UAV-X Communication: Empirical Characterization and Performance Optimization

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UAV-X COMMUNICATION: EMPIRICAL CHARACTERIZATION AND
PERFORMANCE OPTIMIZATION

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UAV-X COMMUNICATION: EMPIRICAL CHARACTERIZATION AND PERFORMANCE OPTIMIZATION

A Dissertation Presented to the Graduate Faculty of the
Lyle School of Engineering
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Major in Electrical Engineering

by

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In emerging wireless networks, the scalability of deploying drones presents an opportunity to design extensive aerial networks. These networks could effectively monitor large agricultural fields from the air and soil for food production with efficient resource utilization. On the one hand, unmanned aerial vehicles (UAVs) have gained interest in agricultural aerial inspection due to their ubiquity and observation scale. On the other hand, agricultural internet-of-thing devices, including buried soil sensors, have gained interest in improving natural resource efficiency in crop production. In this work, we investigate the natural interaction of these two phenomena, where UAVs can be leveraged as flying nodes to collect information from above-ground (AG) and underground (UG) nodes. Additionally, UAVs play a crucial role in bridging farmlands with the core network, facilitating the provision of essential network services. In such a scenario, the UAV can be easily imagined to communicate with AG nodes, UG nodes, neighboring UAVs, and the primary base station (BS) that connects the aerial network to the core network. Therefore, we consider several communication links in a UAV-X communication scenario in a multi-UAV network that is imagined to be deployed by a primary BS to monitor a large field, where X refers to the ground node, UG node, BS, or neighboring UAV. We also consider that the primary BS is equipped with a mobile edge computing server (MEC) that not only assists the aerial network but also serves the communication and computational needs of the respective ground users. Following that, four links can be defined: the Air-to-Air (A2A) link, the Air-to-Ground (A2G) link, the
Air-to-Underground (A2UG) link, and the Ground-to-Ground (G2G) link, all of which are considered in this work to study various research problems.

First, we investigate the multi-antenna channels between two UAVs in terms of antenna correlation and system capacity in the A2A link scenario. The effect of 3D position on multi-antenna channel characteristics is investigated, and significant variation in the channel is observed in relation to the azimuth and elevation angles between the UAV nodes. Based on the findings, we propose an effective machine learning-based technique for estimating the direction of a transmitting node in an A2A link.

Second, we study a UAV-based full-duplex (FD) multi-user communication network in the A2G link scenario, where a UAV is deployed as a multiple-input-multiple-output (MIMO) FD BS to serve multiple FD users on the ground. A novel multi-objective resource allocation problem is designed and solved, which maximizes the sum uplink (UL) and downlink (DL) rates while optimizing the DL beamformer, beamwidth angle, 3D position of the UAV, and UL power of the FD users.

Third, we investigate path loss and fading characteristics between UAV and UG nodes using outdoor measurements, aiming to facilitate energy-efficient data collection to and from A2UG wireless links. A novel model is developed that estimates path loss with reduced errors across various UAV 3D positions than prior models. Accordingly, an energy-efficient aerial data collection strategy is designed.

Last, in the G2G link scenario, we consider a network in which a BS associated with an MEC server provides computing services to uplink user equipment (UUE) and downlink user equipment (DUE). By leveraging FD at the BS, we design a novel time-slotted computational task completion protocol that can efficiently use computation and communication resources in the network. In this setup, we jointly optimize the BS transmitter precoding vector, UUE uplink transmit power, MEC computational resources, and time-slotted computational task shares to minimize the sum weighted energy at the UUE and server while satisfying a completion-time threshold for each user’s task.
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Dedicated to my family
In the past few years, Unmanned Aerial Vehicle (UAV) communication systems have become a focus of researchers for their unique characteristics that produce interesting communications problems. In particular, UAVs are expected to be integral in various applications in 5G wireless systems. Due to the fact that UAVs are easily operable, highly maneuverable, and have increasing payload capability, it is expected that the use of UAVs will increase in the coming years [1]. There are numerous applications of UAVs including emergency search and rescue, communication relaying, package delivery, smart agriculture, emergency broadband service, and infrastructure inspection [2–5]. In most of these applications, a single drone is usually deployed to perform a specific task either through manual commands or autonomous flight missions, where the time length of the mission is limited by the battery capacity of the UAV. Therefore, it becomes challenging for a single UAV to support a large ground area and/or an increasing number of users. However, aerial coverage can be scaled from a single drone to a swarm of drones with efficient coordination to achieve a common task while providing quality service to the users in a vast area [6].

In the agriculture domain, UAVs have emerged as highly adaptable equipment, transforming traditional farming practices with data-driven decision-making to improve crop yields. While UAVs are mostly employed for aerial imaging and surveillance, their potential for collecting underground (UG) and above-ground (AG) sensor data is under-explored yet intriguing. In a similar context, UAVs are imagined to either support ground terrestrial networks [7,8] or form an independent network to serve ground nodes [9]. In addition, networks considered utilizing a single UAV are advancing by incorporating multiple UAVs that distribute the computation and communication complexities among multiple aerial nodes while achieving a common task like sensor data collection [10–14]. An example of a multi-UAV network is depicted in Fig. 1.1, wherein a network consists of a swarm of UAVs and a macro
base station (BS) equipped with an edge server, collaboratively collecting the AG and UG sensors data that are located in multiple farmlands with no local cellular connectivity. The network distinguishes between two categories of nodes: AG nodes, stationed on the ground for environmental monitoring, positioned above farmhouses to serve as network gateways, and managed by humans needing computational and communication support; and UG nodes, buried in soil for root-level monitoring in the agricultural field. In Fig. 1.1, there are 4 types of communication links in the network that can be imagined. Here, we introduce the term UAV-X communication to define the communication links on each UAV, where X can be another UAV, AG node or macro BS, and UG node. The associated links on each UAV are Air-to-Ground (A2G) links, Air-to-Underground (A2UG) links, and Air-to-Air (A2A) links that are utilized on the UAV to communicate with the AG nodes or BS, UG nodes, and neighboring UAVs, respectively. Similarly, the communication links on the BS in addition to the A2G links are Ground-to-Ground (G2G) links, which are either utilized to serve...
respective ground users for their communication or computational needs (via mobile edge computing (MEC)) or connect with the core network. Each link has distinct wireless channel characteristics that can not be interchanged with other links to estimate accurate wireless performance. For instance, in the A2A link, the received signal strength (RSS) is dependent on the azimuth and elevation angles between the aerial nodes besides the direct distance between them [15, 16]. Contrary, in the above-ground-to-underground (AG2UG) link which is similar to the A2UG link, the RSS is dependent on various factors including the depth of the sensor in the soil, the angle of incidence of the propagating wave, and the moisture content of the soil [17]. Therefore, it is necessary to characterize the wireless link before the network deployment.

The literature in all 4 aforementioned links has been studied thoroughly, where some gaps are found that serve as a motivation for this work which are discussed as follows. First, the literature on the empirical characterization of A2A links and their utilization for direction estimation is still limited, especially for multi-antenna communication which is an important aspect in the next-generation networks for directional multi-user communication through aerial nodes. Second, there have been numerous works that considered A2G links for resource allocation optimization problems utilizing both half-duplex (HD) and full-duplex (FD) multiple-input and multiple-output (MIMO) radios on a drone but the aerial coverage optimization is only considered in the single-input and single-output (SISO) systems. Third, the empirical characterization of A2UG links has never been considered in any work that is needed to efficiently communicate with sensors in the soil from an airborne node. Last, G2G links were considered in many works either for channel characterization or optimal network resource allocations. However, the works on MEC with FD communication are still limited, where the concurrent computational task generation on both user and edge server was never considered in any work, which is required in various applications that are discussed in the respective chapter. Therefore, it is essential to conduct studies that focus on and help to comprehend the above problems.
1.1 Summary of Thesis Contributions

Wireless communication properties significantly change when the node takes off from the ground to the air which brings new challenges for the node to optimize its resources for optimal wireless performance. The 3D location, body, and mobility of the aerial node impact the wireless channel and ultimately affect the communication performance in the associated links that are shown in Fig. 1.1. Also, the overall link level performance could deteriorate when the network scales from a single drone to a swarm of drones. However, if the channel is studied in all aspects then it becomes convenient to improve the performance. Moreover, with the effective utilization of resources on the drones, the link level performance and energy efficiency of the node could be improved. This helps the drone to consume less propulsion energy and increase the flight time in the air. This work addresses the above issues and fills the research gaps in different communication links that are summarized as follows.

- In the A2A link, we capture multi-antenna channels between two UAVs through extensive measurements in the field to analyze the impact of the 3D position of the UAV on the spatial correlation of the antennas and overall channel capacity. The results show significant variation in the performance with respect to the 3D position of the receiver node. Following, the application of the results is shown in massive MIMO systems, where the multi-antenna channel estimates are utilized to predict the direction of the aerial node through a novel machine learning (ML) based method. Note that the direction helps select the directional transmission beam to efficiently consume the available wireless channels. Furthermore, the complexity of the proposed direction-finding method is compared with that of the baseline exhaustive beam search method in massive MIMO systems, demonstrating that the former is more computationally efficient.

- In the A2G link, we consider ground coverage optimization along with the other resource allocation of the aerial FD MIMO BS that is deployed to serve FD users on the ground. To do so, a novel multi-objective optimization problem (MOOP) is designed that maximizes the sum of uplink (UL) and downlink (DL) rates in the FD communication between aerial BS and users. The problem is found to be non-convex and
therefore, a joint optimization solution is proposed by dividing the original problems into multiple sub-problems.

- In the A2UG link, we study the characteristics of a novel wireless channel between a UAV and multiple UG nodes in both UL and DL through empirical measurements in the field. The dependency of the path loss and small-scale shadowing on the 3D position of the UAV is analyzed. We show a significant impact from UAV antenna position, UAV 3D location, and soil properties on both path loss and fading. A novel model is developed that estimates path loss with reduced errors across various UAV 3D positions than prior models. The analysis extends to the fading distribution within the channel, which conforms to the Rician distribution, where the Rician-K is contingent upon the UAV’s altitude, elevation angle, and antenna configurations. Specifically, the effects attributed to the altitude and elevation angle can be represented using Gaussian functions with minimal inaccuracies. Based on the findings, initially, a novel altitude optimization mechanism is proposed that minimizes the bit-error rate of the link. Subsequently, we develop an energy-efficient data collection strategy, UAV-Collect, for UAV-based Internet of Underground Things networks, substantially cutting UG sensor node energy use.

- In the G2G link, we consider the co-existence of UL computing users and DL computing users in an MEC network, where both types of users request the task computations from the MEC server concurrently, which was never considered before. The co-existence of the users is achieved through FD communication between an MEC BS and computing users. A novel energy-efficient time-slotted protocol is proposed for the computational task completion of users. Following this, a novel optimization problem is designed that optimizes the computation and communication resources of the BS while minimizing the overall energy consumption of the network. The problem is found to be non-convex and challenging to solve optimally. Therefore, an equivalent convex problem is proposed through approximations which is then solved in iterations until convergence.
1.2 Thesis Overview

This thesis is organized as follows. We provide the background information required to comprehend this work in Chapter 2, where the fundamentals of wireless channels and the technical details of hardware and software setup are discussed. In Chapter 3, we analyze the impact of the 3D position of the UAV on the multi-antenna channel characteristics in the A2A link, followed by the design and empirical evaluation of the proposed ML-based direction estimation method. In Chapter 4, the A2G link is considered, where we design and solve the novel aerial coverage and resource allocation problem in a MIMO UAV FD network. In Chapter 5, the wireless channels in the A2UG and UG2A links are studied under dynamic conditions, to design an energy-saving data collection strategy. In Chapter 6, the G2G link is considered in an MEC network, where a novel framework is proposed to support the coexistence of UL and DL computing users. Finally, we conclude in Chapter 7 and discuss possible future work.
Chapter 2
Background

In this chapter, we first discuss the hardware and software setup that are utilized to design measurement nodes for the in-field experiments in this work. Then, we discuss the basic path loss and small-scale fading models that serve as underlying concepts to comprehend the respective chapters in this work.

2.1 Hardware and Software Setup

As mentioned before, chapter 3 and 5 deal with the empirical characterization of the A2A and A2UG links, respectively. Therefore, for infield experiments in the A2A link, airborne measurement nodes are required that can continuously perform transmission while flying in the air. Similarly, for the A2UG link, in addition to the airborne node, multiple UG nodes are required that can continuously transmit or receive the RF signal from the soil medium. In this work, we utilize software-defined radios (SDRs) to design the measurement nodes in both A2A and A2UG links. SDRs are radio devices with completely programmable and configurable modules that facilitate flexible requirements adaptation and simple deployments. Following, we present the hardware and software setup of the measurement nodes.

2.1.1 Hardware

There are various commercial SDRs available in the market as shown in Fig. 2.1 that vary mainly in terms of transmission power, instantaneous bandwidth, standalone operation, and portability [18]. The main concern in designing the measurement system in this work deals with portability and standalone operation especially when mounted on the UAV. Therefore, we utilized multiple universal software radio peripheral (USRP) E312s from Ettus Research to design both aerial nodes and UG nodes for outdoor measurements in the field. The USRP E312 is a battery-operated 2×2 MIMO transceiver that covers several bands of interest at frequencies ranging from 70 MHz to 6 GHz. It can deliver up to 56 MHz of instantaneous
bandwidth. It can work in two different modes: (i) embedded mode: when the USRP can operate standalone to transmit and receive the In-Phase and Quadrature (IQ) samples and does not require any external connection, and (ii) network mode: when the USRP needs a host machine for command and control. We utilized the embedded mode of the USRP to design aerial and UG measurement nodes. Note that USRP E312 has two RF chains that can simultaneously capture the signal.

Moreover, we mounted USRP E312s on top of commercial UAVs (DJI Matrice 100 and DJI Matrice 300) using a mixture of custom-made and company-provided 3D parts. Two identical UAV nodes are designed for the A2A link experiments. On each UAV, we mounted
two RF antennas in a horizontal and vertical configuration on the body of the DJI Matrice 100 UAV using custom parts, and we connected them to the two RF chains of the USRP E312 using short RF cables. For the A2UG experiments, we employed the DJI Matrice 300 UAV and installed an RF antenna in various configurations on the UAV. These antennas were then connected to the SDR using short RF cables. Following, two separate USRP E312 USRPs were utilized to design 3 UG nodes that are connected with the custom-designed antennas buried under the soil at multiple depths. Note that the body of UAVs is composed of several lightweight components, such as steel, aluminum, plastic, and carbon fiber that could impact the wireless channel mainly when they are between the signal paths [19].

2.1.2 Software

The USRP E312 carries an OpenEmbedded-Linux operating system on the local SD card storage that supports the USRP Hardware Driver (UHD) from Ettus to interface with the RF front ends. As discussed before, USRP E312 works in two distinct modes. Therefore, there are two ways to initiate transmission or reception from the device: Either run the Python or C++ scripts on the device through the automated/manual control of the command line interface or connect the USRP to the host machine and run the scripts via a graphical user interface like GNU Radio. Since the former way (embedded mode) is more appropriate for the airborne node. Therefore, for the aerial measurement nodes in the A2A and A2UG experiments, we first implemented the transmission or reception flow graph in the GNU Radio software. Second, we generated the corresponding Python files from the GNU Radio software and transferred them to the local SD card storage of the USRP. Last, we initiate the transmission or reception on the USRP by running the Python script for a limited time (equal to the UAV flight mission time) through an automated shell script that also logs the start and stop time of the script and onboard gyroscope module data. Note that the shell script is triggered on the USRP via a USB serial cable connection from the host machine, where the serial cable connection is disconnected once the Python script is successfully started. Following, the UG nodes in the A2UG experiments are designed similarly to the aerial node. In all our experiments, the receiver captures the IQ samples in a .dat file for the period of the run time of the Python script which are then post-processed offline in the Matlab software.
2.2 Path Loss and Fading in the Wireless Channel

When the RF signal is transmitted from the antenna and enters into the wireless medium, it undergoes several properties of the medium that impact the quality of the signal before the reception. The transmitted signal is usually attenuated with respect to the direct distance between the transmitter and receiver, where the degree to which the received signal is attenuated with respect to the transmitted signal is called path loss and is defined in decibels (dBs). On the other hand, fading is defined as the variation in the signal attenuation due to various factors such as time, geographical position, and radio frequency. Fading is usually categorized into two types which are small-scale fading and large-scale fading. The former deals with rapid fluctuations of received signal strength over very short distances and short time periods. The latter, however, addresses signal fluctuation brought on by environmental obstructions in the signal path that significantly reduce signal strength. In this work, we focus on characterizing the path loss and small-scale fading in the channel which is further discussed as follows.

There are various path loss models in the literature that model the dependency of path loss on the distance between the transmitter and receiver. The basic model that is commonly utilized to build more efficient models is the log-distance model that predicts the path loss a signal will experience over distance inside buildings or in crowded areas. Mathematically, it can be written as [20]:

\[ PL = PL_0 + 10\alpha \log_{10} \left( \frac{d}{d_0} \right) + X_\beta, \]  

(2.1)

where \( PL \) is the total path loss in dBs, \( PL_0 \) is the path loss at a reference distance \( d_0 \), \( d \) is the distance between the transmitter and receiver, \( \alpha \) is the path loss exponent, and \( X_\beta \) is the random variable that defines the shadowing in the environment which is usually modeled as a Gaussian random variable with 0 mean and \( \sigma \) standard deviation. Note that \( d_0 \) for the large cell is 1 mile and for the micro-cell, it is between 1-10 meters.

The small-scale fading is modeled with respect to the nature of the multi-path environment. When there is no LoS component in the signal exists then the magnitude of the signal that passed through the communication channel will vary according to the Rayleigh
distribution. Contrary, when there is a strong LoS component exists in addition to the other multi-path components, it leads to a received signal with a non-zero mean, and the signal envelope is characterized by a Rician distribution. Mathematically, the Rician probability density function can be written as follows [20]:

$$f(x) = \frac{x}{\sigma^2} \exp\left(-\frac{(x^2 + s^2)}{2\sigma^2}\right) I_0\left(\frac{xs}{\sigma^2}\right),$$  \hspace{1cm} (2.2)

where $I_0$ is the modified Bessel function with the order 0, $s$ in our case is the amplitude of the direct or LoS component in the signal while $2\sigma^2$ is the power in the multi-path or scattered components, and $x > 0$. Moreover, an important parameter that is used to define the fading severity in a Rician fading channel is the Rician $K$ factor which is defined as the ratio between the power in the direct radio propagation path and the reflected or scattered paths. Mathematically, the Rician-$K$ factor can be written as:

$$K = \frac{s^2}{2\sigma^2}. \hspace{1cm} (2.3)$$

Note that the Rician-$K$ factor is commonly used in understanding the behavior of short-range wireless channels, system design, and performance evaluations. In digital communication systems with Rician fading channels, the Rician-$K$ parameter is related to the bit-error rate (BER) performance in several modulation techniques. In the case of medium to high SNR at the receiver, the Rician-$K$ factor is inversely proportional to the BER performance. In this work, we characterize the small-scale fading in the A2UG link and show that the channel is a Rician fading channel through a confidence-based equality test. In addition, we study the impact of UAV position on the Rician-$K$ factor and model the impact to design a novel altitude optimization mechanism and an energy-efficient data collection strategy.
3.1 Introduction

UAVs are finding their way into many day-to-day applications, but most of these applications currently require human intervention for either drone flight or other roles. The scalability of any drone application lies in the capabilities of taking autonomous decisions either related to path planning or dynamic maneuvering in real-world deployments. Any such actions being performed by drones are dependent on many factors among which communication to and from drones is very critical. Many researchers from academia and industry are contributing and solving different underlying challenges related to communication between drones. One such challenge is accommodating a large number of drones in a small aerial field considering the limited spectrum availability along with the energy requirements. Therefore, with the proper understanding of the channels between drones, the spectrum can be efficiently utilized by optimizing the communication resources on the nodes to improve end-to-end performance in aerial networks.

The communication between the aerial nodes is different from the ground nodes in many aspects. One such aspect is the position of the node in the 3D space which sometimes positively and negatively impacts the channel. The negative impact is mostly due to the drone body’s influence on signal propagation, where the blockage of the foil induces attenuation resulting in a compromised communication performance [19]. However, with the diverse antenna orientations on the node, the body impact can be significantly reduced by intelligently switching between the antennas for transmission and reception [16]. Another solution is to optimize the position of the nodes in the space in such a way that the foil blockage is minimal but this increases propulsion energy consumption on the aerial node especially when the
clear line-of-sight position is not near. The intelligent switching of antennas can be easily considered in the case of SISO communication between the nodes. On the other hand, the spectral efficiency of the channel can be improved if a large sum of antennas is utilized on the nodes for communication. Also, with many antennas, directional communication through several beamforming techniques can be realized which boosts the range and improves the energy efficiency. However, the impact of the 3D position of the drone on the performance of the multi-antenna channels is not well studied before.

In the emerging wireless networks and Massive MIMO systems, the phased array antennas and beam steering techniques are utilized at the BS to focus the RF energy towards the ground users [21–24]. In such systems, the radiation space is usually divided into multiple small sub-spaces, and a narrow transmit beam of size equal to the sub-spaced area is steered across all the sub-spaces till the optimal beam is found which is usually in the direction of the receiver node. The major complexity usually comes from searching for the optimal beam which is more likely to increase when the search space scales in 3D for the communication between multiple UAVs. The complexity can be significantly reduced if the direction of the receiver is known at the transmitter. This motivates the need for the design of a computationally efficient method to locate the aerial node with minimum communication overheads which is possible with the proper understanding of the channel.

In this chapter, we study the communication link between two UAV nodes via an A2A link and propose a novel learning-based direction-finding method that can be utilized at the receiver to estimate the direction of the transmit signal. For this purpose, we analyze the capacity and correlation performance of A2A links in terms of azimuth and elevation angles between 2 MIMO UAV nodes. Then, we analyze the performance of the proposed method through empirical evaluations. The main contributions of this chapter are summarized as follows:

1. We measured multi-antenna channels between two UAVs in an A2A link through extensive measurements in the field, where one of the UAVs hovers on the origin of a 3D sphere and other UAV flies at multiple points on the 3D sphere covering various azimuth and elevation angles. We evaluated the performance of the link in terms of the correlation between the signal paths and overall system capacity and found that
the performance varies significantly over the 3D sphere.

2. We propose a novel ML-based direction estimation method for the A2A link between two UAVs by designing the direction-finding problem as a classification problem utilizing the support vector machines (SVM) technique. The method utilizes multi-antenna channel estimates of the A2A link as features to estimate the direction of a UAV node with an accuracy of 85% when at least 2 RF chains with diverse antenna configurations are utilized at both transmitter and receiver.

3. We propose an application model of the ML-based direction estimation method for optimal beam selection in the aerial massive MIMO systems and compare its complexity with the complexity of the conventional beam search algorithm. It is found that the proposed technique significantly reduces the computational complexity at the massive MIMO BS for optimal directional beam selection when a large sum of antennas is utilized for transmission.

The rest of the chapter is organized as follows. In Section 3.2, the related work on A2A channels and networks along with the direction-finding approaches are presented. In Section 3.3, the measurement system and topology are discussed that are utilized to characterize the A2A link and empirical evaluation of the direction estimation method. The equivalent communication model of the measurement system along with the performance metrics are discussed in Section 3.4. The proposed method for direction estimation and its application in the MIMO system is presented in Section 3.5. Section 3.6 presents the empirical characterization of the A2A link and the experimental evaluation of the proposed method. Finally, the chapter is summarized in Section 3.7.

3.2 Related Work

In this section, we first discuss the related work on A2A links in terms of empirical characterization and network optimization. Then, we discuss the related work on direction-finding approaches in wireless communication.

**A2A Channels and Networks:** The communication between UAVs has been considered in many works mainly for resource allocation optimization [10–14]. However, there
are some works that consider the characterization of the channel through outdoor measurements [16,19,25,26]. Like in [25], the authors investigated the impact of antenna directivity, distance, and flight altitude on the channel characteristics of the A2A link. The experiment results demonstrate that the attenuation in signal due to the distance adheres to the Free-space model, the effect of antenna directivity is apparent, and the multipath impact on the channel caused by ground reflection varies with flying height. Authors in [26] conducted the measurements between two UAVs in the C-band over the ground and sea environments to study the multi-path characteristics of the channel. Findings indicate that the received signal on the aerial node is composed of the LoS component and multi-path component formed predominately by the single ground reflected wave. Moreover, the impact of antenna orientation and 3D position of the aerial node on the A2A link performance was considered in [16,19], where significant variation in the received signal has been observed with respect to the 3D position and antenna orientations. For resource allocation optimization in A2A networks, multiple UAVs were considered in [13] to form independent DL networks, where the real-time designs of resource allocations were studied to maximize the long-term rewards. Similarly in [12], authors considered multi-UAV networks and proposed a coverage deployment model based on energy-efficient communication, where a coverage scenario for UAV was built to solve underlying energy shortage problems. Also, authors in [11] considered multiple UAVs in a single-cell network, where the UAVs are deployed to offload collected data of the users to the BS either through UAV to BS link when the signal-to-noise ratio (SNR) is high or through the underlying UAV-UAV link when the SNR is low. Following, a joint optimization solution is proposed for sub-channel assignment and trajectory of the UAV to maximize the UL sum rate. Moreover, in the context of MIMO communication, the resource allocation problem was studied in [14] for multi-UAV aided MIMO DL transmission system where the user clustering, time slot assignment, and transmit power of UAVs were jointly optimized to maximize the system capacity. In all the aforementioned works, the multi-antenna channel characteristics in the A2A links were never studied and considered which can be incorporated to design novel communication strategies for optimal performance in the aerial networks.

