
</tr>
<tr>
<td>GCS</td>
<td>Ground Control Station</td>
</tr>
<tr>
<td>IoT</td>
<td>Internet of Things</td>
</tr>
<tr>
<td>LoS</td>
<td>Line-of-Sight</td>
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<tr>
<td>LP</td>
<td>Linear Programming</td>
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<tr>
<td>LTE</td>
<td>Long Term Evolution</td>
</tr>
<tr>
<td>MEC</td>
<td>Multi-access Edge Computing</td>
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<tr>
<td>ML</td>
<td>Machine Learning</td>
</tr>
<tr>
<td>mMTC</td>
<td>Massive Machine Type Communication</td>
</tr>
<tr>
<td>MNO</td>
<td>Mobile Network Operator</td>
</tr>
<tr>
<td>NLoS</td>
<td>Non-Line-of-Sight</td>
</tr>
<tr>
<td>OBU</td>
<td>On-Board Unit</td>
</tr>
<tr>
<td>OFDMA</td>
<td>Orthogonal Frequency-Division Multiple Access</td>
</tr>
<tr>
<td>QoS</td>
<td>Quality of Service</td>
</tr>
<tr>
<td>RAT</td>
<td>Radio Access Technology</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>------------------------------------</td>
</tr>
<tr>
<td>RQ</td>
<td>Research Question</td>
</tr>
<tr>
<td>RSSI</td>
<td>Radio Signal Strength Indicator</td>
</tr>
<tr>
<td>SINR</td>
<td>Signal-to-Interference-plus-Noise Ratio</td>
</tr>
<tr>
<td>SNR</td>
<td>Signal-to-Noise Ratio</td>
</tr>
<tr>
<td>U2I</td>
<td>UAV-to-Infrastructure communication</td>
</tr>
<tr>
<td>U2U</td>
<td>UAV-to-UAV communication</td>
</tr>
<tr>
<td>UAV</td>
<td>Unmanned Aerial Vehicle</td>
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<tr>
<td>UE</td>
<td>User Equipment</td>
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<tr>
<td>UL</td>
<td>Uplink</td>
</tr>
<tr>
<td>uRLLC</td>
<td>ultra Reliable Low Latency Communication</td>
</tr>
<tr>
<td>UTM</td>
<td>Unmanned aerial system Traffic Management</td>
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1. Introduction

This chapter introduces the context, the problematic and the objective of the thesis. It also presents an initial insight on the main contributions of the thesis and highlights the relationship between the research questions, publications, and dissertation chapters.

1.1 Context, Problematic and Objective of the Thesis

Considered as one of the technologies that are reshaping our daily lives, Unmanned Aerial Vehicles (UAVs) are getting more attention. According to 'Valuates Reports' [1], the global UAV market size is projected to reach USD 133.5 Billion by 2026, at a Compound Annual Growth Rate (CAGR) of 26.4% during 2021-2026. Indeed, UAVs have become an integral part of several critical applications, such as rescue management, first aid, and crowd surveillance. UAVs can also be used to deliver packages from the sky, achieving therefore reduced cost and time compared to terrestrial vehicles. Recently, UAVs have demonstrated potential in providing services related to the Internet of Things (IoT). When equipped with dedicated devices (e.g., sensors, cameras), they can be oriented to a specific area and perform measurements requested by users. However, the increase use of UAVs and their special requirements will be translated into new communication challenges. Indeed, different UAV applications require transmitting massive data generated from the drones, e.g., video streaming on the uplink in case of surveillance application. On the other hand, UAV operations are of critical nature and require control messages that are sent with reliability and low latency, so that the functions of command and control (C2) can be performed efficiently. C2 functions are reflected in the downlink scenario, where the UAVs get control messages to be executed by them. Furthermore, UAV applications are expected to be deployed in
massive numbers. All these facts highlight the importance of relying on an efficient communication infrastructure to enable UAV potentials.

Both scientific and industrial communities perceive an opportunity in using cellular networks as a communication infrastructure for UAVs. This will push the boundary of their applications and take them to a new stage. Indeed, as a consequence of the limited range of their underlying communication technology (e.g. Telemetry radio, WiFi, etc.), the usage of drones is nowadays more restricted to visual line-of-sight (LoS) scenarios. This goes against the potential applications expected from UAVs, where they are supposed to travel far from their control center (e.g., for cargo delivery or for providing IoT services). One of the most important benefits in using mobile networks for UAVs is the achievement of beyond visual line-of-sight (BVLOS), in which the UAVs can use the cellular network to fly for long distances far from their control centers. The latter are today widely deployed, ensuring therefore the necessary coverage for UAVs and their related applications. In addition, drones will also benefit from the efficiency of cellular networks. Through the 5th Generation of mobile networks (5G) and the upcoming 6th generation (6G), UAVs would achieve low delays and higher throughputs, which are very crucial given the critical nature of UAV applications. Furthermore, network slicing would allow the support of several UAV applications with different requirements. Three types of services are distinguished in 5G (namely ultra Reliable Low Latency Communication -uRLLC-, enhanced Mobile Broadband -eMBB- and massive Machine-Type Communication -mMTC-) and these can support the challenging requirements of UAV applications. On the other hand, by equipping UAVs with the required radio access technology (RAT), they can operate as mobile (flying) base stations (BSs) and extend cellular network connectivity to ground devices. This will provide a new type of applications that are enabled by cellular networks.

![Figure 1.1](image)

**Figure 1.1.** Two types of UAV applications in cellular networks: a) UAVs providing services from height; b) UAVs extending network connectivity to ground users.
as shown in Figure 1.1. This has been translated into several industrial projects that are boosting the development of the concept of UAV-aided network communication. In 2016, the Finnish communication company Nokia together with the UK mobile operator EE have shown a proof-of-concept using mini mobile bases station carried by drones [2]. The drones flying at between 30-35m were able to provide 4G coverage over a radius of 5km, achieving real-time video streaming up to 150 Mbps throughput. Other projects such as ABSOLUTE [3] also target the implementation of low-altitude aerial networks consisting of LTE-Advanced (LTE-A) base stations.

To better investigate the communication quality of UAVs in cellular networks, some research works have performed field trials [4–6]. 3GPP (3rd Generation Partnership Project) performed relevant evaluations, considering the inputs from several partners. The obtained results [4] point out that flying UAVs could have poor link quality on the downlink (DL) resulting in low throughput. This is mainly due to the close free-space signal propagation, which is translated into a higher probability of interference from non-serving BSs, and thus, leads to poor link quality. This would result in lower Quality-of-Service (QoS) for the flying UAVs, which may not be tolerable. The effect of this issue on ground user equipment (UEs) is not significant, as the underlying communication model is different compared to that of the flying UAVs. For the uplink (UL) scenario, a UAV can experience better channel conditions compared to a ground UE because of the close free-space signal propagation. However, it was also demonstrated that ground UEs could be affected negatively and their throughput is degraded. This could be a key limiting factor for the development of cellular network-based UAVs, as it directly affects ground and aerial devices. The same issues are also experienced when considering UAVs as flying BS to provide network connectivity to ground devices. Therefore, efficient solutions are required to enhance the performance of mobile network-enabled UAVs.

The objective of the thesis is to contribute to enhancing the performance of UAV communications in cellular networks. While recent works have recently been conducted to tackle this issue, many important aspects are not considered in the literature, for example by considering realistic models, that take into account most of the propagation phenomenon experienced by wireless communications, and deriving expressions to evaluate the performance under these models. In addition, the considera-
tion of cellular networks for UAVs can bring novel communication challenges/opportunities, mainly in terms of supporting the co-existence of different types of users/QoS and exploiting the presence of several users/networks. In this vein, the thesis focuses on the case of multi-copters using cellular networks for network connectivity. It considers the scenario where UAVs are connected to the cellular network to provide services, and also the scenario where UAVs are acting as flying BSs to extend network connectivity (as illustrated in Figure 1.1). The path of such UAVs is based on a set of waypoints (successive geolocations to be automatically visited by the UAVs). It is therefore very crucial to enhance the communication performance throughout the waypoints to visit. Although, such UAVs could operate in an automatic manner (by following a predefined set of waypoints without constant intervention of the human pilot), they still require enhanced communication performance. Indeed, UAVs keep sending telemetry data to report their status and also get C2 messages when required. Given their critical nature, any communication outage could have catastrophic consequences at different levels. Furthermore, UAVs could be part of critical applications that are associated with strict performance guarantees. A number of research questions (RQs) have been developed to be addressed by the thesis. These RQs are summarized in Figure 1.2. The main research question, RQ I, is: "How to enhance the performance of UAV communications in cellular networks?". Six research questions are developed under RQ I. These six research questions, which are addressed by the different contributions of the thesis, are the following:

1. RQ II: How to model UAV communications in cellular networks and how to define the performance indicators?

2. RQ III: How to support the co-existence of UAVs and UEs in cellular networks and enhance the underlying performance?

3. RQ IV: How to support the co-existence of several QoS types in UAV communications?

4. RQ V: Can the presence of several UAVs be exploited to enhance the performance of UAV communications?

5. RQ VI: Can the presence of several mobile network operators (MNOs) be exploited to enhance the performance of UAV communications?

6. RQ VII: How to enable fast optimization to enhance the performance of UAV communications?
How to enhance the performance of UAV communications in cellular networks?

- How to model UAV communications in cellular networks?
- How to define performance indicators?
- What are the key parameters that affect the performance of UAV communications?

Research Question III
- How to support the co-existence of UAVs and UEs in cellular networks and enhance the underlying performance?

Publication VI
Chapter 3

Research Question IV
- How to support the co-existence of several QoS in UAV communications?

Publication VII
Chapter 4

Research Question V
- Can the presence of several UAVs be exploited to enhance the performance of UAV communications?

Publication II
Chapter 5

Research Question VI
- Can the presence of several MNOs be exploited to enhance the performance of UAV communications?

Publication IV
Chapter 6

Research Question VII
- How to enable fast and online optimization to enhance the performance of UAV communications?

Publications VII
Chapter 7

Figure 1.2. Research questions addressed in the publications included in the dissertation.

As depicted in Figure 1.2, RQ II outcomes lay the foundations of the other research questions. Indeed, RQ II aims to build models and defining performance indicators that will be used by the remaining research questions. In order to address the above research questions, a number of contributions have been conducted by the author in the form of scientific publications. These publications are summarized in the following section.

1.2 Summary of Publications

The present dissertation is article-based and uses the publications to tackle the different research questions. Although this dissertation is officially based on 8 publications (which are shown in Table 1.1), the underlying work that supports it is much larger. The author has also contributed to a number of European projects’ deliverables, whose topics are linked to UAV communications as shown in Table 1.2.
Table 1.1. List of scientific publications of the author.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Type of publication</th>
<th>Research area/ Dissertation’s publication</th>
<th>Year of Publication</th>
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<tbody>
<tr>
<td>[7]</td>
<td>Conference</td>
<td>Publication I</td>
<td>2018</td>
</tr>
<tr>
<td>[8]</td>
<td>Journal</td>
<td>Publication II</td>
<td>2018</td>
</tr>
<tr>
<td>[10]</td>
<td>Conference</td>
<td>Publication IV</td>
<td>2019</td>
</tr>
</tbody>
</table>

The contributions of the individual publications that are included in the dissertation and can be summarized as follows:

**Publication I** investigates the impact on the performance of UAV communications in cellular networks. It considers the uplink scenario and derives the expressions of performance indicators reflected in the outage probability for ground UEs and flying UAVs. The publication also provides a solution to reduce the outage probability based on power optimization.

**Publication II** develops an idea that aims to enhance the performance of UAV communications in cellular networks, by exploiting the presence of several UAVs. More precisely, the goal is to reduce UAV communications with cellular networks by shifting part of the control logic from the ground control station to be executed by the UAVs themselves.

**Publication III** examines the downlink scenario in UAV communications using cellular networks. It derives the expressions of the outage probabilities on the downlink for both ground UEs and flying UAVs. It also provides a solution based on graph theory to reduce the outage probabilities.

**Publication IV** considers the availability of different MNOs and addresses the question of exploiting their presence to ensure enhanced performance for the UAVs. The publication considers the expressions of the outage probability derived in publication I and proposes a solution based on a coalitional game to enhance the performance.

**Publication V** considers the problem of communication strategy selection (between direct communication and dual-hop communication via a relay node). The publication derives the expression of a performance indicator reflected in the effective rate for the two strategies. It also provides a solution based on linear programming (LP) to maximize the effective rate of the UAVs.

**Publication VI** is an extension of publication III. Based on the commu-
Table 1.2. List of deliverables contributed by the author.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Project</th>
<th>Research area</th>
<th>Year of Publication</th>
</tr>
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<tbody>
<tr>
<td>[17]</td>
<td>H2020 5G!Drones D1.2</td>
<td>Description of 5G facility for cellular-enabled UAV trials</td>
<td>2019</td>
</tr>
<tr>
<td>[18]</td>
<td>H2020 5G!Drones D1.3</td>
<td>Design of an overall system for cellular-enabled UAV trials</td>
<td>2020</td>
</tr>
<tr>
<td>[20]</td>
<td>H2020 5G!Drones D1.5</td>
<td>Description of 5G facility for cellular-enabled UAV trials</td>
<td>2020</td>
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<tr>
<td>[21]</td>
<td>H2020 5G!Drones D2.1</td>
<td>Definition of a control architecture for cellular-enabled UAV trials</td>
<td>2020</td>
</tr>
<tr>
<td>[22]</td>
<td>H2020 5G!Drones D2.2</td>
<td>Initial implementation of the trial controller for cellular-enabled UAVs</td>
<td>2021</td>
</tr>
<tr>
<td>[23]</td>
<td>H2020 5G!Drones D2.3</td>
<td>Report on algorithms and tools for data analysis in cellular-enabled UAVs</td>
<td>2021</td>
</tr>
<tr>
<td>[24]</td>
<td>H2020 5G!Drones D2.4</td>
<td>Final definition of a control architecture for cellular-enabled UAV trials</td>
<td>2021</td>
</tr>
</tbody>
</table>

The communication model considered in publication III and the derived expressions of the outage probability, the publication advances a solution based on game theory to enhance the performance. The solution aims to jointly optimize sub-carrier and power allocation, and also emphasizes with a series of evaluations.

Publication VII is an extension of publication V. It further derives expressions of performance indicators reflected in the effective rate and the transmission delay, and addresses the question of supporting the coexistence of several QoS types for UAV communications in cellular networks. The proposed solution tackles the joint problem of sub-carrier allocation and UAV deployment. It also introduces an iterative process where each iteration tackles a linear optimization.

Publication VIII focuses on the problem of enabling fast optimization to enhance the performance of UAV communications in cellular networks.
While solutions based on, e.g., game theory or linear optimization might take time and can be considered offline for planning the network, online solutions are also required. This can be achieved by using machine learning (ML) methods. In this context, this publication considers the problem of UAV traffic steering via several MNOs and proposes a Deep Reinforcement Learning (DRL) approach to enhance the performance and reduce the outage probability.

1.3 Structure of the Dissertation

This dissertation is organized into the following chapters. All the chapters contribute to the RQ I (the link between the research questions, the publications and the chapters of the dissertation is summarized in Figure 1.2).

Chapter 2 investigates the impact on UAV communications in cellular networks. As it has been demonstrated that aerial communication is different from that on the ground, this chapter considers a communication model that accounts for different propagation phenomena experienced in wireless signals and derives expressions for performance indicators of UAV communications in cellular networks. These performance indicators are reflected in the outage probability, the effective rate and the transmission delay. Chapter 2 also provides an analysis of the performance of UAV communications in cellular networks and discusses the parameters that affect this performance. It contributes to the RQ II by defining original expressions for the performance indicators of UAV communications in cellular networks. The contributions of this chapter are based on publications I, III, and V.

Chapter 3 builds from the outage probability expressions developed in Chapter 2 and the identified parameters that affect the performance. It addresses supporting the co-existence of UAVs and UEs in cellular networks. It proposes a solution based on game theory to jointly optimize sub-carrier and power allocation in a way to reduce the outage probability of UAVs and UEs. Chapter 3 contributes to the RQ III by advancing a solution to optimize network resources in a way to support the co-existence of UAVs and UEs, and enhance the performance of the underlying communication. The contribution of this chapter is based on publication VI.

Chapter 4 investigates the support of several QoS types of UAV communications in cellular networks and enhancing the associated perfor-
mance indicators. It considers UAVs providing connectivity to ground IoT devices, where each of the latter requires uRLLC and eMBB service types. The chapter builds from the expressions of the effective rate and the transmission delay developed in Chapter 2. It also proposes an iterative approach to jointly optimize UAV deployment and sub-carrier allocation in a way to support the co-existence of the two services (uRLLC and eMBB) for each IoT device served by a UAV. This chapter contributes to the RQ IV and is based on publication VII.

**Chapter 5** elaborates on an idea that aims to enhance the performance of UAV communications in cellular networks. The idea is based on shifting part of the communication control logic from the Ground Control Station (GCS) to be performed by the UAVs themselves, reducing, therefore, the communication with the cellular networks. Chapter 5 contributes to the RQ V by elaborating on exploiting the presence of several UAVs to enhance the communication performance. The contribution of this chapter is based on publication II.

**Chapter 6**, on the other hand, elaborates on the simultaneous use of several cellular networks to enhance the performance of the connected UAVs. It exploits the availability of different MNOs at the communication range of UAVs and develops a solution based on coalitional game to select for each UAV the optimal MNO that ensures the best QoS. Chapter 6 contributes to the RQ V which targets exploiting the presence of several MNOs to enhance the performance of UAV communications in cellular networks. The contribution of the chapter is based on publication IV.

**Chapter 7** focuses on enabling fast optimizations for enhancing the performance of UAV communications in cellular networks. Indeed, solutions based on game theories or linear optimizations take time and can be considered for offline use (e.g., planning the network). This chapter considers the same problem addressed in the previous one (the problem of UAV traffic steering in cellular networks). The solution proposed in this chapter uses Deep Reinforcement Learning to select the MNOs to be used by the UAVs for steering the traffic. Chapter 7, therefore, addresses the RQ VI to enable fast optimization to enhance the performance of UAV communications in cellular networks. The contributions of this chapter are based on publication VIII.

Finally, **Chapter 8** summarizes the achieved objectives and discusses necessary areas for further research.
2. Performance Indicators of UAV Communications in Cellular Networks

This chapter investigates the impact on UAV communications in cellular networks. Compared to terrestrial links, aerial communications present different characteristics that need to be taken into consideration. To this end, this chapter focuses on the performance indicators of UAV communications in cellular networks. More precisely, it considers a communication model that accounts for most of the propagation phenomena experienced by wireless signals, including path loss, fast fading, and interference, and derives the expressions of the outage probability, the effective rate and the transmission delay for UAV communications in cellular networks. The chapter also provides an analysis of the underlying performance and discusses the key parameters that affect the performance of UAV communications. The contributions of this chapter are based on publications I, III, and V.

2.1 Outage Probability

This section derives expressions of the outage probability for cellular-connected UAVs. An outage probability is defined as the probability that a given packet fails to be received and is used in the literature to approximate the packet loss probability. In order to derive the underlying expressions, we consider a communication model that accounts for different phenomena experienced in wireless communications. We first consider the downlink scenario in which the connected users (UEs and UAVs) receive data from their serving BSs. The latter employs an Orthogonal Frequency Division Multiple Access (OFDMA) technique to serve the connected users. Consequently, intra-cell interference is neglected, and the interference can be caused only by non-serving BSs, as shown in Figure 2.1.
Let $Q$, $U$ and $B$ denote respectively the set of UEs, UAVs and BSs. Let us also denote by $v$ the serving BS and by $u$ the receiving device. The received signal at the device $u$ considering the sub-carrier $b \in B$ can be expressed as

$$y_u = \alpha_{vu} \sqrt{P_v} x_v + \sum_{t=1}^{N} \alpha_{tu} \sqrt{P_t} x_t + n_u,$$

(2.1)

where $\alpha_{vu}$ refers to the channel gain between the transmitter $v$ and the receiver $u$. The second term in the right-hand side of (2.1) accounts for the interference impact from non-serving BSs, where $\alpha_{tu}$ is the fading coefficient from the interfering BS $t$ to the receiver $u$. The BSs $v$ and $t$, respectively, transmit the symbols $x_v$ and $x_t$ by employing the power $P_v$ and $P_t$ on the same sub-carrier assigned to the receiving device $u$. As for the third term of (2.1), $n_u$, it refers to a zero-mean complex additive white Gaussian noise with variance $N_0$. The received signal-to-noise ratio (SNR) for the link $vu$, $\gamma_{vu}$, can be expressed as

$$\gamma_{vu} = \frac{P_v |\alpha_{vu}|^2}{N_0}.$$

(2.2)

As the receiving device $u$ can either be a UE or a UAV, the underlying fading characteristics are substantially different. For the case of a UE, the path loss expression provided by 3GPP is considered as [25]

$$PL_{UE}^{vu} = 15.3 + 37.6 \log_{10}(d_{vu}^{UE}),$$

(2.3)

where $d_{vu}^{UE}$ refers to the distance in meter between the BS $v$ and the UE $u$ as shown in Figure 2.1. A Rayleigh distribution is assumed for the fast fading associated with the UEs. As for the mean SNR of the link between
the BS $v$ and the UE $u$, it is denoted by $\bar{\gamma}_{vu}$ and can be expressed as

$$\bar{\gamma}_{vu} = P_{v}^{UE} \times 10^{-\frac{PL_{UE} vu}{10}} / N_0. \quad (2.4)$$

The instantaneous received signal-to-interference-plus-noise ratio (SINR) for the link $vu$ can be defined as

$$SINR_{vu} = \frac{\gamma_{vu}}{1 + \sum_{t=1}^{N} \gamma_{tu}}. \quad (2.5)$$

**Theorem 1. Outage probability on the downlink for a UE**

A UE $u$ fails in receiving packets from its serving BS $v$, on the downlink, iff the $SINR_{vu}$ falls below a threshold $\gamma_{th}$. This event, called outage, occurs with a probability $P_{out, vu}^{UE}$ that can be expressed as

$$P_{out, vu}^{UE}(\gamma_{th}) = 1 + \exp \left( -\frac{\gamma_{th}}{\bar{\gamma}_{vu}} \sum_{t=1}^{N} \frac{\alpha_t}{\bar{\gamma}_{vu} + \gamma_{vu}} \right). \quad (2.6)$$

where $\alpha_t$ are unique values satisfying the following equality (fractional decomposition)

$$\prod_{t=1}^{N} (1 - x^{\bar{\gamma}_{vu}})^{-1} = \sum_{t=1}^{N} \frac{\alpha_t}{x^{\gamma_{vu}}}. \quad (2.7)$$

**Proof.** See Appendix 9.1. \qed

If the receiving device $u$ is a UAV, the path loss differs depending on the line-of-sight (LoS) and the non-line-of-sight (NLoS) conditions. The LoS communication results in a better QoS compared to the NLoS one. For the proposed solution, we consider the path loss equation provided by 3GPP as [4]

$$PL_{UAV}^{vu} = \begin{cases} 28.0 + 22 \log_{10}(d_{vu}^{UAV \times 3D}) + 20 \log_{10}(f_c), & \text{for LoS link}, \\ -17.5 + (46 - 7 \log_{10}(h_u^{UAV})) \log_{10}(d_{vu}^{UAV \times 3D}) + 20 \log_{10}(\frac{40\pi f_c}{3}), & \text{for NLoS link}, \end{cases} \quad (2.8)$$
where the term $h_u^{AV}$ refers to the altitude of the UAV $u$ and the term $d_v^{3D}$ accounts for the Euclidean distance between the BS $v$ and the UAV $u$, as shown in Figure 2.1. The probability of a LoS condition $P_{vu}^{LoS}$ is determined as [4]

$$P_{vu}^{LoS} = \begin{cases} 
1, & \text{if } h_u^{AV} > 100, \\
1, & \text{if } d_v^{3D} \leq d_1, \\
d_1 d_v^{3D} + \exp\left(-\frac{d_v^{3D}}{d_1}\right) \left(1 - \frac{d_1}{d_v^{3D}}\right), & \text{if } d_v^{3D} > d_1, 
\end{cases} \quad (2.9)$$

with $p_1 = 4300 \log_{10}(h_u^{AV}) - 3800$ and $d_1 = \max(460 \log_{10}(h_u^{AV}) - 700, 18)$. The term $d_v^{3D}$ refers to the distance between the BS $v$ and the UAV $u$, as illustrated in Figure 2.1. It is worth noting that the NLoS probability, $P_{vu}^{NLoS}$, can be obtained as $P_{vu}^{NLoS} = 1 - P_{vu}^{LoS}$. The corresponding fast fading follows a Nakagami-$m$ distribution for LoS links, and a Rayleigh distribution for NLoS links. The mean SNRs of the LoS and NLoS links are denoted by $A_{vu}$ and $B_{vu}$, respectively, and are obtained as

$$\begin{align*}
A_{vu} &= P_{vu}^{LoS} \times P_v/N_0 \times 10^{\frac{P_{vu}^{LoS}}{10}}, \\
B_{vu} &= (1 - P_{vu}^{LoS}) \times P_v/N_0 \times 10^{-\frac{P_{vu}^{LoS}}{10}}. 
\end{align*} \quad (2.10)$$

**Theorem 2. Outage probability on the downlink for a UAV**

The outage probability for a UAV $v$ served by the BS $v$ is expressed as

$$P_{out,vu}(\gamma_{th}) = \sum_{j=1}^{m} \left( \frac{\alpha_{i,j}(A_{vu})}{\Gamma(j)} \right)^{j} \Gamma(j) + \sum_{t=1}^{N} \left( \frac{\alpha_{t,j}}{B_{vu}} \right)^{j} \Gamma(j) \\
- \sum_{t=1}^{N} \sum_{j=1}^{m} \frac{\alpha_{t,j}(1)\Gamma(j)}{(j-1)!} \left( f_{j,j}(A_{vu}/m) \right) \\
- \beta_2 B_{vu} \left( 1 + \exp\left(-\frac{\gamma_{th}}{B_{vu}}\right) \left( \frac{\alpha_{t,j}}{B_{vu}} \right)^{j} \Gamma(j) \right), \quad (2.11)$$

where $\beta_{1j}$, $\beta_{2}$, $\alpha_{i,j}'$ and $\alpha_{t,j}$ are unique values satisfying the two following equations (fractional decomposition):

$$\left(1 - \frac{x A_{vu}}{m}\right)^{-m} (1 - x B_{vu})^{-1} = \sum_{j=1}^{m} \frac{\beta_{1j}}{(x - A_{vu})^j} + \frac{\beta_{2}}{(x - B_{vu})}, \quad (2.12)$$

$$\prod_{t=1}^{N} \left(1 - x B_{vu}^{-1}\right) (1 - \frac{x A_{vu}}{m})^{-m} = \sum_{t=1}^{N} \frac{\alpha_{i,j}}{B_{vu}} + \sum_{t=1}^{N} \sum_{j=1}^{m} \frac{\alpha_{t,j}}{(x - A_{vu})^j}. \quad (2.13)$$

The function $f_{j,j'}(S)$ is provided as

$$f_{j,j'}(S) = \sum_{p=1}^{N} S^{j'}(\theta_p)^{j'-1} \lambda_p \Gamma(j, \frac{m \gamma_{th} (\theta_p S + 1)}{A_{vu}}), \quad (2.14)$$
where $\lambda_p$ and $\theta_p$ denote the weight and the zero factors of the $n$-th order Laguerre polynomials, respectively [26]. $\Gamma(a, z)$ is the upper incomplete gamma function defined as $\Gamma(a, z) = \int_z^{\infty} t^{a-1} e^{-t} dt$.