**Direction Finding:** The use of directional antennas in wireless networks has existed
for many years. Some of the advantages of having a directional wireless network [27] which perfectly maps with the requirements of drone communications, are lower interference, improved spatial reuse, longer transmission range, and reduced power requirements [28]. The direction-finding task is performed through multiple possible methods, e.g., from manually moving the directional antennas to listening to the beacon signals to using specialized profiling algorithms to help in predicting the direction of the transmitter. On the basis of this, the direction-finding approaches have been studied in two subcategories as follows:

- **Conventional Approaches:** The direction finding of wireless signals like RF, have been around for many years and found many applications in military and civilian domains. The basic idea is to move the directional receiver in all possible directions and observe the signal strengths. Once the point of maximum signal strength is found based on the SNR ratio, the receiver tries to estimate the direction of the transmitter to an approximate value. This approach is as simple as it sounds and hence has a very low cost of operation [28]. In a work by [29], the authors have used a MAC protocol that transitions from omnidirectional antennas to directional antennas and highlighted the advantages of the same. But, it has an associated limitation, i.e., time required to observe every possible point. For instance, if we consider the object can possibly move in the spherical motion area, then at the very least, it might have 360 points on each 2D plane, and if the whole sphere is divided into $N$ discrete 2D planes, the possible $360 \times N$ planes arise. This makes the total number of possible combinations to millions if not billions. Hence, the conventional non-smart methods fail to match the speed and dynamic mobility requirements those of modern drone applications such as vehicular swarms. Moreover, in the multi-antenna systems, the direction of the node can be estimated using the direction of arrival techniques (DOA) such as MUSIC [30], which requires the snapshot of the signals at multiple antennas, resulting in the increased power consumption at the node. Also, in the presence of unknown signal sources, the estimation accuracy of traditional DOA methods is severely affected.

- **Intelligent Approaches:** As discussed in the previous subsection, the conventional approaches exist to estimate the direction of a wireless transmitter, using characteristics
of wireless signals, but most of these approaches are very time-consuming and above all are not scalable to large systems. Further, as suggested in [31], ML-based intelligent approaches can be of great use in a wide horizon of applications among which gaining deeper insights into the features of the environment like the dynamics of the channels, channels profiling, user context awareness for quality of service (QoS). Moreover with the data-driven capabilities of ML, optimization of wireless networks is possible. Some works like in [32] have explored the use of directional antennas to enable wireless signal relaying along with the use of reinforcement learning for the prediction of directions. In another work [33], authors have highlighted the importance of ML in modeling wireless channels. Similarly in [34], the use of a deep learning-based approach is suggested in effectively predicting the downlink in massive MIMO scenarios. In another work by [35], the authors suggested the use of ML in the design of trajectory for multiple UAV’s Operability.

Further, the wireless signals are greatly impacted by the surroundings in which they propagate. For instance, in closed indoor scenarios, the signals are expected to travel and traverse multiple paths due to the structure of walls and other indoor items. However, the signal propagation profiles tend to change drastically in open outdoor scenarios where there are fewer surfaces to deflect and reflect the signals. Many existing works like [36] and [37] have taken into consideration the indoor localization of wireless channels, but the outdoor is still the field less explored [38] and especially in the context of possibilities of focused transmissions on drones for efficiently managing the spectrum and the probable profiling using the same. Motivated by these key research gaps, the research work in this chapter is taken to make UAV-to-UAV communications more efficient in outdoor 3D spaces.

3.3 Experiment Setup

In this section, the multi-antenna SDR-based measurement system and measurement plan are presented. First, the implementation of the 2×2 Aerial channel sounding system is presented which is utilized to capture MIMO A2A wireless channels. Second, the measurement topology design is presented which is utilized to conduct outdoor wireless experiments.
3.3.1 UAVs based 2×2 Wireless Channel Sounding System

We implemented a 2×2 wireless channel sounding system using two USRP E312 from Ettus research [39] that were mounted on two commercial UAVs. We are interested in capturing UAV-to-UAV channels. Therefore, we utilized the embedded mode of the USRP E312 due to its suitability for our experiments. Moreover, GNU Radio and USRP Hardware Driver libraries in Python are utilized to transmit and receive IQ samples.

We captured the wireless channel only in one direction. Therefore, one of the UAV nodes works as a transmitter and continuously transmits two sinusoidal tones with frequencies 5 and 15 KHz on RF chains TRXA and TRXB of the USRP E312 over a 2.484 GHz carrier frequency with a sampling rate of 200 kSamples/second and transmit power of +15 dBm, respectively. Both the RF chains are equipped with an omnidirectional (VERT2450) antenna with 3 dBi gain. However, the antenna on the TRXA chain is mounted horizontally while the antenna on the TRXB chain is mounted vertically. The transmitter USRP E312 is mounted on the top of the commercial UAV using custom-made 3D-printed parts to secure the SDR and antennas as shown in Fig. 3.1d. The other UAV node works as a receiver and we mounted the USRP and antennas on the receiver UAV node in an identical manner to the transmitter. The transmitted sinusoidal tones are continuously captured at two RF chains of the receiver USRP E312 during the flight of the UAV which are post-processed in MATLAB offline. The received signal on each RF chain is sampled at 200 kSamples/second. Note that the UAV logs the flight details and the USRP captures the transmitted signal, independently. Therefore, to synchronize the received IQ data with the UAV flight log, we recorded the start and stop times of the USRP script, and also logged the data of the IMU sensor (i.e., roll, pitch, and yaw) of the USRP. The data synchronization method and timestamp calculation of the received IQ samples are detailed in [40].

3.3.2 Measurement Plan

We designed a measurement topology that comprises a total of 114 measurement points on the 3D sphere which is shown in Fig. 3.1a, where the origin of the sphere is located at 80m altitude from the ground level and the radius of the sphere is 20 m. The transmitter drone hovers at the origin of the sphere while the receiver drone flies between the points on
the sphere during the flight plan.

Figure 3.1: (a) 3D sphere-based measurement topology which comprises multiple flight plans covering various azimuth and elevation angle points, where the individual markers along the flight plan indicate receiver UAV positions. (b) Spherical coordinate system indicating azimuth and elevation angles between TX and RX UAVs. (c) 2D representation of the sphere-based measurement topology with N, S, E, and W showing the north, south, east, and west points on the sphere, respectively. (d) UAV-based SDR communication setup with vertical and horizontal mounted antennas matched for TX/RX.

We utilized a spherical coordinate system shown in Fig. 3.1b to denote points on the 3D sphere. The 2D representation of the measurement topology in Fig. 3.1a is presented in Fig. 3.1c, where each measurement point is defined using azimuth and elevation angle pairs.
In Fig. 3.1a, \( \Phi \) is measured from the west axis and varies between 0 and 360 degrees in a clockwise manner, and \( \theta \) is defined as the angle above or below the origin which varies between -90 (bottom of the sphere) and +90 (top of the sphere). We took measurements over 16 azimuth and 9 elevation angles with intervals of 22.5 degrees which makes a total of 114 locations on a 3D sphere. Note that at locations directly above or below the origin i.e., \( \theta = \pm 90 \) degrees, \( \Phi \) is undefined. Moreover, the measurement points on the 3D sphere are translated into GPS coordinates using the mapping toolbox in MATLAB, exported to a keyhole-markup-language (.kml) file, and uploaded to the DJI GSPro automated flight planner tool. Note that the flight time of the UAV is limited by the capacity of the battery. Therefore, we designed a total of 8 flights (color-coded in Fig. 3.1a) comprised of 16 measurement points each, where the receiver UAV node begins at \( \theta = 0 \) degree (parallel to the origin), and flies in a vertical circle around the transmitter UAV node (origin) while hovering for 20 seconds at each elevation angle along the flight path. The headings of both the UAV nodes are set to the North during the flight time in each flight plan. Since both the UAVs rely on the onboard GPS system to hold the position during the hove time at the measurement points on the sphere. We found that the transmitter UAV node hovers at the origin of the sphere with a displacement error of 80 mm (average standard deviation) while the receiver UAV node hovers at the measurement points on the sphere with a displacement error of 161 mm, where the errors are negligible compared to the direct distance between transmitter and receiver UAV nodes (20 m).

### 3.4 Communication Model and Performance Metrics

In this section, first, the communication model of our channel sounding system is presented which includes the estimation of the MIMO channel matrix. Second, the wireless performance metrics are presented that are utilized to characterize the MIMO A2A channel.

The equivalent communication model of our measurement system is depicted in Fig. 3.2. The variables \( x_H(k) = 0.7e^{j2\pi f_1k} \) and \( x_V(k) = 0.7e^{j2\pi f_2k} \) are the two sinusoidal signal tones that are used for transmission from the two RF chains of the transmitter USRP, where \( f_1 = 5KHz \), \( f_2 = 15KHz \), and \( k \) is the discrete time index. Similarly, \( y_H(k) \) and \( y_V(k) \) represent the received signal at the two RF chains of the receiver USRP which can be
written as follows:
\[ y(k) = Hx(k) + \Gamma(k), \]  
(3.1)

where \( y(k) = [y_H(k) \ y_V(k)]^T \), \( x(k) = [x_H(k) \ x_V(k)]^T \), \( \Gamma(k) = [\Gamma_H(k) \ \Gamma_V(n)]^T \) represents the effective noise at the 2 receiver RF chains and \( H \) is the channel matrix which can be defined as follows:
\[ H = \begin{bmatrix} h_{HH} & h_{HV} \\ h_{VH} & h_{VV} \end{bmatrix}, \]  
(3.2)

where the norm of \( H \) satisfies \(|H| = \sqrt{2}\), \( h_{HH} \) is the channel between the horizontal transmitter and horizontal receiver antenna, \( h_{VV} \) is the channel between the vertical transmitter and vertical receiver antenna, \( h_{HV} \) is the channel between horizontal transmitter and vertical receiver antenna (diverse combination), and \( h_{VH} \) is the channel between vertical transmitter and horizontal receiver antenna (diverse combination). Next, we estimated the channel matrix \( H \) using the least square (LS) method as follows:
\[ \hat{H} = (X^H X)^{-1} X^H Y, \]  
(3.3)

where \( \hat{H} \in \mathbb{C}^{2\times2} \) is the LS estimate of the channel matrix, \( X \in \mathbb{C}^{2\times N} \) consist of \( N \) consecutive samples of the two transmit signal sinusoidal tones, \( Y \in \mathbb{C}^{2\times N} \) consist of \( N \) consecutive samples of the two received signal sinusoidal tones, and \( X^H \) is the Hermitian transpose of \( X \). We utilized \( N = 100 \) samples for estimation as it provides low mean squared-error performance. Also, for each measurement point on the 3D sphere, we calculated a total of 4,000 consecutive channel matrix estimates using the IQ data captured by the receiver USRP. Note that the channel matrix estimation process is performed offline in MATLAB.

We are interested in analyzing the multi-antenna system performance of A2A channels.
Therefore, we utilize two different types of performance metrics in three distinct multi-antenna communication system configurations to analyze the wireless performance over the 3D sphere. The multi-antenna system configurations in our measurement system are (i) $1 \times 2$ single-input multiple-output (SIMO): when one transmitter RF chain and two receiver RF chains are utilized, (ii) $2 \times 1$ multiple-input single-output (MISO): when two transmitter RF chains and one receiver RF chain are utilized, and (iii) $2 \times 2$ MIMO: when two transmitter RF chains and two receiver RF chains are utilized. The performance metrics are given as follows:

3.4.1 Capacity

We utilize the capacity of the channel as a performance metric to quantify the quality of the link in each multi-antenna system configuration. When channel status information (CSI) is available, the capacity per unit bandwidth for the SIMO system with the horizontal transmitter antenna can be calculated as [41]:

$$ C_{SIMO-H} = E \left\{ \log_2 \left( \left| \mathbf{I}_{n_r} + \frac{\zeta}{n_t} \mathbf{h}_{SIMO-H} \mathbf{h}_{SIMO-H}^H \right| \right) \right\}, \quad (3.4) $$

where $\zeta = P/N_o$ is the average SNR at the receiver antenna elements, $n_t = 1$ is the number of transmitter antennas, $n_r = 2$ is the number of receiver antennas, $\mathbf{I}$ is the identity matrix, $E$ is the expectation operator, $\{|\cdot\}|^H$ is the conjugate transpose and $\mathbf{h}_{SIMO-H} = [h_{HH} \ h_{HV}]^T$. For simplification, in this work, the SNR is normalized by setting $P = 1$ which infers the measurement of the effective noise power in the absence of the transmit signal. Note that the capacity in the multi-antenna system depends on the knowledge of the channel at the nodes. Therefore, with the availability of channel information, multiple antennas in the system lead to independent parallel channels, and the channel capacity is the sum of the capacity of each spatial dimension. For large array antenna systems, the capacity improves linearly with the number of antennas. Similarly, the capacity per unit bandwidth for the SIMO system with the vertical transmitter antenna can be calculated as:

$$ C_{SIMO-V} = E \left\{ \log_2 \left( \left| \mathbf{I}_{n_r} + \frac{\zeta}{n_t} \mathbf{h}_{SIMO-V} \mathbf{h}_{SIMO-V}^H \right| \right) \right\}, \quad (3.5) $$
where \( h_{SIMO-V} = [h_{VH} \ h_{VV}]^T \). The capacity per unit bandwidth for the MISO system with the horizontal receiver antenna can be calculated as follows:

\[
C_{MISO-H} = E \left\{ \log_2 \left( I_{n_r} + \frac{\zeta}{n_t} h_{MISO-H} h_{MISO-H}^H \right) \right\}, \tag{3.6}
\]

where \( n_t = 2, \ n_r = 1 \) and \( h_{MISO-H} = [h_{HH} \ h_{VH}]^T \). Similarly, the capacity per unit bandwidth for the MISO system with the vertical receiver antenna can be written as follows:

\[
C_{MISO-V} = E \left\{ \log_2 \left( I_{n_r} + \frac{\zeta}{n_t} h_{MISO-V} h_{MISO-V}^H \right) \right\}, \tag{3.7}
\]

where \( h_{MISO-V} = [h_{HV} \ h_{VV}]^T \). Last, the capacity per unit bandwidth of the MIMO system with \( n_t = 2 \) and \( n_r = 2 \) can be written as follows:

\[
C_{MIMO} = E \left\{ \log_2 \left( I_{n_r} + \frac{\zeta}{n_t} HH^H \right) \right\}. \tag{3.8}
\]

### 3.4.2 Correlation

We use the correlation between the channel estimate of the antennas as a performance metric to quantify the system performance and efficiency of the antennas. For this purpose, we calculate intra-user correlation for different multi-antenna system configurations [42,43]. The correlation metric for the SIMO system can be described as the correlation between the receiver antenna elements and mathematically, for the signals transmitted from the horizontal antenna of the transmitter, it can be written as follows:

\[
R_{SIMO-H} = \frac{1}{n_r} \sqrt{E[|h_{SIMO-H}^H \times h_{SIMO-H}|]}, \tag{3.9}
\]

where \( n_r = 2 \). Similarly, the correlation metric for the SIMO system utilizing the signals from the vertical antenna of the transmitter can be written as follows:

\[
R_{SIMO-V} = \frac{1}{n_r} \sqrt{E[|h_{SIMO-V}^H \times h_{SIMO-V}|]}. \tag{3.10}
\]

Following, the correlation metric for the MISO system can be described as the correlation between the transmitter antenna elements. Therefore, the correlation for the signals captured
at the horizontal antenna of the receiver can be written as follows:

\[ R_{MISO-H} = \frac{1}{n_t} \sqrt{E[|\mathbf{h}_{MISO-H}^H \times \mathbf{h}_{MISO-H}|^2]}, \]  

(3.11)

where \( n_t = 2 \). Similarly, the correlation metric for the MISO system with a vertical receiver antenna can be written as follows:

\[ R_{MISO-V} = \frac{1}{n_r} \sqrt{E[|\mathbf{h}_{MISO-V}^H \times \mathbf{h}_{MISO-V}|^2]}. \]  

(3.12)

Note that the value of \( R \) varies between 0 and 1 in all multi-antenna system configuration cases, where the \( R = 0 \) infers that all the antenna elements are orthogonal with each other while \( R = 1 \) shows that all the antenna elements are strongly correlated.

### 3.5 Proposed ML-based Direction Estimation Method and Applications

In this section, we first present the proposed technique that can be utilized to estimate the direction of a node in the A2A link. Second, an alternative benchmark direction estimation technique is discussed. Last, we present the application of the proposed technique in the massive MIMO communication nodes to achieve wireless performance gains with limited complexity.

#### 3.5.1 Proposed Direction Estimation using SVM

For direction estimation, the 3D sphere in Fig. 3.1a is partitioned into 8 different regions, where each region comprises several measurement points covering various azimuth and elevation angles which are shown in Table 3.1.\(^1\) The partitioning of the sphere in 2D is shown in Fig. 3.3. The direction problem is approached as a supervised classification problem with a total of 8 classes, where each region in the sphere denotes a quantized direction and represents a class. The size of the regions defines the complexity of the problem and also the resolution of the localization. By increasing the number of classes and decreasing the size of each region, the complexity will be increased. Therefore, with 8 classes in our classification problem, we propose that the width of the directional beam of the transmitter UAV should

\(^1\)Note that the top and bottom in the regions are defined from the perspective of the location of transmitter UAV at the origin of the sphere.
<table>
<thead>
<tr>
<th>Regions</th>
<th>Azimuth angles</th>
<th>Elevation angles</th>
</tr>
</thead>
<tbody>
<tr>
<td>North-West-Top (NW-T)</td>
<td>0 to 90</td>
<td>0 to 90</td>
</tr>
<tr>
<td>North-West-Bottom (NW-B)</td>
<td>0 to 90</td>
<td>0 to -90</td>
</tr>
<tr>
<td>North-East-Top (NE-T)</td>
<td>90 to 180</td>
<td>0 to 90</td>
</tr>
<tr>
<td>North-East-Bottom (NE-B)</td>
<td>90 to 180</td>
<td>0 to -90</td>
</tr>
<tr>
<td>South-East-Top (SE-T)</td>
<td>180 to 270</td>
<td>0 to 90</td>
</tr>
<tr>
<td>South-East-Bottom (SE-B)</td>
<td>180 to 270</td>
<td>0 to -90</td>
</tr>
<tr>
<td>South-West-Top (SW-T)</td>
<td>270 to 360</td>
<td>0 to 90</td>
</tr>
<tr>
<td>South-West-Bottom (SW-B)</td>
<td>270 to 360</td>
<td>0 to -90</td>
</tr>
</tbody>
</table>

Table 3.1: Partitioning of 3D sphere into 8 regions

cover the entire region in the sphere, which gives leverage to the receiver UAV to optimize its position in the region based on other concurrent tasks such as serving the users on the ground without sacrificing the A2A link quality.

In this work, the SVM is adopted for the classification problem as it can provide better prediction accuracy with minimal training dataset, and it is deterministic in nature [44]. In
general, the SVM is a binary classifier that is trained on a set of labeled training samples. For instance, let \((x_i, y_i) \in \mathcal{R}^l \times \{\pm 1\}, i = 1, \ldots, N\) be a set of training samples with \(x_i \in \mathcal{R}^l\) being the input, and \(y_i \pm 1\) being the output. In order to train an SVM, the goal is to identify a hyperplane that divides the samples in such a way that all points bearing the same label are located on the same side of the hyperplane. Following the training, we get the classifier decision function, which is defined as:

\[
f_{w,b} = \text{sgn}(w \cdot x + b),
\]

(3.13)

where \(b\) is the bias of the hyperplane, \(w\) is a coefficient vector, and \(\text{sgn}\) represents a bipolar sign function. The hyperplane of a classifier should meet the following conditions:

\[
y_i[w \cdot x_i + b] \geq 1, \quad \forall i = 1, \ldots, N.
\]

(3.14)

Among all the separable hyperplanes that satisfy criterion (3.14), the separating hyperplane that has the greatest distance to the nearest point is referred to as the optimal separating hyperplane and will yield the optimal generalization. However, in many practical cases, the hyperplane may not be ideal. To allow for the possibility of violating criterion (3.14), it is possible to introduce some slack variables \((e_i \geq 0)\) into (3.14), resulting in the following:

\[
y_i[w \cdot x_i + b] \geq 1 - e_i, \quad \forall i = 1, \ldots, N.
\]

(3.15)

Then, the training of SVM requires finding the parameters \(w, x,\) and \(e_i\) utilizing the following optimization problem:

\[
\min_{w,x,e_i} \frac{1}{2} w \cdot w + \frac{1}{2} C \sum_{i=1}^{N} e_i^2
\]

s.t. (3.15),

(3.16)

where \(C\) is the constant parameter. Moreover, in order to solve non-linear problems, the data can be mapped to another dot product space \(F\) by a non-linear mapping \(\phi : \mathcal{R}^N \to F\), after which the above analysis can be performed in \(F\). Therefore, for non-linear cases, problem
(6.17) still holds with the constraint (3.15) being re-written as $y_i[w \cdot \phi(x_i) + b] \geq 1 - e_i, \forall i = 1, \ldots, N$, where $\phi$ is function that maps the instances to higher dimensional space, and $K(x_i, x_j) \triangleq \phi(x_i) \cdot \phi(x_j)$ is the kernel function. In this work, we use the Gaussian kernel function.

We aim to use multiple features to predict the direction of the receiver node. In particular, channel estimates are considered as features of the A2A link in the SVM classification problem. Let $K$ be the distinct available features extracted from the channel matrix $H$. It is therefore appropriate to have $K$ separate SVM classifiers which can be written as:

$$y_j(x) = f_j(x) = w_j \cdot \phi_j(x) + b_j, j = 1, \ldots, K.$$  \hspace{1cm} (3.17)

Then, the output of the $K$ features SVM classifier system for a given sample $x$ can be written as:

$$f(x) = \sum_{j=1}^{K} f_j(x) = \sum_{j=1}^{K} w_j \cdot \phi_j(x) + b_j.$$ \hspace{1cm} (3.18)

Note that all the base SVM classifiers are first trained to find the values of $w_j$, and $b_j$ using the labeled training samples which are channel matrix estimates in different regions of the sphere. Then, the label/quantized direction/sphere region of a testing sample can be directly determined by (3.18).

3.5.2 Alternative Direction Estimation Method

We also employ an alternative direction estimation method as a benchmark for performance comparison. This approach not only provides a reference point for comparison but also underscores the imperative to integrate ML into direction estimation for A2A communication. The method is defined as follows.

Let $y_p(t)$ be the received signal at the $p \in \{1, 2\}$ antenna on the UAV from a single emitting source, together with noise, $\Gamma_p(t)$, at time instant $t$. The received data snapshot at the UAV is the data vector received at the $P = 2$ antennas of the linear array at a single time instant $t$ which can be written as:

$$y = \alpha s(\psi) + \Gamma$$ \hspace{1cm} (3.19)
where \( s(\psi) \) is the steering vector with direction \( \psi \) and amplitude \( \alpha \). Note that \( \psi \) is the broadside angle, denoting the angle at which the incoming signal arrives perpendicular to the array of sensors or antennas. Also, \( \psi \) is related to the azimuth \( \phi \) and elevation \( \theta \) angles as follows:

\[
\phi = \arcsin \left( \frac{\sin(\psi)}{\cos(\theta)} \right),
\]  

(3.20)

where at \( \theta = 0 \), \( \psi = \phi \). Since we have a linear two-antenna array on the UAV for communication. The direction estimation from incoming signals is limited to the broadside angle. The simplest method to estimate \( \psi \) is through correlation which is defined as:

\[
P_{\text{corr}}(\psi') = s^H(\psi')y,
\]  

(3.21)

where \( \psi' \) is the beam scan angle that varies between 0 and 180 degrees, and at \( \psi' = \psi \), \( P_{\text{corr}}(\psi') \) is maximum, denoting the estimated direction of the signal. Therefore, \( \psi \) is estimated using a one-dimensional search in \( \psi' \). To derive either \( \phi \) or \( \theta \) from \( \psi \), we require at least one of the values \( \phi \) or \( \theta \) as input. Also, there is still an ambiguity in the estimate of \( \psi \) from (3.21) which is due to the limitation of the method/system to estimate the broadside angle in the single hemisphere (either north or south in Fig. 3.1(a)). Therefore, for a fair comparison with the ML method, we extend the above method for direction estimation in the partitioned 3D sphere in Fig. 3.3 by utilizing the dependency of the UAV body and 3D position on the received signal which is seen in prior works [19,40]. Accordingly, the received signal in (3.19) can be reformulated as:

\[
y = \alpha(\phi, \theta) s(\psi) + \Gamma,
\]  

(3.22)

where for a fixed distance, \( \alpha(\phi, \theta) \) is mainly dependent on the transmitter and receiver antenna gains i.e. \( G_T(\phi, \theta) \) and \( G_R(\phi, \theta) \) as well as the attenuation due the UAV body i.e. \( \tau(\phi, \theta) \). Note that it is hard to distinguish \( \tau \) at smaller angles and across the whole 3D sphere. However, in the prior work, [40], it was observed that the received signal in the A2A link varies across different regions in the 3D sphere. Thus, we first employ several channel estimates to compute the received signal across all positions in four hemispheres.
of the 3D sphere i.e. Northern (Top), Southern (Bottom), Eastern (Front), and Western (Behind) hemispheres, subsequently averaging them to find a benchmark received signal solution for each hemisphere, namely, $y_N^e, y_S^e, y_E^e,$ and $y_W^e$. Second, we conduct separate comparisons between the incoming signal $y$ and $y_{N,S}^e$, and between $y$ and $y_{E,W}^e$, by computing the Euclidean distances. Third, we select either the North or South and East or West regions based on the lowest Euclidean distance, serving as an estimate of the hemisphere-half corresponding to the signal direction. Finally, with this hemisphere-half solution, the direction estimation problem is simplified to choosing one of the two partitions according to Fig. 3.3, which is determined by (3.21).

3.5.3 Application in Massive MIMO Systems

In general, massive MIMO systems are considered to be an important part of next-generation wireless networks as they can provide increased bandwidth and spectrum efficiency. In such systems, large antenna arrays are utilized with either fully digital or hybrid (analog and digital) beamforming architectures to achieve optimal communication performance. Following, in the mm-wave band, the IEEE 802.11ad standard indicates high data rates (up to 7 Gbps) utilizing high gain antenna arrays with directional transmission techniques [21–24]. But, optimal directional gains can only be achieved when the receiver lies in the direction of the respective beams of the transmitter. In the IEEE 802.11ad standard, the search space for potential directional beams is partitioned, and the antenna radiation sphere is split into as many as 128 virtual sectors that can handle beam widths of less than 3 degrees. The best sector is selected by an exhaustive search, and the directionality gain is increased by fine-tuning the antennas at both transmission ends [24]. The complexity in searching for the best sector scales with the number of nodes and their sectors. For a single user, the exhaustive search complexity can be defined as $O(M^2 + L^2)$ [45], where $M$ is the number of antennas and $L$ is the number of auxiliary beams or sectors. In the case of aerial networks, the search space size will be greatly increased with UAVs flying at multiple altitudes, and the complexity is expected to increase compared to the ground networks. However, if the direction of the receiver is known at the transmitter, the optimal beam or sector can be easily selected which will greatly reduce the search time and overall energy
consumption.

For aerial networks with UAVs carrying Massive MIMO nodes, the proposed ML-based direction estimation technique can be utilized to select the optimal directional beam for transmission between UAV nodes. The application model of the technique is given in Fig. 3.4, where a UAV is shown to be carrying a Massive MIMO node with a trained direction estimation SVM model and aims to select the optimal transmission beam towards the receiver UAV node (not shown) utilizing the features extracted from CSI of the receiver. The accuracy of the model is periodically checked and an online training of the model is performed when the accuracy is less than a certain threshold. Note that the proposed model utilizes the channel estimates of only 4 antennas which reduces the communication overheads. The prediction complexity of the trained model can be defined as $O(n_{sv}f)$, where $n_{sv}$ is the number of support vectors and $f$ is the number of features, which is significantly lower than the complexity of beam search techniques.

![Diagram](image)

Figure 3.4: Application model of proposed direction estimation technique for optimal beam selection

Following, the benefit of using the proposed direction estimation technique over an exhaustive beam search can be shown by comparing the computation complexities. Since the proposed method predicts the quantized direction among 8 quadrants of the 3D sphere. We compare the computational complexity of both methods with total beam search space or sectors $L = 8$. The proposed method utilizes $f=8$ features and $n_{sv} = 28$ support vectors, where the features are the complex channel estimates of the 4 antennas. The computation
complexity of the exhaustive beam search method is calculated for increasing number of BS antennas and shown with the complexity of the proposed method in Fig. 3.5, where the operations in the vertical axes correspond to the number of computations cycles required to estimate the correct beam sector or user direction. Note that the complexity of the proposed method is independent of the number of antennas. The comparison shows that the proposed method is computationally efficient for \( M > 13 \) and for the BS with large antenna array size \( (M = 100) \), the proposed method has \( 38 \times \) less computation operations than the exhaustive beam search method. Similarly, the complexity is also calculated for different numbers of communicating users \( (U) \) which can be seen in Fig. 3.6, where \( M = 150 \). The complexity in both methods increases with \( U \) due to the linear relationship of \( U \) with the number of operations, and the proposed method achieves significant performance improvement over the exhaustive beam search method. Also, for a large number of sectors in 3D space, the proposed method can be utilized in conjunction with the other beam search algorithms to reduce the beam search space size. For example, with the total number of beam sectors \( L = 128 \), the proposed method can reduce the search space size to only 16 sectors with significantly lower computation operations than the exhaustive beam search method, resulting in reduced computation cycles on the BS. Therefore, for a large sum of antennas in the massive MIMO aerial node, the proposed method can provide a computationally efficient solution to select the direction of the transmission beams for communication performance improvements.

3.6 In-Field Experiment Results

In this section, we first characterize the A2A channel between two UAVs with different multi-antenna system configurations in terms of capacity and correlation metrics. Then, we evaluate the performance of the proposed direction-finding method utilizing the empirical measurement dataset. A detailed analysis of the results is given as follows.

3.6.1 A2A channel characterization

**1×2 SIMO:** The measured capacity and correlation results in the SIMO system configuration are shown in Fig. 3.7, where the horizontal axis is the azimuth angle and the vertical axis is the elevation angle, and the dark color shows the lowest correlation and capacity while the light color shows highest correlation and capacity. It can be seen that the transmitter
Figure 3.5: Exhaustive beam search complexity vs number of BS antennas along with the proposed method complexity

Figure 3.6: Exhaustive beam search and proposed method complexities vs number of users

antenna orientation has a significant impact on both performance metrics. In the case of a horizontal transmitter antenna, the correlation values are on the lower side mostly on the receiver locations between -45 and +45 degrees elevation angles while at the same locations, capacity values do not reduce significantly. Also, the capacity of the system is best when the receiver node is almost or exactly above and below the transmitter node i.e., -67.5 to -90 and +67.5 to +90 degrees elevation angles because these are the points where there is no UAV body obstruction between the channel. In the case of the vertical transmitter antenna,
The results are almost opposite of the horizontal antenna results. It can be seen that the correlation values are significantly low overall when the receiver node is exactly above and below the transmitter node and this is because of the signal blockage due to the UAV body. Also, at the same locations, the capacity values are low compared to the highest capacity results of the system achieved at other locations which mostly lie between −45 and +45 degrees elevation angles.

Figure 3.7: Capacity and correlation results in 1×2 SIMO antenna configuration

2×1 MISO: The measured results in terms of capacity and correlation metrics in the MISO system configuration are shown in Fig. 3.8. It can be seen that the capacity and correlation values vary significantly with the orientation of the receiver antenna which is
similar to the transmitter antenna orientation effect in the SIMO system results. Also, the correlation is low at most of the azimuth and elevation angles in the sphere which infers the orthogonality at the transmitter which is also seen in the SIMO system. The variation of the correlation and capacity values are not consistent with respect to azimuth and elevation angles, and at some adjacent positions on the sphere, the values drop or increase by as much as 5 times. This means that with little deviation in the UAV’s position, the performance will vary significantly. However, for the direction estimation, the variation in values in adjacent locations can benefit in differentiating the azimuth and elevation angle pairs. Moreover, the capacity performance in both the transmitter antenna orientation cases is not similar to the SIMO system and there are very limited locations where the system achieves peak capacity performance on the scale. Therefore, it can be said that the MISO configuration in the A2A link requires the UAV to be positioned accurately in limited azimuth and elevation angles over the sphere in order to achieve high communication performance.

2×2 MIMO: The measured capacity in the MIMO system configuration is shown in Fig. 3.9. It can be seen that the azimuth and elevation angles have a significant impact on the results. The capacity values around the sphere are significantly increased by at least 2.2× compared to the SIMO and MISO configurations. There are limited positions where the receiver achieves the highest capacity on the scale. For instance, the azimuth and elevation angle pairs (22.5,-45) and (67.5, 22.5) are the only two positions where the capacity is greater than 38 bps/Hz. Therefore, for the scenario where receiver node wants to achieve highest capacity performance on the 3D sphere, the node is required to search across 112 positions in the worst case which severely impacts the energy efficiency of the node due to propulsion energy consumption during the search. Moreover, the variation in capacity values among the adjacent positions on the sphere is significant and the overall values around the sphere are different than the MISO and SIMO configuration results.

3.6.2 A2A direction estimation

We analyze the performance of the proposed SVM method for direction estimation in the A2A link over the 3D sphere by utilizing the multi-antenna channel estimates in the A2A link. Also, we aim to show the impact of adding RF chains in the system on the estimation
accuracy of the proposed method. For this purpose, we analyze the performance of SVM in two cases: (i) 3-Antenna system, where either one antenna is used at the receiver and two antennas are used at the transmitter or vice versa, which corresponds to either 1×2 SIMO configuration with the horizontal or vertical transmitter or 2×1 MISO configuration with the horizontal or vertical receiver antenna. Note that we analyze all 4 combinations separately using respective channel estimates; (ii) 4-Antenna system, where both transmitter and receiver utilize 2 antennas. Moreover, we utilize a data set consisting of 4000 realizations of the channel at each location on the 3D sphere. We perform 5-fold cross-validation on the data set. The data set is divided into two random subsets, where one of the sets is used as testing data while the other is used as training data. We evaluate the performance of the proposed direction estimation method by measuring the prediction accuracy of the trained SVM model.
The performance of the proposed direction estimation method in the 4-antenna system is shown through the confusion matrix in Table 3.2, where the total accuracy provides the percentage of correctly classified test data, and the class accuracy shows the percentage of correct labeling for each separate class of test data. The overall accuracy of predicting the correct region on the sphere is 85% and the individual class accuracy ranges between 66.7-95.8%. The inaccurate decisions mostly fall in the cross-diagonal and adjacent regions with respect to the true regions. For instance, in the case of SE-B, the incorrect decisions mostly lie in the NW-B region which is the cross-diagonal region and this is due to the identical characteristics of the channel in such regions that were not perfectly distinguished by the proposed method even with the two diverse antenna configurations at both transmitter and receiver in the 4-Antenna system.

Next, we analyze the impact of adding an RF chain in the system by comparing the performance of the proposed method in the 3-Antenna and 4-Antenna systems. The total accuracy values of the proposed method in various multi-antenna configurations in the 3-Antenna system are calculated. It is found that the accuracy values range between 13.6-15.2%. Comparing the total accuracy values of 3 and 4 Antenna systems shows that the accuracy of the proposed method increased by at least $6.32 \times$ when adding an RF chain in the 3-Antenna system in both SIMO and MISO configurations, and the low accuracy values infer that the proposed method can not be utilized for direction estimation in the 3-Antenna system.
### Table 3.2: Confusion matrix of the SVM in the 4-Antenna system

<table>
<thead>
<tr>
<th>True Class</th>
<th>NE-B</th>
<th>NE-T</th>
<th>NW-B</th>
<th>NW-T</th>
<th>SE-B</th>
<th>SE-T</th>
<th>SW-B</th>
<th>SW-T</th>
</tr>
</thead>
<tbody>
<tr>
<td>NE-B</td>
<td>7442</td>
<td>5</td>
<td>266</td>
<td>4</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>278</td>
</tr>
<tr>
<td>NE-T</td>
<td>8</td>
<td>4757</td>
<td>378</td>
<td>6</td>
<td>28</td>
<td>2</td>
<td>390</td>
<td>831</td>
</tr>
<tr>
<td>NW-B</td>
<td>261</td>
<td>169</td>
<td>8020</td>
<td>12</td>
<td>1476</td>
<td>21</td>
<td>37</td>
<td>4</td>
</tr>
<tr>
<td>NW-T</td>
<td>6</td>
<td>5</td>
<td>4</td>
<td>7474</td>
<td>242</td>
<td>260</td>
<td>831</td>
<td></td>
</tr>
<tr>
<td>SE-B</td>
<td>2</td>
<td>42</td>
<td>1653</td>
<td>326</td>
<td>5892</td>
<td>19</td>
<td>60</td>
<td>9</td>
</tr>
<tr>
<td>SE-T</td>
<td>4</td>
<td>3</td>
<td>15</td>
<td>289</td>
<td>10</td>
<td>6070</td>
<td>9</td>
<td></td>
</tr>
<tr>
<td>SW-B</td>
<td>3</td>
<td>162</td>
<td>34</td>
<td>1</td>
<td>36</td>
<td>11</td>
<td>5739</td>
<td>14</td>
</tr>
<tr>
<td>SW-T</td>
<td>310</td>
<td>1221</td>
<td>7</td>
<td>7</td>
<td>15</td>
<td>41</td>
<td>3199</td>
<td></td>
</tr>
</tbody>
</table>

| Class Accuracy | 93.1% | 74.4% | 80.3% | 93.5% | 73.7% | 94.8% | 95.8% | 66.7% |
| Total Accuracy  |       |       |       |       |       |       |       | 85%   |

The reason deals with the limited ability of the features in the 3-antenna system to distinguish between the different positions and regions in the 3D sphere. For instance, in the case of $1 \times 2$ SIMO configuration, the capacity results with the vertical transmitter in Fig. 3.7 do not significantly vary with respect to the azimuth and elevation angles at the receiver UAV locations that are parallel or almost parallel to the transmitter UAV (−22.5 to +22.5 degrees elevation angles). Similarly, the capacity results with the horizontal transmitter in the same antenna configuration show limited variations when the receiver UAV flies at such locations that are normal or almost normal to the transmitter UAV (+67.5 to +90 and -67.5 to -90 degrees elevation angles). Furthermore, we evaluate the performance of the alternative direction estimation method outlined in Section 3.5.2, resulting in a prediction accuracy of 55.4%.

We also compare the performance of the proposed SVM method with other ML-based classification methods such as decision tree, naive Bayes, artificial neural network (ANN), and k-nearest neighbor (KNN) [46]. For each method, we utilized the same features and dataset as in the proposed method for training and testing. In addition, we also evaluate the performance of the SVM method provided in [47] for direction estimation in the A2A link, where the authors in [47] utilized the received signal strength of the access point node as a feature in the SVM classifier for indoor localization. The direction estimation accuracy of each approach is presented in Table 3.3, along with the associated mathematical representa-
Table 3.3: Performance comparison of the proposed method with various ML-based classification methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy (%)</th>
<th>Complexity</th>
<th>No. of operations</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM [47]</td>
<td>10.2</td>
<td>$O(n_{sv})$</td>
<td>28</td>
</tr>
<tr>
<td>Naive Bayes</td>
<td>25.4</td>
<td>$O(f)$</td>
<td>8</td>
</tr>
<tr>
<td>Decision tree</td>
<td>53.0</td>
<td>$O(\log(T))$</td>
<td>5</td>
</tr>
<tr>
<td>ANN</td>
<td>40.1</td>
<td>$O(A_nA_s)$</td>
<td>10</td>
</tr>
<tr>
<td>KNN</td>
<td>78.7</td>
<td>$O(Df)$</td>
<td>$4.6656 \times 10^5$</td>
</tr>
<tr>
<td>Proposed SVM</td>
<td>85</td>
<td>$O(n_{svf})$</td>
<td>$2.52 \times 10^2$</td>
</tr>
</tbody>
</table>

Method of prediction complexity and the number of operations required for predictions, where $T$ is the depth of the tree in the decision tree method, $A_n$ and $A_s$ are the total number of layers and average number of neurons per layer in the ANN method, respectively, and $D$ is the number of training samples in the KNN method. The comparisons show the superiority of the proposed SVM method in terms of accuracy. The SVM model from [47] provides the lowest accuracy of all because it only uses the received signal strength of a single communication path between the transmitter and receiver as a feature to estimate the direction. The KNN method provides comparable accuracy to the proposed method but at the cost of high complexity which scales with the number of training samples. The decision tree method has the lowest complexity of all but provides insufficient accuracy. Furthermore, the performance of different ML models is assessed across diverse dataset sizes, where 10% samples from the dataset are utilized for testing. The results are shown in Fig. 3.10. It can be seen that the prediction accuracy first increases with the data size and then nearly saturates. The KNN and proposed SVM method provide significantly better performance compared to the other models. The major observation indicates that for smaller training dataset sizes, the KNN method exhibits slightly higher prediction accuracy compared to the proposed SVM method. Conversely, with larger dataset sizes, the SVM method demonstrates superior performance, where the accuracy seems to improve with the data size, rather than reaching a saturation point.

Therefore, with the availability of a channel matrix at the nodes, the proposed method can be utilized to estimate the direction of the UAV in the A2A link with at least 2 diverse
Figure 3.10: Prediction accuracy versus data set size

combinations of antennas at the transmitter and receiver. Moreover, the class accuracy and overall accuracy of the proposed method can be further improved by adding more RF chains and diverse combinations of antennas in the system which can be easily imagined in the massive MIMO UAV systems. The inclusion of additional antennas in the system can provide distinct communication performance over the sphere, aiding the proposed method in more efficiently distinguishing between classes which is achieved by refining the support vectors based on new features. However, it’s crucial to note that the complexity of the proposed method increases linearly with the number of features. Thus, it is desirable to incorporate such features in the proposed method that best contribute to identifying locations on the sphere, ultimately enhancing the accuracy of direction estimation.

3.7 Summary

In this chapter, we analyzed multi-antenna channels in the A2A link between two UAVs and showed the impact of 3D position on the antenna correlation and channel capacity performance of various multi-antenna system configurations. Then, we proposed a novel direction estimation method for the A2A link in a MIMO system that requires channel estimates of at least 2 diverse combinations of antennas at the transmitter and receiver. The
proposed method uses the SVM technique that utilizes correlation and capacity measures of multi-antenna channels in the A2A link as features to estimate the quantized direction of the UAV node in a 3D sphere. For validation of the proposed technique, wireless parameters are measured between 2 UAV communication nodes with each node carrying a USRP with vertical and horizontal mounted antennas, where the transmitter node hovers at the origin of a 3D sphere and the receiver node flies at multiple points on the 3D sphere covering various azimuth and elevation angles. Results indicate that the proposed method estimates the direction of the UAV node with an accuracy rate of 85% which supports the use of learning-based models with the available channel estimates to estimate the direction of the nodes in the A2A link. Moreover, the method for direction estimation can be directly utilized in the UAV-based massive MIMO networks to efficiently select the directional transmission beams without sweeping across multiple angles or partitioned sectors in the 3D space leading to reduced computational complexity and energy consumption at the aerial nodes.
Chapter 4
Rate Maximization in a UAV-Based Full-Duplex Multi-User Communication Network in the A2G links

4.1 Introduction

The increase in wireless data traffic forced the limits of communication systems in terms of reliability and throughput [48]. In-band full duplex (IBFD) communication allows bi-directional communication at the same frequency and time, which doubles the system capacity and improves spectrum efficiency compared to the traditional HD systems [49–51]. Moreover, the IBFD communication can be considered in the communication with UAVs to improve the performance in the A2G link [8,52]. In addition to the spectral efficiency, beamforming with the MIMO system has gained wide research attention for the design of a next-generation wireless network [53–57]. Beamforming is a technique used for directional transmission and reception at a particular device/user, rather than spreading the wireless signal in all directions, thereby reducing interference and increasing the wireless link gain. In the case of A2G networks, where the probability of a line-of-sight link is high, directional transmission through beamforming techniques could easily provide notable performance gains. However, searching for an optimal beam in the 2D or 3D space for multiple users in the multi-user MIMO communication could lead to an increased computation burden on the aerial BS which was discussed in the previous chapter. Following, if the downward coverage area of the aerial BS in the A2G network is optimized, it could benefit the BS in steering the directional beam only in a limited sub-space. The coverage area optimization on the UAV can be realized if adjustable beamwidth antennas are utilized for transmission [58,59]. This could not only help in limited beam steering in the multi-user MIMO network but could also help reduce RF energy leakage in the side lobes observed in the precoding techniques.

To the best of our knowledge, UAV coverage area optimization with resource allocation
was never considered in a MIMO UAV FD network. Coverage area optimization has been considered for traditional HD single antenna systems in the literature [58,59], where antenna beamwidth and altitude of the UAV were optimized to maximize the system performance. For the FD system, an adjustable beamwidth antenna was also considered in [60] for directional communication from UAV. Here, we consider coverage optimization by including adjustable beamwidth antennas in a MIMO FD UAV BS and formulate bi-direction FD rates where interference terms are shown to be a function of antenna beamwidth. In the following, we propose a novel MOOP to maximize the sum UL-DL rate while providing QoS for a multi-user MIMO FD UAV network. The proposed formulation takes into account the coverage area (beamwidth and altitude), beamformer, horizontal location of the UAV, and UL transmit power of the FD users. The optimization problem is non-convex and non-tractable. MOOP was also considered in [61], where a deep learning approach is used to solve the conflicting system objectives. Contrary, we first adopt the weighted Tchebycheff method to convert MOOP to a single-objective-optimization-problem (SOOP) [62]. Second, we divide SOOP into multiple sub-problems and provide an independent solution for each sub-problem. Lastly, we propose a joint optimization algorithm to solve the proposed problem. The main contributions of this chapter are summarized as follows:

- We consider adjustable beamwidth antennas on the FD MIMO UAV in a multi-user aerial network where the users have FD capability and propose a novel optimization problem to optimize the UAV’s coverage area with resource allocation.

- We propose a computationally efficient solution for transmit beamforming from FD MIMO UAV towards the single antenna FD users by utilizing a zero-forcing (ZF) approach.

- We found that the UL power optimization in a multi-user FD aerial network leads to a non-convexity in the optimization problem due to co-channel interference.

- We proposed a joint optimization solution for the optimization of the DL beamformer, coverage area and location of the UAV, and UL power of the users in a multi-user FD aerial network when the objective is to maximize the sum bi-directional FD rate.
Numerical results show that the proposed solution to the MOOP achieves better performance compared to the baseline FD algorithms. Similarly, FD functionality in the proposed system model provides a notable performance improvement over an HD system.

The rest of the chapter is organized as follows. In Section 4.2, related works on resource allocation optimization in the FD, MIMO, and UAV-based communication networks are discussed. In Section 4.3, the system model of a UAV-based FD multi-user communication network is presented, including the channel model and the relevant performance metrics. The proposed MOOP formulation is described in Section 4.4, where the sum UL and DL rates are maximized. The optimization solution, proposed joint resource allocation algorithm, and complexity and convergence analysis of the algorithm are investigated in Section 4.5. The numerical results-based performance analysis of the proposed algorithm is presented in Section 4.6. Finally, the chapter is summarized in Section 4.7.

**Notation:** The boldface lowercase and capital case letters are used to denote vectors and matrices, respectively. $X^H$, Trace$(X)$, Rank$(X)$, and $X^{-1}$ indicate the Hermitian transpose, trace, rank, and inverse of the matrix $X$, respectively. $X \succeq 0$ shows that $X$ is a positive definite matrix. $||.||$ denotes the Euclidean vector norm. $\mathbb{C}^{M \times M}$ and $I_M$ denotes the space of $M \times M$ matrices with complex entries and $M \times M$ identity matrix, respectively. $E(\cdot)$ denotes the expectation with respect to random variable $x$, and $\mathcal{CN}(\mu, \sigma^2)$ denotes the circularly-symmetric complex Gaussian distribution with mean $\mu$ and variance $\sigma^2$.

4.2 Related Work

In the telecommunication domain, a common use of the UAV is a mobile base station (BS) to form a wireless network [63]. In [64], the authors worked on multi-UAV communication systems to serve ground users and primarily focused on designing the UAV trajectories and transmit power to improve throughput. UAVs can also be utilized to work as a relay. The authors in [7] worked on UAV-aided relay systems to minimize outage of the system by optimizing the trajectory and transmit power of the UAV. In [59], authors studied joint optimization of altitude and beamwidth of UAV to improve throughput in three different UAV-enabled multi-user communication models, where the UAV was assumed to have di-
rectional antennas with adjustable beamwidth angles. The results show that the optimal altitude and beamwidth angle critically depend on the communication model. Furthermore, the antenna beamwidth optimization was also considered in [65].

The IBFD systems are of great interest among researchers, and there has been some work in the literature where IBFD systems are utilized with UAVs to propose and solve new problems. For example, in [66], the UAV was deployed as an FD relay to minimize the outage probability of the relaying system. In [52], spectrum sharing planning was studied in a scenario where FD UAV was considered as a relay in device-to-device cellular systems. In [8], an FD UAV-based small cell wireless system was considered, where the UAV was deployed as a base station to serve DL and UL users in an FD manner. The UAV trajectory, user scheduling, and UL user transmit power are alternately optimized to maximize the total capacity of the system.

Beamforming with the MIMO system has also been famous for directional communication and could be used along with IBFD communication. In [53], transmit and receive beamforming optimization for an IBFD cloud radio access network was considered. Similarly, beamforming optimization for power over wireless FD MIMO systems was discussed in [54], where considerable performance gains were achieved over the HD scheme when the time splitting parameter and beamformer are jointly optimized. The UAV-enabled FD relay was considered in [55], where beamforming and power allocation were jointly optimized to maximize the instantaneous data rate of the system. In [56], a sum-rate maximization problem for the FD multi-user MIMO system was considered, where the authors proposed a beamformer design for the UL and DL FD link. Similarly, in [57], a power-efficient resource allocation algorithm was considered in a multi-user FD network. The authors proposed a multi-objective optimization framework to jointly optimize the beamformer at the MIMO FD base station, and the UL transmit power from the HD users.

In recent works, the effectiveness of FD in a UAV network was shown in [60], where the authors considered maximizing the DL sum rate while maintaining the minimum QoS for the UL users, by optimizing the resources and location of the UAV. In [61], FD was considered in a UAV-assisted wireless powered Internet-of-Things (IoT) network, where the FD UAV collects data from the target IoT device and simultaneously charges remaining
devices utilizing fly–hover–communicate protocol. Moreover, a FD UAV relay network was considered in [67], to jointly optimize the HD UL and DL users scheduling, and the UAV trajectory. Finally, in [68], a UAV was considered to charge nodes using wireless-powered communication via backscatter and/or harvest-then-transmit in the IoT network. The UAV trajectory with other resource allocations were optimized to maximize the energy efficiency of the network. The UAV serves all the nodes by sequentially visiting each node in its respective time slot which leads to an increase in energy consumption due to propulsion. Note that the propulsion energy consumption during hover is usually less than the frequent maneuverings [69]. In this chapter, we consider optimal UAV deployment with resource allocation to serve multiple users on the ground.