Proof. See Appendix 9.1. □

Theorems 1 and 2 provide the outage probability on the downlink for a ground UE and a UAV, respectively. The outage expressions have been derived by taking into account path loss, fast fading, and interference. This makes the considered system model realistic since it captures most of the propagation phenomena experienced by wireless signals. These expressions are original and can not be found in the literature. This also reflects a major contribution compared to existing works on UAV communications in cellular networks, as those works do not derive the expression of the outage probability.

Similar to the downlink scenario, we derive the expressions of the outage probabilities on the uplink for UAVs and UEs on the uplink. To this end, we use $uv$ to denote the link from a device $u$ to its serving BS $v$, while $tv$ stands for the link from a device $t$ interfering to the BS $v$. Figure 2.2 shows the system model on the uplink. By considering the same communication model in this section, we can derive the following theorems:

**Theorem 3. Outage probability on the uplink for a UE**

The probability of outage, $P_{\text{out}, uv}$, on the uplink for a UE $u$ connected to a BS $v$ can be expressed as
\[ P_{\text{out,uv}}(\gamma_{th}) = 1 + \exp \left( -\frac{\gamma_{th}}{\bar{\gamma}_{uv}} \right) \left( \sum_{t=1}^{N_1} \frac{\alpha_t}{\gamma_{uv}} + \sum_{t=N_1+1}^{N} \frac{\alpha'_t}{\gamma_{uv}} + \frac{1}{\bar{B}_{tv}} \right) \]

\[ - \sum_{t=N_1+1}^{N} \sum_{j=1}^{m} \frac{\alpha_{t,j}}{(\gamma_{uv} + \frac{m}{A_{uv}})^j (j-1)! \Gamma(j)} \cdot \left( \frac{1}{\bar{B}_{tv}} \right) \]

(2.15)

where \( \Gamma(j) \) is the gamma function. \([1, \ldots, N_1]\) and \([N_1 + 1, \ldots, N]\) refer to the list of interferer UEs and UAVs, respectively. \( \alpha_t, \alpha'_t \) and \( \alpha_{t,j} \) are unique values satisfying the following equality (fractional decomposition)

\[ \prod_{t=1}^{N_1} (1-x\gamma_{tv})^{-1} \prod_{t=N_1+1}^{N} (1-xB_{tv})^{-1} \left( 1 - \frac{x A_{uv}}{m} \right)^{-m} \]

\[ = \sum_{t=1}^{N_1} \frac{\alpha_t}{x - \frac{1}{\tau_{tv}}} + \sum_{t=N_1+1}^{N} \frac{\alpha'_t}{x - \frac{1}{B_{tv}}} + \sum_{t=N_1+1}^{N} \sum_{j=1}^{m} \frac{\alpha_{t,j}}{(x - \frac{m}{A_{uv}})^j}. \]

(2.16)

Proof. See Appendix 9.2.

As for the outage probability of a UAV, we consider the same communication model adopted in this section and we propose the following theorem.

**Theorem 4. Outage probability on the uplink for a UAV**

The probability of outage on the uplink for a UAV \( u \) communicating with a BS \( v \) is expressed as

\[ P^\text{UAV}_{\text{out,uv}}(\gamma_{th}) = \sum_{j=1}^{m} \left( \beta_{1j} \frac{(-1)^j}{(j-1)!} \left( \frac{m}{A_{uv}} \right)^{-j} \left( \Gamma(j) + \sum_{t=1}^{N_1} \alpha_{t,j} (\gamma_{tv}) \right) \right) \]

\[ + \sum_{t=N_1+1}^{N} \sum_{j=1}^{m} \alpha'_{t,j} (B_{tv}) - \sum_{t=N_1+1}^{N} \sum_{j=1}^{m} \alpha_{t,j} \frac{(-1)^j}{(j-1)!} \left( A_{tv}/m \right) \]

\[ - \beta_{21} B_{uv} \left[ 1 + \exp \left( -\frac{\tilde{\gamma}_{th}}{B_{uv}} \right) \left( \sum_{t=1}^{N_1} \frac{\alpha_t}{\gamma_{uv} + \frac{m}{A_{uv}}} + \sum_{t=N_1+1}^{N} \frac{\alpha'_t}{\gamma_{uv} + \frac{1}{B_{tv}}} \right) \]

\[ - \sum_{t=N_1+1}^{N} \sum_{j=1}^{m} \frac{\alpha_{t,j}}{(\gamma_{uv} + \frac{m}{A_{uv}})^j (j-1)! \Gamma(j)} \right]. \]

(2.17)

with \( \beta_{1j} \) and \( \beta_{21} \) are unique values satisfying the following formula

\[ \left( 1 - \frac{A_{uv}}{m} \right)^{-m} \left( 1 - xB_{uv} \right)^{-1} = \sum_{j=1}^{m} \frac{\beta_{1j}}{(x - \frac{m}{A_{uv}})^j} + \frac{\beta_{21}}{(x - \frac{1}{B_{uv}})}. \]

(2.18)
The function \( f_{j,j'}(S) \) is provided as

\[
f_{j,j'}(S) = \sum_{p=1}^{n} S_{j'}^{j'}(\theta_p) j'-1 \lambda_p \Gamma \left( j, \frac{m \gamma_{th}(\theta_p S + 1)}{A_{uv}} \right),
\]

where \( \lambda_p \) and \( \theta_p \) denote respectively the weight and the zero factors of the \( n \)-th order Laguerre polynomials [26]. \( \Gamma(a,z) \) is the upper incomplete gamma function defined as \( \Gamma(a,z) = \int_{z}^{\infty} t^{a-1} e^{-t} dt \).

Proof. See Appendix 9.2.

2.2 Effective Rate

This section derives the expression of the effective rate for UAV communications in cellular networks. The effective rate is used as a performance indicator for eMBB services. Indeed, eMBB services require communication with high transmission rate. To this end, we use the effective rate, defined as the achieved rate at the receiving node, which provides a better QoS evaluation. We consider the scenario where UAVs are equipped with RAT and can serve as flying BSs to provide connectivity to ground IoT devices (for instance, in the case of mission-critical IoT applications, IoT devices equipped with a camera are deployed to provide video streaming on the uplink). As mentioned in Section 1.1, UAV-aided wireless communication can be used to support uncovered or crowded areas [2, 3]. The following system model is considered in order to derive the expression of the effective rate, on the uplink scenario, for the IoT nodes connected to their serving UAVs.

![Figure 2.3. System model (UAV-based network connectivity extension).](image)

Let \( \mathcal{U} \) be the set of IoT devices and \( \mathcal{V} \) the set of serving UAVs. The three-
dimensional plane where the UAV \( v \) can be deployed is denoted \( \mathcal{L}_v \). Let us also denote by \( u \in \mathcal{U} \) the source IoT node and by \( v \in \mathcal{V} \) the serving UAV. The latter employs an OFDMA technique to serve the connected devices. Intra-cell interference is thus neglected and the interference can only be caused by non-served IoT devices, as shown in Figure 2.3. For a node \( u \), the interference originates from nodes in neighboring cell partitions that use the same sub-carriers as \( u \). Let \( B \) denote the set of sub-carriers. The fading coefficient for the link \( uv \) is denoted by \( h_{uv} \) and follows a Nakagami-\( m \) distribution. Note that both LoS and NLoS conditions can be modeled by adjusting the parameters of the Nakagami-\( m \) distribution. Then, the received signal \( r_v \) can be expressed as

\[
r_v = h_{uv} \sqrt{p_u x_u} + \sum_{t=1}^{N_v} h_{tv} \sqrt{p_t x_t} + n_v.
\]  

(2.20)

The second term in the right hand side of (2.20) represents the interference impact from nodes \( t \) \((t = 1, \ldots, N_v, \text{and } N_v \text{ is the number of interfering nodes on the UAV } v)\). The nodes \( u \) and \( t \) transmit the symbols \( x_u \) and \( x_t \) with the powers \( p_u \) and \( p_t \), respectively. As for the third term in (2.20), \( n_v \), it accounts for a zero-mean additive white Gaussian noise with variance \( N_0 \). The instantaneous received SINR for the link \( uv \) can be defined as

\[
\text{SINR}_{uv} = \frac{\gamma_{uv}}{1 + \sum \gamma_{tv}} \approx \frac{\gamma_{uv}}{\sum \gamma_{tv}}.
\]

(2.21)

where \( \gamma_{uv} \) and \( \gamma_{tv} \) respectively stand for the instantaneous received SNR of the links \( uv \) and \( tv \). The approximation in (2.21) is valid if the noise power can be neglected compared to the interference power. This is generally a well-accepted assumption in the literature and is known as an interference-limited regime. Then, we can express the SNR of \( uv \), \( \gamma_{uv} \), as

\[
\gamma_{uv} = p_u h_{uv}^2 / N_0,
\]

(2.22)

and the mean value of \( \gamma_{uv} \), denoted by \( \bar{\gamma}_{uv} \), can be determined as

\[
\bar{\gamma}_{uv} = p_u \mathbb{E}[h_{uv}^2] / N_0 = p_u \times 10^{-\frac{PL_{uv}}{10}} / N_0,
\]

(2.23)

where \( \mathbb{E}[h_{uv}^2] \) reflects the channel variance and \( \mathbb{E}[\cdot] \) stands for the expectation operator. The former can be computed as \( \mathbb{E}[h_{uv}^2] = 10^{-\frac{PL_{uv}}{10}} \), where \( PL_{uv} \) is the path loss in dB scale. In this study, we consider the path loss
model adopted by 3GPP [4] as

\[ PL_{uv} = 28.0 + 22 \ \log_{10}(d_{uv}^{\text{DL}}) + 20 \ \log_{10}(f_c). \]  

(2.24)

d_{uv}^{\text{DL}} \text{ reflects the Euclidean distance between the transmitter and the receiver, while } f_c \text{ accounts for the carrier frequency.}

To denote that the random variable (RV) \( X \) follows a Gamma distribution with parameters \( \alpha \) and \( \beta \), we use the shorthand notation \( X \sim G(\alpha, \beta) \). The SNR \( \gamma_{uv} \) is Gamma distributed with parameters \( \alpha_{uv} \) and \( \beta_{uv} = \gamma_{uv}/\alpha_{uv} \) and can thus be expressed as \( \gamma_{uv} \sim G(\alpha_{uv}, \beta_{uv}) \). The total interference at the UAV \( \gamma_I = \sum_{t=1}^{N_v} \gamma_{tv} \) is the sum of \( N_v \) independent non-identically distributed Gamma RV, with \( t = 1, \ldots, N_v \) refers to the \( N_v \) interfering nodes affecting the UAV \( \gamma_I \sim G(\alpha_v, \beta_v) \). In addition, the probability density function (PDF) of \( \gamma_I \) can be approximated by a Gamma distribution with parameters \( \alpha_v \) and \( \beta_v \) (i.e., \( \gamma_I \sim G(\alpha_v, \beta_v) \)), with

\[
\alpha_v = \frac{\left( \sum_{t=1}^{N_v} \alpha_{tv} \beta_{tv} \right)^2}{\sum_{t=1}^{N_v} \alpha_{tv} \beta_{tv}^2},
\]  

(2.25)

\[
\beta_v = \frac{\sum_{t=1}^{N_v} \alpha_{tv} \beta_{tv}^2}{\sum_{t=1}^{N_v} \alpha_{tv} \beta_{tv}}.
\]  

(2.26)

Furthermore, we also consider the effect caused by packet retransmission. Indeed, a successful reception requires a varying number of packet retransmission. To this end, we consider an Automatic Repeat Request (ARQ) scheme until a successful reception or a maximum number of retransmission \( E^r \) is reached (each node is equipped with a buffer to store the packets before their transmission).

**Theorem 5. Effective Rate on the uplink for an IoT node**

For a node \( u \in U \) transmitting data on ARQ mode with a rate \( R_u \) over the sub-carrier \( b \) to its serving UAV \( v \in V \) deployed at the location \( l \in L_v \), the average effective rate at the receiving UAV can be expressed as

\[ R_{u,l,b}^{\text{eff}} = \frac{R_u \times (I_u)^2}{1 - (1 - I_u)^{E^r}}. \]  

(2.27)

The function \( I_u = I(2^{R_u} - 1, \alpha_{uv}, \beta_{uv}, \alpha_v, \beta_v) \) is expressed as

\[
I(x, \alpha, \beta, \alpha_v, \beta_v) = \left( \frac{x \beta_v}{\beta} \right)^{-\alpha_v} \frac{\Gamma(\alpha + \alpha_v)}{\Gamma(\alpha) \Gamma(1 + \alpha_v)} 2F_1 \left( \alpha_v, \alpha + \alpha_v, 1 + \alpha_v, \frac{-\beta}{\alpha \beta_v} \right),
\]  

(2.28)
where $\text{}_2F_1(a, b, c, z)$ is the Gauss hypergeometric function.

Proof. See Appendix 9.3.

The above theorem provides the effective rate on the uplink scenario. The underlying equations consider path loss, fast fading and interference. The theorem also considers the outage probability, which is expressed as $1 - I_u$ as detailed in Appendix 9.3. This expression is original and can not be found in the literature.

### 2.3 Transmission Delay

This section derives the expression of the transmission delay for UAV communications in cellular networks. The transmission delay is used as a performance indicator for uRLLC services. Indeed, uRLLC services require reliable communication with reduced delay. We consider the same communication model introduced in Section 2.2, where UAVs are deployed to provide network connectivity to ground IoT devices. As mentioned earlier in the previous section, each node is equipped with a buffer to store the packets before their transmission. The use of buffers allows to control the packet flow and is considered as the main source for the delay [27]. The data generated by the node $u$ are assumed to follow a Poisson distribution with parameter $\lambda_u$. In order to model the delay over multi sub-carriers, we consider a parallel $M/M/1$ queuing model where the traffic is equitably shared among the different queues. Consequently, the arrival rate $\lambda_u$ of the IoT node $u$ will be divided on the number of parallel queues $Q_u$. Let $E^d$ be the maximum number of retransmission under the ARQ scheme. Therefore, the expected delay for the direct communication, between the node $u$ and its serving UAV $v$ over the sub-carrier $b$, can be expressed as follows:

**Theorem 6. Communication delay on the uplink for an IoT node**

For a node $u \in \mathcal{U}$ transmitting data on ARQ mode with a rate $R_u^d$ over the sub-carrier $b$ to its serving UAV $v \in \mathcal{V}$ deployed at the location $l \in \mathcal{L}_v$,
the transmission delay can be expressed as

\[
D_{u,l,b,Q_u} = \frac{\lambda_u T_p^2}{Q_u^2(1 - \rho_u)} \left( \frac{1 - (2E^d - 1)(1 - I_u)^E^d}{I_u} \right)
+ \frac{2(1 - I_u)(1 - (1 - I_u)E^d - 1)}{I_u^2} + \frac{T_F}{2} + \frac{1 - (1 - I_u)^E^d}{I_u}T_F, \tag{2.29}
\]

where \(T_F\) refers to time required for a single transmission of, \(I_u = I(2^{R_u} - 1, \alpha_{uv}, \beta_{uv}, \alpha_v, \beta_v)\) and \(\rho_u\) is provided as

\[
\rho_u = \frac{\lambda_u(1 - (1 - I_u)^E^d)T_F}{Q_u^2I_u}. \tag{2.30}
\]

Proof. See Appendix 9.3.

Note that the transmission delay expression formulated in Theorem 6 includes the queuing delay and also the retransmission delay. It also considers the outage probability, which is expressed as \(1 - I_u\) as detailed in Appendix 9.3. This expression is original and cannot be found in the literature. The average delay over all the used sub-carriers by the IoT node \(u\) can therefore be expressed as

\[
\text{Avr}(D_{u,l,Q_u}) = \sum_{b \in B} \frac{1}{Q} D_{u,l,b,Q_u} = \sum_{b \in B} \bar{D}_{u,l,b,Q_u}. \tag{2.31}
\]

2.4 Performance Analysis

We provide in this section an analysis of the performance of UAV communications in cellular networks, considering the indicators developed in the previous sections. We also conduct a discussion on the key parameters that affect the performance of these networks.

We first start by evaluating the outage probabilities of UAV communications in cellular networks. To this end, we develop a simulator using python programming language. The considered communication model is implemented considering a Nakagami model with parameter \(m = 2\), a carrier frequency \(f_c\) equal to 2 GHz, and a noise variance \(N_0\) of -130 dBm [28]. The evaluation is performed in a 1 km x 1 km square area with 12 BSs each one having 11 sub-carriers. The altitude of the UAVs is randomly chosen between 22.5 m and 300 m (the path loss expression provided in [4]
is valid within this range of altitude). The simulation results are presented in what follows.

Figure 2.4 illustrates the average outage probability of UAVs and UEs on the downlink for different values of the parameter $\gamma_{th}$. These results are obtained by using 50 UEs and 50 UAVs in the simulation. Figure 2.4 shows that the outage increases as the value of $\gamma_{th}$ increases. The parameter $\gamma_{th}$ indicates the threshold that the SINR should exceed in order to have successful reception of the packets. It represents the receiver sensitivity threshold. As $\gamma_{th}$ increases, the receiver’s ability to detect weak signals decreases. This highlights the importance of choosing a good value for $\gamma_{th}$. Moreover, we can also see from Figure 2.4 that on average, the outage probability for the UAVs is larger than that of the UEs (on the downlink). This is mainly due to the better channel condition characterizing aerial communication, which is translated into more interference on the UAVs on the downlink. On the other hand, Figure 2.5 presents the same evaluation on the uplink scenario. It shows that the outage probability for the UEs is larger than that of the UAVs (on the uplink). This is mainly due to LoS condition characterizing the UAV communication and leading to a smaller outage probability compared to ground UEs. These comply with the results of field evaluations and show the issue of downlink and uplink communications of UAV communications in cellular networks.

![Figure 2.4. Outage probabilities $P_{\text{out,vu}}(\gamma_{th})$ for different threshold values $\gamma_{th}$ (downlink).](image1)

![Figure 2.5. Outage probabilities $P_{\text{out,uv}}(\gamma_{th})$ for different threshold values $\gamma_{th}$ (uplink).](image2)

To further investigate this problem, we illustrate in Figure 2.6 and Figure 2.7 the impact of the number of devices (UEs and UAVs) on the average outage probability on the downlink and the uplink, respectively. We notice that for both UEs and UAVs, the outage probability increases as the number of deployed devices increases. However, the outage probability of UAVs increases faster compared to the outage probability of UEs for the downlink scenario while the opposite can be noticed on the uplink sce-
nario. These show that as the number of devices in the network increases, it becomes challenging to maintain a good link quality for UAVs as they are more sensitive to interference on the downlink. These also raise the need and the requirement to develop efficient solutions to enhance the performance of UAV communications in cellular networks.

By carefully analyzing the outage expressions on the downlink, considering Theorem 1 and Theorem 2, we can conclude that the outage probabilities depend on the number of interfering BSs and on the impact they are causing as reflected by the terms \( \bar{\gamma}_{tv} \) for Theorem 1, and by the terms \( A_{tu} \) and \( B_{tu} \) for Theorem 2. Minimizing the outage probability would be translated into optimizing the sub-carrier assignment, the transmission power and the deployment of the UAVs. These parameters influence both the number of interfering BSs and their impact. Note that this analysis can also be extended to the uplink scenario, where the associated outage probability expressions are formulated in Theorems 3 and 4.

On the other hand, both of the expressions of the effective rate and the transmission delay, reflected in Theorem 5 and Theorem 6, are based on the outage probability, as detailed in Appendix 9.3. Furthermore, reducing the outage probability is directly translated into enhanced effective rate and transmission delay. This also makes sub-carrier assignment, power allocation and UAV deployment as key factors affecting these two performance indicators. Note that the expressions of the effective rate and the transmission delay are also affected by other factors, such as the maximum number of retransmission and the transmission rate, which have been evaluated in the literature.
2.5 Summary

This chapter investigated the performance impact of UAV communications in cellular networks. More precisely, the chapter focused on defining performance indicators and analysing the key factors that affect the performance. To this end, we considered a realistic model that accounts for most of the propagation phenomena experienced in wireless signals and we derived the expressions of the outage probability, the effective rate and the transmission delay for UAV communications in cellular networks. These expressions are originals and can not be found in the literature. Furthermore, in order to evaluate the impact, we have implemented the model in a simulation environment. The obtained results are aligned with field evaluations and confirm the need for efficient solutions to enhance the performance of UAV communications in cellular networks. The analysis also showed that parameters, namely sub-carrier assignment, power allocation and UAV deployment, are key factors that affect the performance. All the next chapters will build from the developed performance indicators and target optimizing the identified factors to enhance the performance of UAV communications in cellular networks.
This chapter addresses the support of the co-existence of UAVs and UEs in cellular networks, which are both characterized by different channel conditions. This chapter considers the downlink scenario, which reflects the C2 communication for the UAVs. This scenario is very important for UAVs, as any delay in C2 communication could not be tolerable and might have catastrophic consequences, not to mention communication loss. This chapter builds from the outage probability expressions derived in the previous chapter (Chapter 2), and elaborates on optimizing sub-carrier assignment and power allocation on the downlink to reduce the outage probability. Given the underlying complexity of the problem, which is known to be NP-hard, the chapter introduces a solution based on game theory. First, we argue that separating between UAVs and UEs in terms of the assigned sub-carriers reduces the interference impact on the users. This is materialized through a matching game. Moreover, in order to boost the partition, we propose a coalitional game that considers the outcome of the first one and enables users to change their coalitions and reduce their outage probability. Furthermore, a power optimization solution is introduced, which is considered in the two games. A series of performance evaluations are performed to prove the effectiveness of the solution. The contribution of this chapter is based on publication VI.

3.1 Problem Formulation

The problem formulation in this chapter is based on the outage probability expressions defined in Theorem 1 and Theorem 2 of Section 2.1 (Note that the same notations of this section are maintained in this chapter). Let 

\[ P_b = [P_{1,b}, P_{2,b}, \ldots, P_{B,b}] \]

be the transmission power to be used by each BS for the sub-carrier \( b \) (we summarize the notations in Table 3.1). We define
$P_{\text{out,}vu}(P_b)$ as

$$P_{\text{out,}vu}(P_b) = \begin{cases} 
P_{\text{out,}vu}^{\text{UAV}}(P_b), & \text{if } u \in U, \\
P_{\text{out,}vu}^{\text{UE}}(P_b), & \text{if } u \in Q,
\end{cases}$$

(3.1)

Table 3.1. Summary of Notations for the Problem of Supporting the Co-existence of UAVs and UEs.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Q$</td>
<td>Set of UEs ($</td>
</tr>
<tr>
<td>$U$</td>
<td>Set of UAVs ($</td>
</tr>
<tr>
<td>$V$</td>
<td>Set of BSs ($</td>
</tr>
<tr>
<td>$A$</td>
<td>Set of users $A = Q \cup U$ ($</td>
</tr>
<tr>
<td>$B$</td>
<td>Set of sub-carriers ($</td>
</tr>
<tr>
<td>$vu$</td>
<td>Link between the user $u$ and its serving BS $v$.</td>
</tr>
<tr>
<td>$tu$</td>
<td>Link between the user $u$ and an interfering BS $t$ (${1, \ldots, N}$ refer to the list of interfering BSs).</td>
</tr>
<tr>
<td>$P_{u,b}$</td>
<td>Power employed by the BS $v \in V$ on the sub-carrier $b \in B$.</td>
</tr>
<tr>
<td>$\bar{P}_{vu}$</td>
<td>Minimum transmission power a BS $v$ should employ to send data to the user $u$.</td>
</tr>
<tr>
<td>$V(v)$</td>
<td>Set of users connected to the BS $v \in V$.</td>
</tr>
<tr>
<td>$W(b)$</td>
<td>Set of users assigned to the sub-carrier $b \in B$.</td>
</tr>
<tr>
<td>$S$</td>
<td>Set of coalition; $S = {S_1, S_2, \ldots, S_B}$. A coalition $S_i$ is the set of users using the sub-carrier $b \in B$.</td>
</tr>
<tr>
<td>$w(S)$</td>
<td>Characteristic function of the coalition $S$.</td>
</tr>
<tr>
<td>$\Pi_S(u)$</td>
<td>The payoff of the player $u \in S$.</td>
</tr>
<tr>
<td>${S_1, S_2} \triangleright_{u_1} {S'_1, S'_2}$</td>
<td>The transfer operation of the user $u_1 \in S_1$ to the coalition $S_2$. The resulting state of the coalitions are respectively denoted by $S_1$ and $S_2$.</td>
</tr>
<tr>
<td>${S_1, S_2} \triangleright_{u_1}^{u_2} {S'_1, S'_2}$</td>
<td>The operation for exchanging the users $u_1 \in S_1$ and $u_2 \in S_2$. The resulting state of the coalitions are respectively denoted by $S_1$ and $S_2$.</td>
</tr>
</tbody>
</table>

where $P_{\text{out,}vu}^{\text{UAV}}(P_b)$ and $P_{\text{out,}vu}^{\text{UE}}(P_b)$ are the outage probabilities for the link $vu$ provided by Theorem 1 and Theorem 2 respectively. $P_b$ is the transmission power to be used by the set of BSs on the sub-carrier $b$ assigned to the user $u$. To characterize the selected sub-carrier for the communication between a BS $v$ serving a user $u$, the decision Boolean variable $x_{vu,b}$ is defined as

$$x_{vu,b} = \begin{cases} 
1, & \text{If the sub-carrier } b \text{ is used for the link } vu, \\
0, & \text{Otherwise.}
\end{cases}$$

(3.2)

Consequently, the joint problem of sub-carrier assignment and power optimization can be expressed as
minimize $\max_{\{x_{vu,b}\},\{P_{v,b}\}} P_{\text{out,vu}}(P_v)$, \hspace{1cm} (3.3)

\text{s.t.}

\[ \forall v \in V, \forall u \in V(v); \sum_{b \in B} x_{vu,b} = 1, \] \hspace{1cm} (3.4)

\[ \forall v \in V, \forall b \in B; \sum_{u \in V(v)} x_{vu,b} \leq 1, \] \hspace{1cm} (3.5)

\[ \forall v \in V, \forall b \in B; 0 \leq P_{v,b} \leq P_{\text{max}}. \] \hspace{1cm} (3.6)

The objective function in (3.3) is to minimize the outage probability for the set of users connected to the cellular network. Both sub-carrier assignment and power optimization are considered for minimizing the outage probability. (3.4) ensures that each user $u$ is assigned with one sub-carrier from its serving BS $v$. Here, $V(v)$ refers to the set of users connected to the BS $v$, as mentioned in Table 3.1. (3.5) captures the fact that a sub-carrier is used at most by one user. (3.6) is the feasibility constraint for the transmission power. The formulated optimization problem is a non-linear program, which is complex to solve, especially for large networks. This complexity is inherent from the proposed communication model, which considers most of the propagation phenomena characterizing wireless communication. The next section proposes a solution to jointly optimize sub-carrier and power allocation for UAV communications in cellular networks.

3.2 A Game-based Solution for Enhanced Performance

As discussed previously, the QoS on the downlink is affected by the number of interfering BSs and the impact they cause. For this purpose, the joint problem of sub-carrier assignment with power optimization is considered. We propose a solution based on the framework of game theory. The game is divided into two independent sub-games: a matching sub-game and a coalitional sub-game. The matching sub-game, $G_1$, is executed at first. It aims at matching the users to the sub-carriers in a way to meet the preferences of each other. The preferences are defined in a way to optimize the outage probability of the users and to enhance the downlink communication of cellular-based UAVs. The second sub-game, $G_2$, builds on the outcome assignment of the matching game to boost this optimiza-
tion. It is based on the framework of coalitional games and defines operations to enable users to change their coalitions in order to enhance their QoS. The power optimization is taken into account in the two sub-games. The following sections explain our proposed solution in more detail.