4.3 System Model

In this section, we present the UAV-based multi-user FD communication network. We then introduce a multi-user MIMO FD communication model and performance metrics for evaluating our algorithms.

4.3.1 UAV-based multi-user FD communication network

Consider a UAV-based FD communication network as depicted in Figure 4.1. The system consists of a UAV-based FD radio BS and \( N \) FD users. The UAV BS is equipped with \( M_T \) antennas, while each user \( n \in \{1, 2, \ldots, N\} \) is equipped with a single antenna for simultaneous UL and DL transmission in the same frequency band. An example of such a feasible solution is a circulator-based FD radio prototype at both BS and users which can achieve bidirectional transmission on the same antenna while providing low hardware complexity [70]. A UAV is deployed with the altitude \( H \) and the horizontal location \( \mathbf{Q} = (Q^x, Q^y) \) and the location of users are denoted by \( \mathbf{O}_n = (O^x_n, O^y_n) \).
The UAV is equipped with adjustable beamwidth antennas to modify the coverage area for the users. Since the MIMO antennas on the commercial UAVs are usually close to each other, we assume that the azimuth and the elevation half-power beamwidth of all the $MT$ antennas are equal and defined by $2\Phi \in (0, \pi)$ radians. The antenna gain in the direction $(\theta, \Psi)$ can be determined by:

$$G = \begin{cases} \frac{G_o}{\Phi^2} & -\Phi \leq \theta \leq \Phi, -\Phi \leq \Psi \leq \Phi, \\ g \approx 0 & \text{otherwise.} \end{cases} \quad (4.1)$$

Here, $\theta$ and $\Psi$ are the azimuth angle and the elevation angle, respectively. In (4.1), the former interval corresponds to the actual beamwidth of the antenna, and the latter is the range of $\theta$ and $\Psi$ values outside the beamwidth. Additionally, $G_o = \frac{30,000}{2^2} \times \left(\frac{\pi}{180}\right)^2 \approx 2.2846$, and $g$ is the channel gain outside the beamwidth of the antenna [59]. To simplify, we set $g = 0$. In contrast, each user $n$ is equipped with an omni-directional antenna.
the radius of the ground coverage area of the UAV is defined by \( r_c = H \tan(\Phi) \).

4.3.2 Channel Model and Performance Metrics

In this work, we assume that the UL and DL channels between the UAV and user \( n \) have similar channel characteristics. Since a UAV to-user channel is mostly dominated by the line-of-sight path, the UL and DL channels can be written as

\[
\begin{align*}
    h_n &= \frac{\overline{h}_n}{(H^2 + \|Q - O_n\|^2)^\frac{1}{2}}, \quad \forall \ n = 1, 2, \ldots, N. \\
\end{align*}
\]

(4.2)

Here, \( h_n \) and \( \overline{h}_n \in \mathbb{C}^{(M_T \times 1)} \). Each element of \( \overline{h}_n \) is a random variable with zero mean and unit variance, and \( \epsilon \) is the path loss exponent which is taken as \( \epsilon = 2 \). The received signal at the FD BS and FD user \( n \) can be written as (4.3) and (4.4), respectively.

\[
\begin{align*}
    y_{UL} &= G_o \Phi^2 \left( \sum_{n=1}^{N} \sqrt{p_n} h_n^b S_n^b + \sum_{n=1}^{N} h_D \kappa_n S_n^a \right) + \pi_D \\
    y_{DL}^n &= G_o \Phi^2 \left( \sum_{m=1}^{N} \sqrt{p_m} g_{(m,n)} S_m^b S_n^b + \sum_{m=1}^{N} h_n^H \kappa_m S_m^a + \pi_n \right) \\
\end{align*}
\]

(4.3)\quad (4.4)

Here, \( S_n^b \in \mathbb{C} \) and \( \kappa_n \in \mathbb{C}^{M_T \times 1} \) are the information bearing signal and transmit beamforming vector from the FD BS to user \( n \), respectively. \( S_n^b \in \mathbb{C} \) and \( p_n \) are the UL transmit data and power sent from user \( n \) to the FD BS, respectively. \( g_{(m,n)} = \frac{m}{d_{(m,n)}^2} \in \mathbb{C} \) denotes the channel between user \( m \in \{1, 2, \ldots, N\} \) and user \( n \), where \( g_o \) is the channel gain at reference distance of 1 meter, \( d_{(m,n)} \) is the distance between user \( m \) and \( n \), and \( m \neq n \). \( g_{(n,n)} \in \mathbb{C} \) and \( h_D \in \mathbb{C}^{M_T \times M_T} \) are the self-interference (SI) channels at user \( n \) and the FD BS, respectively. \( \pi_D \sim \mathcal{CN}(0, \sigma_D^2 I_{M_T}) \) and \( \pi_n \sim \mathcal{CN}(0, \sigma_n^2) \) denote the additive white Gaussian noise at the FD BS and user \( n \), respectively. In (4.3), the term \( \sum_{n=1}^{N} h_n^b \kappa_n S_n^a \) represents the SI at the FD BS. Without loss of generality, it is assumed that \( E(|S_n^a|^2) = E(|S_n^b|^2) = 1, \forall n \in \{1, 2, \ldots, N\} \). In (4.4), the term \( \sum_{m \neq n} g_{(m,n)} S_m^b \sqrt{p_m} \) denotes the co-channel interference formed by UL transmissions from the users, the term \( g_{(n,n)} S_n^b \sqrt{p_n} \) represents the SI at the user \( n \), and the term \( \sum_{m \neq n} h_n^H \kappa_m S_m^a \) shows the
multi-user interference in the DL channel. Additionally, we assume that the perfect channel state information for all users is known at the FD BS. The FD BS applies a beamformer to the received signal $y_{UL}$. The received signal after beamforming for the information transmitted from user $n$ can be written as

$$y_{UL}^{\text{UL}} = \frac{G_o}{\Phi^2} \left( \sqrt{p_n} h_n^H \omega_n^{\text{a}} s_n^b + \sum_{m \neq n} \sqrt{p_m} h_m^H \omega_m^{\text{a}} s_m^b + \frac{G_o}{\Phi^2} \sum_{m=1}^N \omega_m^H h_m^D \kappa_m^D s_n^a + \omega_n^H \pi_n^D \right). \quad (4.5)$$

Here, $\omega_n \in \mathbb{C}^{M_T \times 1}$ is the receive beamforming vector at the FD BS to decode information transmitted from the user $n$. We adopt ZF beamforming for $\omega_n$ for two main reasons: firstly, it requires low computation resources compared to the MMSE beamforming (Basic analysis and performance comparison of ZF and MMSE beamforming are given in [71]) and, therefore, it can be implemented more efficiently for UAV networks that have limited computational resources, and secondly, the optimization problem is mathematically tractable due to the cancellation of interference terms in UL rate expression as shown below. It is also reported that ZF beamforming approaches the performance of optimum MMSE beamforming when the noise is not a dominating factor or the number of antennas is sufficiently large in the system [72,73]. Additionally, the BS is usually equipped with a low-noise amplifier, which facilitates in reduction in the noise at the BS. The receive beamforming vector for user $n$ is calculated at the FD BS according to:

$$\omega_n^* = \frac{(v_n(Z^H Z)^{-1} Z^H)^H}{|| (v_n(Z^H Z)^{-1} Z^H)^H ||}. \quad (4.6)$$

Here, $v_n = (0, \ldots, 0, 1, 0, \ldots, 0)$, and $Z = [h_1, \ldots, h_N]$. Additionally, to facilitate UL signal detection, the number of antennas on the FD BS is assumed to be higher than the number of users. The DL rate at user $n$ for the information transmitted from FD BS can be written as

$$R_n^{DL} = W \log_2 \left( 1 + \frac{G_o}{\Phi^2} |h_n^H \kappa_n|^2 \sum_{m \neq n} \| \sqrt{p_m} g_{m,n} \|^2 + \| \sqrt{p_n} g_{n,n} \|^2 + \frac{G_o}{\Phi^2} \sum_{m \neq n} |h_m^H \kappa_m|^2 + W \sigma_n^2 \right), \quad (4.7)$$

where $W$ is the system bandwidth. The UL rate at FD BS for the information transmitted
from user $n$ can be written as

$$R_{UL}^n = W \log_2 \left( 1 + \frac{\sqrt{p_n} h_n^H \omega_n}{\sum_{m \neq n} \sqrt{p_m} h_m^H \omega_m} + W ||\omega_n||^2 \sigma_D^2 \right).$$  \hspace{1cm} (4.8)

4.4 Proposed MOOP Formulation

In this work, we study the maximization of two objective functions and formulate an MOOP. We aim to maximize the sum UL and DL rates while maintaining minimum QoS to the ground users by jointly optimizing beamwidth $\Phi$, horizontal location $Q$ and altitude $H$ of the UAV, and UL power of the users. The proposed MOOP is formulated as follows:

$$\max_{\kappa_n, H, \Phi, Q, P_n} \sum_{n=1}^{N} R_{UL}^n \hspace{1cm} (4.9a)$$

$$\max_{\kappa_n, H, \Phi, Q, P_n} \sum_{n=1}^{N} R_{DL}^n \hspace{1cm} (4.9b)$$

$$s.t. \quad R_{UL}^n \geq R_{UL}^{\min}, \quad \forall n = 1, 2, \ldots, N, \hspace{1cm} (4.9c)$$

$$R_{DL}^n \geq R_{DL}^{\min}, \quad \forall n = 1, 2, \ldots, N, \hspace{1cm} (4.9d)$$

$$||\kappa_n||^2 \leq P_D/N, \quad \forall n = 1, 2, \ldots, N, \hspace{1cm} (4.9e)$$

$$||Q - O_n||^2 \leq H^2 \tan^2(\Phi), \quad \forall n = 1, 2, \ldots, N, \hspace{1cm} (4.9f)$$

$$0 \leq p_n \leq P_B, \quad \forall n = 1, 2, \ldots, N, \hspace{1cm} (4.9g)$$

$$H_{\min} \leq H \leq H_{\max}, \hspace{1cm} (4.9h)$$

$$\Phi_{\min} \leq \Phi \leq \Phi_{\max}. \hspace{1cm} (4.9i)$$

Here, $P_D$ and $P_B$ are the maximum DL power for the FD BS and the maximum UL power for the users, respectively. $[H_{\min}, H_{\max}]$ is the range of the UAV altitude $H$, which is determined by local authority regulations. $R_{UL}^{\min}$ and $R_{DL}^{\min}$ are the minimum required data rate for QoS in the UL and DL, respectively. $[\Phi_{\min}, \Phi_{\max}]$ is the half-beamwidth range, which is determined by an antenna beamwidth tuning technique. Constraint (4.9f) guarantees the placement of users in the coverage area of a UAV. Note that the MOOP
helps to learn the trade-off between conflicting system objective functions using the concept of Pareto optimality. In the Pareto optimality or efficiency, a point is only Pareto optimal if there is no other point that improves at least one of the objective functions while keeping the same performance of the other objective functions.

4.5 Solution of the MOOP

The optimization problem (4.9) is non-convex due to non-convex objective functions and constraints. It is hard to find the optimal solution. We approach the proposed problem by first converting the MOOP to SOOP using the weighted Tchebycheff method [62]. Then, we divide the SOOP into three sub-problems and utilize an alternating optimization algorithm to handle them iteratively. In the weighted Tchebycheff method, multiple objective functions are converted to a single objective by applying weights to each objective function. The problem (4.9) can be reformulated as the following SOOP.

\[
\max_{\kappa_n, H, \Phi, Q, p_n} \sum_{n=1}^{N} \left( \alpha R_{n}^{UL} + (1 - \alpha) R_{n}^{DL} \right) \quad (4.10a)
\]

\[s.t. \quad R_{n}^{UL} \geq R_{n}^{UL_{\text{min}}}, \quad \forall n = 1, 2, \ldots, N, \quad (4.10b)\]

\[R_{n}^{DL} \geq R_{n}^{DL_{\text{min}}}, \quad \forall n = 1, 2, \ldots, N, \quad (4.10c)\]

\[||\kappa_n||^2 \leq P_{D}/N, \quad \forall n = 1, 2, \ldots, N, \quad (4.10d)\]

\[||Q - O_n||^2 \leq H^2 \tan^2(\Phi), \quad \forall n = 1, 2, \ldots, N, \quad (4.10e)\]

\[0 \leq p_n \leq P_{B}, \quad \forall n = 1, 2, \ldots, N, \quad (4.10f)\]

\[H_{\text{min}} \leq H \leq H_{\text{max}}, \quad (4.10g)\]

\[\Phi_{\text{min}} \leq \Phi \leq \Phi_{\text{max}}, \quad (4.10h)\]

where \( \alpha \) is weighting coefficient. The weighted Tchebycheff method guarantees to generate a set of Pareto optimal points, even for a non-convex MOOP. The problem (4.10) is still non-convex due to non-convex objective function (4.10a) and constraints (4.10b) and (4.10c). We divide the SOOP into three sub-problems that are described in the three subsequent subsections.
4.5.1 Optimal Downlink Beamformer

With fixed values for $H$, $\Phi$, $Q$, and $p_n$, problem (4.10) can be reformulated as the following sub-problem 1:

Sub-problem 1: $\max_{\kappa_n} \sum_{n=1}^{N} (\alpha R_{n}^{UL} + (1 - \alpha) R_{n}^{DL})$  (4.11a)

subject to $R_{n}^{UL} \geq R_{n}^{UL\min}, \forall n = 1, 2, \ldots, N$,  (4.11b)

$R_{n}^{DL} \geq R_{n}^{DL\min}, \forall n = 1, 2, \ldots, N$,  (4.11c)

$||\kappa_n||^2 \leq P_D / N, \forall n = 1, 2, \ldots, N$.  (4.11d)

Since, $\kappa_n$ is the only optimization variable in problem (4.11), the constraints that are not associated with $\kappa_n$ are not required. The problem (4.11) is still non-convex for the following two main reasons: (i) a multi-user interference term in the DL rate and (ii) an increasing function $\kappa_n$ of DL rate exists, while there is a decreasing function for the UL rate, which makes objective (4.11a) a difference of two concave functions. Therefore, we proceed with the ZF approach to simplify the problem (4.11). We assume that for user $n$, DL beamformer vector $\kappa_n$ creates a null in the direction of the SI channel $h_D$ at the FD BS. Additionally, for user $n$, the projections of the channel vector $h_n$ on the DL beamformer vectors of remaining $N - 1$ users are 0. In other words, the following holds: $h_D \kappa_n = 0, \forall n = 1, 2, \ldots, N$, and $h_n \kappa_m = 0, \forall [m, n] = 1, 2, \ldots, N, m \neq n$.

In order to solve the problem (4.11) efficiently, we reformulate the problem by adopting a semi-definite programming (SDP) method. To assist the SDP, we define $K_n = \kappa_n \kappa_n^H$. 

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\( \mathbf{H}_D = \mathbf{h}_D \mathbf{h}_D^H \), and \( \mathbf{H}_n = \mathbf{h}_n \mathbf{h}_n^H \). The simplified SDP problem is given by:

\[
\begin{align*}
\max_{\mathbf{K}_n} & \quad \sum_{n=1}^{N} (1 - \alpha) W \log_2 \left( 1 + \frac{G_0}{\delta^2} \text{Tr}(\mathbf{H}_n \mathbf{K}_n) \right) \\
\text{s.t.} & \quad W \log_2 \left( 1 + \frac{G_0}{\delta^2} \text{Tr}(\mathbf{H}_n \mathbf{K}_n) \right) \geq R_{n, \text{DL}}^{\min}, \forall n = 1, 2, \ldots, N,
\end{align*}
\]

\( (4.12a) \)

\[
\begin{align*}
\text{Trace}(\mathbf{K}_n) &= P_D / N, \quad \forall n = 1, 2, \ldots, N, \\
\mathbf{K}_n &\succeq 0, \quad \forall n = 1, 2, \ldots, N, \\
\text{Trace}(\mathbf{H}_D \mathbf{K}_n) &= 0, \quad \forall n = 1, 2, \ldots, N, \\
\text{Trace}(\mathbf{H}_n \mathbf{K}_n) &= 0, \quad \forall (n, m) = 1, 2, \ldots, N, m \neq n, \\
\text{Rank}(\mathbf{K}_n) &\leq 1, \quad \forall n = 1, 2, \ldots, N.
\end{align*}
\]

\( (4.12b) \)

\( (4.12c) \)

\( (4.12d) \)

\( (4.12e) \)

\( (4.12f) \)

\( (4.12g) \)

The problem \( (4.12) \) is still non-convex because of the rank constraint \( (4.12g) \). Rank-constrained problems are usually non-polynomial hard problems. Therefore, we relaxed the constraint \( (4.12g) \) by removing it from the SDP problem \( (4.12) \). The relaxed problem is given by:

\[
\begin{align*}
\max_{\mathbf{K}_n} & \quad \sum_{n=1}^{N} (1 - \alpha) W \log_2 \left( 1 + \frac{G_0}{\delta^2} \text{Tr}(\mathbf{H}_n \mathbf{K}_n) \right) \\
\text{s.t.} & \quad W \log_2 \left( 1 + \frac{G_0}{\delta^2} \text{Tr}(\mathbf{H}_n \mathbf{K}_n) \right) \geq R_{n, \text{DL}}^{\min}, \forall n = 1, 2, \ldots, N,
\end{align*}
\]

\( (4.13a) \)

\[
\begin{align*}
\text{Trace}(\mathbf{K}_n) &= P_D / N, \quad \forall n = 1, 2, \ldots, N, \\
\mathbf{K}_n &\succeq 0, \quad \forall n = 1, 2, \ldots, N, \\
\text{Trace}(\mathbf{H}_D \mathbf{K}_n) &= 0, \quad \forall n = 1, 2, \ldots, N, \\
\text{Trace}(\mathbf{H}_n \mathbf{K}_n) &= 0, \quad \forall (n, m) = 1, 2, \ldots, N, m \neq n.
\end{align*}
\]

\( (4.13b) \)

\( (4.13c) \)

\( (4.13d) \)

\( (4.13e) \)

\( (4.13f) \)

The problem \( (4.13) \) is known as a semi-definite relaxed (SDR) problem. Additionally, it is
a convex problem and can be efficiently solved using convex problem solvers such as CVX [74]. Once solved, $\kappa_n^*$ can be found using the eigenvalue decomposition of $K_n$. The solution of problem (4.13) is optimal if the obtained matrix $K_n$ is Rank 1. Otherwise, it provides a lower bound for the problem (4.12). For the case when $\text{Rank}(K_n) \geq 1, \forall n = 1, 2, \ldots, N$, there are multiple methods in literature to improve the solution [75, 76]. We follow the heuristic solution provided in [76], which implies that for user $n$, choose $\kappa_n^*$ as the principle eigenvector of $K_n$, which corresponds to the largest eigenvalue of $K_n$.

4.5.2 Optimal Coverage (Altitude and Beamwidth)

With fixed $\kappa_n^*$, $Q$, $\Phi$ and $p_n$, problem (4.10) can be reformulated as the following subproblem 2a:

\[
\text{Sub-problem 2a : } \max_H \sum_{n=1}^{N} (\alpha A_n + (1 - \alpha)B_n) \tag{4.14a}
\]
\[
s.t. \quad A_n \geq R_n^{UL_{\text{min}}}, \quad \forall n = 1, 2, \ldots, N, \tag{4.14b}
\]
\[
B_n \geq R_n^{DL_{\text{min}}}, \quad \forall n = 1, 2, \ldots, N, \tag{4.14c}
\]
\[
||Q - O_n||^2 \leq H^2 \tan^2(\Phi), \quad \forall n = 1, 2, \ldots, N, \tag{4.14d}
\]
\[
H_{\text{min}} \leq H \leq H_{\text{max}}, \tag{4.14e}
\]

where

\[
A_n = W \log_2 \left( 1 + \frac{|h_n^H \omega_n^* \sqrt{p_n}|^2}{W ||\omega_n^*||^2 \sigma_D^2} \right), \tag{4.15}
\]

and

\[
B_n = W \log_2 \left( 1 + \frac{G_o |h_n^H \kappa_n^*|^2}{\sum_{m\neq n}^N \sqrt{|P_{m,n}|^2 + |P_{n,n}|^2} + W \sigma_n^2} \right) \tag{4.16}
\]

are the updated UL and DL rates after applying the ZF constraints of the DL beamformer, respectively. Similarly, with fixed $\kappa_n^*$, $Q$, $H$ and $p_n$, problem (4.10) can be reformulated as
the following sub-problem 2b.

Sub-problem 2b: \[
\max_{\Phi} \sum_{n=1}^{N} (1 - \alpha) B_n \quad (4.17a)
\]
\[
s.t. \quad B_n \geq R_n^{DL_{\min}}, \quad \forall n = 1, 2, \ldots, N, \quad (4.17b)
\]
\[
||Q - O_n||^2 \leq H^2 \tan^2(\Phi), \quad \forall n = 1, 2, \ldots, N, \quad (4.17c)
\]
\[
\Phi_{\min} \leq \Phi \leq \Phi_{\max}. \quad (4.17d)
\]

The problem (4.14) and (4.17) are convex optimization problems and can be solved using standard Lagrangian methods \[77\]. The Lagrangian functions of the convex problems are given by:

\[
\mathcal{L}(H, \lambda, \Omega, \delta) = \sum_{n=1}^{N} (\alpha A_n + (1 - \alpha) B_n) + \sum_{n=1}^{N} \Omega_n (B_n - R_n^{DL_{\min}})
\]
\[
+ \sum_{n=1}^{N} \lambda_n (A_n - R_{UL_{\min}}) + \sum_{n=1}^{N} \delta_n (H^2 \tan^2(\Phi) - ||Q - O_n||^2). \quad (4.18)
\]

\[
\mathcal{L}(\Phi, U, J) = \sum_{n=1}^{N} (1 - \alpha) B_n + \sum_{n=1}^{N} U_n (B_n - R_n^{DL_{\min}}) + \sum_{n=1}^{N} J_n (H^2 \tan^2(\Phi) - ||Q - O_n||^2). \quad (4.19)
\]

Here, \( \lambda = [\lambda_1, \ldots, \lambda_N] \geq 0, \Omega = [\Omega_1, \ldots, \Omega_N] \geq 0 \) and \( \delta = [\delta_1, \ldots, \delta_N] \geq 0 \) are the Lagrange multipliers associated with constraints (4.14b), (4.14c) and (4.14d) in problem (4.14); and \( U = [U_1, \ldots, U_N] \geq 0 \) and \( J = [J_1, \ldots, J_N] \geq 0 \) are the Lagrange multipliers associated with constraints (4.17b) and (4.17c) in Problem (4.17), respectively. Note that the positive values of the Lagrange multipliers are required to hold the constraints during the optimization process. The Karush–Kuhn–Tucker (KKT) conditions for the Lagrangian function in (4.18) are as follows

\[
\frac{\partial \mathcal{L}}{\partial H} = 0, \quad (4.20)
\]
\[ \Omega_n(B_n - R_{n}^{DL_{min}}) = 0, \ \forall n = 1, 2, \ldots, N, \] (4.21)

\[ \lambda_n(A_n - R_{n}^{UL_{min}}) = 0, \ \forall n = 1, 2, \ldots, N, \] (4.22)

\[ \delta_n(H^2 \tan^2(\Phi) - ||Q - O_n||^2) = 0, \ \forall n = 1, 2, \ldots, N. \] (4.23)

Similarly, the KKT conditions for the Lagrangian function in (4.19) are as follows:

\[ \frac{\partial L}{\partial \Phi} = 0, \] (4.24)

\[ U_n(B_n - R_{n}^{DL_{min}}) = 0, \ \forall n = 1, 2, \ldots, N, \] (4.25)

\[ J_n(H^2 \tan^2(\Phi) - ||Q - O_n||^2) = 0, \ \forall n = 1, 2, \ldots, N. \] (4.26)

Note that the optimal values of \( H \) and \( \Phi \) should satisfy all the respective KKT conditions.

We now use a sub-gradient method to find the optimal values of all the Lagrange multipliers. The sub-gradient equations for \( \lambda, \Omega, \delta, U \) and \( J \) are given by:

\[ \lambda_n(t + 1) = [\lambda_n(t) + \beta_\lambda(A_n - R_{n}^{UL_{min}})]^+, \ \forall n = 1, 2, \ldots, N, \] (4.27)

\[ \Omega_n(t + 1) = [\Omega_n(t) + \beta_\Omega(B_n - R_{n}^{DL_{min}})]^+, \ \forall n = 1, 2, \ldots, N, \] (4.28)

\[ \delta_n(t + 1) = [\delta_n(t) + \beta_\delta(H^2 \tan^2(\Phi) - ||Q - O_n||^2)]^+, \ \forall n = 1, 2, \ldots, N. \] (4.29)

\[ U_n(o + 1) = [U_n(o) + \beta_U(B_n - R_{n}^{DL_{min}})]^+, \ \forall n = 1, 2, \ldots, N, \] (4.30)

\[ J_n(o + 1) = [J_n(o) + \beta_J(H^2 \tan^2(\Phi) - ||Q - O_n||^2)]^+, \ \forall n = 1, 2, \ldots, N. \] (4.31)

Here, \( \beta_\lambda, \beta_\Omega, \beta_\delta, \beta_U \) and \( \beta_J \) are the positive gradient-search step sizes. \( \lambda_n(t), \Omega_n(t) \) and \( \delta_n(t) \) are the values of the Lagrange multipliers at iteration \( t \), and \( U_n(o) \) and \( J_n(o) \) are the
values of the Lagrange multipliers at iteration $o$. Further, the optimal values of $\lambda_n, \Omega_n, \delta_n, U_n,$ and $J_n$ are used in their respective KKT conditions to find the optimal values of $H$ and $\Phi$. In the sub-gradient method, the optimal value of $H$ should also satisfy constraint (4.14e) and $\Phi$ should also satisfy constraint (4.17d) in problem (4.14) and (4.17), respectively. It is to be noted that the optimal values of $H$ and $\Phi$ are independently found using the sub-gradient method in iterative loops with iteration $t$ (fixed $\Phi$) and $o$ (fixed $H$), respectively.

4.5.3 Optimal UAV Location and Uplink Power

For a fixed DL beamformer vector, altitude, and beamwidth, the problem (4.10) can be reformulated as the following sub-problem 3.

Sub-problem 3: \[
\max_{Q,p_n} \sum_{n=1}^{N} (\alpha A_n + (1-\alpha)B_n) \quad (4.32a)
\]

s.t. \[A_n \geq R_{UL}^{n\min}, \forall n = 1,2,\ldots,N, \quad (4.32b)\]
\[B_n \geq R_{DL}^{n\min}, \forall n = 1,2,\ldots,N, \quad (4.32c)\]
\[||Q - O_n||^2 \leq H^2 \tan^2(\Phi), \forall n = 1,2,\ldots,N, \quad (4.32d)\]
\[0 \leq p_n \leq P_B, \forall n = 1,2,\ldots,N. \quad (4.32e)\]

The problem (4.32) is a non-convex optimization problem. Observing the updated DL rate of user $n$ (i.e., $B_n$), the non-convexity in the problem (4.32) is mainly due to the UL power of $N-1$ users. We use an augmented Lagrangian method (ALM) to solve the non-convex problem [78]. In ALM, constraints are augmented to the objective function to create a Lagrangian function. More specifically, a quadratic penalty term is added to the Lagrangian function, which minimizes the duality gap. Additionally, the augmented Lagrangian method is locally convex, when the penalty parameter is sufficiently large. ALM comprises two main steps in iterations: (i) maximizing the augmented Lagrangian function, and (ii) updating the Lagrange multipliers and penalty parameters, until convergence. Note that the multipliers and penalty parameters are fixed in each iteration and updated between iterations. After
applying ALM to the problem (4.32), the augmented Lagrangian function can be written as:

\[
\mathcal{L}_{\mu, \gamma, \zeta, \iota, \xi}(Q, p_n) = \alpha A_n + (1 - \alpha) B_n + \frac{1}{2\xi} \left\{ \sum_{n=1}^{N} \left[ \max\{0, \mu_n - \xi(R_n^{UL_{min}} - A_n)\} \right]^2 - \mu_n^2 \right. \\
+ \sum_{n=1}^{N} \left[ \max\{0, \gamma_n - \xi(R_n^{DL_{min}} - B_n)\} \right]^2 - \gamma_n^2 \right. \\
+ \sum_{n=1}^{N} \left[ \max\{0, \zeta_n - \xi(H^2 \tan^2(\Phi) - ||Q - O_n||^2)\} \right]^2 - \zeta_n^2 \right. \\
+ \sum_{n=1}^{N} \left[ \max\{0, \iota_n - \xi(p_n - P_B)\} \right]^2 - \iota_n^2 \left. \right\}.
\]

(4.33)

Here, \( \mu = [\mu_1, \ldots, \mu_N], \gamma = [\gamma_1, \ldots, \gamma_N], \zeta = [\zeta_1, \ldots, \zeta_N] \) and \( \iota = [\iota_1, \ldots, \iota_N] \) are the Lagrange multipliers associated with constraints (4.32b), (4.32c), (4.32d) and (4.32e) in problem (4.32), respectively. \( \xi \) is the adjustable penalty parameter. As discussed, we need to maximize \( \mathcal{L}_{\mu, \gamma, \zeta, \iota, \xi}(Q, p_n) \) and update the Lagrange multipliers \( (\mu, \gamma, \zeta, \iota) \) and the penalty parameter \( (\xi) \). For an implementation, an iterative algorithm can be utilized to solve the Lagrangian function in (4.33). Moreover, the Lagrange multipliers and the penalty parameter at stage \( l \) are updated as follows:

\[
\mu_n^{(l+1)} = \max\{0, \mu_n^{(l)} - \xi(R_n^{UL_{min}} - A_n(p_n^{(l)}, Q^{(l)}))\}, \forall n = 1, 2, \ldots, N,
\]

(4.34)

\[
\gamma_n^{(l+1)} = \max\{0, \gamma_n^{(l)} - \xi(R_n^{DL_{min}} - B_n(p_n^{(l)}, Q^{(l)}))\}, \forall n = 1, 2, \ldots, N,
\]

(4.35)

\[
\zeta_n^{(l+1)} = \max\{0, \zeta_n^{(l)} - \xi((H^{(l)})^2 \tan^2(\Phi^{(l)}) - ||Q^{(l)} - O_n||^2)\}, \forall n = 1, 2, \ldots, N,
\]

(4.36)

\[
\iota_n^{(l+1)} = \max\{0, \iota_n^{(l)} - \xi(p_B - p_n^{(l)})\}, \forall n = 1, 2, \ldots, N,
\]

(4.37)

\[
\xi^{(l+1)} = 2\xi^{(l)}.
\]

(4.38)

Here, \( \mu_n^{(l+1)}, \gamma_n^{(l+1)}, \zeta_n^{(l+1)}, \) and \( \iota_n^{(l+1)} \) are the updated values of Lagrange multipliers, \( \xi^{(l+1)} \) is the updated value of penalty parameter, \( p_n^{(l)} \) and \( Q^{(l)} \) are the optimized values of the UL power of users, and the horizontal location of the UAV at stage \( l \). Note that to satisfy the lower bound of constraint (4.32e), we select \( p_n^{(l)} = \max(0, p_n^{(l)}) \) for each user \( n \), where \( p_n^{(l)} \) is
the optimized value calculated in the first step (maximization) of ALM at stage $l$.

4.5.4 Proposed Joint Optimization Algorithm

In this work, we propose a joint optimization algorithm to solve the DL beamformer, beamwidth, altitude, and location of the UAV and also the UL power from the users in a UAV-based multi-user FD communication network. Algorithm 1 illustrates the method and clarifies the joint optimization. It utilizes an alternating optimization approach which is shown in Figure 4.2. The algorithm comprises three main parts as follows: Initialization, where the initial values of optimization variables, Lagrange multipliers, and other variables are set; Iterative loop 1 (steps 2–21), where sub-problem 1 and sub-problem 2 (both a and b) are solved using the CVX program and the sub-gradient method, respectively; Iterative loop 2 (steps 13–18), where sub-problem 3 is solved using the ALM. Note that the loop 2 is a nested loop of the loop 1. Loop 2 iteratively runs until the convergence of ALM and loop 1 iteratively runs until all the optimization variables are converged or a maximum number of iterations $\hat{v}$ is achieved.

Figure 4.2: Alternating optimization method for the proposed problem.
Algorithm 1 Proposed Solution for Joint Optimization

1: **Initialize**: set tolerance $\rho$, max iteration $\hat{v}$, iteration $v = 0$, penalty parameter ($\xi(0)$), and initial values of $p_n^{(0)}$, $Q^{(0)}$, $\Phi^{(0)}$, $H^{(0)}$, $\mu^{(0)}$, $\gamma^{(0)}$, $\zeta^{(0)}$ and $\iota^{(0)}$

2: **Repeat**

3: With fixed $p_n^*(v), \Phi^*(v), H^*(v), Q^*(v)$, calculate $K_n^*(v)$ using the solution of sub-problem 1.

4: **For** $n = 1$ to $N$

5: **If**: Rank ($K_n^*(v)$) = 1

6: Calculate $\kappa_n^*(v)$ using the eigen value decomposition of $K_n^*(v)$

7: **Else**: Choose $\kappa_n^*(v)$ as the principle eigen vector of $K_n^*(v)$, which corresponds to largest eigen value of $K_n^*(v)$

9: **End If**

10: **End For**

11: With fixed $\kappa_n^*(v), p_n^*(v), \Phi^*(v)$ and $Q^*(v)$ Calculate $H^*(v)$ as a solution of sub-problem 2a

12: With fixed $\kappa_n^*(v), p_n^*(v), H^*(v)$ and $Q^*(v)$ Calculate $\Phi^*(v)$ as a solution of sub-problem 2b

13: **Initialize**: $l = 0$

14: **Repeat**

15: With fixed $\kappa_n^*(v), H^*(v)$ and $\Phi^*(v)$, calculate $Q^{(l)}, p_n^{(l)}$ as a solution of max $\mathcal{L}_{\mu,\gamma,\zeta,\iota}(Q, p_n)$ in (4.33)

16: Update $\mu^{(l+1)}, \gamma^{(l+1)}, \zeta^{(l+1)}$ and $\iota^{(l+1)}$ by (4.34)–(4.37), respectively.

17: Update penalty parameter $\xi^{(l+1)}$ by (4.38)

18: Increment $l$ by 1.

19: **Until convergence**

20: Set $p_n^*(v + 1) = p_n^{(l)}$ and $Q^*(v + 1) = Q^{(l)}$

21: Increment $v$ by 1.

22: **Until convergence or** $v \leq \hat{v}$

23: Optimized values of $\kappa_n, p_n, Q, \Phi$ and $H$ are found
4.5.5 Complexity and Convergence Analysis

The computational complexity in Algorithm 1 is dominated by (i) step 3, where the DL beamformer of the UAV for each user $n$ is calculated by using the SDR problem (4.13) in a CVX program, (ii) steps 11–12, where the altitude and beamwidth of the UAV are optimized by using the sub-gradient method, and (iii) steps 14–19, where the horizontal location of the UAV and UL power of the users are independently optimized by using ALM. The complexity order for handling sub-problem 1 is $O(max(N, M_T)\frac{4}{M_T}M_T^{1/2}\log(1/\rho))$ [75], for sub-problem 2a and 2b is $O(N/\rho^2)$, and for sub-problem 3 is $O(L^2)$, where $\rho > 0$ is the solution accuracy. Therefore, the overall complexity of the proposed joint optimization Algorithm 1 is $O(\hat{v}(max(N, M_T)\frac{4}{M_T}M_T^{1/2}\log(1/\rho) + 2N/\rho^2 + L^2))$.

The convergence rate of the CVX program depends on the precision value, which can be manually defined in the toolbox. For the sub-gradient method, the convergence rate is $1/\rho^2$. On the other hand, the convergence of ALM mainly relies on the adjustable penalty parameter ($\xi$). Generally, a faster convergence rate is obtained by a large penalty parameter. Additionally, the convergence rate tends to a constant value, which is proportional to the ratio $(1/\xi)$, where $\xi$ is greater than a threshold value $\bar{\xi} > 0$.

4.6 Numerical Results

In this section, we present the simulation-based results to validate our proposed optimization algorithm. The simulation parameters are given as follows. We consider that the MIMO FD UAV is equipped with $M_T = 8$ antennas and deployed to serve $N = 5$ FD ground users which are located randomly in the circle with a radius of 100 meters. The minimum and maximum altitudes of the UAV are $H_{\text{min}} = 50$ meters and $H_{\text{max}} = 200$ meters. The QoS parameters are selected as $R_{UL}^{\text{min}} = R_{DL}^{\text{min}} = 100$ Kbps. The FD system bandwidth $W$ is 10 MHz. The beamwidth range is between $\Phi_{\text{min}} = 0.2$ radians and $\Phi_{\text{max}} = 1.2$ radians. The UL reference channel gain $g_o = 1.42 \times 10^{-2}$. The noise power values at the UAV and users are $\sigma_D^2 = \sigma_n^2 = -169$ dBm/Hz.

For performance comparison, we consider following two baseline FD algorithms by fixing optimization variables in Algorithm 1: (i) fixed UAV location, where the location of the UAV is fixed and randomly chosen inside the radius $r_c$, and (ii) fixed coverage (similar to
the approach in [8]), where the altitude and beamwidth of the UAV are fixed and randomly chosen to satisfy constraint (4.9f).

We analyze the performance of the proposed system and validate its dependency on the maximum DL power in Figures 4.3 and 4.4. The maximum achievable sum FD rate for $\alpha = 0.5$, $P_B = -10 \text{ dBm}$, and different values of maximum DL power $P_D$ is shown in Figure 4.3. Similarly, the maximum achievable sum UL and DL rates are shown separately in Figure 4.4. It can be seen in Figure 4.3 that the sum FD rate is an increasing function with respect to the maximum DL power for all the considered algorithms. In Figure 4.4, the sum DL rate increases with $P_D$ while the sum UL rate is constant and does not depend on the $P_D$ due to the feasibility of constraint (4.13e) in problem (4.13). Moreover, even after the lower value of $P_B$ than $P_D$ and equal weights for UL and DL objectives, the sum UL rate is higher than the sum DL rate. This is mainly because of the co-channel interference which reduces the DL SINR at the users. The performance comparison of the algorithms shows that the proposed algorithm outperforms the other baseline algorithms because the proposed algorithm considers the joint optimization of the DL beamformer, beamwidth, altitude, and location of the UAV, as well as the UL power of the users. Additionally, we observed that the UAV’s coverage optimization is more crucial than the location and it significantly improves the FD performance. It can be seen in Figure 4.3 that the fix UAV location algorithm has improved FD rate values than the fix coverage algorithm due to optimized altitude and beamwidth.
Figure 4.3: Maximum achievable sum FD rate versus maximum DL power.

Figure 4.4: Maximum achievable sum DL and sum UL rate versus maximum DL power.
We analyze the trade-off between sum UL and sum DL rates of the proposed system in Figure 4.5. The trade-off region for $P_D = 33.97$ dBm is obtained by varying the weight coefficient $\alpha$ from 0.1 to 0.9. As expected, the sum DL rate decreases, while the sum UL rate increases with $\alpha$. From numerical results, it can be seen that the proposed algorithm provides improvement in the sum UL and DL rates compared to the baseline algorithms. To balance the rate performance on the UL and DL, $\alpha$ can be optimized through a one-dimensional search. In the case, where UL or DL is the only priority then $\alpha$ can be chosen as 1 or 0 in the proposed algorithm, respectively.

![Figure 4.5: Trade-off region between sum UL and sum DL rates.](image)

In addition, we also calculated the FD energy efficiency (EE) as

$$EE = \frac{\sum_{n=1}^{N} \alpha R_{n}^{UL} + (1 - \alpha)R_{n}^{DL}}{P_D + \sum_{n=1}^{N} p_n},$$

(4.39)

where $P_D + \sum_{n=1}^{N} p_n$ is the total FD power consumption. We examine the FD link power con-
sumption in the proposed system by altering the maximum DL power. Figure 4.6 shows the maximum achievable FD energy efficiency for different values of $P_D$. For all the considered algorithms, EE degrades with the increment in $P_D$, mainly due to increased power consumption in the DL. It can be seen that the proposed algorithm has marginal EE improvement compared to the other baseline algorithms.

![Figure 4.6: Maximum achievable FD energy efficiency versus maximum DL power $P_D$.](image)

Figure 4.6: Maximum achievable FD energy efficiency versus maximum DL power $P_D$. 
To show the impact of the coverage area on sum UL and DL rates, we optimize sum UL and DL rates using a fixed coverage algorithm for different values of coverage area radius \( r_c \) and show the results in Figure 4.7. It is easy to see that both the sum rates decrease with an increase in the coverage area and the effect is more prominent in the DL. Finally, we compare the proposed FD system with a similar HD system. In other words, we consider that the UAV and users are equipped with HD radio in Figure 4.1, where \( M_T \) antennas are utilized for transmission and reception at separate and equal time instants. Therefore, we consider that \( R_{UL}^{HD} = 0.5 R_{UL}^{n} \), \( R_{DL}^{HD} = 0.5 R_{DL}^{n} \), and co-channel and self interference are neglected. Figure 4.8 shows the performance comparison between proposed FD and HD systems. For a fair comparison, we consider that maximum UL and DL powers in the HD system are equal and defined by a single variable \( P \) in Figure 4.8. Additionally, \( P_D \) in the FD system is equal to \( P \). From the comparison, we found that on average, the FD system provides rate improvement of 0.9399 Gbps and 1.0266 Gbps over the HD system’s UL and DL rates, respectively.

![Figure 4.7: Maximum achievable sum DL and sum UL rate versus coverage area radius \( r_c \).](image)

\[ R_{UL}^{HD} = 0.5 R_{UL}^{n}, \quad R_{DL}^{HD} = 0.5 R_{DL}^{n} \]
Figure 4.8: Maximum achievable sum rate versus maximum power.

4.7 Summary

In this chapter, we have proposed a UAV-based FD multiuser communication network in which a UAV is deployed as a MIMO FD BS to serve multiple FD users on the ground. We formulated a resource allocation MOOP that maximizes the achievable bi-directional sum rate of all users while providing QoS. The proposed MOOP is a non-convex problem that was converted to SOOP by using the Tchebycheff method to ease the design of a resource allocation algorithm. The SOOP was divided into three sub-problems with an independent solution for each sub-problem. Further, a joint optimization algorithm was proposed, which optimizes the resources, such as the DL beamformer, UL power of users, and location and coverage of the UAV BS.

We evaluated the performance of the proposed algorithm through simulations and compared them with the performance of baseline FD algorithms. A trade-off region between sum UL and sum DL rate was unveiled, which can be used to prioritize UL or DL performance in an FD MOOP. It was found that the proposed algorithm significantly improves the FD rate performance compared to the other baseline algorithms while providing QoS to all the users.
We also considered the HD radio scheme in the proposed system model for comparison. Our results show that the proposed FD scheme outperformed the HD scheme by $1.8616 \times$ in the UL and $2.0221 \times$ in the DL.
Chapter 5
Empirical Characterization and Energy Efficient Data Collection in UAV-enabled Internet of Underground Things Networks (A2UG link)

5.1 Introduction

The Internet of Underground Things (IoUT) is a growing field that has applications in a variety of commercial and noncommercial sectors like agriculture and petroleum [79,80]. Often underground (UG) sensors are deployed for different purposes in these application areas (e.g., environment monitoring, geophysical studies, and assessment of infrastructural health). Some commonly used UG sensors include seismic sensors, moisture sensors, temperature sensors, and chemical sensors [81–83]. All these sensors behave differently in terms of their characteristics and there are possible signal characterization differences for different soil types, moisture content, sensor depth, and other factors [84,85]. The primary goal behind deploying these sensors is to collect data from and characterize underground properties. Hence, the following become critical issues to empirically study: signal behavior, system design and optimization, performance assessment, deployment planning, adaptation to changing conditions, interference and noise mitigation, and validation of models. In particular, the empirical signal characterization in UG sensors becomes essential to design, optimize, and deploy sensor systems that can operate reliably in dynamic and complex UG environments [86–88]. There are different possibilities for getting data from the UG sensors, where some clusters of UG sensors can be formed and they can be provided with an above-ground (AG) point of communication, whether via fixed infrastructure or aerial vehicles. In either of the approaches, the AG sensors pose challenges for deployment and maintenance. Hence, the possibilities of other approaches like direct UG to Air communication as well as the reverse channel could potentially be leveraged directly to infer soil properties. Before such a possibility, the way the signal behaves in such scenarios requires better understanding.
This serves as motivation for this work where we empirically characterize UG2A and A2UG channels.

In this work, we analyze and model the large and small-scale wireless channel characteristics of the A2UG and UG2A links using in-field measurements conducted at two separate locations. These measurements were taken between a UAV and UG nodes, encompassing dynamic UAV 3D locations, UAV antenna positions, and UG soil conditions. Accordingly, a UAV-based IoUT network is explored to develop an energy-efficient data collection mechanism that has the potential to serve as an application for novel empirical findings of the proposed work. The novel contributions of this chapter are:

- Measurements of the return loss of a wide-band antenna with and without the drone body are performed which suggests the impact of the drone body is significant on the antenna characteristics.

- The impact of antenna position on the drone and its noticeable impact on the path loss and fading in the channel is studied. Findings suggest the antenna mounted on the bottom plate of the UAV provides lower path loss and higher Rician-K performance than the antenna mounted on the UAV’s arm.

- Channel characteristics in the A2UG and UG2A channels are observed and it is found that the two are nearly equal and may be modeled identically. Based on this, a new path loss model is proposed that estimates the path loss in both directions of the considered channel at various UAV 3D positions with RMSE between 1.88-8.52 dB and errors less than the AG2UG model in [87].

- Findings suggest that the fading in the A2UG and UG2A channels follows Rician distribution and we validate our claim by using the confidence-based equality test. Also, Rician-K is dependent on the altitude and elevation angle of the UAV which could be modeled with Gaussian functions with an RMSE between 2.86-4.38 db in the altitude and 1.89-6.1 dB in the elevation angle.

- We show that the lowest possible altitude does not always minimize BER. Accordingly, we develop a novel mechanism to optimize the UAV altitude, which minimizes the BER
of DBPSK modulation in a Rician fading channel.

- Finally, we cast a UAV-based energy minimization data collection problem with UG sensors based on empirical channel models. Accordingly, an energy-efficient data collection scheme, UAV-Collect, capable of achieving lower energy consumption on the UG sensors compared to the benchmark schemes is developed.

The remainder of the Chapter is organized as follows: In Section 5.3, the path loss and fading models for UG communications are described. Section 5.4 outlines the experimental setup, measurement procedures, and soil parameters associated with the measurement locations. Section 5.5 presents the empirical results obtained in dynamic measurement scenarios along with their comparisons. The proposed path loss and fading variation models for A2UG and UG2A channels are detailed in Section 5.6. In Section 5.7, a UAV-based IoUT network is presented as an application for our empirical findings, and an energy-energy efficient data collection scheme is proposed. Finally, the Chapter is summarized in Section 5.8.

5.2 Related Work

For a buried UG device, there are two relevant link types: (i) UG2UG link when two nodes are buried in the UG medium and (ii) UG2AG (uplink)/AG2UG (downlink) when one of the nodes is above ground (AG), and other is buried. Propagation characteristics of UG2UG and UG2AG links have been characterized separately. In [89], the UG2UG link in a soil medium was modeled as a three-wave, closed-form UG channel and validated through testbed experiments. The channel models of UG2AG and AG2UG links were developed in [90,91] and supported by empirical measurements in an IoUT testbed. In [92], the UG soil medium was considered to model the statistical propagation characteristics of both UG2UG and UG2AG links, where antennas were buried in the soil, and measurements were taken between the antennas, showing dependence on the soil type, soil moisture, antenna depth, and transmission frequency, and the root mean square delay spread of the link followed a log-normal distribution.

Researchers have also shown interest in using UG communication in Low Power Wide Area Networks (e.g., LoRa). In [93], authors developed a LoRa-based testbed to study UG2UG and UG2AG links in four different soils. They found that the maximum transmission
coverage in UG2UG and UG2AG links depended on the soil properties, varying between 4-20 m and 100-200 m, respectively. In [94], authors considered LoRa for the UG2AG and AG2UG links. The dependency of LoRa performance on soil properties was studied. Further, the BER of LoRa was formulated as a function of the soil parameters based on statistical UG channel models in [87,92] and validated using measurements in an outdoor environment. It was also found that the antenna return loss changes with the burial depth [88]. The main challenge with IoUT is the relatively lower communication range because of the attenuation in the soil path. This leads to the need for local gateways [81,83].

An alternative to deploying gateways in agricultural fields may be to utilize UAVs. UAVs have become very popular in providing Internet of Things (IoT) communication services. UAVs have numerous applications in wireless communication, such as communication relaying and broadband services [95–97]. In IoT, UAVs are utilized for data collection of ground sensors. For example, we considered a wireless-powered communication network (WPCN) [98], where a UAV is deployed to serve wireless-powered sensors on the ground by transferring power in the downlink direction and collecting data in the uplink direction. UAVs are easily operable and highly maneuverable and could potentially be used with IoUT devices.

The communication links between UAV and UG nodes were considered in limited works. In [99], a UAV is utilized to collect sensor data from UG LoRa nodes at various depths, to characterize the impact of increasing sensor depth and UAV’s altitude on the signal strength of LoRa communications. UAVs have been utilized in many prior works for efficient data collection from over-the-ground sensing nodes in IoT networks, where the researchers mostly focused on either minimizing the UAV’s flight time and the energy consumption of the ground sensors or maximizing the communication rate while completing the data collection task [100–102]. In [100], a UAV-enabled wireless sensor network is considered with practical air-to-ground (A2G) Rician fading channels between a UAV and multiple AG sensor nodes, where the objective is to optimize the minimal average data collection rate from all nodes while adhering to reliability constraints. In [101], a similar network is considered to design a data collection strategy with a focus on minimizing the energy consumption of the nodes. In [102], the authors consider multiple UAVs in a wireless sensor for data collection, where
the UAV trajectory, wake-up scheduling, and association for nodes are optimized to reduce the maximum mission completion time while making certain that every node can reliably upload the desired amount of data within the allotted energy limit. However, the literature on efficient data collection methods in UG sensor networks, particularly with UAVs, remains scarce.

5.3 Background

In this section, we present the large-scale and small-scale radio propagation characteristics (i.e., path loss and fading) and related models in UG communication.