3.2.1 Matching Sub-Game Optimization

The framework of many-to-one matching game [29] is adopted to model the problem. A related projection of this framework is the college admissions problem where colleges are receiving the applications of students and each college has a fixed quota for accommodation. Both colleges and students have an order of preference. The goal is to model the interactions between these entities and to achieve a matching stability satisfying as much as possible their preferences.

The game $G_1$ is defined as $G_1 = (A, B, \succeq^u, \succeq^b)$, where $A = Q \cup U$ is the set of UEs and UAVs (considered as students) while $B$ is the set sub-carriers (considered as colleges). $\succeq^u$ and $\succeq^b$ are, respectively, the preference relation for a user $u \in A$ and a sub-carrier $b \in B$. The goal of the game is to associate each user $u \in A$ to a sub-carrier $b \in B$, while meeting certain constraints and preferences. Indeed, each sub-carrier $b$ has a quota of only $V$ (number of BSs). Moreover, a sub-carrier can accommodate at most one user connected to a given BS. This is due to the fact that each of the connected users to a given BS will be served by different sub-carriers. Let $W(b)$ be the set of users assigned to the sub-carrier $b$. Consequently, the matching game should maintain the following condition:

$$\forall b \in B, \forall v \in V; \quad |W(b) \cap V(v)| \leq 1. \quad (3.7)$$

To define the order of preference, one would rely on equations (2.6) and (2.11) as they express the objective function to minimize (minimizing the outage probability for each user). However, as it can be seen from those equations, computing the outage probability for a user depends on the terms $\bar{\gamma}_{tu}$ (for a UE) or $A_{tu}$ and $B_{tu}$ (for a UAV). These terms reflect the interference part from the non-serving BSs $t$ using the same sub-carrier as $u$. In other words, an interdependence is present between users to specify a sub-carrier, based on (2.6) and (2.11), as it depends on the choice of the other users in using the same sub-carrier or not. This makes the direct usage of those equations for defining the order of preference very complex.
In order to set a preference order for the users, we propose to rely on minimizing the interference impact over the link $t_u$ for each user $u$. We first evaluate the interference amount over the links $t_u$. The associated terms reflect the mean SNR from the interfering BS to the user $u$ ($\bar{\gamma}_{tu}$ in the case of a UE, and $A_{tu}$ and $B_{tu}$ in the case of a UAV). The formulas for the mean SNR are expressed in (2.4) and (2.10). Therefore, the terms related to the links $t_u$ depend on the power employed by the interfering BS for transmitting data to the served users. The power value would be larger than the one employed to serve users in an interference-free situation. Indeed, if a user fails in receiving packets from its serving BS in an interference-free environment, it will definitely fail in the presence of interference. We consider this fact to estimate the minimum transmission power employed by a BS $v$ to serve its user $u$.

**Lemma 1.** A UE $u$ will fail in receiving data from its serving BS $v$ iff the transmission power employed by the latter is less than a value given as

$$\bar{P}_{vu} = SNR_{th}N_0/10^{-\frac{PL_{UE}^{vu}}{10}},$$

where, $SNR_{th}$ reflects the receiver sensitivity. As for a UAV $u$, the value is given as

$$\bar{P}_{vu} = SNR_{th}N_0/(P_{vu}^{LoS}10^{-\frac{PL_{UAV}^{vu}}{10}} + P_{vu}^{NLoS}10^{-\frac{PL_{UAV}^{vu}}{10}}).$$

Equations (3.8) and (3.9) of the above lemma can be derived from equations (2.4) and (2.10), respectively. They provide the minimum transmission power a BS $v$ should employ to send data to the user $u$. Below this value, the user will definitely fail in receiving the data. A numerical evaluation of $\bar{P}_{vu}$ for both UEs and UAVs, considering the same $SNR_{th}$, shows that UAVs require less transmission power compared to ground UEs. This result is due to the better channel condition characterizing aerial communication. Consequently, the interference impact, over the link $t_u$, is bigger when the interfering BS $t$ is serving a UE compared to the case where it is serving a UAV. We exploit this fact to order the preferences in a way to reduce the interference impact. The following two rules are introduced.

1. As per the previous discussion, users of the same type (either UEs or UAVs) would prefer to be gathered in the same sub-carriers. Indeed, the heterogeneity in terms of channel conditions between flying UAVs and ground UEs is behind the issue of UAV communications in cellular
networks. Due to the close free-space signal propagation, a flying UAV might require less power to receive data on the downlink than what is required for a UE on the ground having the same distance. Consequently, having UEs and UAVs on the same sub-carrier might result in considerable interference on UAVs from the BSs serving UEs. Separating between UAVs and UEs in the assigned sub-carriers would reduce this impact. This constitutes the preference of the users.

2. The sub-carriers will receive the application of the users. The admitted users within a given sub-carrier will be subject to interference from non-serving BSs whose served users are also admitted in this sub-carrier. As discussed before, the interference terms reflect the mean SNR and depend on the power employed by the non-serving BSs. To reduce the interference impact, each sub-carrier would prefer having users requiring less transmission power from their serving BSs. In addition, a sub-carrier accommodating users requiring large transmission powers would admit fewer users. The power value $\bar{P}_{vu}$ is used to compare between users’ transmission power. This represents the basis for sub-carriers to order their preferences of the users.

Considering the first rule, the users are not able to know which sub-carriers they are gathered in, so they can make their choices and set the preferences. In order to overcome this issue, we consider that the sub-carriers are ordered ($B = [b_1 \ldots b_B]$). Consequently, users from the same type can easily be gathered in the same sub-carriers by choosing to be near one of the two ends. We consider that the UEs would prefer being in the first sub-carriers while the UAVs would rather be interested in the last ones. As for the second rule, a sub-carrier uses the transmission power $\bar{P}_{vu}$ to order its preferences from the candidate users of each BS. It prefers at most one user per BS, thus maintaining condition (3.7).

Based on this discussion, we define the preference relation for users/sub-carriers and the admission criteria as follows.

**Definition 1. Ordering of preferences and admission criteria**

For a UE $u \in U$, the preference order of the sub-carriers is defined as follows:

$$
Pref^{UE}(u) \iff b_1 \succeq^u b_2 \succeq^u \ldots \succeq^u b_B.
$$  

(3.10)

For a UAV $u \in U$, the preference order of the sub-carriers is defined as
Each sub-carrier $b \in B$ receives applications of the candidate users and prefers at most one user per BS. The preference relation $\succeq_b$ is defined between two users $u_1$ and $u_2$ connected to the same BS $v$ ($u_1, u_2 \in V(v)$) as follows

$$u_1 \succeq_c u_2 \iff \bar{P}_{vu_1} < \bar{P}_{vu_2}.$$  

(3.12)

The above definition allows ordering the preferences for both users and sub-carriers. As discussed before, UEs prefer being in the first sub-carriers while the UAVs would rather be interested in the last ones. This is, respectively, reflected by equations (3.10) and (3.11) of Definition 1. Here, $b_i \succeq u b_j$ means that the user $u$ prefers the sub-carrier $b_i$ on $b_j$. On the other hand, the sub-carriers use the transmission power $\bar{P}_{vu}$ to establish the preference order of the candidate users connected to a BS $v$. As previously discussed, the preferred user is the one having the smallest value of $\bar{P}_{vu}$. This is materialized through equation (3.12) of Definition 1.

The matching will result in assigning the UEs to the first sub-carriers and the UAVs to the last ones. When there are some BSs having fewer users than the number of sub-carriers, the matching will end up with some free sub-carriers in between the two types of users. However, this means that a sub-carrier in the middle might have no users while others are filled. In order to overcome this situation, we introduce virtual users to the network in a way to complete the network. These virtual users are considered to complete the number of users for each BS. They will be removed once the matching is done. Moreover, in order to enable sub-carriers to accommodate users requiring large transmission powers to admit fewer users (rule 2), the virtual users are distributed to have more large values of the $\bar{P}_{vu}$ parameter. A half-normal distribution is used to distribute $\bar{P}_{vu}$ between the smallest and the biggest values.

One important notion in the matching game is the stability. It defines the situation where players are matched and have no incentive to change their association. The matching algorithm should lead to a stable situation, which is defined as follows.

**Definition 2. Matching stability**

The matching is said to be unstable if there are two users $u_1$ and $u_2$
connected to the same BS $v$ ($u_1, u_2 \in V(v)$) such as $u_1$ is matched to $b_1$ and $u_2$ is matched to $b_2$, although $u_2$ prefers $b_1$ to $b_2$ and $b_1$ prefers $u_2$ to $u_1$. Formally, this is expressed as

$$\begin{cases} \exists v \in V, \exists u_1, u_2 \in V(v), \exists b_1, b_2 \in B; \\
u_1 \in W(b_1) \text{ and } u_2 \in W(b_2) \text{ and } b_2 \succeq_{u_1} b_1 \text{ and } u_1 \succeq_{u_2} u_2. \end{cases}$$  

(3.13)

Once the sub-carriers are matched with the users, a power optimization procedure is considered. This would allow reducing the interference impact from non-serving BSs, after the matching process, while maintaining the outage probability for the concerned users under a certain threshold. The power optimization procedure will be considered for each sub-carrier of the set of BSs. As it can be noticed from (2.6) and (2.11), the outage probability for a user is impacted by the transmission power employed by the serving and interfering BSs. This is referred respectively by the terms $\bar{\gamma}_{vu}$ and $\bar{\gamma}_{tu}$ in Theorem 1 and by the terms $A_{vu}, B_{vu}, A_{tu}$ and $B_{tu}$ in Theorem 2. This shows the interdependence between the transmission powers that should be employed by the different BSs, and also the complexity of deriving these powers from equations (2.6) and (2.11). On the other hand, when the transmission powers of the interfering BSs are unchanged (over the links $tu$), the outage probability of the user $u$ decreases as the transmission power from the serving BS increases (over the link $vu$). This can be derived from the outage probability definition, which is $P_{\text{out}}(\gamma_{th}) = P(\gamma_{vu}/(1 + \sum_{t=1}^{N} \gamma_{tu}) \leq \gamma_{th})$. This consideration is exploited to propose the power optimization described through Algorithm 1.

Algorithm 1 presents the power optimization procedure for a sub-carrier $b \in B$ of all the BSs. Initially, the maximum transmission power is used (line 1). For each BS $v \in V$, if it is serving a user $u$ through the sub-carrier $b$ (lines 5 and 6), a power optimization is considered; The transmission power of the BS $v$ is reduced until having the maximum outage probability smaller than a threshold $P_{\text{out},th}$, while maintaining the power larger than the minimum value, $P_{vu}$ (lines [8-10]). As explained in the previous paragraph, when the transmission powers from the interfering BSs are unchanged, the outage probability for the user $u$ increases as the transmission power from the serving BS decreases. Since changing the transmission power of a BS also influences the outage probability of users subject to interference, this power optimization is repeated. Lines [11-14] evaluate if the transmission power has changed after executing
lines [8-10]. The variable ‘Stable’ is used to characterize the stable situation, where no BS needs to reduce its transmission power. This will allow reducing the transmission power of the BSs while maintaining desired outage probabilities.

Algorithm 1 Power optimization for users using \( b \in B \).

\[
\text{Require: } P_{\text{out,th}}, \text{SNR}_{\text{th}}, P_{\text{stab}}, P_{\text{max}}
\]

1: \( \hat{P}_b = P_{\text{max}} \)

2: \text{while True do}

3: \text{Stable }= \text{True}

4: \text{for each BS } v \in V \text{ do}

5: \text{if } W(b) \cap V(v) \neq \text{null then}

6: \( u = W(b) \cap V(v) \)

7: \( \hat{P}_b = \hat{P}_b \)

8: \text{while } P_{\text{out,vu}}\left(\hat{P}_1, b, \hat{P}_{2}, b, \ldots, \hat{P}_{u,b} - P_{\text{stab}}, \ldots, \hat{P}_{|V|,b}\right) \leq P_{\text{out,th}} \text{ and}

9: \( P_{v,b} - P_{\text{stab}} > P_{vu} \text{ do}

10: \( \hat{P}_b = [\hat{P}_1, b, \hat{P}_{2}, b, \ldots, \hat{P}_{v,b} - P_{\text{stab}}, \ldots, \hat{P}_{|V|,b}] \)

11: \text{end while}

12: \text{if } \hat{P}_b \neq \hat{P}_b \text{ then}

13: \( \hat{P}_b = \hat{P}_b \)

14: \text{Stable }= \text{False}

15: \text{end if}

16: \text{end for}

17: \text{if Stable then}

18: \text{Break}

19: \text{end if}

20: \text{end while}

21: \text{return } \hat{P}_b

The parameters \( P_{\text{max}}, \hat{P}_{vu} \) and \( P_{\text{stab}} \) denote, respectively, the maximum value for the transmission power, the minimum value for the transmission power, and the unit value for reducing the power.

3.2.2 Coalitional Sub-Game Optimization

The matching game provided in the previous section will result in sub-carriers assignment with power optimization. This assignment is a heuristic and might not be optimal. The objective of the second sub-game is to boost this optimization by progressively reducing the outage probability for each user. To this end, we consider the framework of coalitional game. The cooperative nature of this game would allow the enforcement of the optimization achieved in the first sub-game.

Formally, the game \( G_2 \) is defined as \( G_2 = (A, S, w) \); with \( A \) being the set of users (UEs and UAVs) and \( S \) the set of coalitions. A coalition \( S_b \) represents the set of users using the sub-carrier \( b \in B \). The initial coalition assignment is indeed the result of the first matching game. Having said that, the number of coalitions is exactly the number of sub-carriers. We can therefore write \( S = \{S_1, S_2, \ldots, S_B\} \) with \( S_b \subseteq A \). We
note that each two coalitions involves entirely two different set of players; i.e. \( \forall S_1, S_2 \in S : S_1 \neq S_2 \implies S_1 \cap S_2 = \emptyset \) (a user connected to a BS will be served using only one sub-carrier). \( w \) represents the characteristic function and is defined by the payoff of each player, \( w(S_b) = (\Pi_{S_b}(u), u \in S_b) \), as

\[
\Pi_{S_b}(u) = 1 - P_{out, u}(\hat{P}_b). \tag{3.14}
\]

As it can be seen from (3.14), the outage probability is considered in the definition of the payoff of the corresponding player belonging to a coalition. This is coupled with power optimization, \( \hat{P}_b \), leading therefore to an optimized outage probability for all the players in the coalition. As for the benefit of a coalition, it is defined as

\[
w(S_b) = \sum_{u \in S_b} (\Pi_{S_b}(u)). \tag{3.15}
\]

In the context of coalitional game, the users change from one coalition to another in order to have a better payoff. Within our framework, we define two types of operations to enable users to change their coalitions and increase their benefits. These operations are user transfer and user exchange. In the first case, a user belonging to a coalition will be transferred to another one. This could happen when the receiving coalition does not have another user connected to the same BS as the candidate user. In the second case, two users connected to the same BS will be exchanged from their respective coalitions. The execution of these operations would result in two new coalitions instead of the originals\(^1\). The transfer or the exchange would be useful if it leads to an enhanced payoff for the players belonging to the new resulting coalitions. Formally, we define the transfer and the exchange rules as follows:

**Definition 3. Transfer and exchange rules**

A user \( u_1 \in S_1 \) served by a BS \( v \) would be transferred to another coalition \( S_2 \) (does not have another user served by the same BS; i.e., \( V(v) \cap S_2 = \emptyset \)), resulting respectively into two coalitions \( S'_1 \) and \( S'_2 \), iff:

\[
\{S_1, S_2\} \triangleright^u \{S'_1, S'_2\} \iff w(S'_1) - w(S_1) > w(S_2) - w(S'_2). \tag{3.16}
\]

Two users \( u_1 \in S_1 \) and \( u_2 \in S_2 \) served by the same BS \( v \) \((u_1, u_2 \in V(v))\) would be exchanged, resulting into two coalitions \( S'_1 \) and \( S'_2 \) respectively, \(^1\)The number of coalitions is always the same. We mean by 'new coalitions' the original ones after executing the operations (transfer or exchange).
iff:

\[
\begin{align*}
\{S_1, S_2\} \xrightarrow{\alpha_{u_1}} \{S'_1, S'_2\} & \iff \\
\left(\Pi_{S'_2}(u_1) \geq \Pi_{S_1}(u_1) \land \Pi_{S'_1}(u_2) \geq \Pi_{S_2}(u_2)\right) \quad (3.17.1) \\
\text{And} \\
\left(\forall u \in S_1 \cap S'_1 : \Pi_{S'_1}(u) \geq \Pi_{S_1}(u) \land \forall u \in S_2 \cap S'_2 : \Pi_{S'_2}(u) \geq \Pi_{S_2}(u)\right) \quad (3.17.2) \\
\text{And} \\
\left(\Pi_{S'_2}(u_1) > \Pi_{S_1}(u_1) \lor \Pi_{S'_1}(u_2) > \Pi_{S_2}(u_2) \lor \exists u \in S_1 \cap S'_1 : \Pi_{S'_1}(u) > \Pi_{S_1}(u) \lor \exists u \in S_2 \cap S'_2 : \Pi_{S'_2}(u) > \Pi_{S_2}(u)\right) \\
(3.17.3)
\end{align*}
\]

The definition in (3.16) means that a player \(u_1\) will be transferred from the coalition \(S_1\) to the coalition \(S_2\), resulting respectively into two coalitions \(S'_1\) and \(S'_2\), if the gain of this operation on the first coalition is larger than the loss on the second coalition. Indeed, transferring a player from a coalition (without exchange) would be translated into withdrawing an interferer from the coalition. This would enhance the outage probability of the coalition’s users and increase the underlying utility function. On the other hand, the receiving coalition will have a new user causing interference and leading therefore to decreased utility function. The transfer operation would be approved only when the gain is greater than the loss.

As for the exchange rule, the definition in (3.17) means that two players \(u_1 \in S_1\) and \(u_2 \in S_2\) will be exchanged, and leading to two coalitions \(S'_1\) and \(S'_2\), if at least the payoff of one player will be increased after the operation (through conditions in (3.17.3)), while that of all other players remain unaffected (including both the exchanged players (3.17.1) and the other players (3.17.2)). We note that while the transfer rule focuses on the global benefit and payoff of the coalitions, the exchange rule is more centered on the individual profit of the users.

The users change from one coalition to another as defined in the above definition. This process is repeated iteratively. The situation (partition of coalitions) where there is no incentive to do a change is said to be stable.

**Definition 4. Coalitions stability**

A partition of coalitions is said to be stable when the transfer and exchange rules can not be applied (defined in equations (3.16) and (3.17)).
$i.e.,$

$$\begin{align*}
\forall S_1, S_2 \in S, \forall u_1 \in S_1; & \quad \exists S_1', S_2' \subseteq A : \{S_1, S_2\} \triangleright \{S_1', S_2'\} \\
\text{and} & \quad \forall S_1, S_2 \in S, \forall u_1 \in S_1, u_2 \in S_2; & \quad \exists S_1', S_2' \subseteq A : \{S_1, S_2\} \triangleright \{S_1', S_2'\}
\end{align*}$$

(3.18)

### 3.2.3 Global Game and General Algorithm

Based on the framework of game theory, we propose two sub-games to enhance the performance of UAV communications in cellular networks. While the matching sub-game provides an initial assignment of users to sub-carriers with power optimization, the coalitional game boosts this optimization. Algorithm 2 shows the execution steps of the global game.

The matching sub-game will assign a sub-carrier $b \in B$ to each user $u \in A$ (line 1). This assignment respects the ordering of preferences provided in Definition 1. In the logic of the assignment, users (UEs or UAVs) apply for their preferred sub-carriers, while the latter accept or reject the candidates according to their preferences. Lines 3 and 4 identify, respectively, the UEs and the UAVs not yet assigned to a sub-carrier. As per the preference order of the users, the most preferred sub-carrier for the UEs is the lower one while the upper one is the most preferred sub-carrier for the UAVs (equations (3.10) and (3.11) respectively). This is materialized in lines 6 and 11 respectively. The target sub-carriers accept the users as per their preference order defined in equation (3.12). The admission of UEs and UAVs is shown in lines [7-8] and lines [12-13], respectively. Each rejected user will apply for its next preferred sub-carrier.

The coalitional sub-game considers the outcome of the matching game as initial partition of coalitions (line 17). Thereafter, the transfer and exchange operations will be attempted. For each two coalitions $S_1$ and $S_2$ and each BS $v \in V$ (lines [20-21]), the operations will be attempted depending on whether the BS has players in these coalitions. If the BS has a player in each coalition, an exchange operation will be attempted (lines [22-27]). However, if the BS has a player in only one coalition, the transfer operation will be attempted to the other one (lines [28-33] and lines [34-39]). As defined in Definition 3, the transfer and exchange operations will be approved only when they lead to enhanced payoff. The variable ‘Stable’ is used to characterize the stability situation as defined in Definition 4; i.e., the situation where no exchange or transfer rules need to be applied.
Algorithm 2 Global game.

Require: $A = Q \cup \mathcal{U}, \mathcal{V}$
// 1st sub-game
1: while $A \setminus \bigcup_{b \in \mathcal{B}} W(b) \neq \emptyset$ do
2: \hspace{1em} $T = A \setminus \bigcup_{b \in \mathcal{B}} W(b)$
3: \hspace{1em} $Q^{UE} = T \cap Q$
4: \hspace{1em} $Q^{UAV} = T \cap \mathcal{U}$
\hspace{1em} // UEs apply for their preferred sub-carriers using $Pref^{UE}(u)$
5: \hspace{1em} if $Q^{UE} \neq \emptyset$ then
6: \hspace{2em} $b = \text{lower sub-carrier not yet targeted by UEs}$
7: \hspace{2em} $D = \{ \hat{u} \in Q^{UE}, \hat{u} \preceq_b u \ \forall u \in Q^{UE} \cap V(\hat{v}) \}$
8: \hspace{2em} $W(b) = W(b) \cup D$
9: \hspace{1em} end if
\hspace{1em} // UAVs apply for their preferred sub-carriers using $Pref^{UAV}(u)$
10: \hspace{1em} if $Q^{UAV} \neq \emptyset$ then
11: \hspace{2em} $b = \text{upper sub-carrier not yet targeted by UAVs}$
12: \hspace{2em} $D = \{ \hat{u} \in Q^{UAV}, \hat{u} \succeq_b u \ \forall u \in Q^{UAV} \cap V(\hat{v}) \}$
13: \hspace{2em} $W(b) = W(b) \cup D$
14: \hspace{1em} end if
\hspace{1em} // Rejected users will apply for their next preferences
15: \hspace{1em} end while
16: $P = \hat{P}$ \hspace{1em} // for each $b \in \mathcal{B}$ using Algorithm 1
// 2nd sub-game
17: Initialize $S$ from $\mathcal{B}$
18: \hspace{1em} while True do
19: \hspace{2em} Stable = True
20: \hspace{2em} for each two coalitions $S_1, S_2$ do
21: \hspace{3em} for each BS $v \in \mathcal{V}$ do
22: \hspace{4em} if $V(v) \cap S_1 \neq \emptyset$ and $V(v) \cap S_2 \neq \emptyset$ then
23: \hspace{5em} let $u_1 = V(v) \cap S_1$ and $u_2 = V(v) \cap S_2$
\hspace{5em} // try exchanging $u_1$ and $u_2$
24: \hspace{5em} if $\{S_1, S_2\} \triangleright^m_{u_1} \{S_1, S_2\}$ then
25: \hspace{6em} $S_1 = S_1; S_2 = S_2$
26: \hspace{6em} Stable = False
27: \hspace{5em} end if
28: \hspace{4em} else if $V(u) \cap S_1 \neq \emptyset$ then
29: \hspace{5em} let $u_1 = V(v) \cap S_1$
\hspace{5em} // try the transfer of $u_1$
30: \hspace{5em} if $\{S_1, S_2\} \triangleright^m_{u_1} \{S_1, S_2\}$ then
31: \hspace{6em} $S_1 = S_1; S_2 = S_2$
32: \hspace{6em} Stable = False
33: \hspace{5em} end if
34: \hspace{4em} else if $V(v) \cap S_2 \neq \emptyset$ then
35: \hspace{5em} let $u_2 = V(v) \cap S_2$
\hspace{5em} // try the transfer of $u_2$
36: \hspace{5em} if $\{S_2, S_1\} \triangleright^m_{u_2} \{S_2, S_1\}$ then
37: \hspace{6em} $S_1 = S_1; S_2 = S_2$
38: \hspace{6em} Stable = False
39: \hspace{5em} end if
40: \hspace{4em} end if
41: \hspace{3em} end for
42: end for
43: \hspace{1em} if Stable then
44: \hspace{2em} Break
45: \hspace{1em} end if
46: \hspace{1em} end while
As shown in Algorithm 2, the execution of the global game starts with the matching sub-game, then the coalitional one. The convergence of the global game depends on the convergence of the two sub-games. We have proved the convergence of the proposed matching and coalitional sub-games, as per the following two theorems, and we have provided the proofs in Appendix 9.4.

**Theorem 7. Matching game convergence**

The matching game of Algorithm 2 (1st sub-game) is guaranteed to converge to a stable matching.

*Proof.* See Appendix 9.4.

The convergence of the coalitional sub-game has also been proved in Appendix 9.4 which implies, together with the matching stability, the convergence of the global game.

**Theorem 8. Coalitional game convergence (Algorithm 2)**

Starting from an initial partition of the players on the coalitions $S = \{S_1, S_2, \ldots, S_B\}$, the coalitional game of Algorithm 2 (2nd sub-game) is guaranteed to converge to a final and optimal partition.

*Proof.* See Appendix 9.4.

### 3.3 Performance Evaluation

This section provides the performance evaluation of the proposed solution for efficient communication in cellular-based UAVs. The solution aims to enhance the QoS for the UAVs, reflected by the outage probability, by jointly optimizing the sub-carrier and power allocation. The simulation parameters are summarized in Table 3.2.

**Table 3.2.** Summary of simulation parameters for joint sub-carrier and power allocation problem.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulation area</td>
<td>1000m x 1000m</td>
</tr>
<tr>
<td>Altitude of the UAVs</td>
<td>22.5 - 300 m [4]</td>
</tr>
<tr>
<td>BSs</td>
<td>10 BSs (each with 11 sub-carriers)</td>
</tr>
<tr>
<td>$P_{\max}$, $P_{\text{stop}}$</td>
<td>20w, 0.1w (resp.)</td>
</tr>
<tr>
<td>$f_c$</td>
<td>2 GHz</td>
</tr>
<tr>
<td>$N_0$</td>
<td>-130 dBm [28]</td>
</tr>
<tr>
<td>Nakagami parameter $m$</td>
<td>2</td>
</tr>
<tr>
<td>$P_{\text{out,th}}$</td>
<td>0.1</td>
</tr>
</tbody>
</table>
In Figure 3.1, we evaluate the performance of our proposed solution in reducing the average outage probability of UAVs. Additionally, we compare our proposed algorithm to two baseline solutions. The first baseline solution uses random assignment of the sub-carriers, while the second baseline solution is inspired from graph theory and utilizes maximum independent set for sub-carrier assignment. The second baseline solution was proposed in [9]. The average outage probability is evaluated for different values of the number of devices in the network, and the obtained results are presented in Figure 3.1. The line labeled 'power optimization' refers to the case when directly performing the power optimization on the random partition without considering the rules for assigning the sub-carriers in the matching sub-game. This allows us to verify the validity of the proposed rules. By comparing this result with that from considering the first sub-game, we can see that the proposed rules show their effectiveness, especially when the network is saturated. From this figure, we also notice that our proposed solution allows us to reduce the average outage probability significantly compared to the other baseline solutions. Moreover, the gain of using our solution becomes more significant as the number of devices in the network increases. In this way, if a predefined QoS is required for the set of UAVs, our proposed solution allows us to accommodate more devices in the network compared to the baseline solutions. Compared to the random partition, the first sub-game allowed to reduce the outage probability by 13.72% and 35.11% when considering 70 and 100 users in the network, respectively. As for the second sub-game, it allowed reducing the outage probability by 57.62% and 48.71% when considering 70 and 100 users in the network, respectively. We have also evaluated the number of unstable solutions for power optimization before the effective one. This reflects the parameter $\hat{S}$ considered in the definition of the complexity of Algorithm 1 as $O(\hat{S} \times V \times (\frac{L_{max}}{\mu_{pwr}} + 1))$. Note that the details on how the different complexities have been derived in given in Publication VI. Through the different evaluations, $\hat{S}$ was on average equal to 6.42. It has also reached 14 as a maximum value. This result complements the evaluation of the complexity of Algorithm 1.

Figure 3.2 provides the distribution of users on the sub-carriers after executing Algorithm 2 (Global game). As detailed in the previous section, the last sub-game is based on the framework of coalitional game. It allows users to change their coalitions in a way to enhance their payoffs. The obtained results show that, after reaching stability, more UEs are as-
Supporting the Co-existence of UAVs and UEs in Cellular Networks

Figure 3.1. Evaluation of the outage probability for the proposed solutions.

Figure 3.2. User distribution on the sub-carriers after running the game.

signed to the first sub-carriers while more UAVs are assigned to the last ones. This comes to support the idea defended in this dissertation that separating between UAVs and UEs in terms of the assigned sub-carriers would enhance the quality of communication. The heterogeneity of the channel conditions between the two types of users is translated into different power requirements to be employed by the serving BS. Consequently, having different types of users in the same sub-carriers could increase the interference impact.

The matching sub-game is very quick and its complexity is $O(A)$. This complexity can even be reduced to $O(A^{\frac{1}{2}}V)$ when users belonging to different BSs are assigned in parallel. The second sub-game is meant to further reduce the outage probabilities by performing a series of transfer/exchange operations starting from the partition achieved by the first one. The complexity of the second sub-game is $O(\tilde{S} \times B(B-1) \times V)$, where $\tilde{S}$ is the number of unstable solutions found before reaching the effective one. Through the different evaluations, the average value of $\tilde{S}$ was 4.36 and has reached 6 as a maximum value. We have compared the complexity of the second sub-game (upper bound, $O((B(B-1))^C)$) with that of the brute-force search solution. The complexity of the latter is $O((B!)^V)$. Indeed, $B!$ corresponds to the number of combinations of the users on the sub-carriers of a given BS. The evaluation is reflected in Figure 3.3 (each BS has 11 users each assigned to a sub-carrier). As it can be seen from this figure, the coalitional game is associated with a very low complexity compared to the brute-force search. Furthermore, we have also implemented the algorithm that looks for the optimal solution (brute-force search) and compared the achieved average outages probabilities with that from the proposed solution. The obtained results are shown in Figure 3.4. This evaluation is considered for a small network of 10 BSs, where each one
has 3 sub-carriers. As we can see, the proposed solution achieves a near-optimal solution that has the same trend as the optimal solution generated by the brute-force search, especially when the network is not complete (some sub-carriers are free).

![Figure 3.3. Comparison between the complexity of brute-force search with the coalitional game.](image1)

![Figure 3.4. Comparison of the proposed solution with brute-force search (10 BSs).](image2)

### 3.4 Related Works

The potential of UAV applications has attracted attention from both industrial and academic communities. 3GPP working activities in UAVs, translated into different technical/specification reports, including TR 36.777 [4], TR 22.825 [30], and TS 22.261 [31], demonstrate the interest of mobile network organizations in cellular UAVs. This interest is also materialized in real field evaluations to investigate communication quality better. Compared to ground devices, the evaluations showed that flying UAVs could have poor link quality and even impact terrestrial communications [4, 6, 32].

The authors in [33] addressed minimizing the transmit power of BS-UAVs, serving ground users, while satisfying the transmission rate requirements of these users. To this end, the authors investigated the power minimization problem using transport theory and facility location. In [34], authors addressed optimizing 3D placement and mobility of BS-UAVs collecting data from ground IoT. In terms of sub-carriers assignment, the authors used a constrained K-mean clustering strategy to assign different channels to devices that are located in the proximity of each other. As for power control, while the transmit power of each device is computed only based on the channel gain between the device and its serving UAV for the interference-free scenario, an iterative optimization is...
considered for the interference scenario. The problem of power allocation for UAV-enabled wireless networks has been addressed in [35]. The authors proposed a price-based power allocation scheme, and modeled the interaction between the UAVs and the ground users as a Stackelberg game. The ground user selects an optimal power strategy to maximize its own utility. The problem of sub-carrier selection and transmission power for UAV-assisted communication is also addressed in [36].

In addition to BS-UAVs, some works have addressed the quality of the communication link for cellular-connected drones. Authors in [37] proposed an interference-aware path planning scheme for UAV communications in cellular networks. The problem is modeled as a dynamic game among UAVs to achieve a tradeoff between maximizing energy efficiency and minimizing latency and interference level caused on the ground. In [38], authors considered sub-carrier and power allocation for multi-UAV systems. The problem is addressed by formulating a weighted mean square error (MSE) problem, which can be solved via alternating optimization.

3.5 Summary

This chapter addressed the support of the co-existence of UAVs and UEs in cellular networks. It built from the expressions of the outage probabilities proposed in Chapter 2 and tackled the joint problem of sub-carrier assignment and power allocation. It also proposed a solution based on the framework of game theory. The game is composed of two sub-games. First, we argued that separating between the UAVs and UEs in terms of the assigned sub-carriers can reduce the interference impact on the users. This idea has been formulated using a matching sub-game. Furthermore, a coalitional sub-game has also been proposed to boost the optimization. The coalitional sub-game organizes the players based on the outcome of the first game and defines the mechanisms allowing them to change their coalitions and to reduce the outage probability of the users. In addition, a power optimization algorithm is proposed for this communication model, which is considered in the two sub-games. A series of performance evaluations has been conducted to prove the effectiveness of the approach.

The solution proposed in this chapter focused on supporting the co-existence of UAVs and UEs, which is a very crucial research question when integrating UAVs into cellular networks that are already deployed to serve ground users. However, the chapter only considered one perfor-
mance indicator related to the probability of packet loss. On the other hand, UAV applications in cellular networks can be associated with different types of services that need to optimize in the same time. This underpins the focus of the next chapter, in which we elaborate on the co-existence of several services for UAV communications in cellular networks.
4. Supporting the Co-existence of Several Services for UAV communications in cellular networks

This chapter focuses on supporting the coexistence of several QoS types for UAV communications in cellular networks. More precisely, we consider UAVs serving as flying BSs and providing connectivity to ground IoT devices. As mentioned in Section 1.1, UAV-aided wireless communication can be used to support uncovered or crowded areas [2,3]. Each IoT device requires two different service types; namely uRLLC and eMBB (e.g., in the case of mission-critical IoT applications, the same IoT device can be equipped with a camera, to provide video streaming on the uplink, and also with a temperature sensor to provide measurements with strict performance guarantees.). This chapter builds from the expressions of the effective rate and the transmission delay derived in Chapter 2, and elaborates on optimizing sub-carrier allocation and UAV deployment to jointly optimize the two performance indicator for each IoT node. The proposed solution introduces an iterative approach, where each iteration tackles linear optimizations. A series of performance evaluations is conducted to prove the effectiveness of the proposed approach. The contribution of this chapter is based on publication VII.

4.1 Problem Formulation

The problem formulation in this chapter is based on the expressions of the effective rate and the transmission delay defined in Theorem 5 and Theorem 6 of Section 2.2 and Section 2.3, respectively (Note that the same notations of this section are maintained in this chapter). The considered system model is illustrated in Figure 4.1. Let us denote by \( \mathcal{U} \) the set of IoT devices deployed in a geographical area \( \mathcal{A} \subset \mathbb{R}^2 \). Each IoT device is sending two types of packets requiring different service types. Let \( c \in \mathcal{C} = \{r, d\} \) denote the service type, where \( r \) refers to the service type
Supporting the Co-existence of Several Services for UAV communications in cellular networks

uRLLC and $d$ refers to the service type eMBB. More notations are provided in Table 4.1. On the other hand, a set $\mathcal{V}$ of UAVs is considered as flying base stations to provide uplink wireless communication to the ground IoT devices. As shown in Figure 4.1, the area $\mathcal{A}$ is divided into cell partitions where $A_v$ refers to the partition that gathers the IoT nodes that will be served by the UAV $v \in \mathcal{V}$. Note that the partitions $A_v$ are disjoint (i.e., $\forall v_1, v_2 \in \mathcal{V}; A_{v_1} \cap A_{v_2} = \emptyset$ and $\bigcup_{v \in \mathcal{V}} A_v = \mathcal{A}$). In order to effectively serve the ground IoT nodes, each UAV needs to head towards an adequate location and provide connection to its associated IoT nodes. The problem of UAV deployment and resource allocation is crucial to enable multi-services support for the IoT devices. The three-dimensional plane where the UAV $v$ can be deployed is denoted $\mathcal{L}_v$.

![Figure 4.1. Multi-service support scenario: each IoT node has two types of traffic, with different requirements, to be sent to the serving UAV.](image)

In order to enable multi-service support for ground IoT devices, this chapter addresses the joint problem of UAV deployment and resource allocation. To this end, we first start by modeling the problem as a non-linear integer program. We define the Boolean variable $X_{v,l}$ that indicates whether the UAV $v \in \mathcal{V}$ will be deployed at the location $l \in \mathcal{L}_v$ as

$$X_{v,l} = \begin{cases} 
1, & \text{if the UAV } v \text{ will be deployed at the location } l \in \mathcal{L}_v, \\
0, & \text{otherwise.}
\end{cases}$$

(4.1)
Table 4.1. Summary of Notations for the Problem of Multi-service Support.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mathcal{U} )</td>
<td>Set of IoT devices.</td>
</tr>
<tr>
<td>( \mathcal{V} )</td>
<td>Set of UAVs.</td>
</tr>
<tr>
<td>( \mathcal{B} )</td>
<td>Set of sub-carriers.</td>
</tr>
<tr>
<td>( \mathcal{B}_u )</td>
<td>Set of sub-carriers assigned to the IoT node ( u \in \mathcal{U} ).</td>
</tr>
<tr>
<td>( \mathcal{C} )</td>
<td>Set of service types. ( \mathcal{C} = { r, d } ) where ( r ) refers to the service type uRLLC and ( d ) refers to the service type eMBB.</td>
</tr>
<tr>
<td>( \mathcal{A}_v )</td>
<td>IoT devices belonging to the cell partition associated to the UAV ( v ).</td>
</tr>
<tr>
<td>( \mathcal{L}_v )</td>
<td>Set of locations for the UAV ( v ).</td>
</tr>
<tr>
<td>( u^{uv} )</td>
<td>Link between the IoT device ( u \in \mathcal{U} ) and its serving UAV ( v \in \mathcal{V} ).</td>
</tr>
<tr>
<td>( t = 1, \ldots, N_v )</td>
<td>Refers to the ( N_v ) interfering nodes affecting the UAV ( v ).</td>
</tr>
<tr>
<td>( R^c_u )</td>
<td>Transmission rate of the IoT ( u \in \mathcal{U} ) for the service type ( c \in \mathcal{C} ).</td>
</tr>
<tr>
<td>( R^e_{u,l,b} )</td>
<td>Effective rate from the IoT device ( u \in \mathcal{U} ) to its serving UAV ( v \in \mathcal{V} ) deployed at the location ( l \in \mathcal{L}_v ) over the sub-carrier ( b ).</td>
</tr>
<tr>
<td>( D_{u,l,b,Q} )</td>
<td>Transmission delay between the IoT device ( u ) and its serving UAV ( v \in \mathcal{V} ) deployed at the location ( l \in \mathcal{L}_v ) over ( Q ) sub-carriers.</td>
</tr>
<tr>
<td>( E^c )</td>
<td>Maximum number of retransmission for the service type ( c ).</td>
</tr>
<tr>
<td>( E(T_u) )</td>
<td>Average number of retransmissions for the IoT device ( u ).</td>
</tr>
<tr>
<td>( X_{v,l} )</td>
<td>Boolean variable that indicates whether the UAV ( v \in \mathcal{V} ) will be deployed at the location ( l \in \mathcal{L} ).</td>
</tr>
<tr>
<td>( Z^c_{u,b} )</td>
<td>Boolean variable that indicates whether the IoT device ( u ) uses the sub-carrier ( b \in \mathcal{B} ) for transmitting data related to the service type ( c \in \mathcal{C} ).</td>
</tr>
</tbody>
</table>

As for the problem of resource allocation, we define the variable \( Z^c_{u,b} \) as

\[
Z^c_{u,b} = \begin{cases} 
1, & \text{if the IoT device } u \text{ uses the sub-carrier } b \in \mathcal{B} \\
& \text{for transmitting data related to the service type } c \in \mathcal{C}, \\
0, & \text{otherwise}. 
\end{cases}
\]  

Considering the service type eMBB, the corresponding optimization problem for optimizing the effective rate, N-LP-R (which stands for non-linear
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The objective function (4.3) of the above optimization problem aims to maximize the minimum effective rate for the set $U$ of IoT devices, while ensuring constraints (4.4) - (4.8). Constraints (4.4) and (4.5) limits the value of the decision variables $X_{v,l}$ and $Z_{u,c,b}^c$ to $\{0, 1\}$. Constraint (4.6) forces each UAV to choose one and only one location. Constraint (4.7) states that a node $u$ will use a certain number of sub-carriers for transmitting data related to the service type $c$ to its serving UAV. Constraint (4.8) ensures that a sub-carrier $b$ within one cell partition $A_v$ will be used at most by one node.

As for the service type uRLLC, the aim is to reduce the transmission delay. Following the same logic considered for the service type eMBB, the optimization problem for optimizing the delay, N-LP-D (which stands for
non-linear program for optimizing the delay), can be expressed as

\[
\text{N-LP-D :} \quad \minimize_{\{x_{v,l}, \{d_{u,b}\}\}} \max_{u \in U} \sum_{l \in L} \sum_{b \in B} x_{v,l} d_{u,b} \sum_{1 \leq i \leq |B|} P_{u,i} \bar{D}_{u,l,b,i}, \tag{4.9}
\]

subject to

\[
\forall u \in U; \quad Q_u = \sum_{b \in B} d_{u,b}, \tag{4.10}
\]

\[
\forall u \in U, \forall i \in [1, \ldots, |B|]; \quad P_{u,i} \in \{0, 1\}, \tag{4.11}
\]

\[
\forall u \in U; \quad \sum_{1 \leq i \leq |B|} P_{u,i} = 1, \tag{4.12}
\]

\[
\forall u \in U, \forall i \in [1, \ldots, |B|]; \quad Q_u \leq i + (1 - P_{u,i}) \times \infty, \tag{4.13}
\]

\[
\forall u \in U, \forall i \in [1, \ldots, |B|]; \quad i \leq Q_u + (1 - P_{u,i}) \times \infty. \tag{4.14}
\]

The above optimization problem aims to minimize the delay for the set of IoT devices \(U\), by selecting the optimal allocation of sub-carriers and locations of the serving UAVs. As captured in the objective function (4.9), the delay for the IoT node \(u\) is expressed as the average from the \(Q_u\) used sub-carriers for the node \(u\), as defined in equation (2.31); Indeed, condition (4.10) enables computing the total number of selected sub-carriers for each IoT node \(u\). \(P_{u,i}\) is a binary variable, as specified in condition (4.11), that indicates the number of selected sub-carriers; i.e., \(P_{u,i} = 1 \iff Q_u = i\). The delay function is expressed as defined in (2.31). Finally, condition (4.12) forces one \(P_{u,i}\) to equal to 1 for each node \(u\), while conditions (4.13) and (4.14) ensure that this corresponds to the case where \(Q_u = i\).

However, the optimization problem N-LP-R is not linear, which is due to the expression of the effective rate in the objective function (4.3). Indeed, computing the effective rate for an IoT node \(u\) depends on the chosen sub-carriers by this node but also on the selected sub-carriers by nodes connected to the other UAVs, as the expression of the effective rate considers the interference impact. Moreover, the objective function (4.3) expresses a product of variables \((x_{v,l} d_{u,b})\). On the other hand, the optimization problem N-LP-D is also not linear. This is due to the objective function (4.9), that expresses a product of variables \((x_{v,l} d_{u,b} P_{u,i})\), and also to the expression of the delay which is not linear.

Furthermore, the two optimization problems N-LP-R and N-LP-D will optimize each service type separately and will not reach a trade-off solu-
tion optimizing the two service types. In the next section, we introduce our solution to jointly optimize sub-carrier allocation and UAV deployment in a way to enhance multi-services in aerial communication for the IoT.

4.2 An Iterative Approach for Multi-service Support for UAV Communications in Cellular Networks

This section introduces the proposed solution for joint resource allocation and UAV deployment to support multi-services in cellular communication for the IoT. The proposed solution relies on the optimization problems N-LP-R and N-LP-D defined in the previous section. To this end, i) we introduce a set of transformations allowing to linearize the constraints in the previous optimization problems, ii) we also propose an iterative algorithm allowing to linearize the expressions of the effective rate and the transmission delay, furthermore iii) a trade-off solution is thereafter provided to jointly optimize the two service types.

Considering N-LP-R, the objective function expresses the product of variables ($\mathcal{X}_{v,l}$ and $\mathcal{Z}_{u,b}^r$). We therefore define a new variable $T_{u,l,b}^r = \mathcal{X}_{v,l} \mathcal{Z}_{u,b}^r$ which will be forced to equal 1 when $\mathcal{X}_{v,l} = \mathcal{Z}_{u,b}^r = 1$ by considering the following constraints:

$$T_{u,l,b}^r \leq \mathcal{X}_{v,l}, \quad (4.15)$$
$$T_{u,l,b}^r \leq \mathcal{Z}_{u,b}^r, \quad (4.16)$$
$$T_{u,l,b}^r \geq \mathcal{X}_{v,l} + \mathcal{Z}_{u,b}^r - 1. \quad (4.17)$$

The two conditions (4.15) and (4.16) together will force $T_{u,l,b}^r$ to 0 when $\mathcal{X}_{v,l}$ or $\mathcal{Z}_{u,b}^r$ is equal to 0. As for condition (4.17), it forces $T_{u,l,b}^r$ to 1 when both $\mathcal{X}_{v,l}$ and $\mathcal{Z}_{u,b}^r$ and equal to 1. However, the expression of the effective rate is not linear and is more complex. The underlying complexity is due to the fact the expression of the effective rate depends on the interfering nodes using the same sub-carriers. Thus, computing the effective rate also depends on the values of the decision variables $\mathcal{Z}$ associated to the nodes connected to the other UAVs.

In order to tackle this issue, we propose an iterative process where each iteration consists of linear optimization problems. Indeed, when optimizing the effective rate only for the IoT nodes connected to a given UAV $v$, the objective function becomes linear (the decision variables related to the
nodes connected to the other UAVs are not being changed). This allows selecting the UAV deployment and sub-carrier allocation for a given UAV \( v \in V \) in a way to enhance the effective rate of the served IoT devices \( u \in A_v \). The following optimization problem is proposed for an iteration, where \( v \) refers to the UAV in question and \( c_t \) is a constant.

\[
\text{LP-R}(v, c_t) : \quad \maximize \min_{\{X_{v,l}, \{Z_{u,b}^c\}\}} \sum_{l \in L_v} \sum_{b \in B} T_{u,l,b}^r \rho_{u,l,b}^{\text{eff}} \quad (4.18)
\]

\[
\text{s.t.} \quad \forall l \in L_v: \quad X_{v,l} \in \{0, 1\}, \quad (4.19)
\]

\[
\forall u \in A_v, \forall c \in C, \forall b \in B: \quad Z_{u,b}^c \in \{0, 1\}, \quad (4.20)
\]

\[
\forall u \in A_v, \forall c \in C: \quad \sum_{l \in L_v} X_{v,l} = 1, \quad (4.21)
\]

\[
\forall u \in A_v, \forall c \in C: \quad \sum_{b \in B} Z_{u,b}^c \geq 1, \quad (4.22)
\]

\[
\forall b \in B: \quad \sum_{c \in C} \sum_{u \in A_v} Z_{u,b}^c \leq 1, \quad (4.23)
\]

\[
\forall u \in A_v, \forall l \in L_v, \forall b \in B: \quad T_{u,l,b}^r \leq X_{v,l}, \quad (4.24)
\]

\[
\forall u \in A_v, \forall l \in L_v, \forall b \in B: \quad T_{u,l,b}^r \leq Z_{u,b}^r, \quad (4.25)
\]

\[
\forall u \in A_v, \forall l \in L_v, \forall b \in B: \quad T_{u,l,b}^r \geq X_{v,l} + Z_{u,b}^r - 1, \quad (4.26)
\]

\[
\text{SUM\_RATE}(V) \geq c_t. \quad (4.27)
\]

The objective function (4.18) in the above optimization problem LP-R (which stands for Linear Program for optimizing the Rate) is derived from the objective function (4.3) of N-LP-R with focus on the nodes \( u \in A_v \); it aims to maximize the effective rate for these nodes. Moreover, the constraints (4.19) - (4.23) are also derived from those of N-LP-R considering the IoT nodes \( u \in A_v \). Note that the linear transformations of the constraints have been considered in LP-R. As for constraint (4.27), it aims to express a global condition imposing to increase the sum of the effective rate for all the nodes above a constant \( c_t \). This would also ensure that optimizing the effective rate for the nodes \( u \in A_v \) will not come at the expense of other nodes.

As we can see, an iteration considers the optimization problem LP-R to successively optimize the effective rate for the nodes connected to each UAV \( v \in V \). The iterative process is expressed in Algorithm 3.

Algorithm 3 shows the proposed iterative process for optimizing the effective rate. The linear optimization problem (LP-R(\( v, c_t \))) will be consid-
Algorithm 3: An Iterative algorithm for optimizing the effective rate.

Require:
1: \( c_t = 0 \)
2: while True do
3:     Stable = True
4:     for \( v \in V \) do
5:         LP-R\((v, c_t)\)
6:         if \( c_t > \text{SUM\_RATE}\(V) \) then
7:             Stable = False
8:         end if
9:         \( c_t = \text{SUM\_RATE}(V) \)
10:     end for
11:     if Stable then
12:         break
13:     end if
14: end while

The effective rate is considered for each UAV \( v \in V \) (lines 4 - 10). This allows to optimize the effective rate for the served IoT nodes connected to \( v \), while maintaining the total effective sum rate of all the nodes above a constant \( c_t \). The latter is updated with the new effective sum rate obtained after each optimization (line 9). This process is repeated until reaching stability, which reflects a situation where the total effective sum rate can no longer be increased.

As for the optimization problem N-LP-D, its objective function includes a product of variables. To this end, we introduce the variable \( T_{d,u,l,b,i}^d = X_{v,l} Z_{a,b}^d P_{u,i} \). In addition, we define the following conditions allowing to force \( T_{u,l,b,i}^d \) to 1 only when \( X_{v,l} \), \( Z_{a,b}^d \) and \( P_{u,i} \) are equal to 1 as

\[
T_{u,l,b,i}^d \leq X_{v,l}, \quad (4.28)
\]
\[
T_{u,l,b,i}^d \leq Z_{a,b}^d, \quad (4.29)
\]
\[
T_{u,l,b,i}^d \leq P_{u,i}, \quad (4.30)
\]
\[
T_{u,l,b,i}^d \geq X_{v,l} + Z_{a,b}^d + P_{u,i} - 2. \quad (4.31)
\]

Note that the expression of the delay is not linear since the delay over a sub-carrier, as per the equation (2.31), depends on the interfering nodes using the same sub-carrier. In order to tackle this issue, we propose a similar iterative approach as the one introduced in LP-R. Indeed, the objective function becomes linear when optimizing the delay only for the IoT nodes connected to a given UAV. The following optimization problem is therefore proposed for an iteration, where \( v \) refers to the UAV in question.
and \( ct \) is a constant.

The optimization problem \( \text{LP-D}(v, ct) \) is derived from \( \text{N-LP-D} \), in the same way as \( \text{LP-R} \). This optimization problem focuses on the IoT nodes \( u \in A_v \) and aims to minimize the delay of these nodes. Constraint (4.42) aims to express a global condition imposing to decrease the sum of the delays of all the nodes below a constant \( ct \). The function \( \text{SUM_DELAY}(V) \) is defined in the same way as the function \( \text{SUM_RATE}(V) \).

Algorithm 4 shows the iterative process for optimizing the delay of the IoT devices in the network.

As mentioned before, the two service types have different requirements and each of the underlying optimization problems aims to maximize the corresponding service type individually. In order to reach a trade-off optimization, we adopt the approach considered in [39]. This allows to achieve a trade-off between the different service types by sharing the same utility function. Two points, \( \theta_b = (\theta^r_b, \theta^d_b) \) and \( \theta_d = (\theta^r_d, \theta^d_d) \), are introduced to this end. \( \theta_b = (\theta^r_b, \theta^d_b) \) reflects best utility that can be achieved for each service type, while \( \theta_d = (\theta^r_d, \theta^d_d) \) represents the worst one (disagreement).
Algorithm 4 An iterative algorithm for optimizing the delay.

Require:
1: $ct = \max$
2: while True do
3:   Stable = True
4:   for $v \in V$ do
5:     LP-D($v, ct$)
6:     if $ct < \text{SUM\_DELAY}(V)$ then
7:       Stable = False
8:     end if
9:     $ct = \text{SUM\_DELAY}(V)$
10:   end for
11:   if Stable then
12:     break
13: end if
14: end while

Let $\hat{X}$ and $\bar{X}$ be the two matrices of $X_{v,l}$ obtained from resolving LP-R and LP-D respectively. In addition, let $\hat{Z}$ and $\bar{Z}$ be the two matrices of $Z_{c u,b}$ obtained by respectively resolving the same optimization problems. Then, $\theta_b = (\theta^r_b, \theta^d_b)$ and $\theta_d = (\theta^r_d, \theta^d_d)$ can be computed as

$$
\begin{align*}
\theta^r_b &= \min_{u \in U} \sum_{l \in L_v} \sum_{b \in B} \hat{X}_{v,l} \hat{Z}_{c u,b}^r R_{u,l,b}^\text{eff}, \\
\theta^d_b &= \min_{u \in U} \sum_{l \in L_v} \sum_{b \in B} \bar{X}_{v,l} \bar{Z}_{c u,b}^r R_{u,l,b}^\text{eff}, \\
\theta^r_d &= \max_{u \in U} \sum_{l \in L_v} \sum_{b \in B} \hat{X}_{v,l} \hat{Z}_{c u,b}^d \bar{D}_{u,l,b,Q_u}, \\
\theta^d_d &= \max_{u \in U} \sum_{l \in L_v} \sum_{b \in B} \bar{X}_{v,l} \bar{Z}_{c u,b}^d \bar{D}_{u,l,b,Q_u}.
\end{align*}
$$

The trade-off solution (fair optimization) can therefore be expressed as
To jointly optimize the effective rate and the transmission delay, the optimization problem N-LP-F (which stands for Non-Linear Program for optimizing the rate and delay - Fair) defines a new objective function $F$ which is shared between the two service types, as reflected in conditions (4.45) and (4.46). The variables $\varpi^r$ and $\varpi^d$ in these two conditions respectively reflect the minimum effective rate and the maximum transmission delay, as expressed in (4.47) and (4.48). Therefore, the objective function of the above optimization problem will jointly maximize the minimum rate and minimize the maximum delay.