5.3.1 Path Loss Model

The communication channels between aerial and UG nodes are presented in Fig. 5.1, where the channel in the downward direction corresponds to the downlink (DL) or A2UG channel while the upward direction channel refers to the uplink (UL) or UG2A channel, $h_{UG}$ is the depth of the UG node in the soil, $h_{AG}$ is the height of the air node, $d_{AG}$ and $d_{UG}$ are the length of the AG and UG components of the channel, and $\theta_I$ and $\theta_R$ are the incident and refractive angles with green text color showing the angles in the UL channel and red text color showing the angles in the DL channel, respectively. The path loss models of the links between UG and stationary AG nodes are well studied in [87, 90, 91, 103]. The communication link between the nodes in Fig. 5.1 consists of UG and AG radio propagation paths, where the former path corresponds to propagation in the soil medium and the latter
refers to propagation in the air medium. The radio propagation path loss is defined as:

\[ PL^{\rightarrow}[dB] = PL_{UG}(d_{UG}) + PL_{OTA}(d_{AG}) + PL_{R^{\rightarrow}}, \]  

(5.1)

where the superscript \( \rightarrow \) shows the propagation direction i.e. DL or UL, \( PL_{UG} \) is the path loss associated with the UG path that depends on the signal path distance between the UG node and the ground surface \( d_{UG} \). Similarly, \( PL_{OTA} \) is the path loss in the air medium that depends on the over-the-air (OTA) signal path distance \( d_{AG} \). \( PL_{R^{\rightarrow}} \) is the refraction loss caused by the air-soil interface which is dependent on the propagation direction in the UL and DL. The individual path loss terms in (5.1) are defined as follows [87]:

\[ PL_{UG}(d_{UG}) = 6.4 + 20 \log(d_{UG}) + 20 \log(\beta) + 8.69 \alpha d_{UG}, \]  

(5.2)

\[ PL_{OTA}(d_{AG}) = -147.6 + 10 \eta \log(d_{AG}) + 20 \log(f), \]  

(5.3)

\[ PL_{DL}^{R} = 10 \log \left( \frac{\cos \theta_I + \sqrt{\epsilon'_s - \sin^2(\theta_I)}}{4 \cos \theta_I \sqrt{\epsilon'_s - \sin^2(\theta_I)}} \right)^2, \]  

(5.4)

\[ PL_{UL}^{R} = 10 \log \frac{(1 + \sqrt{\epsilon'_s})^2}{4 \sqrt{\epsilon'_s}}, \]  

(5.5)

where \( \alpha \) and \( \beta \) refer to the attenuation and phase shift of the wave in soil, respectively, \( \eta \) corresponds to the AG attenuation coefficient, \( f \) is the carrier frequency of the propagating signal, \( \epsilon'_s \) is the real part of the relative dielectric constant of the soil-water mixture, \( \theta_I \) is the angle of incidence calculated from Snell’s law, \( PL_{DL}^{R} \) is the refraction loss in the DL direction, and \( PL_{UL}^{R} \) is the refraction loss in the UL direction. Note that \( PL_{UL}^{R} \) is independent of \( \theta_I \) and \( \theta_R \). This is because in [87], \( PL_{UL}^{R} \) is calculated based on the assumption that the height of the AG node \( h_{AG} \) is significantly lower than the OTA path distance \( d_{AG} \). Also, since the dielectric constant of the air medium is much smaller than the soil medium, the UL signals with an incident angle \( \theta_I \) greater than the critical angle \( \theta_c \) will be reflected and with \( h_{AG} << d_{AG} \), \( \theta_I \) is approximately equal to \( \theta_c \) and refracted angle \( \theta_R \) is approximately equal to 90°. Thus, the horizontal distance between the AG and UG nodes \( d \) is approximately equal to \( d_{AG} \).
The permittivity of the soil, which depends on soil properties such as moisture, texture, and bulk density, has a major influence on signal propagation in the soil medium. Therefore, the impact of soil permittivity on wireless propagation needs to be characterized. The complex-valued permittivity of the soil can be defined as 

\[ \varepsilon_s = \varepsilon'_s - i\varepsilon''_s, \]

where \( \varepsilon'_s \) and \( \varepsilon''_s \) are the real and imaginary parts of relative permittivity of the soil. In [104], \( \varepsilon'_s \) and \( \varepsilon''_s \) are experimentally characterized for the frequency range of 300-1300 MHz as

\[ \varepsilon'_s = (1.15[1 + \frac{\rho_b}{\rho_s}(\varepsilon'_m - 1) + (m_v)v'(\varepsilon'_{fw})^\delta - m_v]^{\frac{1}{2}} - 0.68) \]

and

\[ \varepsilon''_s = [(m_v)v''(\varepsilon''_{fw})^\delta]^{\frac{1}{2}}, \]

where \( \rho_b \) and \( \rho_s \) represent the bulk density and particle density of the soil, respectively. \( m_v \) is the volumetric moisture content, \( \varepsilon_m \) is the dielectric constant of the soil solids which is defined as

\[ \varepsilon_m = (1.01 + 0.44\rho_s)^2 - 0.062, \]

\( \delta = 0.65 \) is the constant that is determined empirically, \( v' \) and \( v'' \) are the constants that are dependent on the soil and defined as

\( v' = 1.2748 - 0.519S - 0.152C \)

and

\( v'' = 1.33797 - 0.603S - 0.166C, \)

where \( C \) and \( S \) are the mass fractions of clay and sand in the soil mixture, respectively. \( \varepsilon'_{fw} \) and \( \varepsilon''_{fw} \) are the real and imaginary parts of the dielectric constant of water which are described in [85,103,104]. Furthermore, the complex propagation constant \( \gamma \) of the electromagnetic wave in the soil is defined as

\[ \gamma = \beta + i\alpha \]

where \( \alpha \) and \( \beta \) can be determined as follows [87]:

\[ \alpha = \omega \sqrt{\frac{\mu\varepsilon_s}{2} \left[ \sqrt{1 + \left( \frac{\varepsilon''}{\varepsilon_s} \right)^2} - 1 \right]}, \]  

(5.6)

\[ \beta = \omega \sqrt{\frac{\mu\varepsilon_s}{2} \left[ \sqrt{1 + \left( \frac{\varepsilon''}{\varepsilon_s} \right)^2} + 1 \right]}, \]  

(5.7)

where \( \omega \) is the angular velocity and \( \mu \) is the magnetic permeability of the soil. For transmit power \( P_{TX} \), the received power \( P_{RX} \) can be written as [105]:

\[ P_{RX}^\rightarrow = P_{TX} + G_{RX} + G_{TX} + 10\log_{10} \left( 1 - 10^{-\frac{RL}{10}} \right) - PL^\rightarrow, \]  

(5.8)

where \( G_{RX} \) and \( G_{TX} \) are the receiver and transmitter antenna gains, respectively, and \( RL \) corresponds to the return loss of the antenna in the soil medium. It is widely known that the antenna’s return loss changes when buried in the soil [88]. The variation in return loss is because of the impedance mismatch of the antenna which is determined by the changes in
the permittivity of soil and reflection from the soil-air interface at a given depth. Therefore, the resonant frequency of an antenna changes due to the variations in signal wavelength because of the soil properties. In this work, we use a patented wide-band antenna in both the UG and aerial nodes for channel measurements [106]. Additionally, a commercial dipole antenna is utilized on the UAV for the same purpose.

5.3.2 Small-Scale Fading Model

The small-scale fading in the AG situation has been extensively studied in the literature for communication between the aerial node and the ground node [100,107,108]. In [108], the small-scale fading in the A2G channel is empirically characterized with a Rician distribution, and the Rician-$K$ factor in the channel is found to be significantly dependent on the elevation angle between the communicating nodes. Accordingly, the Rician-$K$ factor ($K$) as a function of the elevation angle in the A2G channel is modeled in [100] as follows:

$$K(\theta) = A_1 \times e^{A_2 \times \theta},$$

(5.9)

where $\theta = \arcsin(h_{AG}/d_{AG})$ is the elevation angle between the aerial and ground nodes, and $A_1$ and $A_2$ are the environmental dependent constant coefficients which are determined as $K_{\text{min}} = A_1$ and $K_{\text{max}} = A_1 \times e^{A_2 \times \pi/2}$ with $K_{\text{min}}$ and $K_{\text{max}}$ being the minimum and maximum Rician-$K$ factor in the environment. Note that $\theta$ in (5.9) is measured from the ground surface. Therefore, $K_{\text{max}}$ is found when the aerial node is exactly above the ground node i.e. $\theta = 90$ degrees. However, in this Chapter, we measure $\theta$ from the ground surface normal.

The small-scale fading in the UG communication is discussed in the prior work mainly for the communication between the nodes in the soil medium where both the transmitter and receiver nodes are buried at certain depths [85,103]. In [85], the communication between two UG nodes is considered, where the signal propagation between the nodes that are buried near the ground surface comprises the direct path and the ground surface reflected path. The reflected path can be neglected when the UG nodes are buried at high depths. Moreover, the UG channel is considered a multi-path Rayleigh fading channel where the randomness in the channel is due to the location of the nodes in the soil as opposed to the time. Thus, each path in the channel is Rayleigh-distributed and the signal envelope from each path is
modeled as an independent Rayleigh-distributed random variable. With this knowledge, one can deduce that the UG path component of the A2UG/UG2A channel in Fig. 5.1 is Rayleigh distributed. However, in this work, the small-scale fading in the A2UG and UG2AG channels with UG nodes buried at 0.1 and 0.2m depths follows the Rician distribution with a strong Rician-\(K\) factor. This means that the signal propagation in the A2UG channel has a stronger direct component compared to the reflected or scattered components. The propagation from air to soil medium does not reduce the power in the direct component such that the ratio of the power in the direct component versus the non-direct components is still high.

To show the significance of the small-scale fading in the A2UG channel. We now show that combining the small-scale fading in the air medium (Rician) and soil medium (Rayleigh) does not follow the fading in the A2UG channel (Rician). Let, \(u(t)\) be the signal that arrives at the ground surface from the UAV with a certain position at time \(t\) in Fig. 5.1. Then, the received signal at the ground surface can be written as:

\[
u(t) = x(t)h_{AG}^c(t) + n(t), \tag{5.10}
\]

where \(h_{AG}^c(t) = \sqrt{\zeta_{AG}(t)}g_{AG}(t)\) is the AG channel of the path between UAV and ground surface with \(\zeta_{AG}(t)\) representing the attenuation due to AG distance-dependent path loss and \(g_{AG}(t)\) referring to the small-scale fading which is defined as \(\mathcal{CN}\left(\sqrt{\frac{K}{K+1}}, \frac{1}{K+1}\right)\), \(x(t)\) is the input signal, \(n(t)\) is the AWGN noise, and \(|h_{AG}^c|\) follows Rician Distribution. Let \(y(t)\) be the received signal at the UG node which can be written as:

\[
y(t) = u(t)h_{UG}^c(t) + n(t) = x(t)h_{AG}^c(t)h_{UG}^c(t) + \tilde{n}(t) \tag{5.11}
\]

where \(h_{UG}^c(t) = \sqrt{\zeta_{UG}(t)}g_{UG}(t)\) is the UG channel of the path between the ground surface and UG node with \(\zeta_{UG}(t)\) representing the attenuation due to UG node depth and soil properties and \(g_{UG}(t)\) referring to the small-scale fading which is defined as \(\mathcal{CN}(0, 1)\), \(\tilde{n}(t) \approx n(t)\), and \(|h_{UG}^c|\) follows Rayleigh Distribution. Let \(h^c(t)\) be the total channel between UAV and the UG node in Fig. 5.1 where \(|h^c|\) follows the Rician distribution based on the findings in this
work. Therefore, the received signal on the UG node can now be written as:

\[ y'(t) = x(t)h'(t) + n(t) \]  \hspace{1cm} (5.12)

It can be seen from (5.11) and (5.12) that for \( K > 0 \), \( y(t) \neq y'(t) \). Therefore, the small-scale fading in the A2UG channel of the composite Air and UG paths should be modeled with a Rician distribution. In this work, in addition to the path loss, we also analyze the small-scale fading for various UAV locations in both A2UG and UG2A links.

5.4 In-Field Experiment Setup

The measurement system used for in-field outdoor measurements is first presented in this section. Second, we present the measurement campaign and location-specific information, such as the characteristics of the soil and wireless propagation environment.

5.4.1 Air-to-Underground Measurement System

We utilize USRP E312 SDRs [18] on both transmitter and receiver to take path loss measurements. The system comprises 3 USRP E312 as depicted in Fig. 5.2 where one of the USRP is mounted on the commercial UAV and the other two USRPs are connected with three UG antennas through 0.5m cables that are buried at 0.1, 0.2 and 0.3m soil depths. For the DL measurements, the UAV-mounted USRP transmits a continuous sinusoidal signal that is captured at three UG antennas simultaneously. While in the UL, the 0.1m UG antenna first transmits a continuous sinusoidal signal that is captured by the UAV, followed by the 0.2m antenna. In this way, UL measurement data is captured in two separate flights. Note that we only conducted UL measurements at 0.1 and 0.2m depths. The transmitter
and receiver scripts are implemented in Python via GNU Radio libraries and transferred to the USRPs. Before each flight, the Python scripts are executed for a limited flight time in the USRPs via a shell script that also logs the start and stop time of the scripts for data synchronization. Note that the receiver captures the IQ samples in a file continuously for the fixed duration of the UAV flight time which is then post-processed in Matlab to generate results.

Furthermore, we utilize a wideband patch antenna at the UG nodes. For the UAV, we employ two different antennas, as depicted in Fig. 5.3, and perform measurements separately for each antenna configuration. The first antenna is a tri-band omnidirectional antenna, while the second antenna matches the one used at the UG nodes. The patch antenna has a strong radiation pattern on the single side of the plane, and the antenna can easily be designed and merged with the UAV body. However, in previous work, it has been reported that the antenna placement on the UAV body has a significant impact on the antenna radiation characteristics [16]. Therefore, to analyze such an impact on communication between UAV and UG nodes, we mount the patch antenna on the UAV body frame at two distinct positions that are shown in Fig. 5.3b and 5.3c and conduct wireless propagation measurements in each case separately. Note that in the remainder of the chapter, measurements with the patch antenna mounted on the bottom plate of the UAV are referred to as "Bottom" and measurements with the patch antenna mounted on the arm of the UAV are referred to as "Arm". Table 5.1 lists the remaining measurement system parameters.
Table 5.1: Measurement system parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carrier Frequency</td>
<td>1.241 GHz</td>
</tr>
<tr>
<td>TX Power</td>
<td>15.5 dBm</td>
</tr>
<tr>
<td>Sampling rate</td>
<td>300K samples/seconds</td>
</tr>
<tr>
<td>UAV Antenna</td>
<td>Tri-band (SMA-703), custom wide-band</td>
</tr>
<tr>
<td>UG Antenna</td>
<td>Custom wide-band</td>
</tr>
<tr>
<td>Transmit signal</td>
<td>Sine wave</td>
</tr>
<tr>
<td>UAV</td>
<td>DJI Matrice 300 RTK</td>
</tr>
</tbody>
</table>

5.4.2 In-Field Experimentation Plan

We aim to measure the radio propagation characteristics in the channel at various 3D positions of the UAV. In that context, measurements are conducted at two locations with distinct features in the environment. The aerial view of the locations is shown in Fig. 5.4. The first location (referred to as Location 1) is enclosed in a wooden fort structure with an open interior courtyard and high trees in the vicinity. The second location (referred to as Location 2) has a pair of medium-height trees neighboring the UG antennas on the north side, the south side is wide open, the west side has two small adobe structure homes, and
the east side also has multiple medium-height trees. At Location 1, measurements are taken only in the DL with a tri-band antenna mounted on the UAV, according to the topology shown in Fig. 5.5a, where the antennas are buried at 0.1, 0.2, and 0.3m soil depths and the UAV varies its altitude from 5 to 26m while flying straight overhead the antenna at a depth of 0.2m and hovering for 20 seconds every 3 meters through an automated flight plan. At Location 2, measurements are taken in both UL and DL with a patch antenna mounted on the UAV, based on two distinct topologies which are shown in Fig. 5.5b and 5.5c, wherein both topologies, antennas are buried at 0.1 and 0.2m depths. In the former topology, the UAV flies between 5 and 29m altitudes, while in the latter, the UAV flies at a fixed distance of 21 meters from the 0.2m antenna, varying the elevation angle between 0 and 75 degrees while hovering every 15 degrees for 20 seconds. Since the receiver captures the IQ data continuously, the recorded UAV flight data is utilized in the post-processing along with the receiver script timestamps to extract the received IQ data of each hovering waypoint from the receiver data file.

Figure 5.5: Measurement topologies with: (a) Altitude variations at Location 1, (b) Altitude variations at Location 2, and (c) Elevation angle variations at Location 2.
To measure soil moisture, Watermark sensors [109] are buried alongside each UG antenna as shown in Fig. 5.4a (top) and 5.4b (top). These sensors measure soil water tension in centibars (cB), which has an inverse relationship with soil moisture. Since soil moisture has a significant impact on the channel in UG communication. All the communication measurements at Location 1 are taken under two different soil moisture levels with measured soil water tension values of 0 centibars (cB) (saturated wet soil) and 8 cB. Similarly, at location 2, measurements are taken at 7 (wet soil) and 239 cB (dry soil) soil moisture levels.

5.4.3 Soil Properties

The soil texture at both measurement locations is sandy clay loam at all depths. The soil’s bulk density and the textural composition (sand, silt, and clay percentages) marginally vary with depth. At 0.1m, the percentages of sand, silt, and clay contents in the soil are 56, 23, and 21, respectively. Similarly, at 0.2m, the percentages are 56, 20, and 24, and at 0.3m, the percentages are 59, 17, and 24. The bulk density values at 0.1, 0.2, and 0.3m depths are 0.58, 0.89, and 0.70 gr/cm$^3$, respectively.

5.5 Infield Characterization of the A2UG and UG2A channels

In this section, we analyze the path loss and small-scale fading characteristics of A2UG and UG2A channels through outdoor measurements. Specifically, at Location 1, we investigate the effects of soil depth and moisture on the A2UG channel. Similarly, at Location 2, we explore the influence of the UAV antenna position, soil depth, and moisture on both A2UG and UG2A channels. Additionally, we assess the impact of the UAV body and UG soil medium on the return loss of the wide-band antenna. The respective results at Locations 1 and 2 are presented as follows:

5.5.1 Empirical Results at Location 1

5.5.1.1 Antenna Return Loss

The return loss of the wide-band antenna, as shown in Fig. 5.6, is measured using a vector network analyzer in the AG and UG settings. The return loss of the tri-band omnidirectional transmitter antenna which is mounted on the UAV is also shown in Fig. 5.6. Since 10 dB return loss corresponds to 90% of the transmitted power. We consider a return loss of -
Figure 5.6: Return loss of the TX antenna mounted on UAV, and the custom wide-band antenna placed at AG and UG.

10 dB as a threshold to compare the results at all frequencies. It can be seen that the return loss of the wide-band antenna significantly changes in the UG soil compared to the AG. For instance, the return loss at 0.1 GHz in the AG is significantly higher than the -10 dB while in the UG, the return loss is lower than the -10 dB at all depths which infers that the 0.1 GHz frequency can be utilized for transmission in UG. Contrary, the return loss at 0.58 GHz in the AG is lower than the -10 dB threshold while in the UG, the return loss is above the -10 dB threshold at all depths. Following, at the transmission frequency 1.241 GHz, the return loss of the wide-band antenna in the UG is lower than -10 dB at 0.1m, and 0.2m depths while at 0.3m, the return loss is almost equal to the -10 dB. Similarly, the return loss of the TX antenna mounted on the UAV is significantly lower than -10 dB at the transmission frequency which infers that the TX antenna is suitable to communicate with the wide-band antenna buried in the UG. Moreover, the impact of soil moisture on the return loss of wide-band antenna in the UG can be found in [110].

5.5.1.2 A2UG Channel Path Loss

The measured path loss values are calculated for measurement topology Fig. 5.5a using the received IQ samples. The path loss results at all UG antennas are shown in Fig. 5.7. It can be seen that the path loss increases with the increase in direct distance between UG antennas and UAV at all antenna depths. At 8 cB, the path loss increases by 5.9 dB and 17.6 dB on average when the antenna depth changes from 0.1m to 0.2m and 0.2m to 0.3m, respectively. The path loss variation at 0 cB, and 0.1-0.2m antenna depth is very similar to
that of 8 cB results while at 0.3m, the path loss values show that the received signal is lost after 5 m altitude. The increase in soil moisture shows that the path loss increases by 3.0 dB, and 4.5 dB at 0.1m, and 0.2m depths, respectively. Also, note that the fading in the path loss (error bars) is not consistent with the altitude, and the highest fading is found at 26 m altitude. Next, the path loss is estimated at 0.1-0.3m antenna depths using the path loss model in Section 5.3. The estimated path loss results are also shown in Fig. 5.7, while the measurement area-specific soil parameters used in the model are listed in Table 5.2. It is found that the path loss model fits our results well and the RMSE values between the estimated and measured results at 0.1m and 0.2m depths, and soil moisture 0 cB are 3.8 dB and 1.6 dB, respectively. Similarly, at 8 cB, RMSE values are 4.1 dB, and 1.1 dB. For the 0.3m depth, we estimated the path loss at only 8 cB and the RMSE value is 2.8 dB. Also, it is found that the UG 0.3m antenna has a very high penetration loss and low signal-to-noise ratio which becomes more severe with the increase in soil moisture. Therefore, we do not include the results at 0.3m soil depth in the further analysis. The comparison between measured and estimated results shows that the AG2UG link model can be utilized to model the path loss in the A2UG channel when the UAV flies above the UG nodes.

![Path loss at multiple altitudes, antenna depths, and soil moisture levels.](image)

Figure 5.7: Path loss at multiple altitudes, antenna depths, and soil moisture levels.
Table 5.2: Soil parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_s (gr/cm^3)$</td>
<td>2.65 [111]</td>
</tr>
<tr>
<td>$\rho_b (gr/cm^3)$</td>
<td>0.58 (0.1m), 0.89 (0.2m), 0.70 (0.3m)</td>
</tr>
<tr>
<td>$m_v$</td>
<td>0.35 [112,113]</td>
</tr>
<tr>
<td>$S$</td>
<td>0.56 (0.1m, 0.2m), 0.59 (0.3m)</td>
</tr>
<tr>
<td>$C$</td>
<td>0.21 (0.1m), 0.24 (0.2m, 0.3m)</td>
</tr>
<tr>
<td>$\epsilon_o$, $\epsilon_{fw}'$, $\mu$, $\epsilon_{w0}$, $\epsilon_{w\infty}$</td>
<td>55.26 [94], 79.71, 6 [114], 80.1 [113], 4.9 [113]</td>
</tr>
<tr>
<td>$\epsilon_{fw}$</td>
<td>25.31 (0.1m), 40.27 (0.2m), 31.81 (0.3m)</td>
</tr>
<tr>
<td>$\delta_{eff}$</td>
<td>0.08 (0.1m), 0.17 (0.2m), 0.11 (0.3m)</td>
</tr>
<tr>
<td>$2\pi\tau_w(s)$</td>
<td>$0.58 \times 10^{-10}$ [113]</td>
</tr>
</tbody>
</table>

5.5.1.3 A2UG Channel Small-Scale Fading

The received signal magnitude results are utilized to model fading in the A2UG channel. We model small-scale fading in our measurements with a Rician distribution due to the line of sight scenario between the UAV and ground path. For each waypoint, the Rician distribution function is fitted on the measured signal using the maximum likelihood estimation. As a result, the Rician distribution parameters (i.e., non-centrality ($s$) and scale ($\sigma$)) are generated. Furthermore, the Rician-$K$ value is calculated.

For measurement topology (Fig. 5.5a), the Rician-$K$ values at soil moisture levels 0 cB and 8 cB are shown in Fig. 5.8a. It can be seen that in all cases, the Rician-$K$ value first increases and then decreases with the altitude of the UAV. The increase in soil moisture decreases the Rician-$K$ value by 4.3 dB and 2.4 dB (on average) at the depths of 0.1m and 0.2m, respectively. At 8 cB, the antenna at a depth of 0.1m performs better overall. On the other hand at 0 cB, the 0.2m-depth antenna has performance gains over the 0.1m-depth antenna at most altitudes. The reasons for the performance gain of the 0.2m-depth antenna are the better return loss at the transmission frequency and the variation of soil properties from 0.1 to 0.2m depth. Note that the Rician distribution can be approximated by a Gaussian when $K \gg 1$. Gaussian is a much simpler distribution than Rician. More
specifically, the Gaussian function with altitude, $\chi$, can be defined as:

$$g(\chi) = a \exp \left( -\frac{(\chi - b)^2}{2c^2} \right), \quad (5.13)$$

where $a$, $b$, and $c$ are the amplitude, centroid, and width of the Gaussian peak, respectively. Following, we fitted the Gaussian function on the Rician-$K$ values in Fig. 5.8a. The results are shown in Fig. 5.9. It can be seen that the Gaussian function captures the estimated Rician-$K$ values well at all soil depths and moisture values. The RMSE ranges between 0.4-1.3 dB, where the highest error is mostly found at the maximum value of the Rician-$K$ across all altitudes. The set of fitted Gaussian function parameters $\{a, b, c\}$ at 0.1m soil depth are $\{14.5, 5.1, 39.5\}$ at 0 cB moisture level, and $\{18.8, 14.3, 25.7\}$ at 8 cB moisture level. Similarly, at 0.2m, the set of fitted Gaussian function parameters are $\{14.8, 13.3, 20.8\}$ at 0 cB, and $\{17.4, 12.7, 22.1\}$ at 8 cB. It is observed that the $\{a, b, c\}$ values vary with soil depth and moisture values. Also, the peak value of the Gaussian peak is significantly reduced by the soil moisture compared to soil depth. We can conclude that the Gaussian function can be used to estimate Rician-$K$ values at all UAV altitudes.
Next, the two-sample K-S test is performed on the results to check the goodness-of-fit of the proposed fading distribution on the measured results. The two-sample K-S test is an equality test that is useful for testing whether the two observed sets of samples are from the same distribution. Therefore, the empirical CDF of the measured data and the CDF of the respective fitted Rician distribution are calculated, and the K-S test is performed on all the waypoints in the measurement topology (Fig. 5.5a). The empirical CDF of the received signal magnitude and corresponding fitted Rician CDF at waypoints 1-6 (5-20 m altitudes) in the measurement topology are shown in Fig. 5.8b. It can be seen that the fitted Rician CDF follows the empirical CDF at all waypoints with an error less than $10^{-10}$. It is also found that the K-S test is passed at all the waypoints with a 10% significance level which shows that the small-scale fading in the A2UG link follows Rician distribution and it can be utilized to predict wireless communication performance in the A2UG link.

Last, to show the significance and impact of Rician-$K$ on the BER performance, we present a novel UAV altitude optimization mechanism to minimize the BER of the A2UG link. Usually, the communication rate requirement in an IoT network is limited. Therefore, we utilize the BER expression of DBPSK modulation in the Rician fading channel given in [115] as a performance metric to optimize the UAV altitude. The BER as a function of UAV altitude in the Rician fading channel for DBPSK modulation can be written as:

$$P_b(\chi) = \frac{1}{2} \exp \left[ -\frac{\hat{K}(\chi)\gamma(\chi)}{1 + \hat{K}(\chi) + \gamma(\chi)} \right], \quad (5.14)$$
where $\gamma(x)$ is the average SNR for the Rician fading distribution channel and is defined as $\gamma(\chi) = (1 + \hat{K}(\chi))2\sigma^2 E_b/N_0$, $\hat{K}(\chi)$ is the estimated value of Rician-$K$ parameter using the Gaussian model in (5.20), i.e., $\hat{K}(\chi) = g(\chi)$, and altitude $\chi$ is the same vertical distance as the $d_{AG}$ in (5.17). The altitude optimization problem to minimize the BER can be written as:

$$\min_{\chi} P_b(\chi) \tag{5.15a}$$

subject to

$$C_1 : \lambda_{\min} \leq \lambda, \quad C_2 : \chi_{\min} \leq \chi \leq \chi_{\max},$$

where $\lambda = \frac{E_b}{N_0}$, $\lambda_{\min}$ corresponds to the minimum signal-to-noise ratio per bit required for reliable communication, and $\chi_{\min}$ and $\chi_{\max}$ are the minimum and maximum altitude for the safe operation of the UAV, respectively. The objective function (5.15a) is convex with respect to the UAV altitude, $\chi$, where $\frac{d}{d\chi} P_b(\chi) > 0, \forall \chi > 0$. Therefore, problem (13) can be solved by taking the first order derivative of the objective function (5.15a) with respect to $\chi$ i.e., $\frac{d}{d\chi} P_b(\chi) = 0$ and finding the close form solution for the $\chi$. Moreover, to satisfy the constraint $C1$, we assume minimal signal-to-noise ratio per bit for transmission in (5.15a) i.e., $\lambda = \lambda_{\min}$. By solving $\frac{d}{d\chi} P_b(\chi) = 0$ to find $\chi$, we found that $\chi = b$ which means that the optimum altitude of UAV is found at the centroid of the Gaussian peak and to satisfy the constraint $C2$, the final optimal solution can be written as:

$$\chi^* = \min\{\max\{b, \chi_{\min}\}, \chi_{\max}\}. \tag{5.16}$$

Fig. 5.10 shows the BER calculated for different UAV altitudes at multiple antenna depths and moisture values. An important observation is that the lowest possible altitude does not minimize the BER, $P_b$, which first decreases and then increases with the altitude. Accordingly, the best altitude in Fig. 5.10 is calculated using the solution of the proposed optimization problem given in (5.16), where we assume $\chi_{\min} = 5$ and $\chi_{\max} = 25$. The best altitude varies with the soil depth and moisture values. At 0 cB, by optimizing the UAV altitude, similar bit-level performance can be achieved for antennas buried at different soil depths. Accordingly, UAV altitude optimization minimizes the impacts of increasing burial
depth. This allows for better root monitoring capabilities with deeper soil moisture sensor deployments. Moreover, by utilizing the proposed solution in (5.16) to optimize the UAV altitude, the BER at 0.1m soil depth improves by $4.19 - 4.25$-fold (0 cB-8 cB), and at 0.2m, the BER improves by $6.49 - 8.61$-fold, when compared with worst performing altitude.

5.5.2 Empirical Results at Location 2

5.5.2.1 Antenna Return Loss

The return loss of the antenna is measured through a vector network analyzer in AG, UG (dry soil), and UAV-mounted settings. The measured return loss values are presented in Fig. 5.11. It can be seen that the return loss changes significantly between AG and UG cases which is also seen in the results from Location 1 (Fig. 5.6). The return loss varies marginally between the soil depths and at the transmission frequency, the return loss is at approximately -20 dB which infers that the antenna is suitable for communication when buried in the UG. Moreover, by comparing the results of AG and UAV body cases, it is evident that the UAV body has a significant impact on the antenna characteristics. For
instance, the return losses at most frequencies between 1.4-2.2 GHz increased by 1.7 – 7.5 dB compared to the AG results which caused the return loss to increase above the -10 dB threshold. Similarly, at 300 MHz, and 570 MHz, the return loss increased by 9.5 – 11.1 dB and lie above the -10 dB threshold. We also found that there are variations in return loss values with respect to the placement of the antenna on the Bottom versus the Arm of the UAV. There are a few frequencies that are more suitable for transmission when the antenna is placed on the Arm versus the Bottom of the UAV, and vice versa. For example, the return loss at 1.07 GHz frequency is 2.1 dB above the -10 dB threshold in UAV Bottom results while in UAV Arm results, the return loss is 7 dB below the threshold level at the same frequency. In contrast, the return loss at 1.32 GHz frequency is above the -10 dB threshold by 2.3 dB in UAV Bottom results while in UAV Arm results, the return loss is 5.8 dB below the threshold level at the same frequency. Therefore, it is important to consider the impact of the UAV body on the antenna characteristics before the aerial network deployment.

5.5.2.2 A2UG and UG2A Channels Path Loss

The measured path loss values in A2UG and UG2A channels at multiple UAV altitudes for various soil depths, soil moisture, and UAV antenna positions are shown in Fig. 5.12. It can be seen that, while the path loss varies considerably between several cases, it always rises with UAV altitude. The path loss comparison between UL and DL cases shows similar performance and on average, the difference is only 2.2 dB, where the variation is mainly found in the measurements with the Bottom antenna, which infers approximately identical large-scale performance in the bi-directional channels. The impact of an increase in soil
<table>
<thead>
<tr>
<th>Altitude (meters)</th>
<th>Path loss (dB)</th>
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<tr>
<td>100</td>
<td>140</td>
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<td>120</td>
<td>140</td>
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**Downlink**
- Bottom, 239 cB: 111 dB
- Bottom, 7 cB: 100 dB
- Arm, 239 cB: 239 dB
- Arm, 7 cB: 7 dB

**Uplink**
- Bottom, 239 cB: 111 dB
- Bottom, 7 cB: 100 dB
- Arm, 239 cB: 239 dB
- Arm, 7 cB: 7 dB

Figure 5.12: Measured and estimated path loss at various UAV altitudes

Moisture from 239 to 7 cB shows that the path loss with the Bottom antenna increases by 10.91 and 9.9 dB at 0.1 and 0.2m depth, and with the Arm antenna, it increases by 8.75 and 8.05 dB at 0.1 and 0.2m depth, respectively. Comparably, the effect of increasing the depth from 0.1 to 0.2m shows that the path loss increases by 6.28 and 5.98 dB at 239 cB and 7 cB for the Bottom antenna and by 7.67 and 6.98 dB at 239 cB and 7 cB for the Arm antenna, respectively. The variation with respect to the UAV antenna position is also seen in the results. The main observation is that the slope of change in path loss values with respect to the altitude is lower in the Bottom antenna compared to the Arm antenna. This means that at higher altitudes, the bottom antenna provides lower path loss values than the Arm antenna which is beneficial in improving the communication range. This is because the overall body of the UAV serves as a reflector and directs radio waves to or from the bottom plate of the UAV such that the signal strength in the main lobe of the antenna increases compared to the side lobes. Next, the path loss values are estimated at multiple UAV altitudes using the model in (5.1) and the area-specific soil parameters provided in Table 5.2. The estimated results are also shown in Fig. 5.12. As can be observed, overall, the path loss model captures the empirical data with minimal errors. The RMSE values between the measured and estimated results range between 1.86-4.38 dB in the DL and 2.01-6.70 dB in the UL, where the measurements taken with the Bottom antenna, particularly at higher altitudes, are where the majority of the large estimation errors are found.

Following, the impact of elevation angle on the path loss in A2UG and UG2A channels are shown in Fig. 5.13. It can be seen that the measured path loss values significantly
change between 0 and 75 degrees elevation angles in both UL and DL. We observed that the variation in path loss with elevation angle is significantly dependent on the antenna position on the UAV. In the bottom antenna results, the trend shows that the path loss mainly increases with the increase in the elevation angle with some exceptions found in the results at 239 cB moisture and 0.1m depth, where the 15 degrees elevation angle provides a similar or a little lower path loss values than the 0-degree elevation angle. Accordingly, on average, the path loss values from 0 to 75 degrees drop by 29.14 and 25.16 dB at 239 and 7 cB, respectively. Contrary to this, the path loss first decreases and then increases with the elevation angle in the Arm antenna results, where the elevation angles with the lowest path loss values are mostly found at 30 or 45 degrees which infers that the UAV position directly above the UG antennas does not provide the optimal performance. Therefore, choosing the angle with the lowest path loss value improves the performance by 18.32 and 16.6 dB at 239 and 7 cB, respectively, when compared with the worst UAV position with a 75-degree angle.

Afterward, the path loss is estimated at various elevation angles using the model in (5.1), where we utilize refraction loss given in (5.4) in both DL and UL results. Note that the path loss results in the UL are strongly dependent on the elevation angle. However, in the prior work [87], the UL refraction loss is modeled without the inclusion of the elevation angle based on the assumption that the height of the stationary AG node is significantly smaller than the direct distance between the UG and AG nodes, therefore, the AG distance between the nodes is approximately equal to the horizontal distance. The aforementioned assumptions can not be made in the UG2A link due to two main reasons. First, the UAV’s altitude or
height is often greater than that of fixed AG data collection nodes, mostly due to ground infrastructure requirements for safe operation. Second, the UAV can easily fly near or over the UG nodes for data collection. Therefore, it is not valid to model refracted loss in UL without the elevation angle as in (5.5).

The estimated path loss results at various elevation angles are also shown in Fig. 5.13 with the dotted lines. The estimated results in most cases show the inability of the path loss model in (5.1) to represent the empirical measurements. This is because the refraction loss in (5.4) is a monotonically increasing function in elevation angle while there are two measurement trends found in Bottom and Arm antenna cases that we discussed before. Also, the estimated path loss does not increase significantly with the elevation angle compared to the measured results. The higher estimation errors are mostly found at elevation angles greater than 30 degrees and it seems that there are additional losses in the channel which are more significant at large elevation angles. The performance of the model is quantified using the RMSE values. The average RMSE in the Bottom antenna results with 239 cB soil moisture is 15.98 and 12.24 dB at 0.1 and 0.2m depths, and with 7 cB soil moisture, it is 10.25 and 3.20 dB at 0.1 and 0.2m depths, respectively. Similarly, the RMSE of the Arm antenna results is 6.48 and 5.90 dB at 0.1 and 0.2m depths with 239 cB soil moisture, and 5.09 and 4.23 dB at 0.1 and 0.2m depths with 7 cB soil moisture, respectively. Accordingly, we propose a new path loss model in Section 5.6 for A2UG and UG2A channels that provides significantly better estimation performance compared to (5.1).

5.5.2.3 A2UG and UG2A Channels Small-Scale Fading

The small-scale fading in the A2UG and UG2A channels is modeled using the received signal magnitude results acquired by post-processing the received IQ samples. In Section 5.5.1, we modeled the small-scale fading in the A2UG channel using the Rician distribution and verified with a confidence-based equality test. Therefore, we model the UG2A channel as a Rician fading channel and show the validity by comparing the empirical CDF and fitted Rician CDF in the UL measurements. For each measurement case, the Rician distribution function is fitted on the measured signal using the maximum likelihood estimation. We found that the Rician CDF follows the empirical CDF in all the measurement cases in the UG2A
channel with an error less than $10^{-8}$. The empirical and fitted Rician CDF of the received signal at UAV (bottom antenna) with 5m altitude for the signal transmitted from the UG antenna at 0.1m depth with soil moisture 239 cB is shown in Fig. 5.14. It can be seen that the Rician CDF fits the empirical results well and can be utilized to model the fading in the channel. We also estimated the received signal magnitude CDF using (5.11), where AG and UG paths in the channel are modeled with Rician and Rayleigh fading distribution, respectively. The estimated CDF of the bivariate fading distribution is also shown in Fig. 5.14, where a significant difference between the empirical and bivariate CDF is found. This means that the fading in both AG and UG paths in the channel should be modeled with a signal Rician random variable.

Next, the Rician-$K$ values are calculated from the estimated Rician distribution parameters. The Rician-$K$ values with respect to the altitude at various soil depths, moisture levels, and UAV antenna positions are shown in Fig. 5.15. There are multiple observations in the results which are as follows. The Rician-$K$ parameter is dependent on the altitude, and the antenna position on the UAV has a significant impact on the variation. Overall, the bottom antenna results show that the Rician-$K$ in both UL and DL initially increases and then decreases with altitude, whereas it only decreases with altitude in Arm antenna results. Also, on average, the Rician-$K$ value in the bottom antenna is approximately 9 dB higher than the Arm antenna which means that the overall body of the UAV positively influences the signal propagation to or from the bottom antenna position of the UAV such that the antenna observes weaker signal reflections or stronger direct signal path. Furthermore, an increase in soil moisture content from 239 to 8 cB increases the Rician-$K$ value by 3.27 dB with the Arm antenna, but the impact is insignificant in the measurements with the bottom

Figure 5.14: Empirical CDF of the received signal magnitude, and corresponding estimated Rician and Bivariate CDFs.
antenna. In most cases, the overall influence of increasing burial depth has a negligible effect on Rician-$K$ values, although some noticeable variations are observed at lower altitudes.

Following, the impact of elevation angle on the Rician-$K$ in A2UG and UG2A channels are shown in Fig. 5.16. It can be seen that in all cases, the Rician-$K$ value is significantly dependent on the elevation angle. However, the variation in the values is dependent on the antenna position on the UAV similar to the path loss results. The Rician-$K$ values first
increase and then decrease with the elevation angle. The elevation angles with the highest Rician-$K$ values are 15-30 degrees in the bottom antenna and 30-45 degrees in the Arm antenna. An important observation is that choosing the appropriate elevation angles for communication can provide comparable Rician-$K$ performance between Bottom and Arm antenna cases such that the impact of UAV antenna position on Rician-$K$ is minimized. Also, the Rician-$K$ values do not drop to a significantly lower value even at a 75-degree elevation angle (close to the ground) which shows that the radio signals reaching the ground-soil interface are not completely reflected and there is a signal wave propagating along the ground surface (i.e. lateral wave) that is reaching the UG node in the DL and the UAV in the UL. Note that the authors in [108] showed that Rician-$K$ in the A2G communication is only decreasing in the elevation angle and the variation is modeled by (5.9) in [100].

We now estimate the Rician-$K$ variation with respect to the elevation angle in A2UG and UG2A channels using the model in (5.9). The estimated results are also shown in Fig. 5.16 with dotted lines, where the empirically determined model parameters $A_1$ and $A_2$ in (5.9) are 12.571 and 0.0079, respectively. The comparison between empirical and estimated results shows that the model in (5.9) is incapable of representing the Rician-$K$ values in the A2UG and UG2A channels due to large estimation errors. This is because the estimate Rician-$K$ values from (5.9) monotonically decreases with elevation angle and varies between maximum and minimum Rician-$K$ value in the environment which is not the general trend in the empirical measurements. The RMSE values range between 5.42 and 6.94 dB in the Arm antenna measurements while in the Bottom antenna, it ranges between 4.4 and 8.2 dB. Note that the empirical results trends in Fig. 5.15 and 5.16 can be captured by a Gaussian function when $K >> 1$. Therefore, we propose models in Section 5.6 that can be utilized to estimate the Rician-$K$ factor at various altitudes and elevation angles with lower estimation errors than (5.9).

5.6 Proposed Model for A2UG and UG2A channels

In this section, we develop new models based on the preceding section’s findings. In particular, a new path loss model for A2UG and UG2A channels is presented. Followed by the fading distribution variation models that can be utilized to estimate Rician-$K$ in the
channels for various altitudes and elevation angles between the UAV and UG nodes.

Based on the analysis in the previous section, we found that the path loss model in (5.1) estimates the path loss variation for elevation angles with large estimation errors. This is mainly due to the additional losses in the channel at large elevation angles. Furthermore, the model lacks consideration for elevation angle-dependent losses in the AG path of the channel, likely contributing to unsatisfactory estimation performance. Consequently, we devise a new path loss model that can be utilized to estimate path loss in both A2UG and UG2A channels which is defined as:

\[
PL[dB] = PL_{UG}(d_{UG}) + PL_{OTA}(d_{AG}) + PL_R + PL_{OTA-\theta} + \kappa, \tag{5.17}
\]

where \(\kappa\) is a random variable that follows a Rician distribution, \(PL_{UG}(d_{UG})\) is defined in (5.2), \(PL_{OTA}(d_{AG})\) is defined in (5.3), \(PL_{OTA-\theta}\) correspond to the path loss in the OTA path of the channel due to the change of elevation angle between the communicating nodes which is defined as:

\[
PL_{OTA-\theta} = 32.55 - 32.55 \cos(1.184\theta) - 32.55w \sin(1.184\theta) \tag{5.18}
\]

with \(w\) referring to the weight of the second sinusoidal term and \(\theta\) being the elevation angle between the Air and UG nodes, and \(PL_R\) is defined as:

\[
PL_R = 10 \log \frac{\cos \theta + \sqrt{\epsilon_s - \sin^2(\theta)}}{4 \cos \theta \sqrt{\epsilon_s - \sin^2(\theta)}}. \tag{5.19}
\]

Note that \(\theta\) is approximately equal to \(\theta_I\) and \(\theta_R\) in the A2UG and UG2A channels in Fig. 5.1, respectively, and the terms 32.55 and 1.184 are empirically determined constants. Also, \(PL_{OTA-\theta}\) is modeled based on the path loss variations across various elevation angles in the in-field measurements where the first and second sinusoidal terms model the decreasing, and increasing variation in the path loss with respect to the elevation angles, respectively, and weight controls the descend and growth rate of the path loss depending on the antenna position on the drone. The path loss model in (5.17) is an extension of the model in (5.1) and
thus, at a 0-degree elevation angle, $P_{L_{OTA-\theta}} = 0$, resulting in (5.17) being approximately equivalent to (5.1).

Following, to show the effectiveness of the path loss model, we estimate the path loss at various elevation angles, soil depth, soil moisture, and UAV antenna positions and presented the results in Fig. 5.13, where the parameter $w$ in (5.18) is 0.20 and 0.52 in the Bottom and Arm antenna results, respectively. It can be seen that the path loss model captures the empirical results well in nearly all the measurement cases, compared to the model in (5.1). The RMSE value in the Bottom antenna results with 239 cB soil moisture is 5.53 and 3.04 dB at 0.1 and 0.2m depths, and with 7 cB soil moisture, it is 5.74 and 8.52 dB at 0.1 and 0.2m depths, respectively. Similarly, the RMSE value in the Arm antenna results with 239 cB soil moisture is 1.96 and 4.93 dB at 0.1 and 0.2m depths, and with 7 cB soil moisture, it is 1.88 and 2.45 at 0.1 and 0.2m depths, respectively. The RMSE values show significant estimation performance improvement compared to the prior model and thus, the path loss model can be utilized to estimate path loss in the A2UG and UG2A channels.

Next, the small-scale fading results in the previous section show that the fading follows Rician distribution and distribution parameters vary with the altitude and elevation angles in both UL and DL channels. In Section 5.5.1.3, we modeled the Rician-$K$ variation with the altitude in the DL channel at Location 1 using the Gaussian function. The measurement trends in Fig. 5.15 and 5.16 show that the Rician-$K$ variations can be captured with two separate Gaussian functions which are given as follows:

$$g(\chi) = a \exp \left( -\frac{(\chi - b)^2}{2c^2} \right),$$

$$g(\theta) = a \exp \left( -\frac{(\theta - b)^2}{2c^2} \right),$$

(5.20)

where $\chi$ is the altitude of the UAV, and the parameters $a$, $b$, and $c$ are the amplitude, centroid, and width of the Gaussian peak, respectively, which should be determined based on the antenna position on the drone for a given environment. Accordingly, we fitted the functions $g(\chi)$ and $g(\theta)$ on the empirical Rician-$K$ values from Fig. 5.15 and 5.16 using the maximum likelihood estimation, respectively. The estimated results are also shown in Fig. 5.15 and 5.16. The RMSE of the fitted $g(\chi)$ function in Fig. 5.15 varies between 2.86-4.38 dB.
dB, with the substantial estimation errors mostly found in the 239 cB soil moisture and 0.2m depth results due to the limited variation of Rician-K with altitude. In the Bottom and Arm antenna findings, the fitted Gaussian function parameters \{a, b, c\} are \{26.42, 18.63, 23.52\} and \{18.85, 5, 31.86\}. The RMSE of the fitted \(g(\theta)\) function in Fig. 5.16 ranges between 2.1 and 6.1 dB in the Bottom antenna results while it ranges between 1.89 and 3.14 dB in the Arm in antenna results. The corresponding fitted Gaussian function parameters \{a, b, c\} are \{25.42, 8.17, 53.42\} and \{22.13, 39.24, 36.73\} in the Bottom and Arm antenna results, respectively. Comparing the Rician-K estimated results from exponential function in (5.9) and \(g(\theta)\) in Fig. 5.16 shows that the \(g(\theta)\) captures the measured Rician-K values with significantly lower estimation error in each case. Hence, it can be concluded that the Gaussian functions in (5.20) can be utilized to estimate Rician-K for various altitude and elevation angles in A2UG and UG2A channels.

5.7 UAV-Collect: Energy Efficient Data Collection in UAV-IoUT Networks

In this section, we consider an application of our findings in the prior section for optimal data collection in the UG sensor networks. For this purpose, we first present the system model of the network and cast the energy minimization problem. Accordingly, the solution to the problem, \textit{UAV-Collect} algorithm, is presented. Last, numerical results are presented to show the effectiveness of UAV-Collect and models.