However, the optimization problem N-LP-F is not linear, which is due to constraints (4.47) and (4.48). We therefore consider the proposed iterative algorithm adopted in LP-R and LP-D. The linear optimization problem LP-F (which stands for Linear Program for optimizing the rate and delay)
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- Fair) for $v \in V$ can be expressed as

\[
\text{LP-F}(v, ct^r, ct^d): \\
\text{maximize } F, \\
\text{s.t.} \\
F = \frac{\omega^r - \theta^r_d}{\theta^r_b - \theta^r_d}, \\
F = \frac{\omega^d - \theta^d}{\theta^d_b - \theta^d}, \\
(4.19), (4.20), (4.21), (4.22), (4.23), (4.24), (4.25), (4.26), \\
(4.33), (4.34), (4.35), (4.36), (4.37), (4.38), (4.39), (4.40), (4.41), \\
\forall u \in A_v; \omega^r \leq \sum_{l \in L} \sum_{b \in B} T_{u,l,b} R_{u,l,b}^{\text{eff}}; \\
\forall u \in A_v; \omega^d \geq \sum_{l \in L} \sum_{b \in B} \sum_{1 \leq i \leq |B|} T_{u,l,b,i} D_{u,l,b,i}; \\
\text{SUM_RATE}(V) \geq ct^r, \\
\text{SUM_DELAY}(V) \leq ct^d.
\]

The optimization problem LP-F focuses on the IoT devices $u \in A_v$ and jointly maximizes the effective rate of the transmission delay of these nodes. The constraints (4.54) and (4.55) aim to express global conditions imposing to increase the sum rate and decrease the sum delay for all the IoT nodes. The iterative process for the trade-off optimization is shown in Algorithm 5.

**Algorithm 5** An iterative algorithm for joint rate and delay optimization.

**Require:**
1: $ct^r = 0$
2: $ct^d = max$
3: while True do
4: Stable = True
5: for $v \in V$ do
6: LP-F($v, ct^r, ct^d$)
7: if $ct^r > \text{SUM_RATE}(V)$ or $ct^d < \text{SUM_DELAY}(V)$ then
8: Stable = False
9: end if
10: $ct^r = \text{SUM_RATE}(V)$
11: $ct^d = \text{SUM_DELAY}(V)$
12: end for
13: if Stable then
14: break
15: end if
16: end while
4.3 Performance Evaluation

This section provides the performance evaluations of the proposed approach. The solution aims to jointly optimize resource allocation and UAV deployment to enable multi-service support in aerial communication for the Internet of Things. Two different services are considered which are reflected by maximizing the effective rate and minimizing the average delay for the served IoT devices. The simulation has been performed in a 1000m x 1000m square area with varying numbers of UAVs and IoT nodes. We have considered a carrier frequency $f_c$ of 2GHz. The altitude of the UAVs was set between 22.5 – 300m, which is the feasibility range associated to the path loss model [4]. We have also considered a noise variance $N_0$ of $-130$dBm [28]. We have considered a single packet transmission time for uRLLC service, $T_{F}$, of 0.5ms, and transmission rates of 1 bit/s/Hz for uRLLC service and 7 bit/s/Hz for eMBB service [40]. We have also set the maximum number of retransmission, $E_c$, to 4 for the service eMBB, and to 2 for the service uRLLC.

We have evaluated the three optimization solutions, namely LP-R, LP-D and LP-F, in terms of the achieved effective rate at the serving UAVs and the transmission delay. The results are respectively depicted in Figure 4.2 and Figure 4.3. These evaluations consider 30 IoT nodes and 12 UAVs. In terms of optimizing the effective rate (Figure 4.2), the two optimization solutions LP-R and LP-F achieve better results compared to LP-D. Indeed, starting from the initial allocation of resources and deployment of UAVs, the optimization solutions LP-R and LP-F increase the effective rate for the IoT nodes at each iteration whereas the optimization solution LP-D does not take it into account. The LP-R and LP-F algorithms achieve 47.82 and 27.29 times larger average effective rate than the LP-D algorithm, respectively. As for optimizing the transmission delay (Figure 4.3), the optimization solutions LP-D and LP-F reached better results compared to LP-R. While the two solutions LP-D and LP-F managed to decrease the average transmission delay in each iteration of the algorithm, the optimization LP-R do not take it into account. The LP-D solution has 2.04 times shorter delay compared to the LP-R optimization while LP-F has reached 1.90 times shorter delay compared to the same optimization.

We have also evaluated the effective rate and the transmission delay of the proposed trade-off approach against the initial allocation/deployment, while varying the number of IoT nodes (for a fixed number of serving
UAVs equal to 12). The obtained results are respectively depicted in Figure 4.4 and Figure 4.5. We can see that the average effective rate decreases with the number of considered IoT nodes while the average transmission delay increases with the same number. This is due to the fact that the more IoT nodes are considered in the network, the fewer sub-carriers can be assigned to each node, which directly affects the average effective rate and transmission delay for those nodes. However, the proposed trade-off approach achieves better results compared to the initial allocation. Indeed, it starts from the initial allocation and performs a number of iterations to successively reach optimal resource allocation and UAV deployment, leading to enhanced effective rate and transmission delay.

In order to evaluate the proposed trade-off approach, we have considered baseline solutions. We therefore defined the following LP which reflects a
multi-objective optimization characterized by the parameter $\alpha$ as

$$\text{LP-}\alpha(v, ct^r, ct^d) :$$

$$\begin{align*}
\text{maximize } F, \\
\text{s.t. } F = \alpha \varpi^r + (1 - \alpha)(D_{\text{max}} - \varpi^d), \\
(4.19), (4.20), (4.21), (4.22), (4.23), (4.24), (4.25), (4.26), \\
(4.33), (4.34), (4.35), (4.36), (4.37), (4.38), (4.39), (4.40), (4.41), \\
(4.52), (4.53), \\
(4.54), (4.55).
\end{align*}$$

The above optimization problem characterizing the baseline solutions is defined in the same way as the proposed LP-F; It introduces a weighting parameter $\alpha$ between the two objective functions (as reflected in the condition (4.57)) and aims to jointly optimize them using the iterative approach (which is subject to the set of constraints defined in (4.58)). Note that $\varpi^r$ and $\varpi^d$ respectively reflect the minimum effective rate and the maximum transmission delay, as defined in (4.52) and (4.53). We have considered three values of $\alpha$ which are 0.2, 0.5, and 0.8.

We have first evaluated the proposed approach against the baseline solutions (multi-objective optimizations) considering different numbers of IoT nodes and a fixed number of UAVs (12 serving UAVs). The obtained results, in terms of average effective rate and transmission delay, are respectively depicted in Figure 4.6 and Figure 4.7. As stated earlier, the effective rate decreases with the number of considered IoT nodes while the transmission delay increase with this number. As we also can see, the three solutions LP-\(\alpha\) ($\alpha \in \{0.2, 0.5, 0.8\}$) achieve similar results in terms of the effective rate and transmission delay. Furthermore, the three solutions provide better optimization of the effective rate (Figure 4.6) compared to the transmission delay (Figure 4.7), which is similar to the behavior of the LP-R optimization solution. This is due to the fact that the above optimization problem for jointly optimizing the two objective functions does not take into consideration the scales of the values of the two functions, meaning that the value 0.5 for $\alpha$ can not reach the trade-off between the two objective functions. Indeed, considering the condition (4.57) that defines the variable $F$ to be maximized by the objective function, while the values of the variable $\varpi^r$ are in the scale of $10^9 \text{ (bit/s/Hz)}$, the...
values of the part \((D_{\text{max}} - \varpi_d)\) are in the scale of \(10^{-3}\) (ms). This has favored the optimization of the effective rate when averaging between the two objective functions using the values 0.2, 0.5 and 0.8 for the parameter \(\alpha\). Note that the variables \(\varpi_r\) and \(\varpi_d\) are respectively defined in the two conditions (4.52) and (4.53). On the other hand, the proposed approach LP-F can achieve a trade-off between the two objective functions while considering the scale of their values, thanks to the definition of a shared objective function between the two optimizations (as defined in (4.49), (4.50) and (4.51)).

Figure 4.6. Evaluation of the effective rate for the proposed approach LP-F and the baseline solutions LP-\(\alpha\) \((\alpha \in \{0.2, 0.5, 0.8\})\) as a function of the number of IoT nodes.

Figure 4.7. Evaluation of the transmission delay for the proposed approach LP-F and the baseline solutions LP-\(\alpha\) \((\alpha \in \{0.2, 0.5, 0.8\})\) as a function of the number of IoT nodes.

We have also evaluated the proposed approach against the baseline solutions considering different numbers of UAVs serving a fixed number of IoT nodes (30 IoT nodes). The obtained results in terms of the effective rate and transmission delay are respectively depicted in Figure 4.8 and Figure 4.9. We can see from the two figures that the average transmission rate increases with the number of serving UAVs, while the average transmission delay decreases with this number. As mentioned earlier, this is due to the fact that increasing the number of serving UAVs is translated into more sub-carriers that can be allocated to the IoT nodes. Furthermore, we can also see that the three baseline solutions provide similar results, which tend to favor the optimization of the effective rate at the expense of the transmission delay. As mentioned earlier, the baseline solutions do not consider the scale of the values related to the two objective functions, which is translated in favor of optimizing the effective rate for the values 0.2, 0.5 and 0.8 of \(\alpha\). On the other hand, the proposed LP-F approach achieves a better trade-off by sharing the same objective function and considering the scale of the related values.
4.4 Related Works

Different works studied the use of UAVs as flying BSs to provide connectivity to ground users. Such applications are particularly interesting to provide communication support in a specific region or to extend the network coverage to rural areas. In [33], the authors were interested in the transmit power of UAVs, serving ground users, and the transmission rate requirements of these users. The authors considered transport theory and facility location to address the power minimization problem while satisfying users’ requirements. In [35], the authors addressed the problem of power allocation for UAV-assisted wireless networks. A price-based power allocation scheme is proposed and a Stackelberg game is considered to model the interaction between the UAVs and the ground users. The problem of optimizing 3D placement and the mobility of UAVs collecting data from ground IoT is investigated in [34]. The authors proposed a framework for jointly optimizing the 3D placement and the mobility of the UAVs, device-UAV association, and uplink power control. In [36], the authors studied the problem of sub-carrier and transmission power selection for UAV-enabled wireless communication. An iterative algorithm is proposed along with a Lagrangian dual decomposition method to solve it. In [41], the authors addressed delay-optimal cell association of UAV-aided cellular networks. More precisely, the aim is to minimize the average network delay under any arbitrary spatial distribution of the ground users. The mobility management of a UAV providing connectivity services to a cluster of ground users is investigated in [42]. The paper considered the cases where the geographical characteristics of the cluster and the radio
environment are unknown. The joint 3D deployment and power allocation of a UAV-aided network for maximizing the system throughput is investigated in [43]. The authors proposed a solution based on DRL to learn the optimal 3D hovering location and power allocation. The joint uplink-downlink optimization for a UAV-aided network is investigated in [44,45].

However, IoT applications can be associated with different service types having different requirements. Existing works do not consider the support of multi-services for each IoT node. This underpinned this chapter's focus in which we considered that each IoT node is requiring two service types, namely uRLLC and eMBB. To this end, we addressed the joint problem of resource allocation and UAV deployment in order to maximize the efficiency of each service type per IoT node.

4.5 Summary

This chapter addressed the support of the coexistence of several QoS types for UAV communications in cellular networks. It considered UAVs acting as BS and providing connectivity to ground IoT devices. While the latter can be characterized by different service types, few works in the literature considered that each IoT node requires several service types. To this end, the chapter addressed the case where each IoT node requires eMBB and uRLLC services, and built from the expressions of the effective rate and the transmission delay developed in Chapter 2. It also tackled the joint problem of sub-carrier allocation and UAV deployment. Given the complexity of the problem, we have proposed an iterative algorithm where each iteration optimizes linear problems. Furthermore, in order to jointly optimize the two services types, a trade-off solution is also proposed. The conducted performance evaluations prove the effectiveness of the proposed approach. We have evaluated the three optimization solutions, namely LP-R, LP-D and LP-F, in terms of the achieved effective rate and the transmission delay. The LP-F algorithm achieves a larger average effective rate than the LP-D algorithm. Moreover, the LP-F algorithm reduces the transmission delay compared to the LP-R algorithm.

The solutions proposed in both Chapter 3 and 4 addressed a direct communication scheme, where UAVs only communicate with their serving BS/served IoT nodes. However, the consideration of cellular networks as a communication infrastructure for UAVs brings new opportunities that can be exploited to further enhance the performance. The next chapter
elaborates on an idea that exploits the presence of several UAVs to enhance the performance of UAV communications in cellular networks.
This chapter elaborates on exploiting the presence of several UAVs connected to cellular networks to enhance the underlying communications. It aims at providing another way to enhance the QoS, which goes beyond the direct communication scheme between the UAVs and the cellular network. To this end, the present chapter advances the idea of Aerial Control System (ACS), in which part of the control logic is shifted from the Ground Control Station (GCS) to be performed in the air by the UAVs themselves. Indeed, operating UAVs requires the use of a GCS to send C2 packets and collect telemetry data. Shifting part of the control logic to be performed in the air will consequently reduce the impact on cellular network communications. This principle can be considered in situations characterized by a level of automation, such as ‘auto mode’, where a predefined mission is executed by the UAVs. The chapter also emphasizes with initial evaluations of the proposed concept. The contribution of this chapter is based on publication II.

5.1 A UAV orchestration framework for ACS

The control and the management of UAVs imply a constant exchange of control messages with the GCS, so the latter can monitor and direct the UAVs to meet the expectations of the underlying applications, such as indicating and updating the path to be followed by each UAV, organizing the UAVs in swarms, disseminating information among the UAVs to avoid obstacles, etc. The critical nature of UAVs makes such control messages very important and must be sent at a high frequency. As presented in Figure 5.1.a, each UAV communicates with the GCS through UAV-to-Infrastructure (U2I) communication. Consequently, the network may be congested with control messages, leaving therefore less bandwidth
Figure 5.1. Different levels to perform UAV control; a) at the GCS level; b) at edge level; c) at the UAV level.

for data from on-board IoT devices or other UEs on the ground. Real field evaluations performed by 3GPP [4] showed that UAV-based communication through a cellular network decreases considerably the throughput of the connected devices, including UEs on the ground. This is mainly due to the close to free-space propagation that characterizes UAV-BS communication. Compared to ground UEs, UAVs cause more interference on non-serving BSs.

As the GCS and its control logic are far from the controlled UAVs, making this logic closer to the drones may reduce the overhead. This can be achieved with the use of Multi-Access Edge Computing (MEC). Indeed, MEC is deemed as a key enabling technology of 5G. It allows overcoming cloud limitations associated with latency and enables applications that require response times in the range of milliseconds. MEC is based on reforming the cloud hierarchy and performing the computation processes near end-users. Consequently, the response time is shorter compared to the case of a centralized cloud. The MEC principle can be considered for UAV applications by pushing the control logic to the edge servers nearest to the base stations drones are connected to. This would allow the control logic to be closer to the UAVs. In addition, the advances in MEC would maintain the expected QoS throughout the drone mobility. Dynamic creation and migration of services can ensure that the computation resources follow the object mobility by being always performed in the nearest edge server. As presented in Figure 5.1.b, such an approach can be seen as Mobile Control System (MCS) whereby the management logic follows the UAVs’ mobility (similar in spirit to the Follow-Me-Cloud or Follow-Me-Edge concepts [46]). This would reduce the response time for controlling the UAVs and decrease crowding the network with control messages (between the cellular base stations and the GCS).

While moving the control logic to the vicinity of UAVs, leveraging MEC,
Aerial Control System for UAV Communications in Cellular Networks

would allow reducing the response time, the issue of degrading the network performance remains the same. Even by being closer to the UAVs at the edge level, the control of UAVs still requires intense communication with the base stations. It is clear that this approach alleviates the congestion that may occur between the core network and the GCS, but the congestion issue at cellular BSs remains unsolved. To overcome this issue, we propose moving partially or fully the control logic further and performing it in the air by a selective set of UAVs. Indeed, UAVs can be organized in clusters, in a flying ad-hoc networking (FANET) manner. Depending on different factors, such as energy budget or on-board equipment, a UAV can be elected as a cluster head (CH) and that is similar to past research works on ad-hoc networks. The head of the cluster can hold the control logic of its cluster leading therefore to the concept of aerial control system. This concept is mainly justified by the presence of different UAV applications characterized by a degree of automation. This reflects the cases where the control logic of the UAVs is predefined, such as flying in swarm considering a predefined path. The control messages that used to pass through U2I communication can therefore be directed to the CH through UAV-to-UAV (U2U) communication (Figure 5.1.c). This would save more network spectrum that can be actually used by IoT devices or other user equipment on the ground for data delivery. It is very important that U2U communication uses a different network, such as WiFi or LoRa.

The concept of ACS leverages the automatic nature characterizing some
UAV applications to enable performing the orchestration by the UAVs in the air. Indeed, many UAVs can nowadays operate, partially or completely, in the autopilot mode. This allows UAVs to follow a pre-programmed mission rather than being controlled in real-time by the GCS. The mission specifies all the navigation parameters regarding the flight such as the paths, the altitude, and the velocity. Even if the missions are pre-planned, they can be adjusted during the flights to react to changes related to the application (arrow 1a in Figure 5.2). This introduced a revolution in UAVs which alleviated heavy tasks for humans. It is clear that without this principle, each flying drone would require total follow-up and command by humans that are standing behind the GCS. The ACS concept takes advantage of the automatic nature of the UAVs and moves the control logic to be performed in the air by selective UAVs. Consequently, the CH will be responsible for ensuring the proper application of UAVs’ missions established on the ground by the GCS, or even adjusting and re-planning the missions.

A key aspect of the ACS framework is the cluster formation and management. Indeed, the UAVs can be organized in a FANET manner and interconnected through U2U links. The CH can be elected (and re-elected periodically) so to maintain efficient management of the cluster in varying situations. Different criteria could be considered for this purpose, such as optimizing nodes’ resources, the number of hops control messages need to pass through, etc. Once the group is formed and the CH is elected, the latter receives the necessary information from the GCS about the members’ missions so it can ensure efficient control, as depicted in Figure 5.2 through arrows 1b and 2, respectively. The GCS monitors the UAVs only through the CH, reducing therefore crowding the mobile network with control messages of the entire group.

Enabling U2U communication would also allow adding a new dimension in providing connectivity to on-board IoT services. Indeed, in addition to communicating IoT data through U2I links, U2U communication can also be used for this purpose. The cluster of UAVs can be seen as a network where each node participates in relaying data to a given destination, that can pursue the transmission through U2I. This would allow responding to different QoS required by the underlaying applications. The services offered by the on-board IoT devices (carried or served by the UAV-BS, and depicted by arrow 3 in Figure 5.2) can differ in terms of the required QoS (e.g., bandwidth and time). By intelligently steering data communication
between U2U and U2I, such a framework can meet the QoS expected by each application. In addition, this would also enhance the availability of IoT services by relying on many paths for data transport.

5.2 Performance Evaluation

In the present section, we show the benefit of the ACS concept in reducing the overhead on the network, comparing it to the baseline approaches that use GCS. Moreover, using the NS3 simulator, we evaluate the impact of the number of UAVs on the control packet rate and the packet loss, which are important parameters for ensuring the proper functionality of UAVs. The performance evaluation is carried using a 3D topology, deployed in a 1000m x 1000m square area with an altitude between 22.5 – 300m [4], and free space propagation model. U2U communication is based on the IEEE 802.11n standard with RTS/CTS disabled.

As shown in Figure 5.3.a, moving the control logic towards the UAVs reduces considerably the number of control messages exchanged via the cellular network, which has a positive impact on the spectrum efficiency. This difference is very important when the number of UAVs is large, which is the case in some applications. In addition, the more UAVs are
organized in a cluster, the more the number of control messages that pass through the cellular base station is reduced. This directly affects the spectrum efficiency of the network and enhances the throughput for both IoT devices and UEs on the ground. It is worth noting that the messaging was based on the MAVLink protocol with 50 Hz rate update and 263 Byte packet size.

An evaluation of the impact of the number of UAVs on the packet throughput is conducted in Figure 5.3.b. As shown in the figure, the packet throughput decreases along with the number of UAVs inside the cluster. Indeed, the more UAVs are grouped in a cluster, the more U2U spectrum is congested. However, the obtained results show that the packet throughput in the proposed approach is within the requirements defined by 3GPP for aerial vehicles connectivity. As mentioned in Table 5.1, efficient operations would require data rates in the range of 60-100 Kbps. Even in the case of a cluster of large size (i.e., 45 UAVs), the proposed approach ensures largely the required throughput (i.e., more than 1 Mbps).

Figure 5.3.c depicts the impact of the number of UAVs on the packet loss. The first observation that we can draw from the figure is that the number of UAVs in the cluster has a negative impact on packet loss. This is mainly due to the interference that increases along with the number of UAVs and their mobility. From Table 5.1, an efficient management of UAVs requires a network reliability in the order of $10^{-3}$ packet error loss rate. However, from Figure 5.3.c, we observe that the packet loss rate exceeds $10^{-3}$, which can affect the control of UAVs. It is worth noting that we considered in this evaluation a scenario where each node sends at a high rate (100 Mbps). Reducing the transmission rate would decrease the packet loss to acceptable levels.

To evaluate the U2I communication, we also considered the outage probability defined in Chapter 2. Figure 5.3.d shows the outage probability for ground UEs, which defines the probability that a UE fails in sending its packets because of the channel capacity. As we can see, grouping UAVs and performing their control in the air lead to decreased outage probability for ground UEs. This proves that pushing the control logic to the

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Latency</td>
<td>50ms (one way from eNB to UAV)</td>
</tr>
<tr>
<td>Data rate</td>
<td>60-100 kbps</td>
</tr>
<tr>
<td>Reliability</td>
<td>Up to $10^{-3}$ Packet Error Loss Rate</td>
</tr>
</tbody>
</table>

Table 5.1. C2 requirements for aerial vehicles connectivity [4].
cluster head and reducing the control messages in the U2I links ensure also good communication links for terrestrial UEs in the ground.

5.3 Related Works

Given their potential benefits, the usage of mobile networks for UAVs has attracted a lot of attention. For instance, the authors of [47–49] consider cellular networks for data offloading. This allows offloading computation tasks from the UAVs to an edge server, reducing therefore the energy consumption of the UAVs. Furthermore, given the amount of resources that an edge server can have, the offloaded task will be executed in a shorter time. On the other hand, UAVs have demonstrated their potential in providing wireless connectivity to ground devices. When equipped with the required radio access technologies, UAVs can operate as mobile (flying) BSs and provide network connectivity to the ground devices from height. These vehicles are easy and fast to deploy, more flexible to configure, and offer better communication channels due to the use of short-range LoS links [50]. In [51], the authors provided an overview of this concept and introduced a basic networking architecture and main channel characteristics. The authors also highlighted key design considerations as well as the new opportunities. In addition, the ability to maneuver them provides new opportunities to enhance the network performance by directing UAVs to specific targets. This makes UAVs a very important enabler in providing 5G connectivity. In [52], the authors elaborated on the network coverage to rural areas or to establish temporary coverage in zones where ground network infrastructure might fail. The authors focused on the scheduling of beaconing periods as an efficient means of energy consumption optimization. The interest in UAV communications in cellular networks has also been translated into several projects by different organizations. For instance, Facebook started working on its Aquila drone which is intended to provide Internet access to rural areas [53]. The drone can circle with others in the sky over a specific region to deliver broadband connectivity. The ABSOLUTE project also envisions the implementation of low-altitude aerial networks consisting of LTE-Advanced (LTE-A) base stations on-board of balloons (Helikite platform) to serve ground users [3].

The work proposed in this chapter introduces a novel approach. It advances the concept of ACS that aims to enhance the performance of UAV communications in cellular networks by exploiting the presence of several
UAVs.

5.4 Summary

This chapter elaborated on an idea to enhance the performance of UAV communications in cellular networks, by exploiting the presence of several UAVs. It advances the concept of aerial communication system, in which part of the traffic control is shifted from the ground control station to be performed in the air by the UAVs. This would consequently reduce the communication and the impact on the cellular network. The initial evaluation came to support such principles.

Other than exploiting the presence of several UAVs to enhance the communication performance, different mobile network operators can also be present on the other hand. Exploiting the availability of MNOs at the communication range of UAVs constitutes an interesting research question, which is tackled in the next chapter.
6. Traffic Steering for UAV Communications in Cellular Networks

The use of cellular networks as a communication infrastructure for UAVs could bring many new opportunities. Particularly, the UAVs can flexibly switch their connections with different MNOs within their coverage range for routing the traffic, aiming to significantly improve the QoS. Indeed, some new OBU’s (On-Board Units), which are used to enable vehicular communications to cellular networks, integrate the possibility to connect to several mobile networks at the same time. As illustrated in Figure 6.1, an OBU is connected via two networks (MNO1 and MNO2) to a steering service residing in an edge server nearby the BSs of the concerned MNOs. The traffic can only be directed using one selected MNO and the steering service ensures seamless connection to the internet by preserving one IP address if a steering operation happens. Although an OBU module is being originally considered for vehicular communications, this principle can be also considered for UAVs. A crucial issue for these OBU-equipped mobile UAVs is how to constantly select the right MNO to connect to for ensuring enhanced QoS and accordingly steer traffic. This chapter addresses the problem of UAV traffic steering in cellular UAVs. It builds from the expression of the outage probability derived in Chapter 2 and proposes a solution based on the framework of coalitional game to efficiently select the MNO to which the traffic will be steered. Performance evaluations are conducted to prove the effectiveness of the proposed approach. The contribution of the chapter is based on publication IV.

![Figure 6.1](image)

Figure 6.1. An OBU module can enable the connection to several mobile networks at the same time.


6.1 Problem Formulation

The problem formulation in this chapter is based on the outage probability expression in the uplink scenario defined in Theorem 3 of Section 2.1 (Note that the same notations of this section are maintained in this chapter). In addition, let us consider a set $\mathcal{O}$ of $O$ mobile operators providing connection through their deployed base stations. We denote by $\mathcal{V}_o$ the set of BSs belonging to the MNO $o \in \mathcal{O}$. Each UAV is connected to different mobile networks and transmits data through only one network at a given time, as schematized in Figure 6.2. The goal is to steer the connection to the MNO ensuring the best QoS for each UAV. Let us denote by $uv_o$ the link between the UAV $u \in \mathcal{U}$ and its serving BS $v_o \in \mathcal{V}_o$ from the MNO $o \in \mathcal{O}$. The problem would therefore be translated into choosing for each UAV the serving BS from the available MNOs, while minimizing their outage probability.

![Figure 6.2. A UAV can connect to different MNOs and steer the traffic only via one selected MNO.](image)

To characterize the choice to be taken by each UAV, we define the Boolean variable $x_{uo}$ as follows

$$x_{uo} = \begin{cases} 
1 & \text{If the UAV } u \text{ chooses the MNO } o \in \mathcal{O} \\
0 & \text{Otherwise.} 
\end{cases} \quad (6.1)$$

Consequently, the steering problem would be expressed as

$$\minimize_{\{x_{uo}\}} \max_{u \in \mathcal{U}} \left( \sum_{o \in \mathcal{O}} x_{uo} P_{out,uv_o}(\gamma) \right), \quad (6.2)$$

s.t.
Traffic Steering for UAV Communications in Cellular Networks

\[
\sum_{o \in O} x_{uo} = 1, \quad \forall u \in U, \quad \text{(6.3)}
\]

\[
x_{uo} \in \{0, 1\}, \quad \forall u \in U, \forall o \in O. \quad \text{(6.4)}
\]

In the above optimization problem, constraint (6.3) ensures that each UAV selects one and only one MNO to be used for transmitting data. Constraint (6.4) limits the value of the decision variable to \(\{0, 1\}\). On the other hand, the objective function (6.2) aims to reduce the outage probability for the UAVs. This function is non-convex and very complex. This complexity is inherent from the consideration of most of the propagation phenomena characterizing wireless communication. This shows the difficulty of achieving an optimal solution and raises the necessity of new solutions. The next section presents our proposed coalitional game optimization for UAV traffic steering in mobile network-enabled UAVs.

6.2 A Coalitional Game for UAV Traffic Steering in Cellular Networks

In order to steer the connection to the MNO ensuring the best QoS for the UAVs, we propose a coalitional game-based solution. A summary of the used notations is provided in Table 6.1. The game is defined among the set of users \(U\), where each UAV is considered as a player. The goal is to form the coalitions, such that the payoff of the different players is maximized.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(O)</td>
<td>Set of MNOs ((</td>
</tr>
<tr>
<td>(U)</td>
<td>Set of players.</td>
</tr>
<tr>
<td>(S)</td>
<td>Set of coalitions ((S = {S_1, S_2, \ldots, S_O})).</td>
</tr>
<tr>
<td>(\Pi_{S_o}(u))</td>
<td>Payoff of the player (u \in S_o).</td>
</tr>
<tr>
<td>(w(S_o))</td>
<td>Characteristic function of the coalition (S_o).</td>
</tr>
<tr>
<td>(S_i \triangleright_u S_j)</td>
<td>The transfer function of the player (u) from the coalition (S_i) to the coalition (S_j).</td>
</tr>
</tbody>
</table>

A coalition \(S_o\) represents a set of players that will rely on the MNO \(o\) for communication (a UAV \(u \in S_o\) will be served by its corresponding serving BS in the MNO \(o\)). Note that the number of coalitions equals to the number of available MNOs. Let \(S = \{S_1, S_2, \ldots, S_O\}\) be the set of coalitions (\(S_o \subseteq U\)). As each UAV uses one MNO to transmit data at a
given time, each two coalitions involve an entirely different set of players; i.e. \( \forall S_1, S_2 \in S : S_1 \neq S_2 \implies S_1 \cap S_2 = \emptyset \). The payoff of each player \( u \) belonging to a coalition \( S_o \) can be obtained as follows

\[
\Pi_{S_o}(u) = 1 - P_{\text{out,uv}_{\text{out},uv}}, \quad u \in S_o. 
\]  

(6.5)

As we can see from (6.5), the payoff of a player is defined based on the outage probability of the corresponding UAV within the coalition. In fact, the payoff in (6.5) represents the probability of successful communication for player \( u \). The player increases its payoff by reducing its outage probability and consequently increasing its success probability. As for the characteristic function of a coalition, it is defined as

\[
w(S_o) = \sum_{u \in S_o} \Pi_{S_o}(u). 
\]  

(6.6)

It is worth mentioning that the players are selfish and each one aims to increase its payoff without caring about the others. They change their coalitions in order to obtain a better payoff, leading therefore to decreased outage probability for all the players in their corresponding coalitions. To this end, we define the transfer operation which allows the UAVs to change their coalitions. This operation should ensure that the resulting partitioning is associated with a better payoff for the set of players.

**Definition 5.** A player \( u \) belonging to a coalition \( S_i \) \((u \in S_i)\) would be transferred to another coalition \( S_j \) \((S_i \neq S_j)\) iff:

\[
S_i \triangleright_u S_j \iff \begin{align*}
\Pi_{S_j\cup\{u\}}(u) &> \Pi_{S_i}(u) \quad \text{(6.7.1)} \\
\text{And} & \quad w(S_i\setminus\{u\}) - w(S_i) > w(S_j) - w(S_j \cup \{u\}). \quad \text{(6.7.2)}
\end{align*}
\]  

The definition in (6.7) means that a player \( u \) would be transferred from a coalition \( S_i \) to another coalition \( S_j \), if the concerned player will increase his payoff after the transfer (materialized by the condition (6.7.1)), while the gain of this operation on the coalition \( S_i \) is larger than the loss on the coalition \( S_j \) (condition (6.7.2)). Indeed, transferring a player from coalition \( S_i \) to \( S_j \) could potentially enhance the payoff of coalition \( S_i \) (withdrawing a potential interferer) and decrease the payoff of coalition \( S_j \). Condition (6.7.2) ensures that if the transfer operation incurs a loss on coalition \( S_j \), this loss should not be larger than the benefit obtained by coalition \( S_i \). The players keep changing their coalitions in order to enhance their payoffs.
Algorithm 6 Coalitional Game Algorithm.

Require: $S = \{S_1, \ldots, S_O\}$

1: while True do
2:     Stable = True
3:     for each two coalitions $S_i, S_j \in S$ do
4:         for each player $u \in S_i$ do
5:             if $S_i \triangleleft_u S_j$ then
6:                 $S_i = S_i \setminus \{u\}$
7:                 $S_j = S_j \cup \{u\}$
8:                 Stable = False
9:         end if
10:     end for
11: end for
12: if Stable then
13:     break
14: end if
15: end while

Algorithm 6 illustrates our steering solution which is based on coalitional game. The execution of the game starts with an initial partition of the players on the coalitions. This initial partitioning is performed in a random manner. For each two coalitions $S_i, S_j \in S$, the transfer operation is evaluated (lines [3 - 5] of Algorithm 6). This evaluation is performed according to equation (6.7). If the transfer conditions are satisfied, the two coalitions will be updated (lines [6 - 7] of Algorithm 6). This process will be repeated.

An important feature in coalitional game is the stability. A stable partition is reached if the players have no incentive to leave their coalitions since no player can increase his payoff by moving from one coalition to another. The stable partition is the optimal solution that maximizes the total sum-payoff. If no stable partition exists, the coalitional game is unstable. The variable ‘Stable’ in Algorithm 6 is used to characterize this state.

**Theorem 9.** Coalitional game convergence (Algorithm 6)

Starting from an initial random partition of the players on the coalitions, Algorithm 6 is guaranteed to converge towards a final stable and optimal partition.

Proof: As defined in Algorithm 6, the initial partition will be subject to players transfers applied sequentially. Let us express this transfer as follows:
where each $S^{(i)}$ represents the set of coalitions, $S$, after transfer operation number $i$ and $S^{(0)}$ is the first partition. The symbol $\rightarrow$ reflects a transformation operation from one state to another which is materialized by a transfer of one player. As the number of coalitions and the number of players are limited, the possible states of the coalitions are also limited.

**Lemma 2.** To prove the convergence of Algorithm 6, it suffices to prove that the transfer operation does not lead to repeated partitions.

The above lemma is justified by the fact that the number of partitions is limited. If the partitions do not repeat, the sequence defined in (6.8) will converge to a final partition. This sequence is governed by the transfer operation defined in (6.7). The latter can also be written as follows

$$
S_i \triangleright_u S_j \iff \left\{ \begin{array}{l}
\Pi_{S_j \cup \{u\}}(u) > \Pi_{S_i}(u) \\
\text{And} \\
w(S_i \setminus \{u\}) + w(S_j \cup \{u\}) > w(S_j) + w(S_i).
\end{array} \right. \quad (6.9.2)
$$

From condition (6.9.2) we can see that the resulting states of the two concerned coalitions, together, have better payoffs compared to their original states. In addition, the other coalitions, not concerned by the transfer operation, will not be affected. In other words, their payoffs remain the same. Consequently, we can write the following

$$
S^{(i)} \rightarrow S^{(j)} \Rightarrow \sum_{S_{k}^{(i)} \in S^{(i)}} w(S_{k}^{(i)}) < \sum_{S_{l}^{(j)} \in S^{(j)}} w(S_{l}^{(j)}). \quad (6.10)
$$

Consequently, the transfer operation leads to different partitions. As per Lemma 2, Algorithm 6 does not lead to repeated partition and therefore converges to a final stable partition. Moreover, the sum of the payoffs of the resulting coalitions, after a transfer operation, increases as illustrated by (6.10). This shows that the final obtained partition has the largest sum-payoff and is thus optimal, which proves Theorem 9. \(\square\)
6.3 Performance Evaluation

In this section, we present the evaluation results of the proposed coalition game for UAV traffic steering in mobile network-enabled UAVs. The communication model is implemented considering a Nakagami model with \( m = 2 \), a carrier frequency \( f_c \) of 2 GHz, a noise variance \( N_0 \) of \(-130\) dBm [28], and a sensitivity threshold \( \gamma_{th} \) of \(10^{-3}\) [7]. The evaluation is performed in a 1 km x 1 km square area. The altitude of the UAVs is randomly attributed between 22.5 m and 300 m, which is the applicability range for the used path loss model [4]. In each evaluation, we have used 12 BSs per MNO, with a varying number of UAVs and MNOs.

Figure 6.3 depicts the benefit of our coalition game-based solution, on the outage probability, for a varying number of UAVs and MNOs. Our proposed scheme is compared to a random selection of the serving MNO by each UAV. The different sub-figures, Figure 6.3(a), Figure 6.3(b) and Figure 6.3(c), have been obtained considering respectively two, three and four MNOs. These curves resulted from averaging the outage probability of all the considered UAVs. As we can see from these sub-figures, for a fixed number of UAVs, increasing the number of the MNOs reduces the outage probability for these UAVs. Indeed, as each UAV selects only one MNO to be used for transmitting data, the other non-serving MNOs will not be subject to interference from this UAV. We can also see that the outage probability is reduced, when increasing the number of MNOs, even with a random selection. This shows the potential of exploiting several mobile networks to enhance the QoS for flying UAVs. In addition, Figure 6.3 illustrates the effectiveness of the proposed solution in enhancing the QoS for the flying UAVs. The MNO selection based on the coalition game achieves better outage probability compared to the random selection, for different numbers of MNO and UAV. The coalition game starts with a random selection, on which a sequence of player transfer operations will be applied. As shown in equation (6.10), the transfer operation enhances the sum of the characteristic function of the coalitions. Consequently, the final selection provided by the game ensures better payoff for the players, which is translated into reduced outage probability for the corresponding UAVs.

In Figure 6.4, we have evaluated the sum of the payoffs for a fixed number of UAVs (120 UAVs) and different numbers of MNOs. The sum of the payoffs also reflects the sum of the coalitions’ characteristic func-
Figure 6.3. The performance evaluation of the proposed coalitional game scheme for a varying number of UAVs and MNOs.

tions. As it can be seen from this figure, the sum-payoff increases with the number of considered MNOs. Since we consider a fixed number of UAVs, the increase of the sum payoff signifies that the average individual payoff per UAV increases as a larger number of MNOs is employed. Consequently, the corresponding UAVs will have better QoS. Moreover, the evaluation shows that the proposed solution outperforms the random selection scheme by yielding a larger sum-payoff. Note as well that the gain in terms of sum-payoff obtained by using our proposed solution instead of the random selection increases as we increase the number of MNOs.

Meanwhile, Figure 6.5 depicts the number of transfer operations ex-
executed by the algorithm before reaching the stability. This reflects the convergence speed of the algorithm. A larger number of transfer operations induces a longer time for the algorithm to reach an optimal stable partition. From Figure 6.5, we see that the number of transfer operations increases, in general, with the number of considered MNOs and the connected UAVs. Indeed, these two parameters reflect respectively the number of coalitions and the number of players. The number of players’ transfer attempts is executed according to the size of these two parameters (lines 3 and 4 in Algorithm 6). This demonstrates the impact of these two parameters on the convergence speed of the algorithm. On the other hand, we also take note that in a few situations, the number of transfer operations can decrease when passing to more MNOs or UAVs. For example, as it can be seen from Figure 6.5, the number of transfers considering three MNOs and 60 UAVs is less than that using 55 UAVs. This is due to fact that the initial partition is random (random selection of the serving MNO). As expressed by equation (6.8), the initial partition is subject to a sequence of player transfer operations until reaching the stability. Each operation allows enhancing the sum of the characteristic function of the coalitions. This shows that the initial partition plays also a role in increasing the convergence speed of the algorithm. If the initial random partition is closer to the final stable partition, a smaller number of transfer operations is needed for the algorithm to converge to the final optimal partition. It is important to mention that the results in Figure 6.5 were obtained by averaging over 9 trials. By averaging over several trials, we decrease the variance of the obtained results.

![Figure 6.5. Evaluation of the number of transfer operations.](image-url)
6.4 Related Works

In the literature, some works considered the concept of connection steering to route the traffic between different network functions [54]. However, this principle is less studied for the part between the connected device and the serving BSs. The work in [55] focused on LTE-connected vehicles. The authors target enhancing the communication by anticipating QoS degradation and directing the traffic to different RAT. In [56], the authors considered the problem of connection steering for UAV communications in cellular networks. The proposed solution steers UAV communication to the mobile network ensuring the best Radio Signal Strength Indicator (RSSI) quality. The work is analyzed by applying Discrete Time Markov Chain (DTMC) to evaluate the performance of the testbed results. However, while RSSI can be considered as a good indicator for terrestrial communication, aerial communication presents different characteristics imposing the revision of such indicators.

In contrast, this chapter addressed the problem of steering the communication between the cellular devices and the serving BSs, which is not well covered in the literature. Furthermore, we have considered a communication model that accounts for most the of propagation phenomena in wireless communication, which makes it more realistic.

6.5 Summary

This chapter elaborated on exploiting the presence of several MNOs to enhance the performance of UAV communications. To this end, the chapter considered the problem of UAV traffic steering, where the aim is to select, for each UAV, the MNO that provides the best QoS for transmitting data in the network. The chapter built from the outage probability expression derived in Chapter 2 and formulated it as an optimization problem for minimizing the maximum outage probabilities. Given the complexity of the underlying non-linear and non-convex problem, we have proposed a solution based on the framework of coalitional game. The goal is to form UAV coalitions around the MNOs in a way to enhance their QoS. A transfer operation is defined to enable UAVs to change their coalitions, reduce their outage probability, and increase their payoff. Through simulation, we have shown the potential of exploiting several MNOs to enhance the UAVs’ QoS. We demonstrated the effectiveness of our proposed coalitional
game approach in converging to a stable partition that maximizes the sum-payoff of the aggregate network.

The solutions proposed in the previous chapters are based on techniques such as game theories and linear programming. However, the application of such solutions is associated with time and can be considered for offline use. For instance, when the flight plans of the UAVs are predefined, such optimization can be used to plan the network resources/UAV deployment and trajectory. In order to address online optimization, it is highly important to elaborate on solutions that perform fast optimization. The next chapter considers the same problem tackled in this chapter (UAV traffic steering) and proposes a solution that can be considered for real-time use. These solutions are based on the framework of deep reinforcement learning.
7. Enabling Fast Optimization to Enhance the Performance of UAV communications in Cellular Networks

This chapter focuses on enabling fast optimization to enhance the performance of UAV communications in cellular networks. Indeed, the above chapters consider solutions such as game theories and linear optimization, and can be considered in an offline environment. For instance, when the flight plans of the UAVs are predefined, such optimizations can be used to plan the network resources or the UAV deployments. However, as solving these optimization takes time, they are not adequate for real-time use. To this end, this chapter addresses the issue of enabling fast optimization to enhance the performance of UAV communications in cellular networks. This can be achieved by using ML-based approaches. This chapter considers the problem of UAV traffic steering, tackled in the previous chapter (Chapter 6), which is built from the expression of the outage probability derived in Chapter 2. It introduces a solution based on the framework of deep reinforcement learning to enable fast and online traffic steering for UAV communications in cellular networks. Performance evaluations are conducted to prove the effectiveness of the proposed solution. The contribution of this chapter is based on publication VIII.

7.1 A Deep Reinforcement Learning Approach for UAV Traffic Steering in Cellular Networks

We address in this chapter the problem of traffic steering for UAV communications in cellular networks, in which each UAV needs to select the MNO that enhances the performance of UAV communications. To this end, we consider the same formulation of the problem proposed in Section 6.1 (the reader can refer to this section for further details on the problem formulation). Unlike the solution proposed in Chapter 6, we introduce in this chapter a solution based on the framework of deep reinforcement learning which can be used to enable fast optimization. A DRL model can be trained to learn complex tasks and effectively takes decisions through
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the interaction with the environment based on trial and error processes. Unlike supervised and unsupervised machine learning algorithms, reinforcement learning techniques do not require a prior dataset. In what follows, we present the architecture of the proposed DRL framework for UAV traffic steering. Thereafter, we introduce the underlying learning process.

### 7.1.1 Architecture of the Proposed DRL Framework

The general architecture of the proposed DRL framework is depicted in Figure 7.1. A DRL agent periodically interacts with an environment, observes the current state $s^t$ (arrow 1 in Figure 7.1), then executes an action $a^t$ (arrow 2 in Figure 7.1). Subsequently, the agent will observe a new state $s^{t+1}$ and receives a corresponding reward $r^t$ (arrow 3 in Figure 7.1). We also design a replay memory to store the history of experiences that will be used during the learning process (arrow 4 in Figure 7.1). At a time step $t$, the agent experience is defined as tuple $(s^t, a^t, r^t, s^{t+1})$. The replay memory has a limited size and it will be used to extract random samples to train the neural network (arrow 5 in Figure 7.1). Thereafter, we define the state of the system, the action space and the system reward.

**Figure 7.1.** Architecture of the DRL framework.

**System State**

The system state is defined in a way to capture the feature of the current deployment. To this end, we consider the mean SNR to the serving BS of the selected MNO for each UAV in defining the system state.
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Furthermore, it is very important to define the system state in a way to accommodate the dynamic of the network, so effective decisions can be made when the number of UAVs changes. In this regard, the number of MNOs, BSs, and sub-carriers does not change frequently in practice. Taking this into consideration, we define the function \( w(v_o,c_o) \) that returns the UAV \( u \) being served by the MNO \( o \) and assigned with the sub-carrier \( c_o \) from the BS \( v_o \in V_o \). At a time step \( t \), the system state can be defined as \( s^t = (s^t_{o,v_o,c_o})_{o,v_o,c_o} \in \mathbb{R}^{\mid O \mid \times \mid V_o \mid \times \mid C_o \mid} \), where

\[
s^t_{o,v_o,c_o} = \begin{cases} 
A_{uv_o} + B_{uv_o}, & \text{If } \exists u \in U | u = w(v_o,c_o), \\
0, & \text{Otherwise}.
\end{cases} \tag{7.1}
\]

As it can be seen, a system state is based on the mean SNR from each UAV to the serving BS of the selected MNO.

**Action Space**

After receiving a state, optimal selection of the target MNOs needs to be performed. The action therefore consists of the target MNOs to be selected by each UAV and is defined as \( a^t = (a^t_{v_1,c_1})_{v_1,c_1} \in \mathcal{O}^{\mid V_1 \mid \times \mid C_1 \mid} \). The actions are also applied to the UAVs in their assignment order to the first MNO. This allows to make a mapping between the captured state and the taken action, in terms of the order of the UAVs. This order will also be considered for the system reward as detailed in what follows.

**System Reward**

The goal is to select for each UAV the best MNO ensuring the enhanced QoS in the network. The system reward is therefore defined by considering the outage probabilities achieved by the UAVs after executing the received actions. More precisely, a reward for a UAV \( u \) is based on \( P_{uv_o}^{out}(\gamma_{th}) \), where \( v_o \) is the served BS of the selected MNO after executing the action. The system reward is therefore defined as \( r^t = (r^t_{v_1,c_1})_{v_1,c_1} \in [0,1]^{\mid V_1 \mid \times \mid C_1 \mid} \), where

\[
r^t_{v_1,c_1} = \begin{cases} 
1 - P_{uv_o}^{out}(\gamma_{th}), & \text{If } \exists u \in U | u = w(v_1,c_1), \\
1, & \text{Otherwise}.
\end{cases} \tag{7.2}
\]

As we can see, the system reward is based on the outage probabilities of UAVs according to their assignment order to the first MNO, as is the case for the action.
7.1.2 Learning Process

In the proposed framework, we consider two important reinforcement learning algorithms, namely Deep Q-Network (DQN) and Advantage Actor-Critic (A2C). A DQN agent relies on replaying experiences to ensure a stable learning. It uses Q-values (which is the maximum expected reward) and computes the temporal difference error based on the distance between Q-targets (which is the maximum value that can be captured from the next states) and the predicted Q-values. Two networks are used in our implementation of the DQN agent, namely Q-network and target network, to reduce the relevance between choosing actions and training the model [57]. In the A2C algorithm, we consider two networks, i.e., the actor and critic networks. The Actor observes the environment and selects a given action by outputting a probability distribution across the action space. After that, the Critic evaluates the quality of the selected action regarding both the current state and the next state [58]. Furthermore, we use a replay memory to store experience in our framework, which is implemented as part of the agent.

Algorithm 7 DRL algorithm.

```
Require: Agent (DQN or A2C)
1: for episode t = 1 to E do
2: Observe the state s^t
3: a^t = Agent.select_action(s^t)
4: Execute action a^t
5: Get the reward r^t
6: Observe the state s^{t+1}
7: Agent.push_replay_memory(s^t, a^t, r^t, s^{t+1})
8: Agent.learn()
9: end for
```

Algorithm 7 summarizes the learning process adopted in the proposed approach. This process is executed in episodes until reaching a maximum value $E$. This process is common for both DQN and A2C agents. At each episode $t$, the agent gets the system state $s^t$ from the environment. Thereafter, the agent selects an action $a^t$. This action is chosen based on the Q-network in the case of the DQN agent, and based on the Actor network in the case of A2C agent. After executing the selected action, the agent gets the immediate reward $r^t$ and the new state $s^{t+1}$. This allows to construct the transition $(s^t, a^t, r^t, s^{t+1})$ and store it in the replay memory. Finally, the agent takes samples from the replay memory and learns from them. This is translated into updating the Q-network in the case of the
DQN agent, and both Actor and Critic networks in the case of the A2C agent.

### 7.2 Performance Evaluation

In this section, we provide the performance evaluation of the proposed reinforcement learning approach. The simulation environment is implemented using python. We considered a carrier frequency $f_c$ of 2 GHz, a noise variance $N_0$ of $-130$ dBm [28], and a Nakagami parameter $m = 2$. Furthermore, in order to reduce the action space we limit the detected area for UAVs to a region of $500m \times 500m$ and of 4 BSs and 20 UAVs in total. The altitude of the UAVs is fixed between 22.5 m and 300 m, which is the applicability range for the used path loss model [4]. As for the DRL programming environment, we used Pytorch 1.7.1 [59]. For the hyperparameters, we considered a learning rate of 0.003 for the two agents.

We evaluated the proposed DRL-based approach for traffic steering considering DQN and A2C algorithms in terms of the achieved outage probabilities. The obtained results are respectively depicted in Figure 7.2 and Figure 7.3. These evaluations have been performed considering 5000
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Figure 7.3. Evaluation of the average reward and outage probabilities for the A2C agent.

episodes and a varied number of MNOs. In terms of the outage probabilities, we have compared the achieved results using the DRL approach against the initial deployments consisting of a grid topology and uniform distributions of MNOs on the UAVs (plotted in an orange color (the more light color in black-and-white printed form) in Figure 7.2 and Figure 7.3). As we can see, both agents are able to learn optimal solutions in selecting the MNOs to be used to steer the connection for UAVs. The obtained results show that the agents are able to increase the reward function, which is translated into reduced outage probabilities as shown in Figure 7.2 and Figure 7.3 (note that the reward function is the inverse of the outage probability, as provided in Equation (7.2)). Furthermore, the achieved reward increases with the number of considered MNOs. This observation is valid for the two agents. Indeed, the more MNOs are available, the more choices are present to distribute the MNOs on the UAVs in a way to achieve more enhanced performance. The evaluation also shows that the A2C agent achieves better results compared to the DQN agent, especially when the number of MNOs increases. Indeed, increasing the number of MNOs is translated into increasing the action space. In this regard, the A2C agent demonstrates its effectiveness in supporting a
large action space compared to the DQN agent. Compared to the initial assignment, the outage probabilities have been reduced by 4.13%, 4.08%, and 3.56% when considering the DQN agent on a deployment of 2 MNOs, 3 MNOs and 4 MNOs, respectively. It has also been reduced by 8.04%, 8.31%, and 11.13% when considering the A2C agent on a deployment of 2 MNOs, 3 MNOs and 4 MNOs, respectively.

We have also evaluated the execution time for selecting the target MNOs considering the two agents. The result of the evaluation is depicted in Figure 7.4. This evaluation has been conducted by averaging 5000 trials. As we can see, the application of the proposed DRL approach involves a short time which is less than 5 ms. On average, the execution time was 0.27 ms for the DQN agent and 4.5 ms for the A2C agent. This makes the DQN agent 16 times faster than the A2C agent. This is due to the fact that the A2C uses two networks during the selection, in addition to the application to a distribution function. Nevertheless, the execution time remains very short which is in the order of milliseconds. This demonstrates the applicability of such solutions for fast optimization. We can also observe that increasing the MNOs, from 2 to 4, did not affect the execution time. In our implementation, increasing the number of MNO is translated into increasing the action space and the corresponding neural networks only at the output layer. We note that these evaluations have been performed on an x86_64 machine with 8 CPUs of 2397.224 MHz, and recent studies have validated the deployment of the DRL algorithm for real UAVs.

![Figure 7.4. Evaluation of the execution time for DQN and A2C agents.](image)

### 7.3 Related Works

Recently some studies have proposed the use of DRL for UAV communications in cellular networks, mainly for path planning and resource man-
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management. In [60], the authors proposed a DRL for UAV communications in cellular networks. The goal is to optimize UAV path planning while taking resource management into consideration by achieving a trade-off between maximizing energy efficiency and minimizing both wireless latency and interference. The authors in [61] tackled the problem of UAV navigation in a way to have the best UAV-ground link. The authors considered massive multiple-input-multiple output (MIMO) and proposed a deep Q-learning for selecting the optimal policy. In [62], the authors considered the problem of wireless charging with collecting sensor data from sensor devices scattered in the physical environment. A reinforcement learning based approach is proposed to plan the route of UAV, where the problem is formulated as a Markov decision process and Q-learning is used to find the optimal policy. The authors in [63] considered the problem of providing computation resources to ground UE using Flying Mobile Edge Computing (F-MEC) on top of UAVs. A reinforcement learning-based algorithm is proposed to optimize the trajectory of the UAVs. In another work [64], the authors focused on network-aided UAVs, where UAVs serve as aerial base stations for multiple ground users. The trajectory design is investigated to maximize the expected uplink sum rate with inaccessibility to user-side information, such as locations and transmit power as well as channel parameters. The problem is formulated as a Markov decision process and solved with model-free reinforcement learning.

7.4 Summary

This chapter addressed the problem of enabling fast optimization for UAV communications in cellular networks. It considered the same problem tackled in Chapter 6 which builds from the expression of the outage probability on the uplink derived in Chapter 2 and aims to select the MNO ensuring the best QoS for each UAV. To this end, the chapter proposed an approach based on deep reinforcement learning. Two important DRL algorithms, namely DQN and A2C, have been considered. The simulation results showed that the two algorithms can learn optimal decisions in selecting the MNO to be used for steering the traffic.Remarkably, the results showed that the implemented A2C algorithm can achieve better results than the DQN algorithm, especially when the number of MNOs increases. On the other hand, while the execution time of the two algorithms is very short, the implemented DQN agent is faster than the A2C
agent.
8. Conclusion

This dissertation presented the author’s work on enhancing the performance of UAV communications in cellular networks. While cellular networks are expected to be the main communication infrastructure to enable the challenging applications of UAVs, a number of challenges needs to be addressed. This is mainly due to the fact that cellular networks are deployed to serve ground users, while aerial communication presents different characteristics that need to be taken into consideration. Cellular networks also bring new opportunities that can be exploited by UAV communications to enhance the underlying performance.

8.1 Discussion

In order to address the objective established by the dissertation, we have developed 7 research questions. RQ I is the main research question (which is “How to enhance the performance of UAV communications in cellular networks?”) that covers the remaining RQs. First, as aerial communication presents different characteristics compared to ground communication, we raised RQ II on how to model UAV communication in cellular networks, how to define the performance indicators and what are the key parameters affecting the indicators. This also represents a fundamental research question that ensures a solid basis for the work developed in the dissertation. Thereafter, we raised RQ III which focuses on supporting the co-existence of UAVs and UEs in cellular networks, and how to enhance the underlying performance. On the other hand, as UAV applications can be associated with different service types, we raised RQ IV which focuses on supporting the co-existence of several QoS types in UAV communications. Furthermore, as cellular networks can bring new opportunities, we elaborated in RQ IV on the possibility of exploiting the presence of several
UAVs to enhance the performance of UAV communications. On the other hand, the presence of several MNOs can also be exploited to enhance the performance of UAV communications. We have translated this into RQ V, which is formulated as "Can the presence of several MNOs be exploited to enhance the performance of UAV communications?". Finally, we also raised RQ VI that targets enabling fast optimization to enhance the performance of UAV communications in cellular networks.

The second research question focused on modeling UAV communications in cellular networks and the definition of the underlying performance indicators. As aerial communications present different characteristics compared to terrestrial links, we have considered a model that accounts for most of propagation phenomenon experienced in wireless signals (e.g., path loss, interference and fast fading), and we have derived expressions for the outage probability, the effective rate and the transmission delay. The proposed expressions in this dissertation are original and can not be found in the literature. Furthermore, we have also provided analysis and discussion on some key parameters affecting these performance indicators (i.e., sub-carrier assignment, power allocation and UAV deployment).

The outcome of this research question served as a basis for the remaining questions; the latter built from the defined expressions of the performance indicators and targeted optimizing the identified parameters to enhance the performance of UAV communications in cellular networks.

The third research question focused on supporting the co-existence of UAVs and UEs in cellular networks, by enhancing their underlying performances. Indeed, cellular networks are initially deployed to serve ground UEs and it is crucial to elaborate on supporting the co-existence with UAVs. Therefore, in order to tackle this research question, we have considered a cellular network serving both ground UEs and flying UAVs, and we have addressed the joint-problem of sub-carrier assignment and power allocation on the downlink to reduce the outage probabilities. Given the complexity of the problem, we proposed a solution based on the framework of game theories where two sub-games are introduced. We argued that separating between UAVs and UEs in terms of the assigned sub-carriers can reduce the interference impact. This principle has been implemented using the framework of matching sub-game. In addition, in order to boost this allocation, a coalitional sub-game has also been proposed. The stability of the two sub-games has been proved. Furthermore, a power optimization solution has been introduced and considered in the
two sub-games.

The fourth research question focused on supporting the co-existence of several QoS types in UAV communications. To this end, we considered the case of UAVs serving as flying BSs and providing network connectivity to ground IoT devices, where each of the latter requires two service types, namely uRLLC and eMBB. In order to tackle this issue, we addressed the joint-problem of sub-carrier assignment and UAV deployment to jointly reduce the transmission delay and enhance the effective rate for each IoT node. The definition of the associated problem resulted in a non-linear and non-convex optimization. To solve this problem, we proposed an iterative approach, where each iteration tackles an optimization problem. Furthermore, in order to jointly enhance the two service types, we proposed a trade-off optimization. The evaluation showed that the consideration of the proposed approach allows to achieve a fair optimization between the two services.

The fifth research question elaborated on exploiting the presence of several UAVs to enhance performance of UAV communications in cellular networks. In this regard, we have considered the process of UAV control, where C2 messages and telemetry data are constantly being exchanged between the flying UAVs and the GCS. We have introduced the concept of aerial control system where part of the control logic is shifted from the GCS to be performed by the UAVs themselves. This exploits the automatic nature of some UAV applications and is meant to reduce the communication with the cellular networks. Instead, U2U communication is established to ensure the control logic that is managed by a given UAV, named cluster head. Analytical evaluations showed that shifting part of the control logic to be performed by the UAVs, instead of a systematic communication between all the UAVs and the GCS, has a direct impact on enhancing the spectral efficiency for effective data to be transmitted by UAVs or the ground UEs.

The sixth research question focused on exploiting the presence of several MNOs to enhance the performance of UAV communications in cellular networks. In this regard, we have addressed the fundamental issue of traffic steering in which each UAV needs to steer its traffic though one out of several MNOs in a way to enhance the overall performance of the communication. We have modeled the problem as an optimization problem for minimizing the maximum of outage. This is a non-linear and non-convex problem which is difficult to resolve. To this end, we proposed a solution
based on the framework of coalitional game in which UAVs are considered as player while the MNOs are considered as coalitions. We have also defined a transfer operation (allowing a player to change its coalition and increase its payoff) and proved the stability of the game. The evaluations showed that the consideration of several MNOs can effectively be translated into enhanced performance for UAV communications in cellular networks. While this is a valid approach, it will be swiftly superseded once 5G networks become the norm as such an approach could be more easily realized through cross-operator network slicing and multi-connectivity.

The last research question targeted enabling fast optimization for enhanced performance of UAV communications in cellular networks. Indeed, the optimizations in the previous contributions are based on solutions such game theory and linear programming. Such solutions can be considered for offline use (e.g., planning the network) and are not adequate for online environment, as the latter requires fast optimization. This can be achieved by considering machine learning techniques. To this end, we considered the problem of UAV traffic steering and we proposed an approach based on deep reinforcement learning. The solution introduced a design that models DRL elements (including, the system state, the action space and the system reward) as well as the learning process. Furthermore, we have considered two important DRL algorithms, which are DQN and A2C, in our design. The evaluations showed that the proposed approaches (deep learning and reinforcement learning) are able to learn and select optimal allocation of the MNOs on the UAVs in a very short time, which is in the order of milliseconds.

### 8.2 Open Issues and Research Challenges

This dissertation addressed enhancing the performance of UAV communications in cellular networks and proposed a number of solutions with numerical results. Nonetheless, we believe that the following topics need to be investigated further.

In terms of real-world applications, the execution of the developed solution requires information captured from the system state. This includes information from the BSs (e.g., the position of the BSs, the employed power, the set of sub-carriers, etc.) as well as information from the connected users (e.g., the position of the UAVs/UEs, the employed power, etc.). The exact required information depends on the tackled problem and the
communication scenario. The solutions provided in the dissertation are centralized. For instance, considering power optimization on the downlink for UAVs requires information on the base stations and also on the connected users. On the users’ side, the geographical position of each UAV is required. All this information is mainly provided by the cellular network operator. Indeed, an operator owns the base stations and has access to their geographical positions, their transmission powers and their used sub-carriers. Furthermore, the geographical position of the users can be known in advance (e.g., prior to its flight, the UAV operator submits the flight plan to the UTM - Unmanned aerial system Traffic Management which can be communicated to the mobile operator) or be provided by the mobile network using MPS (Mobile Positioning System). All this information will feed the optimization solution to allow the cellular network to provide enhanced QoS. However, other scenarios, such as UAV traffic steering on the uplink, require communicating the results of the optimization to the connected devices. This raises questions on synchronization to achieve the target objective and constitutes a future research challenge.

The different optimization solutions provided in the thesis are based on a centralized approach. Exploring distributed approaches for enhancing the performance of UAV communications in cellular networks is an open research direction of the thesis. For instance, the DRL-based solution for the problem of UAV traffic steering proposed in Chapter 7 is based on a centralized agent. The latter collects the experiences from the different UAVs, trains a model and decides the actions to be executed by the UAVs. Such an approach leads to a communication overhead between the UAVs and the centralized agent, and might not be applicable in scenarios where UAVs are not willing to share their experiences due to privacy. It is therefore very important to explore distributed approaches, such as Federated Reinforcement Learning, where optimization actions are performed locally (by the UAVs themselves in this case).

The addressed challenges in this dissertation does not tackle the UAV path planning. Indeed, the different contributions presented in the dissertation focus more on optimizing network resources and UAV deployment. Therefore, it is interesting to extend the work to also cover the path planning of the UAVs. This can be achieved by introducing the notion of time, where the system state can be captured at each timestep. In this regard, the different proposed solutions in this dissertation can be used as a basis to perform network/UAV path planning while including the notion of
In the context of providing wireless connectivity from the sky, UAVs are envisioned to play a key role under the umbrella of a non-terrestrial network (NTN). The latter comprises of satellites and high altitude platforms providing cellular services [65]. More precisely, a NTN incorporates different flying components which include UAVs, High-Altitude platforms (HAPs), Low Earth Orbit satellites (LEOs), and Geostationary Equatorial Orbit satellites (GEOs). In terms of distance from earth, while UAVs are usually flying in an altitude less than \(1 km\), HAPs flies in an altitude \(20 km\), LEOs flies in an altitude of \(300 – 1500 km\), and GEOs flies \(35786 km\) from the earth. This would ensure connections at different levels. In this regard, extending the proposed works in this thesis to consider NTN is an interesting open research direction. Indeed, Chapter 4 addressed the issue of providing network connectivity to ground IoT devices from flying UAVs. While terrestrial network is considered as a backhaul in this chapter, using non-terrestrial backhauling is an interesting research direction.

Another research direction that can be considered as a continuation of the work conducted in this dissertation is radio resource scheduling. Indeed, radio resource scheduling is related to the medium access control (MAC) layer. In this regard, 3GPP has advanced several technical reports to standardize and define MAC aspects as well as physical layer aspects in radio technology. This includes 3GPP TR 38.801 [66], 3GPP TR 38.802 [67], 3GPP TR 38.803 [68] and 3GPP TR 38.804 [69]. It is therefore very interesting to address the problems related to radio resource scheduling to enhance the performance of UAVs in cellular networks, while considering the definitions and the framework advanced by 3GPP. The solutions provided in this dissertation constitutes a basis that can be used by the MAC layer to enable optimized scheduling of the resources.

While the different contributions advanced in this dissertation have been validated by simulations and analytical evaluations, they lack field experiments. Implementing the proposed solutions reflects an open research challenge that can complete the work conducted in this dissertation.
This appendix is reserved to provide proofs of the theorems proposed in the dissertation. It is divided into four parts, where the first part addresses the proof of Theorems 1 and 2 of Chapter 2, the second part provides the proof of Theorems 3 and 4 of Chapter 2, the third part provides that of Theorems 5 and 6 of Chapter 2, while the fourth part provides that of Theorems 7 and 8 of Chapter 3. Note also that the notation in each part follows that of the corresponding chapter.

9.1 Proof of Theorems 1 and 2

This part of the appendix provides the proofs of Theorems 1 and 2. The outage probability expressions on the downlink are derived for both a UE and a UAV. This probability is defined as $P_{\text{out}}(\gamma_{th}) = P(SINR \leq \gamma_{th})$. Let us recall the expression of the SINR which is given as

$$SINR_{vu} = \frac{\gamma_{vu}}{1 + \sum_{t=1}^{N} \gamma_{tu}} = \frac{\gamma_{vu}}{1 + I} = \frac{\gamma_{vu}}{I'},$$

(9.1.1)

where, the term $I = \sum_{t=1}^{N} \gamma_{tu}$ includes all the interfering BSs. Consequently, the outage probability for the ink $vu$ can be written as

$$P_{\text{out}}(\gamma_{th}) = P(SINR \leq \gamma_{th}) = P\left(\frac{\gamma_{vu}}{I'} \leq \gamma_{th}\right)$$

$$= E_{I'}\left[P(\gamma_{vu} \leq \gamma_{th}y|I' = y)\right] = \int_{1}^{\infty} F_{\gamma_{vu}}(\gamma_{th}y)P_{I'}(y)dy,$$

(9.1.2)

where the term $F_{\gamma_{vu}}(x)$ refers to the Cumulative Distribution Function (CDF) of $\gamma_{vu}$ (computed as $F_{\gamma_{vu}}(x) = \int_{0}^{x} P_{\gamma_{vu}}(y)dy$), while $P_{I'}(y)$ is the
Probability Density Function (PDF) of $I'$. The expression of these functions differs on whether the receiver equipment $u$ is a UE or a UAV.

**The receiver equipment $u$ is a UE**

Let us compute the Moment Generating Function (MGF) and the PDF of $\gamma_{vu}$. Their expressions can be given as

\[
M_{\gamma_{vu}}^{UE}(s) = (1 - s\bar{\gamma}_{vu})^{-1}, \quad (9.1.3)
\]

\[
P_{\gamma_{vu}}^{UE}(x) = \frac{1}{\bar{\gamma}_{vu}} \exp \left( -\frac{x}{\bar{\gamma}_{vu}} \right). \quad (9.1.4)
\]

The MGF of $I$ includes all the interfering BSs and can be deduced as

\[
M_{I}(s) = \prod_{t=1}^{N} M_{\gamma_{tu}}(s) = \prod_{t=1}^{N} (1 - s\bar{\gamma}_{tu})^{-1} = \sum_{t=1}^{N} \frac{\alpha_{t}}{s - \frac{1}{\bar{\gamma}_{tu}}}, \quad (9.1.5)
\]

where $\alpha_{t}$ is the same as in Theorem 1, satisfying (2.7), and is obtained using fractional decomposition (multinomial theorem [70]). The PDF $P_{I}(x)$ of $I$ can be obtained, by computing the inverse Laplace transform of $M_{I}(s)$ in (9.1.5), as

\[
P_{I}(x) = L^{-1}[M_{I}(s)] = L^{-1} \left[ \sum_{t=1}^{N} \frac{\alpha_{t}}{s - \frac{1}{\bar{\gamma}_{tu}}} \right] = \sum_{t=1}^{N} \alpha_{t}(-1) \exp \left( -\frac{x}{\bar{\gamma}_{tu}} \right). \quad (9.1.6)
\]

Using (9.1.6) and the fundamental theorem of transformation of random variables [71], the PDF $P_{I'}(y)$ of $I'$ is computed as

\[
P_{I'}(y) = \sum_{t=1}^{N} \alpha_{t}(-1) \exp \left( -\frac{y - 1}{\bar{\gamma}_{tu}} \right). \quad (9.1.7)
\]

As for the CDF $F_{\gamma_{vu}}^{UE}(x)$ of $\gamma_{vu}$, it is determined from (9.1.4) as

\[
F_{\gamma_{vu}}^{UE}(x) = \int_{0}^{x} P_{\gamma_{vu}}^{UE}(y) dy = 1 - \exp \left( -\frac{x}{\bar{\gamma}_{vu}} \right). \quad (9.1.8)
\]

Consequently, the outage probability can be computed as
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\[ P_{\text{out}}^{UE}(\gamma_{th}) = \int_1^\infty F_{\gamma_{vu}}(\gamma_{th}y) P_I'(y) dy \]
\[ = 1 - \int_1^\infty \exp\left(-\frac{\gamma_{th}y}{\gamma_{vu}}\right) P_I'(y) dy \]
\[ = 1 + \exp\left(-\frac{\gamma_{th}}{\gamma_{vu}}\right) \sum_{t=1}^N \frac{\alpha_t}{\gamma_{vu} + \gamma_{vu}}. \quad (9.1.9) \]

Note that (9.1.9) is the outage probability provided in Theorem 1.

The receiver equipment \( u \) is a UAV

Aerial communication is characterized by both LoS and NLoS conditions. As defined in (2.10), the terms \( A_{vu} \) and \( B_{vu} \) reflect the mean SNR related to the two conditions. Let us compute the MGF \( M_{UAV}^{\gamma_{vu}}(s) \) of \( \gamma_{vu} \).

\[ M_{UAV}^{\gamma_{vu}}(s) = M_{\gamma_{LoS, vu}} \cdot M_{\gamma_{NLoS, vu}} = \left(1 - \frac{sA_{vu}}{m}\right)^{-m} \left(1 - sB_{vu}\right)^{-1} \]
\[ = \sum_{j=1}^m \frac{\beta_{1j}}{(s - \frac{m}{A_{vu}})^j} + \frac{\beta_{21}}{(s - \frac{1}{B_{vu}})^j}, \quad (9.1.10) \]

where \( \beta_{1j} \) and \( \beta_{21} \) are the same as in Theorem 2, satisfying (2.12). They are obtained using fractional decomposition. The PDF of \( P_{\gamma_{vu}}^{UAV}(x) \) can be obtained from the MGF \( M_{\gamma_{vu}}^{UAV}(s) \) of \( \gamma_{vu} \) using the inverse Laplace transform as

\[ P_{\gamma_{vu}}^{UAV}(x) = \sum_{j=1}^m \left( \beta_{1j} x^{j-1} \exp\left(-\frac{mx}{A_{vu}}\right) \frac{(-1)^j}{(j-1)!} \right) - \beta_{21} \exp\left(-\frac{x}{B_{vu}}\right). \quad (9.1.11) \]

As for the MGF of \( I \) it is computed as

\[ M_{I}(s) = \prod_{t=1}^N M_{\gamma_{tu}}(s) = \prod_{t=1}^N \left(1 - sB_{tu}\right)^{-1} \left(1 - \frac{sA_{tu}}{m}\right)^{-m} \]
\[ = \sum_{t=1}^N \frac{\alpha_t'}{s - \frac{m}{B_{vu}}} + \sum_{t=1}^N \sum_{j=1}^m \frac{\alpha_{t,j}}{(s - \frac{m}{A_{vu}})^j}, \quad (9.1.12) \]

where \( \alpha_t' \) and \( \alpha_{t,j} \) are the same as in Theorem 2, satisfying (2.13). They are obtained using fractional decomposition. Now, we can compute the PDF of \( I \) as
\[ P_I(x) = L^{-1}(M_I(s)) = L^{-1}\left[ \sum_{t=1}^{N} \frac{\alpha'_t}{s - \frac{1}{B_{tu}}} + \sum_{t=1}^{N} \sum_{j=1}^{m} \frac{\alpha_{t,j}}{(s - \frac{m}{A_{tu}})^j}\right] \]

\[ = \sum_{t=1}^{N} -\alpha'_t \exp\left(-\frac{x}{B_{tu}}\right) + \sum_{t=1}^{N} \sum_{j=1}^{m} \alpha_{t,j} \frac{(-1)^j x^j}{(j-1)!} \exp\left(-\frac{mx}{A_{tu}}\right). \]  

(9.1.13)

Considering the fundamental theorem of transformation of random variables, \(P_I'\) is obtained as

\[ P_I'(y) = \sum_{t=1}^{N} \alpha'_t \exp\left(-\frac{y - 1}{B_{tu}}\right) \]

\[ + \sum_{t=1}^{N} \sum_{j=1}^{m} \alpha_{t,j} \frac{(-1)^j}{(j-1)!} \exp\left(-\frac{m(y - 1)}{A_{tu}}\right) (y - 1)^j \]  

(9.1.14)

As for the CDF of \(\gamma_{vu}\), it is computed as

\[ F_{UAV}(x) = \int_{0}^{x} F_{\gamma_{vu}}(y)dy = \sum_{j=1}^{m} \left( \beta_{1j} \frac{(-1)^j}{(j-1)!} \right) \]

\[ \int_{0}^{x} y^{j-1} \exp\left(-\frac{my}{A_{vu}}\right) dy - \beta_{21} \int_{0}^{x} \exp\left(-\frac{y}{B_{vu}}\right) dy, \]  

(9.1.15)

with

\[ \{ \begin{array}{l} K_1 = \left(\frac{m}{A_{vu}}\right)^{-j} \left(\Gamma(j) - \Gamma\left(j, \frac{mx}{A_{vu}}\right)\right), \\
K_2 = B_{vu} \left(1 - \exp\left(-\frac{x}{B_{vu}}\right)\right) \end{array} \]  

(9.1.16)

Finally, the outage probability can be computed as

\[ P_{out}(\gamma_{th}) = \int_{1}^{\infty} F_{\gamma_{vu}}(\gamma_{th}y) P_I'(y)dy \sum_{j=1}^{m} \left( \beta_{1j} \frac{(-1)^j}{(j-1)!} \left(\frac{m}{A_{vu}}\right)^{-j}\right) \Gamma(j) - \]

\[ \int_{1}^{\infty} \Gamma\left(j, \frac{m\gamma_{th}y}{A_{vu}}\right) P_I'(y)dy\right) - \beta_{21} B_{vu} \left(1 - \int_{1}^{\infty} \exp\left(-\frac{\gamma_{th}y}{B_{vu}}\right) P_I'(y)dy\right) \]  

(9.1.17)
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\[
\sum_{j=1}^{m} \left[ \beta_{1j} \frac{(-1)^j}{(j-1)!} \left( \frac{m}{A_{vu}} \right)^{-j} \left( \Gamma(j) + \sum_{t=1}^{N} \alpha_{t} \sum_{p=1}^{n} B_{tu} \lambda_{p} \Gamma \left( j, \frac{m \gamma_{th}(\theta_{p} B_{tu} + 1)}{A_{vu}} \right) \right) \right] - \sum_{t=1}^{N} \sum_{j'=1}^{m} \alpha_{t,j'} \frac{(-1)^{j'}}{(j'-1)!} \left( \sum_{p=1}^{n} (A_{tu}/m)^{j'} \right) \lambda_{p}^{-1} \Gamma \left( j, \frac{m \gamma_{th}(\theta_{p} (A_{tu}/m) + 1)}{A_{vu}} \right) - \beta_{21} B_{vu} \left( 1 + \sum_{t=1}^{N} \alpha_{t} \right) \exp \left( -\frac{\gamma_{th}}{B_{vu}} \right) \Gamma(j) \right)
\]

\[\left( \sum_{t=1}^{N} \sum_{j'=1}^{m} \frac{\alpha_{t,j'}}{B_{vu} + m A_{vu}} - \sum_{t=1}^{N} \sum_{j=1}^{m} \frac{\alpha_{t,j}}{B_{vu} + m A_{vu}} \frac{(-1)^j}{(j-1)!} \Gamma(j) \right) \right) . \quad (9.1.18)
\]

The integrals in (9.1.17) involve the Gamma function with the exponential function. The Laguerre polynomial, defined as \( \int_{0}^{\infty} e^{-x} f(x) dx = \sum_{p=1}^{n} \lambda_{p} f(\theta_{p}) \), is used to perform a numerical evaluation, where \( \lambda_{p} \) and \( \theta_{p} \) are the weight and the zero factors of the \( n \)-th order Laguerre polynomials, respectively. The result in (9.1.18) is obtained using a change of variable. Note that the expression of \( f_{j,j'}(S) \) is provided in equation (2.14). The result in (9.1.19) is the same as the outage probability expression presented in Theorem 2.

Note that Theorem 1 is a special case of Theorem 2. Using the expression of the outage in (9.1.19), we can derive the following 4 special cases.

**Special Case 1:** \( P_{vu}^{NLoS} = 0 \), \( P_{vu}^{NLoS} = 1 \), \( P_{tu}^{LoS} = 0 \), and \( P_{tu}^{NLoS} = 1 \). This implies that in (9.1.10) the parameters \( \beta_{1j} = 0 \) and \( \beta_{21} = -1/B_{vu} \), whereas in (9.1.13) the parameters \( \alpha_{t,j} = 0 \) and \( \alpha'_{t,j} = -1/B_{tu} \). Thus, the outage probability for special case 1 can be computed using (9.1.19) as

\[
P_{out}(\gamma_{th}) = 1 + \exp \left( -\frac{\gamma_{th}}{B_{vu}} \right) \left( \sum_{t=1}^{N} \frac{\alpha'_{t,j}}{B_{vu} + 1/B_{vu}} \right), \quad (9.1.20)
\]

which matches with the outage probability provided in Theorem 1.

**Special Case 2:** \( P_{vu}^{LoS} = 1 \), \( P_{vu}^{NLoS} = 0 \), \( P_{tu}^{LoS} = 1 \), and \( P_{tu}^{NLoS} = 0 \). This implies that in (9.1.10) the parameters \( \beta_{1j} \neq 0 \) and \( \beta_{21} = 0 \), whereas in
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(9.1.13) the parameters $\alpha_{t,j} \neq 0$ and $\alpha'_{t} = 0$. Thus, the outage probability for special case 2 can be computed using (9.1.19) as

$$P_{\text{out}}(\gamma_{th}) = \sum_{j=1}^{m} \left( \beta_{1j} \frac{(-1)^j}{(j-1)!} \left( \frac{m}{A_{vu}} \right)^{-j} \left( \Gamma(j) - \sum_{t=1}^{N} \sum_{j'=1}^{m} \alpha_{t,j'} \frac{(-1)^{j'}}{(j'-1)!} f_{j,j'}(A_{tu}/m) \right) \right). \quad (9.1.21)$$

Special Case 3: $P_{vu}^{\text{LoS}} = 1, P_{vu}^{\text{NLoS}} = 0, P_{tu}^{\text{LoS}} = 1, P_{tu}^{\text{NLoS}} = 0$, and $m = 1$. This implies that in (9.1.10) the parameters $\beta_{11} = -1/A_{vu}, \beta_{1j} = 0$ for $j = 2, \ldots, m$ and $\beta_{21} = 0$, whereas in (9.1.13) the parameters $\alpha_{t,1} = -1/A_{tu}, \alpha_{t,j} = 0$ for $j = 2, \ldots, m$, and $\alpha'_{t} = 0$. Thus, the outage probability for special case 3 can be computed using (9.1.19) as

$$P_{\text{out}}(\gamma_{th}) = 1 + \exp \left( -\frac{\gamma_{th}}{A_{vu}} \left( \sum_{t=1}^{N} \frac{\alpha'_{t,1}}{A_{vu} + \frac{1}{A_{vu}}} \right) \right). \quad (9.1.22)$$

Special Case 4: $P_{vu}^{\text{LoS}} = 0, P_{vu}^{\text{NLoS}} = 1, P_{tu}^{\text{LoS}} \neq 0$, and $P_{tu}^{\text{NLoS}} \neq 0$. This implies that in (9.1.10) the parameters $\beta_{1j} = 0$ and $\beta_{21} = -1/B_{vu}$, whereas in (9.1.13) the parameters $\alpha_{t,j} \neq 0$ and $\alpha'_{t} = -1/B_{tu}$. Thus, the outage probability for special case 4 can be computed using (9.1.19) as

$$P_{\text{out}}(\gamma_{th}) = 1 + \exp \left( -\frac{\gamma_{th}}{B_{vu}} \left( \sum_{t=1}^{N} \frac{\alpha'_{t}}{B_{vu} + \frac{1}{B_{vu}}} \right) \right) - \sum_{t=1}^{N} \sum_{j=1}^{m} \left( \frac{\gamma_{th}}{B_{vu} + \frac{m}{A_{tu}}} \right)^{j} \frac{(-1)^{j}}{(j-1)!} \Gamma(j). \quad (9.1.23)$$

9.2 Proof of Theorems 3 and 4

This part of the appendix derives the proofs of Theorems 3 and 4. Theorem 3 (Theorem 4) provides the expression of the outage probability for the uplink channel between the BS $v$ and a UE (a UAV) $u$. An outage event occurs if the $\text{SINR}_{uv}$ falls below a threshold $\gamma_{th}$. To determine the outage probability, we must compute the CDF (Cumulative Distribution Function) of $\text{SINR}_{uv}$ [72]. The $\text{SINR}_{uv}$ is expressed as
where $\gamma_{uv}$ is the instantaneous SNR of the desired signal and $\gamma_{tv}$ is the interference signal from node $t$. Note that $u$ and $t$ can be either a UE or a UAV. In our model, we take into account the impact of pathloss and fast fading. We assume that the fast fading follows a Rayleigh distribution for the case of UE and UAV with NLoS link to the BS. However, for UAV with LoS link to the BS, we assume a Nakagami distribution for the fast fading. We denote by $\bar{\gamma}_{uv}$ and $\bar{\gamma}_{tv}$ the mean values of $\gamma_{uv}$ and $\gamma_{tv}$, respectively.

For the UE, the Moment Generating Function (MGF) and the Probability Density Function (PDF) can be expressed as

$$
M_{\gamma_{uv}}^U(s) = (1 - s\bar{\gamma}_{uv})^{-1}, \quad (9.2.25)
$$

$$
P_{\gamma_{uv}}^U(x) = \frac{1}{\bar{\gamma}_{uv}} \exp \left( -\frac{x}{\bar{\gamma}_{uv}} \right). \quad (9.2.26)
$$

For a UAV, it can have a LoS link to the BS with a probability $P_{uv}^{LoS}$ and NLoS link with a probability $P_{uv}^{NLoS}$. Therefore, the MGF in the case of UAV can be computed as

$$
M_{\gamma_{uv}}^U(s) = \left( 1 - s \frac{A_{uv}}{m} \right)^{-m} \left( 1 - s B_{uv} \right)^{-1} = \sum_{j=1}^{m} \left( \frac{\beta_{1j}}{(s - \frac{m}{A_{uv}})} \right) + \frac{\beta_{21}}{(s - \frac{1}{B_{uv}})}, \quad (9.2.27)
$$

where the expressions of $A_{uv}$ and $B_{uv}$ are mean SNRs for the LoS and NLoS of the link $uv$. The left hand side of (9.2.27) is obtained using fractional decomposition [70, Eq. (11)]. Note that $\beta_{1j}$ and $\beta_{21}$ are the same in Theorem 4 satisfying equation (2.18). From the MGF of $\gamma_{uv}$, we can obtain the PDF using the Inverse Laplace transform as

$$
P_{\gamma_{uv}}^U(x) = \sum_{j=1}^{m} \left( \beta_{1j} L^{-1} \left[ \frac{1}{(s - \frac{m}{A_{uv}})} \right] \right) + \beta_{21} L^{-1} \left[ \frac{1}{(s - \frac{1}{B_{uv}})} \right] = \sum_{j=1}^{m} \left( \beta_{1j} x^{j-1} \exp \left( -\frac{mx}{A_{uv}} \right) \frac{(-1)^j}{(j-1)!} \right) - \beta_{21} \exp \left( -\frac{x}{B_{uv}} \right). \quad (9.2.28)
$$

With $I = \sum_{t \notin U \cup V} \gamma_{tv}$ and $I' = 1 + I$, we can redefine the SINR as
\[
SINR_{uv} = \frac{\gamma_{uv}}{1 + I} = \frac{\gamma_{uv}}{I'}.
\] (9.2.29)

\(I\) includes both UE and UAV interferers. In the same manner, the MGF of \(I\) is obtained as

\[
M_I(s) = \prod_{t=1}^{N_1} M_{\gamma_{tv}}(s) = \prod_{t=1}^{N_1} (1 - s \bar{\gamma}_{tv})^{-1} \prod_{t=N_1+1}^{N} (1 - s B_{tv})^{-1} (1 - \frac{s A_{tv}}{m})^{-m}
\]
\[
= \sum_{t=1}^{N_1} \frac{\alpha_t}{s - \frac{1}{\bar{\gamma}_{tv}}} + \sum_{t=N_1+1}^{N} \frac{\alpha'_t}{s - \frac{1}{B_{tv}}} + \sum_{t=N_1+1}^{N} \sum_{j=1}^{m} \frac{\alpha_{t,j}}{s - \frac{m}{A_{tv}}},
\] (9.2.30)

where \([1, \ldots, N_1]\) and \([N_1 + 1, \ldots, N]\) refer respectively to the list of UEs and UAVs interferers. Note that the last line of the above equations is the result of the fractional decomposition. \(\alpha_t, \alpha'_t\) and \(\alpha_{t,j}\) (which are the same parameters in Theorems 3 and 4) can be computed using multinomial Theorem. The PDF of \(I\) can be obtained as

\[
P_I(x) = L^{-1}[M_I] = L^{-1} \left[ \sum_{t=1}^{N_1} \frac{\alpha_t}{s - \frac{1}{\bar{\gamma}_{tv}}} + \sum_{t=N_1+1}^{N} \frac{\alpha'_t}{s - \frac{1}{B_{tv}}} + \sum_{t=N_1+1}^{N} \sum_{j=1}^{m} \frac{\alpha_{t,j}}{s - \frac{m}{A_{tv}}}) \right]
\]
\[
= \sum_{t=1}^{N_1} \alpha_t (-1)^t \exp \left( -\frac{x}{\bar{\gamma}_{tv}} \right) + \sum_{t=N_1+1}^{N} \alpha'_t (-1)^t \exp \left( -\frac{x}{B_{tv}} \right)
\]
\[
+ \sum_{t=N_1+1}^{N} \sum_{j=1}^{m} \alpha_{t,j} \frac{(-1)^j}{(j-1)!} \exp \left( -\frac{m x}{A_{tv}} \right) x^{j-1}.
\] (9.2.31)

Now, we can determine the outage probability as

\[
P_{out}(\gamma_{th}) = P(SINR \leq \gamma_{th}) = P \left( \frac{\gamma_{uv}}{I'} \leq \gamma_{th} \right)
\]
\[
= E[I' | P(\gamma_{uv} \leq \gamma_{th}, I' = y)] = \int_1^{\infty} F_{\gamma_{uv}}(\gamma_{th} | y) P_I(y) dy,
\] (9.2.33)

where \(F_{\gamma_{uv}}(x)\) is the CDF of \(\gamma_{uv}\), which is defined as \(F_{\gamma_{uv}}(x) = \int_0^x P_{\gamma_{uv}}(y) dy\).

If \(\gamma_{uv}\) is associated with a UE, the corresponding CDF is

\[
F^{UE}_{\gamma_{uv}}(x) = \int_0^x P^{UE}_{\gamma_{uv}}(y) dy = 1 - \exp(-\frac{x}{\gamma_{uv}}).
\] (9.2.34)

If \(\gamma_{uv}\) is associated with a UAV, \(F_{\gamma_{uv}}\) is given by
\[ F_{\gamma_{uv}}^{UAV}(x) = \int_0^x p^{UAV}_{\gamma_{uv}}(y) dy \]
\[ = \sum_{j=1}^m \left( \beta_1 \frac{(-1)^j}{(j-1)!} \int_0^x y^{j-1} \exp\left(-\frac{my}{A_{uv}}\right) dy \right) - \beta_2 \int_0^x \exp\left(-\frac{y}{B_{uv}}\right) dy, \]
\[ (9.2.35) \]

with
\[ K_1 = \left( \frac{m}{A_{uv}} \right)^{-j} \left( \Gamma(j) - \Gamma\left(j, \frac{mx}{A_{uv}}\right) \right), \]
\[ K_2 = B_{uv} \left( 1 - \exp\left(-\frac{x}{B_{uv}}\right) \right), \]
\[ (9.2.36) \]
\[ (9.2.37) \]

where \( \Gamma(j) \) being the gamma function and \( \Gamma(j, \frac{mx}{A_{uv}}) \) is the upper incomplete gamma function defined as
\[ \Gamma(a, z) = \int_z^\infty t^{a-1} \exp(-t) dt. \]

As for the PDF \( p_I'(y) \), it is determined using equation (9.2.32) and the fundamental Theorem for the transformation of random variables [71] as
\[ p_I'(y) = \sum_{t=1}^{N_1} \alpha_t (-1) \exp\left(-\frac{y - 1}{\gamma_{tv}}\right) + \sum_{t=N_1+1}^N \alpha'_t (-1) \exp\left(-\frac{y - 1}{B_{tv}}\right) + \sum_{t=N_1+1}^N \sum_{j=1}^m \alpha_{t,j} \frac{(-1)^j}{(j-1)!} \exp\left(-\frac{m(y - 1)}{A_{tv}}\right) (y - 1)^{j-1}. \]
\[ (9.2.38) \]

Finally, the outage probability if \( u \) is a UE can be expressed as
\[ P_{out}^{UE}(\gamma_{th}) = \int_1^\infty F_{\gamma_{uv}}(\gamma_{th}y) p_I'(y) dy = 1 - \int_1^\infty \exp\left(-\frac{\gamma_{th}y}{\gamma_{uv}}\right) p_I'(y) dy \]
\[ = 1 + \exp\left(-\frac{\gamma_{th}}{\gamma_{uv}}\right) \left( \sum_{t=1}^{N_1} \frac{\alpha_t}{\gamma_{tv}} + \frac{1}{\gamma_{tv}} \right) + \sum_{t=N_1+1}^N \alpha'_t \frac{1}{B_{tv}} \]
\[ - \sum_{t=N_1+1}^N \sum_{j=1}^m \frac{\alpha_{t,j}}{\gamma_{tv}} \left( \frac{m}{A_{tv}} \right)^j (j-1)! \Gamma(j), \]
\[ (9.2.39) \]

which is the result presented in Theorem 3.

In the case that \( u \) is a UAV, the corresponding outage probability will be
\[ P_{\text{out}}^{UAV}(\gamma_{th}) = \int_{1}^{\infty} F_{\gamma_{th} y} P_{I'}(y) dy \]
\[ = \sum_{j=1}^{m} \left( \beta_{1j} \left( \frac{(-1)^j}{(j-1)!} \left( \frac{m}{A_{uv}} \right)^{-j} \left( \Gamma(j) - \int_{1}^{\infty} \Gamma(j, \frac{m\gamma_{th}y}{A_{uv}}) P_{I'}(y) dy \right) \right) \right) \]
\[ - \beta_{21} B_{uv} \left( 1 - \int_{1}^{\infty} \exp\left( -\frac{\gamma_{th}y}{B_{uv}} \right) P_{I'}(y) dy \right) \] (9.2.40)
\[ = \sum_{j=1}^{m} \left( \beta_{1j} \left( \frac{(-1)^j}{(j-1)!} \left( \frac{m}{A_{uv}} \right)^{-j} \left( \Gamma(j) + \sum_{t=1}^{N_1} \alpha_t \left( \sum_{p=1}^{n} \gamma_{tv} \lambda_p \right) \Gamma\left( j, \frac{m\gamma_{th}(\theta_p \gamma_{tv} + 1)}{A_{uv}} \right) \right) + \sum_{t=N_1+1}^{N} \alpha_t' \left( \sum_{p=1}^{n} B_{tv} \lambda_p \right) \Gamma\left( j, \frac{m\gamma_{th}(\theta_p B_{tv} + 1)}{A_{uv}} \right) \right) \right) \]
\[ - \beta_{21} B_{uv} \left( 1 - \int_{1}^{\infty} \exp\left( -\frac{\gamma_{th}y}{B_{uv}} \right) P_{I'}(y) dy \right) \] (9.2.41)
Note that the result in (9.2.43) is the same as the outage probability expression. We start by providing the general expression of the effective rate and the delay on the uplink communication. This section provides the proof of theorems 5 and 6, where we derive the expressions of the effective rate and the delay on the uplink communication.

### 9.3 Proof of Theorems 5 and 6

This section provides the proof of theorems 5 and 6, where we derive the expressions of the effective rate and the delay on the uplink communication. We start by providing the general expression of the effective rate.
which is given as

$$R_{\text{eff}}^{u,l,b} = \frac{R_u^r \times (1 - P_{\text{out}}(R_u^r))}{E(T_u)}, \quad (9.3.44)$$

where $R_u^r$ is the transmission rate of the source IoT node $u$. $P_{\text{out}}(R_u^r)$ is the probability of a packet transmission failure if the source IoT node uses a transmission rate $R_u^r$ and $E(T_u)$ denotes the average number of retransmission from the node $u$. In the ARQ mode, packets are retransmitted until a successful reception or when reaching a maximum number $E^c$ of retransmission. A similar expression of the average effective rate has been provided in [73]. The expression of $P_{\text{out}}(R_u^r)$ can be provided as

$$P_{\text{out}}(R_u^r) = P[\log_2(1 + \text{SINR}) < R_u^r] \quad (9.3.45)$$

$$= P[\text{SINR} < 2^{R_u^r} - 1], \quad (9.3.46)$$

where the SINR is computed as

$$\text{SINR}_{uv} = \frac{\gamma_{uv}}{1 + \sum \gamma_{tv}} \approx \frac{\gamma_{uv}}{\sum \gamma_{tv}}. \quad (9.3.47)$$

The approximation in (9.3.47) is valid if the noise power can be neglected compared to the interference power. This is generally a well accepted assumption in the literature and is known as an interference-limited regime.

In the uplink scenario, the source IoT node $u$ transmits its packets to its serving UAV $v$. We can therefore define the outage probability for the link $uv$ as

$$P_{\text{out}}(x) = P(\text{SINR}_{uv} < x) \quad (9.3.48)$$

$$= P\left(\frac{\gamma_{uv}}{\gamma_{Iv}} < x\right) = E_{\gamma_{Iv}}\left(P[\gamma_{uv} < x\gamma_{Iv}]\right) \quad (9.3.49)$$

$$= \int_0^\infty F_{\gamma_{uv}}(xy)f_{\gamma_{Iv}}(y)dy, \quad (9.3.50)$$

where $F_{\gamma_{uv}}(\cdot)$ is the Cumulative Distribution Function (CDF) of $\gamma_{uv}$ and $f_{\gamma_{Iv}}(\cdot)$ is the PDF of $\gamma_{Iv}$. The channel coefficient $h_{uv}$ for link $uv$ is assumed to be Nakagami distribution, and thus $\gamma_{uv}$ is Gamma distributed, i.e., $\gamma_{uv} \sim \mathcal{G}(\alpha_{uv}, \beta_{uv})$, with the corresponding PDF given as

$$f_{\gamma_{uv}}(x) = \frac{x^{\alpha_{uv} - 1}}{\beta_{uv}^{\alpha_{uv}} \Gamma(\alpha_{uv})} exp\left(-\frac{x}{\beta_{uv}}\right), \quad (9.3.51)$$

where $\alpha_{uv}$ is the Nakagami fading parameter for the link $uv$, and $\beta_{uv} = \frac{\bar{\gamma}_{uv}}{\alpha_{uv}}$. 

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The CDF of $\gamma_{uv}$ can be computed as

$$F_{\gamma_{uv}}(x) = 1 - \frac{\Gamma(\alpha_{uv}, x/\beta_{uv})}{\Gamma(\alpha_{uv})}, \quad (9.3.52)$$

where $\Gamma(\alpha_{uv}, x/\beta_{uv})$ is the upper incomplete gamma function defined as $\Gamma(s, x) = \int_x^\infty t^{s-1}e^{-t}dt$. As for the PDF of $f_{\gamma_{tv}}(y)$, it represents the PDF of the interference which is the sum of independent and non-identical Gamma distributions, where $\gamma_{tv} \sim G(\alpha_{tv}, \beta_{tv})$ and $\beta_{tv} = \frac{\bar{\gamma}_{tv}}{\alpha_{tv}}$. The PDF of the total interference $\gamma_I$ can be approximated by a Gamma distribution with parameters $\alpha_v$ and $\beta_v$ which are given as

$$\alpha_v = \frac{(E[\gamma_I])^2}{\text{Var}(\gamma_I)}, \quad (9.3.53)$$

$$\beta_v = \frac{\text{Var}(\gamma_I)}{E[\gamma_I]}. \quad (9.3.54)$$

As for $E[\gamma_I]$ and $\text{Var}(\gamma_I)$, they are computed as

$$E[\gamma_I] = \sum_{t=1}^{N_v} E[\gamma_{tv}] = \sum_{t=1}^{N_v} \alpha_t \beta_t, \quad (9.3.55)$$

$$\text{Var}(\gamma_I) = \sum_{t=1}^{N_v} \text{Var}(\gamma_{tv}) = \sum_{t=1}^{N_v} (E[(\gamma_{tv})^2] - (E[\gamma_{tv}])^2). \quad (9.3.56)$$

Consequently, $\alpha_v$ and $\beta_v$ will be computed as

$$\alpha_v = \frac{\left(\sum_{t=1}^{N_v} \alpha_{tv} \beta_{tv}\right)^2}{\sum_{t=1}^{N_v} \alpha_{tv}^2 \beta_{tv}^2}, \quad (9.3.57)$$

$$\beta_v = \frac{\sum_{t=1}^{N_v} \alpha_{tv} \beta_{tv}^2}{\sum_{t=1}^{N_v} \alpha_{tv} \beta_{tv}}. \quad (9.3.58)$$

Thereafter, the outage probability can be expressed as

$$P_{\text{out}}(x) = 1 - \int_0^\infty \frac{\Gamma(\alpha_{uv}, xy/\beta_{uv})}{\Gamma(\alpha_{uv})} f_{\gamma_{tv}}(y)dy$$

$$= 1 - \int_0^\infty \frac{\Gamma(\alpha_{uv}, xy/\beta_{uv})}{\Gamma(\alpha_{uv})} \frac{y^{\alpha_v-1}}{\beta_v^\alpha \Gamma(\alpha_v)} \exp\left(-\frac{y}{\beta_v}\right)dy$$

$$= 1 - I(x, \alpha_{uv}, \beta_{uv}, \alpha_v, \beta_v). \quad (9.3.60)$$

The integral $I(x, \alpha_{uv}, \beta_{uv}, \alpha_v, \beta_v)$ can be computed as
\[
\mathcal{I}(x, \alpha_{uv}, \beta_{uv}, \alpha_v, \beta_v) = \left(\frac{x \beta_v}{\beta_{uv}}\right)^{-\alpha_v} \frac{\Gamma(\alpha_{uv} + \alpha_v)}{\Gamma(\alpha_{uv}) \Gamma(1 + \alpha_v)} \\
\times 2 F_1 \left(\alpha_v, \alpha_{uv} + \alpha_v, 1 + \alpha_v, \frac{-\beta_{uv}}{x \beta_v}\right), \quad (9.3.61)
\]

where \(2 F_1(.)\) is the Gauss hypergeometric. Thus expression of \(P_{\text{out}}(x)\) can be written as

\[
P_{\text{out}}(x) = 1 - \mathcal{I}(x, \alpha_{uv}, \beta_{uv}, \alpha_v, \beta_v) \quad (9.3.62)
\]

and the expression of the outage probability if the source IoT node uses a transmission rate \(R_u\) can thus be expressed as

\[
P_{\text{out}}(R_u) = 1 - \mathcal{I}(R_u, \alpha_{uv}, \beta_{uv}, \alpha_v, \beta_v) = 1 - \mathcal{I}_u. \quad (9.3.63)\]

As for the average number of retransmissions \(E(T_u)\), it can be computed as [74]

\[
E(T_u) = 1 + \sum_{e=1}^{E^e-1} P(F_u^1, \ldots, F_u^e) \\
= 1 + \sum_{e=1}^{E^e-1} (1 - \mathcal{I}_u) \quad (9.3.64)
\]

\[
= \sum_{e=0}^{E^e-1} (1 - \mathcal{I}_u) \\
= 1 - (1 - \mathcal{I}_u)^{E^e}, \quad (9.3.66)
\]

where \(P(F_u^1, \ldots, F_u^e)\) refers to the probability of the reception failure at the \(1^{st}, \ldots, e^{th}\) retransmissions for the IoT node \(u\).

With the help of equations (9.3.44), (9.3.64) and (9.3.68), the effective rate expression for the link \(uv\) can be expressed as

\[
R_{\text{eff}}^{u,l,b} = R_u \times \left(\frac{\mathcal{I}_u^2}{1 - (1 - \mathcal{I}_u)^{E^e}}\right). \quad (9.3.69)
\]

The result in (9.3.69) is the same as the effective rate provided in Theorem 5.

As for the expression of the delay, we consider a parallel \(M/M/1\) queuing model where the traffic is equitably shared among the different queues. The arrival rate \(\lambda_u\) of the node \(u\) is therefore divided on the number of
parallel queues $Q_u$. In this case, the delay can be evaluated using the Pollaczeck-Khinchin equation as [75]

$$D_{u,l,b}^{[\lambda_u/Q_u]} = W_{u,b}^{[\lambda_u/Q_u]} + \mathbb{E}(T_u)T_F,$$  \tag{9.3.70}$$

where $W_{u,b}^{[\lambda_u/Q_u]}$ is the average waiting time for a data packet in the buffer of the IoT node $u$ over the sub-carrier $b$. $W_{u,b}^{[\lambda_u/Q_u]}$ can be obtained as [75]

$$W_{u,b}^{[\lambda_u/Q_u]} = \frac{\lambda_u \mathbb{E}(T_u^2)T_F^2}{Q_u 2(1 - \rho_u)} + \frac{T_F}{2},$$ \tag{9.3.71}$$

where $\rho_u$ is represents a parameter which satisfies the stability condition

$$\rho_u = \frac{\lambda_u \mathbb{E}(T_u)T_F}{Q_u} < 1.$$ \tag{9.3.72}$$

As for the term $\mathbb{E}(T_u^2)$, it represents the second-order moment of the number of retransmission $T_u$. This term can be derived as [74]

$$\mathbb{E}(T_u^2) = 1 + \sum_{e=1}^{E^c} (2e + 1)P(F_u^1, \ldots, F_u^e) \tag{9.3.73}$$

$$= 1 + \sum_{e=1}^{E^c} (2e + 1)(1 - I_u) \tag{9.3.74}$$

$$= \sum_{e=0}^{E^c-1} (2e + 1)(1 - I_u) \tag{9.3.75}$$

$$= 1 - (2E^c - 1)(1 - I_u)^{E^c} \frac{I_u}{T_u^2} + \frac{2(1 - I_u)(1 - (1 - I_u)^{E^c-1})}{T_u^2}. \tag{9.3.76}$$

With the help of equations (9.3.70), (9.3.71) and (9.3.76), the delay can be expressed as

$$D_{u,l,b}^{[\lambda_u/Q_u]} = \frac{\lambda_u T_F^2}{Q_u 2(1 - \rho_u)} \left( \frac{1 - (2E^d - 1)(1 - I_u)^{E^d}}{I_u} \right) \frac{I_u}{T_u^2} + \frac{T_F}{2} + \frac{1 - (1 - I_u)^{E^d}}{I_u} T_F. \tag{9.3.77}$$
The result in (9.3.77) is the same as the average delay provided in Theorem 6.

9.4 Proof of Theorems 7 and 8

This section provides the proof of theorems 7 and 8, where we prove the convergence of the matching and coalition sub-games respectively. Note that the same notations employed in Chapter 3 are maintained in this section.

From Definition 2, a matching would be unstable if a user and a sub-carrier consider the change an improvement. This is materialized by equation (3.13). Let us recall the instability situation;

\[
\exists v \in V, \exists u_1, u_2 \in V(v), \exists b_1, b_2 \in B; \\
\begin{align*}
&u_1 \in W(b_1) \text{ and } u_2 \in W(b_2) \text{ and } b_2 \succeq^{\nu_1} b_1 \text{ and } u_1 \succeq^{\nu_2} u_2, \\
&(9.4.78)
\end{align*}
\]

where the part (9.4.78.a) corresponds to a matching achieved after executing the algorithm, while the parts (9.4.78.b) and (9.4.78.c) reflect the instability. Let us suppose that equation (9.4.78) is correct after the execution of the first sub-game of Algorithm 2. According to this Algorithm, the users connected to each BS apply for the sub-carriers according to their order of preferences. This is defined by equation (3.10) for the UEs and (3.11) for the UAVs.

At most, two sub-carriers will receive the candidates as the UEs prefer the first sub-carriers while the UAVs prefer the last ones. Each sub-carrier prefers the users having the smallest value of \(\bar{P}_{vu}\) from each BS, as defined in (3.12). The users that got rejected will apply for their next preferred sub-carriers. Having said that, the UEs of each BS will be in the first sub-carriers while the UAVs will be in the last ones. Moreover, the UEs are ordered in the sub-carriers according to their \(\bar{P}_{vu}\) values while the UAVs are ordered according to the inverse of this parameter.

For two sub-carriers \(b_1\) and \(b_2\), the order can be either \(b_1\) before \(b_2\) or the inverse. Let us suppose that \(b_1\) is ordered before \(b_2\) (the same logic holds if \(b_2\) has an order before \(b_1\)) and consider the part (9.4.78.a) of equation (9.4.78), which we are supposing its correctness. As per the previous paragraph (the order of the users in the sub-carriers), three situations are possible for \(u_1\) and \(u_2\), which are the following.
If we consider the two situations (9.4.79.1) and (9.4.79.2), $u_1 \in Q$, they are in contradiction with the part (9.4.78.b), $b_2 \succeq^{u_1} b_1$. Indeed, if $b_1$ is ordered before $b_2$, UEs would prefer $b_1$ on $b_2$ (equation (3.10)). Now, the only situation that might hold is (9.4.79.3). As $b_1$ is ordered before $b_2$, and $u_1$ has bigger value of the $\bar{P}_{vu}$ parameter than $u_2$ (UAVs are ordered according the inverse of the parameter $\bar{P}_{vu}$, as per the previous discussion). Nevertheless, this also contradicts the part (9.4.78.c), $u_1 \succeq b_2 u_2$, as a sub-carrier prefers users with smaller value of the parameter $\bar{P}_{vu}$. Consequently, regarding equation (9.4.78), if (9.4.78.a) holds, (9.4.78.b) or (9.4.78.c) do not. This proves the incorrectness of the instability assumption and concludes the proof of Theorem 7.

As for the coalitional game convergence, the initial partition of the players on the coalitions $S$ is the result of the first sub-game. This coalition will be the subject of transformations applied sequentially. Let us express this sequence by the following equation

$$S^{(0)} = S^{(G_1)} \rightarrow S^{(1)} \rightarrow S^{(2)} \rightarrow S^{(3)} \ldots$$  \hspace{1cm} (9.4.80)

where $S^{(0)}$ is the initial state of the coalitions which is the result of the matching game $(S^{(G_1)})$. $\rightarrow$ reflects the applied transformation which can be a transfer or an exchange operation. $S^{(i)}$ is the state of the coalitions after the $i^{th}$ transformation. As the number of coalitions, the number of players and the number of states a player can have in a coalition (used transmission power) are limited, the number of partitions is also limited. We therefore define the following lemma.

**Lemma 3.** The convergence of the sequence of equation (9.4.80) is guaranteed when the transformations do not lead to repeated partitions.

The above lemma is based on the fact that the number of partitions is limited. If the produced partitions are not repeated, this would lead to a final partition $S^{(final)}$. In addition, as each derived partition is optimized compared to the previous (transfer and exchange are approved only when
there are enhancements), the final partition is optimal. Consequently, proving Theorem 8 comes down to proving that the derived partitions do not repeat. To this end, we consider two types of operations: transfer and exchange. In the case of a transfer operation, equation (3.16) is considered. This equation can also be written as

\[
\{S_1, S_2\} \triangleright^u \{S'_1, S'_2\} \iff w(S'_1) + w(S'_2) > w(S_2) + w(S_1),
\]  

(9.4.81)

which implies that the resulting coalitions, together, have better payoff than the originals. In addition, user transfer from one coalition to another does not affect the other coalitions (i.e., \(\forall S_i \in S \setminus \{S_1, S_2\}, w(S_i)\) remains the same). Consequently, we can write the following

\[
S^{(i)} \rightarrow S^{(i+1)} \iff \sum_{S \in S^{(i)}} w(S) < \sum_{S \in S^{(i+1)}} w(S).
\]  

(9.4.82)

On the other hand, the exchange operation is ruled by equations (3.17). As it is clearly stated by these equations, the exchange is approved only when at least the payoff of one player is increased while those of the other players, in the two coalitions, remain unchanged. Besides, as in the case of transfer, the other coalitions are not affected by the exchange operation. These facts guarantee the equivalence in equation (9.4.82) even for the exchange operation. This means that each derived partition is different from the previous and therefore not repeated. Moreover, the sum of benefits of the coalitions increases after each transformation. This concludes the proof of Theorem 8.
References


References


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