5.7.1 Efficient Data Collection for UAV-IoUT System Model

We consider a UAV-enabled IoUT network, where a UAV is deployed for mission time \(T_{\text{max}}\), to collect data from \(M\) battery-operated underground sensors (SNs) that are buried in an agriculture field at various soil depths for soil monitoring. The location of each SN is defined by \((w_m, h_{UG_m}), \forall m \in \mathcal{M} = \{1, \ldots, M\}\), where \(w_m = [x_m, y_m]^T \in \mathbb{R}^{2 \times 1}\) corresponds to the horizontal location coordinates of the SNs. The 3D trajectory of the UAV is defined by \(q(t) = [x(t), y(t)]^T\) and \(\chi(t)\), denoting the horizontal location and altitude of the UAV at time instant \(t\), respectively. The UAV’s initial or takeoff position is defined by \((q^I, \chi^I)\) with \(q^I = [x^I, y^I]^T \in \mathbb{R}^{2 \times 1}\) corresponding to the horizontal coordinates and \(\chi^I\) is the altitude. The UAV lands at the respective takeoff position \(q^I\) after completing the sensor data collection.
The wireless channel between the SN $m$ and UAV can be written as:

$$h^c_m(t) = \sqrt{\zeta_m(t)} g_m(t), \forall m, \forall t, \quad (5.21)$$

where $\zeta_m(t)$ is the average large-scale channel power gain that accounts for signal attenuation due to path loss and $g_m(t)$ is the small-scale fading coefficient. $\zeta_m(t)$ can be calculated from (5.8) and (5.17) as:

$$\zeta_m(t) = 2.93 \times 10^{11} \gamma_m(t) G_{TX} G_{RX} (1 - 10^{RL/10}) \frac{\cos(\theta_m(t)) \sqrt{e'_sm - \sin(\theta_m(t))^2}}{(\cos(\theta_m(t)) + \sqrt{e'_sm - \sin(\theta_m(t))^2})^2}, \forall t, \forall m \quad (5.22)$$

$$\gamma_m(t) = 10^{-0.869 \alpha_m d_{UGm} \times 10^{3.255 \cos(1.185\theta_m(t)) + 3.255w \sin(1.185\theta_m(t))}}, \forall t, \forall m \quad (5.23)$$

Moreover, $g_m(t)$ is modeled with a Rician fading as $g_m(t) = \sqrt{\frac{K_m(t)}{K_m(t) + 1}} g + \sqrt{\frac{1}{K_m(t) + 1}} \hat{g}, \forall t, \forall m$, where $g$ denotes the direct signal path component with $|g| = 1$, $\hat{g}$ represents the reflected/scattered signal paths components which is a circularly symmetric complex Gaussian random variable with zero mean and unit variance, and $K_m$ denotes the Rician-$K$. During the flight mission, the UAV adopts the TDMA protocol to collect data from SNs, with each SN transmitting data after being woken up by the UAV within the scheduled time frame. In this manner, the SNs conserve energy and only consume it when triggered by the UAV. Further, we define a binary variable $x_m(t) \in \{0, 1\}$ for communication scheduling, where $x_m(t) = 1$ shows that SN $m$ is scheduled or waked up by UAV for data transmission at time instant $t$ and stays in sleep mode otherwise. Due to the utilization of TDMA protocol, only a single SN is waked up for data collection by a UAV at any time instant $t$. We also assume that each SN is only served once during the flight mission. As a result, we have the following scheduling constraints:

$$\sum_{m=1}^{M} x_m(t) \leq 1, \forall t, \quad (5.24)$$

Let $p_m(t)$ denote the uplink transmit power of the SN $m$ at time $t$, which should satisfy the power constraint: $0 \leq p_m(t) \leq P_{\text{max}}$, where $P_{\text{max}}$ is the peak transmit power of the SNs. Then, assuming that SN $m$ is scheduled for transmission at time instant $t$, the achievable
The uplink rate can be written as:

\[ C_m(t) = \log_2 \left( 1 + \frac{p_m(t)|h_m^c(t)|^2}{N_o} \right). \]

(5.25)

where \( N_o \) is the noise power. Note that \( C_m(t) \) is not exactly known before the flight. This is because \( h_m^c(t) \) is dependent on the undetermined moisture content of the soil at each SN as well as the instantaneous channels that change with the movement of the UAV. Therefore, one of the solutions is to consider an adaptive transmission rate scheme that is upper-bounded by the worst-case channel condition of the saturated wet soil with 0 cB moisture value. However, in the case when the soil condition around most of the sensors is dry. The UAV and SN will be consuming more energy to exchange the data bits while the SNs could transmit at a higher transmission rate to conserve the energy consumption utilized for transmission. To solve this issue, we adopt an adaptive transmission rate scheme, where the UAV determines the rate \( R_m(t) \) in the flight by estimating the soil moisture content of the SNs through prior spatial moisture correlation information among the SN locations. More specifically, the UAV flies to the first SN, collects the data with a transmission rate corresponding to the worst channel case of saturated wet soil condition, processes the collected data to estimate the moisture content of the first SN, estimates the moisture content of the remaining SNs through spatial correlation information, and select the transmission rate for remaining SNs that correspond to the estimated moisture content information. Note that the soil moisture over an area is highly spatio-temporally correlated which depends on the rainfall and vegetation in a particular area [116]. The spatial correlation in the soil moisture content between two SNs is modeled as [116,117]:

\[ \rho_s(i,j) = (1 + 0.25\rho_Rd_{ij}) \exp(-0.5\rho_Rd_{ij}), \]

(5.26)

where \( d_{ij} \) is the distance between SN \( i \) and SN \( j \), and \( \rho_R \) is the mean rain cell radius. Therefore, provided the moisture content of the first SN, the moisture content of the rest of the SNs can be estimated using \( \rho_s \). Following, the outage probability that the UAV will not
successfully receive the transmitted data from SN \( m \) at time \( t \) is given as:

\[
P_m(t) = \mathbb{P}(C_m(t) < R_m(t)) = \mathbb{P}\left(|g_m(t)|^2 < \frac{N_o(2^{(R_m(t) - 1)} \zeta_m(t)p_m(t))}{r}\right) = F(r),
\]

where \( F(r) \) denotes the CDF of \(|g_m(t)|^2\), and for Rician fading, it can be expressed as

\[
F(r) = 1 - Q\left(\sqrt{2K_m}, \sqrt{2(K_m + 1)r}\right),
\]

where \( Q \) is the Marcum-Q function. To ensure that the UL data is reliably received by the UAV, \( R_m(t) \) should be selected such that \( P_m(t) = \epsilon \), where \( \epsilon \) is the maximum tolerable outage probability which practically ranges between 0 and 0.1 [100]. The outage-aware transmission rate can be written as:

\[
R_m(t) = \log_2 \left(1 + \frac{E[p_m(t)]|h_m^c(t)|^2 f_m(t)}{N_o}\right)
\]

where \( f_m(t) = F^{-1}(\epsilon) \) is defined as effective fading power in the prior work [100]. When \( F(1) < \epsilon \), \( f_m(t) = 1 \). Also, \( f_m(t) \) depends on the Rician-\( K \) that changes with the altitude and elevation angle between UAV and SN. In prior works, \( f_m(t) \) is only modeled for elevation angles [100, 118]. Due to the lack of an explicit form of the inverse Marcum-Q function, effective fading power \( f \) is approximated by [100]:

\[
f = \frac{w^2}{2(K + 1)},
\]

where \( w \) is defined as:

\[
w = \begin{cases} 
-2 \ln(1 - \epsilon) e^{K/2}, & K \leq K_{th}/2 \\
\sqrt{2K} + \frac{1}{2Q^{-1}(\epsilon)} \ln \left(\frac{\sqrt{2K}}{\sqrt{2K} - Q^{-1}(\epsilon)}\right) & K > K_{th}/2 
\end{cases}
\]

in which \( Q^{-1} \) is the inverse Q-function and \( K_{th} \) is the intersection of sub functions at \( \sqrt{2K} > Q^{-1}(\epsilon) \). The above formulation of \( f \) is still complicated. Thus, in [100], \( f \) as a function of \( \theta_m \) for A2G channels is approximated by a logistic model, where the approximation is based on the exponential relationship of the Rician K factor concerning \( \theta_m \) in (5.9) which did
not fit our empirical results in Fig. 5.16, and the approximation concerning the altitude is not defined. Therefore, we approximate \( f \) in the UG2A and A2UG channels for \( \theta_m \) and \( \chi \) separately using linear regression. We first generate the numerical values of \( f \) for \( \theta_m \) between 0 and 75 degrees and \( \chi \) between 5 and 29m using (5.20) with Gaussian parameters from both UAV antenna cases. Then, we analyze the variation of \( f \) for \( \theta_m \) and \( \chi \), as shown in Fig. 5.17. We find that the \( f \) varies similarly to the Gaussian estimated Rician-\( K \) values. We test fitting a Gaussian function to the numerical results as shown in Fig. 5.17 and find that the Gaussian can be utilized to approximate \( f \) with RMSE less than 0.049, Therefore, we approximate the \( f \) with respect to \( \chi_m \) and \( \theta_m \) as:

\[
\begin{align*}
    f_{m\chi}(t) &\approx A_1 \exp\left(-\frac{(\chi_m(t) - B_1)^2}{2(C_1)^2}\right), \\
    f_{m\theta}(t) &\approx A_2 \exp\left(-\frac{(\theta_m(t) - B_2)^2}{2(C_2)^2}\right).
\end{align*}
\]

Consequently, we approximate the total effective fading power as \( f_m(t) \approx f_{m\theta}(t) \times f_{m\chi}(t) \).

The fitted Gaussian parameters \( \{A_1, B_1, C_1, A_2, B_2, C_2\} \) in Fig. 5.17 are \( \{0.70, 18.73, 19.83, 0.70, 12.86, 30.38\} \) and \( \{0.379, 7.22, 15.08, 0.57, 39.32, 20.68\} \) in the Bottom and Arm antenna results, respectively. Next, the energy consumption of the SN can be written as:

\[
E_m = \int_{t=0}^{T_{\text{max}}} x_m(t)(p_m(t) + p_c), \forall m,
\]

where \( p_c \) corresponds to the circuit power of the SN during the wakeup mode which is a constant value. To ensure that UAV collects at least \( D_m \) bits from each SN in the mission time \( T_{\text{max}} \) and bandwidth \( W \), we must have the following constraint.

\[
\int_{t=0}^{T_{\text{max}}} x_m(t)WR_m(t) \geq D_m, \forall m
\]

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5.7.2 Problem Formulation for Efficient Data Collection

In this work, we consider the UG SNs that are powered by a battery with limited capacity to monitor soil conditions. It is crucial to note that, once the SNs are deployed, it is hard to recharge or replace the battery without removing the SNs from the soil. Considering the field deployment cost of each sensor, it is more important to optimize the resources on the SNs compared to the UAVs, to reduce energy consumption for operation time maximization. Moreover, it is also important to consider fairness among the SNs in terms of energy consumption during the data collection task because fair energy consumption of the SNs leads to similar operation times of the sensors. This helps to schedule maintenance of all the SNs at once. Accordingly, we consider an aerial data collection optimization problem that minimizes the maximum energy consumption among the SNs by jointly optimizing UAV 3D trajectory \((q(t), \chi(t))\), transmission scheduling \(x_m(t)\), and uplink transmit power \(p_m(t)\) while satisfying the data collection requirement of each SN. Formally, the optimization problem can be written as follows.

\[
P1 : \min_{\xi, q(t), \chi(t), p_m(t), x_m(t)} \xi \quad \text{s.t} \quad \begin{align*}
    E_m &\leq \xi, \forall m, \\
    \|v_{xy}(t)\| &\leq V_{xy}, \|v_z(t)\| \leq V_z, \forall t, \\
    (q(0), \chi(0)) &= (q^I, \chi^I), \\
    (q(T_{\text{max}}), \chi(T_{\text{max}})) &= (q^I, \chi^I), \\
    \chi_{\text{min}} &\leq \chi(t) \leq \chi_{\text{max}}, \forall t.
\end{align*}
\]

Figure 5.17: Effective fading power \(f\) versus \(\theta\) and \(\chi\) with \(\epsilon = 0.01\).
\[ 0 \leq p_m(t) \leq P_{\text{max}}, \forall t, \forall m, \quad (5.40) \]
\[ (5.24), (5.33), \]

where \( v_{xy} \) and \( v_z \) are the horizontal and vertical instantaneous velocity of the UAV, \( V_{xy} \) and \( V_z \) are the maximum horizontal and vertical velocity of the UAV, and \( \chi_{\text{min}} \) and \( \chi_{\text{max}} \) are the authority regulated minimum and maximum UAV altitudes, respectively. The constraints (5.37) and (5.38) ensure that the UAV takes off from the initial position \((q_I, \chi_I)\) at \( t = 0 \) and lands at the initial position at \( t = T_{\text{max}} \). The constraint (5.36) is the maximum velocity constraint on the UAV.

5.7.3 UAV-Collect

Note that the problem \( P_1 \) is a mixed-integer non-convex problem which is difficult to solve. Therefore, we approach this problem by adopting the fly, hover, and communicate protocol [102, 119], where the UAV flies to a set of hovering locations in a sequence and collects the data from each SN during the hover time. Then, the optimal trajectory is the UAV flying in a straight line between the hovering locations with the maximum horizontal and vertical speed (proof given in [102]). Let \( \Lambda = (\lambda_1, \ldots, \lambda_M) \) be the SN serving sequence of the UAV, \( \hat{x}_m \in \{0, 1\} \) be the SN wakeup schedule, \( \bar{p}_{\lambda_m} \) be the average uplink power, and \( (q_{\lambda_m}^H, \chi_{\lambda_m}^H) \) and \( \tau_{\lambda_m}^H \) be the hovering location and hovering time for the UAV to collect data from SN \( \lambda_m \), \( \forall m \), respectively. Then, the optimal serving sequence is the one that minimizes the total traveling distance of the UAV while ensuring that each hovering location is visited exactly once, which is equivalent to the traveling salesman problem (TSP) with \( M \) cities. Therefore, for a given set of hovering locations, \( \Lambda \) and \( \hat{x}_m \) can be obtained by solving the TSP problem using efficient TSP solver algorithms to find approximate solutions [120]. Also, the optimal \( \tau_{\lambda_m}^H \) is the one that satisfies that the \( D_{\lambda_m} \) bits are collected from the SN for a given rate \( R_{\lambda_m} \) i.e. \( \tau_{\lambda_m}^H = D_{\lambda_m}/WR_{\lambda_m} \). Therefore, for a given SN serving sequence \( \Lambda \), hovering time \( \tau_{\lambda_m}^H \), and wakeup schedule \( \hat{x}_m \), problem \( P_1 \) can be reformulated as follows:
\[ P2 : \min_{\xi, q_{\lambda_m}^H, \chi_{\lambda_m}^H} \xi \]  
\[ \text{s.t. } \frac{D_{\lambda_m}}{WR_{\lambda_m}}(\hat{p}_{\lambda_m} + p_c) \leq \xi, \forall m, \]  
\[ \sum_{m=1}^{M} \frac{D_{\lambda_m}}{WR_{\lambda_m}} + \sum_{m=1}^{M+1} \frac{||q_{\lambda_m}^H - q_{\lambda_{m-1}}^H||}{V_{xy}} + \frac{||\chi_{\lambda_m}^H - \chi_{\lambda_{m-1}}^H||}{V_z} \leq T_{\text{max}}, \]  
\[ \chi_{\text{min}} \leq \chi_{\lambda_m}^H \leq \chi_{\text{max}}, \forall m, \]  
\[ 0 \leq \hat{p}_{\lambda_m} \leq P_{\text{max}}, \forall m, \]  

where \( q_{\lambda_0}^H = q^I, q_{\lambda_{M+1}}^H = q^I, \chi_{\lambda_0}^H = \chi^I, \chi_{\lambda_{M+1}}^H = \chi^I, \) and (5.43) ensures that the total hovering time and flying time is less than the maximum flight time \( T_{\text{max}}. \) The problem \( P2 \) is still non-convex because the \( R_{\lambda_m} \) is a non-convex function for the respective optimization variables. We approach problem \( P2 \) by dividing the problem into two sub-problems and solving them independently. For a fixed uplink power, problem \( P2 \) can be written as:

\[ P2.1 : \min_{\xi, q_{\lambda_m}^H, \chi_{\lambda_m}^H} \xi \]  
\[ \text{s.t. } (5.42), (5.43), (5.44). \]  

The problem \( P2.1 \) is still non-convex and it is hard to find the optimal solution. Therefore, we solve the problem by adopting the ALM as in Chapter 4. ALM can be applied to the problem \( P2.1 \) by minimizing the following Lagrangian function.

\[ \mathcal{L}_{\pi, \Delta, \iota}(\xi, q_{\lambda_m}^H, \chi_{\lambda_m}^H) = \xi + \frac{1}{2\nu} \left\{ \sum_{m=1}^{M} ((\max\{0, \pi_m + \nu(\frac{D_m}{WR_m}(\hat{p}_m + p_c) - \xi)\})^2 - \pi_k^2) \right. \]  
\[ + \left. (\max\{0, \Delta + \nu(\sum_{m=1}^{M} \frac{D_m}{WR_m} + \sum_{m=1}^{M+1} \frac{||q_{\lambda_m}^H - q_{\lambda_{m-1}}^H||}{V_{xy}} + \frac{||\chi_{\lambda_m}^H - \chi_{\lambda_{m-1}}^H||}{V_z}}) - T_{\text{max}}\}^2 - \Delta^2) + \sum_{m=1}^{M} (\max\{0, \iota_m - \nu(\chi_{\lambda_m}^H - \chi_{\text{max}})\})^2 - \iota_m^2) \right\}, \]  

where \( \pi = [\pi_1, \ldots, \pi_M], \Delta, \iota = [\iota_1, \ldots, \iota_M] \) are the Lagrange multipliers associated with constraints (5.42), (5.43) and (5.44), respectively, and \( \nu \) is the adjustable penalty parameter. The ALM consists of two main steps, where the first step deals with the minimization of
\[ \mathcal{L}_{\pi, \Delta, \iota}(\xi, q^{H}_{\lambda_m}, \chi^{H}_{\lambda_m}) \]

and second step deals with the update of the multipliers and penalty parameter. An iterative algorithm can be used to solve both the aforementioned steps until convergence. The Lagrange multipliers and penalty parameter at stage \((l)\) are updated as follows:

\[
\pi_{m}^{(l+1)} = \max\{0, \pi_{m}^{(l)} + \nu^{(l)}(\frac{D_m}{R_m(q^{H(i)}_{\lambda_m})}(\hat{p}_m + p_c) - \xi^{(l)})\}, \forall m, \tag{5.48}
\]

\[
\Delta^{(l+1)} = \max\{0, \Delta + \nu(\sum_{m=1}^{M} \frac{D_m}{R_m(q^{H(i)}_{\lambda_m})} + \sum_{m=1}^{M+1} \frac{||q^{H(i)}_{\lambda_m} - q^{H(i)}_{\lambda_{m-1}}||}{V_{xy}} + \frac{||\chi^{H(i)}_{\lambda_m} - \chi^{H(i)}_{\lambda_{m-1}}||}{V_z} - T_{\text{max}})\} \tag{5.49}
\]

\[
\iota_{m}^{(l+1)} = \max\{0, \iota_{n}^{(l)} - \nu(\chi^{H(i)}_{\lambda_m} - \chi_{\text{max}})\}, \forall m, \tag{5.50}
\]

\[
\nu^{(l+1)} = 2\nu^{(l)}, \tag{5.51}
\]

where, \(\pi_{m}^{(l+1)}, \iota_{m}^{(l+1)}\) and \(\Delta^{(l+1)}\) are the updated values of Lagrange multipliers, \(\nu^{(l+1)}\) is the updated value of penalty parameter, and \(q^{H(i)}_{\lambda_m}\) and \(\chi^{H(i)}_{\lambda_m}\) are the optimized values of the horizontal and vertical location of the UAV at stage \(l\), respectively. Note that to satisfy the lower bound of constraint \((5.44)\), we select \(\chi^{H(i)}_{\lambda_m} = \max(\chi_{\text{min}}, \chi^{H(i)}_{\lambda_m})\), where \(\chi^{H(i)}_{\lambda_m}\) is the optimized value calculated in the first step (minimization) of ALM at stage \(l\). In this way, the sub-optimal horizontal and vertical hovering positions i.e. \(q^{H*}_{\lambda_m}\) and \(\chi^{H*}_{\lambda_m}\) are found.

For fixed horizontal and vertical hovering positions, problem \(P2\) can be written as:

\[
P2.2 : \min_{\xi, \hat{p}_{\lambda_m}} \xi \tag{5.52}
\]

\[s.t \quad (5.42), (5.43), (5.45).\]

The problem \(P2.2\) is non-convex due to the non-convex constraints \((5.42)\) Therefore, we approach this problem by introducing the slack variables \(\delta_{\lambda_m} > 0, \forall m\) and reformulating the
The problem \( P2.3 \) is convex for all the optimization variables and can be solved with standard convex solvers such as CVX [74]. By combining the solutions of each sub-problem, the problem \( P2 \) can be solved using Algorithm 2.

**Algorithm 2** Algorithm to solve \( P2 \)

1. Set \( \mathbf{q}_m^H = \mathbf{w}_m \) and initial feasible value of \( \hat{p}_\lambda m \).
2. Find the SN serving sequence \( \Lambda \) and wake up schedule \( \hat{x}_m \) using the TSP method.
3. Obtain the optimized horizontal \( \mathbf{q}_m^{H*} \) and vertical \( \chi^{H*}_m \) hovering locations using ALM.
4. Obtain the optimized uplink power \( \hat{p}_\lambda m \) by solving problem \( P2.3 \) using a convex solver such as CVX.
5. Construct the UAV path incorporating the maximum flying speed and line segments, using the acquired serving sequence, hover positions, and hover durations.

### 5.7.4 Empirical Evaluation of Optimized UAV Trajectories

The performance of UAV-Collect is verified using the numerical simulation. We consider a system with \( M = 5 \) SNs with UG depths \( h_{UGm} = 0.1m, \forall m \), which are randomly located in a \( 500 \times 500 \) m\(^2\) area as shown in Fig. 5.18a. We set \( N_0=-110\text{dBm}, \chi_{\text{min}}=5m, \chi_{\text{max}}=29m, \)
Figure 5.18: (a) UAV trajectory (b) SNs’ wakeup schedule (top) and min-max energy versus $D_{\lambda_m}$ (bottom)

$V_{xy}=V_z=50$ m/s, $W=1$MHz, $\eta=2$, $P_{\text{max}}=1$W, $p_c=10^{-3}$, unit antenna gains, and rest of the effective fading and path loss model parameters from the Bottom antenna estimated results. The soil moisture value of the first SN that UAV visits is assumed to be 239 cB and the rest of the SNs’ soil moisture values are obtained using the spatial moisture correlation function $\rho_s$ with $\rho_R = 0.01$. We consider the following two benchmark trajectory schemes for performance comparison: (i) Fixed location (FL): Where the hovering locations of the UAV in Algorithm 2 are fixed and set above the SNs (ii) Fixed Altitude (FA): Where only the altitude of the UAV is fixed in Algorithm 2.

The optimized trajectory of the UAV with the Algorithm 2 is shown in Fig. 5.18a and the corresponding SNs’ wakeup schedule is shown in Fig. 5.18b, where $T_{\text{max}}=60$s and $D_{\lambda_m}=1$Mbits. It is observed that the UAV visits each SN and hovers at an optimized 3D position near the SN for a particular time, and the SNs are only woken up when the UAV reaches the corresponding hovering positions and remain silent otherwise. The performance comparison between UAV-Collect and benchmark methods is shown in Fig. 5.18b, where the min-max energy consumption in each scheme is calculated for various values of $D_{\lambda_m}$ with $T_{\text{max}}=100$s. It can be seen that UAV-Collect outperforms all the benchmark schemes, where the performance gains are significant. This is because UAV-Collect finds the optimal
hovering positions to communicate with each SN that provides the best channel conditions in terms of path loss and small-scale fading. Also, the comparison between FL and FA schemes shows that it is more important to optimize the horizontal position of the UAV than the altitude.

5.8 Summary

In this chapter, the wireless channel characteristics between UAV and UG nodes are investigated using in-field outdoor measurements at two distinct locations. The path loss and fading in the A2UG and UG2A channels are obtained at various altitudes and elevation angles, demonstrating the effect of soil depth, soil moisture, UAV 3D location, and UAV antenna position on signal propagation. Furthermore, it appears that the channels in both directions are comparable, and much like the A2UG channel, the UG2A channel’s path loss depends on the incidence and refracted angles along the propagation. Accordingly, a novel path loss model is proposed for A2UG and UG2A channels which provides low estimation errors compared to the prior model in the literature. The small-scale fading distribution is analyzed at UAV and UG nodes that follow the Rician distribution. The Rician-\(K\) parameter is calculated which is found to be significantly dependent on the UAV’s altitude, elevation angle, and antenna position. Also, it is shown that the Gaussian function provides more accurate estimates of the Rician-\(K\) at various UAV 3D positions compared to the A2G exponential model. Moreover, the empirical findings and models are applied to a UAV-based IoUT network to find an energy-efficient data collection strategy while satisfying the sensor data collection requirements. The numerical results demonstrate that the proposed scheme saves a considerable amount of energy on the SNs compared to baseline schemes. Therefore, the suggested approach could potentially be applied to prolong the operational lifespan of the sensors in the soil during the planned data-collecting activities, in addition to expanding the coverage in IoUT networks.
Chapter 6

On the Use of Full-Duplex and Edge Computing Technologies for the Coexistence of Uplink and Downlink Computing Users in the G2G links

6.1 Introduction

In recent years, there has been an explosive growth in the number of mobile devices accessing wireless networks [121]. Advanced applications that have a high computational load (e.g., virtual reality, natural language processing, interactive gaming, speech-to-text, and image processing) are being developed for these mobile devices. To address the demand for advanced applications from a large number of mobile devices, mobile edge computing (MEC) has emerged as a promising solution [122, 123], as it relocates the cloud computing resources close to mobile users. Therefore, the tasks can be completed with ultra-low latency.

MEC is considered in a variety of networks, where the computational tasks are generated by users with limited computational resources. The task generation at the user end occurs for applications such as fingerprint, iris, or face recognition, natural language processing, and interactive gaming. In [124–126], a BS associated with an MEC server supports users with task computation requirements while optimizing the communication and computation resources to improve the overall energy consumption. In [127–129], FD technology is utilized at the BS equipped with an MEC server to simultaneously serve the traditional cellular users and computing users, where performance gains are achieved over HD technology. In recent times, computing users equipped with energy harvesters are considered in an MEC-based FD WPCN, where it is assumed that the computing users have limited energy resources for transmission and require RF energy to harvest and offload the task bits. Like in [130], computing users utilize energy signals transmitted from the nearby energy transmitters (ETs) to offload the share of computational task bits to the small BS which simultaneously back-hauls the bits to the macro MEC-BS for task computation. While in [131], the computing
Users utilize the associated energy signals from an MEC-based hybrid access point (HAP) to offload task bits in return. Moreover, MEC is also considered for applications, where tasks are generated at the MEC server end. Task generation at the server end occurs in different applications, such as VR, and multimedia content delivery. In [132,133], VR and multimedia content delivery applications are considered, where the MEC BS generates the tasks, pre-processes them, and delivers the processing results to the users for the requested content. This approach significantly reduces the transmission data and latency.

However, none of the previous works investigated the communication and computation resource allocation in the presence of two different types of computing users, which are defined as follows: First, users that generate and offload the tasks to the MEC server for computation. We refer to this user as uplink user equipment (UUE) in this work. Second, users that request the pre-processed content from the MEC server, where a request is made on the user end while the generation and processing of the task are performed at the MEC server end. We refer to this user as downlink user equipment (DUE) in this work. An application example of the co-existence of UUE and DUE is when one user requests to offload a task like fingerprint scanning while the other user requests particular multimedia content or VR video from the MEC server. Another application for the co-existence of users can be considered when UUE and DUE are co-located, like an online testing service where the testing material that includes multimedia content is delivered on the host machines while the activity of the students is monitored through live webcam streaming [134].

In this work, we consider an MEC network that supports the co-existence of the UUEs and DUEs. In particular, we design an energy-efficient transmission and task completion time-slotted protocol to simultaneously serve DUEs and UUEs computational tasks by considering FD capability at the multi-antenna BS equipped with an MEC server. The BS utilizes a multi-user MIMO technique to receive tasks that are offloaded by the UUEs in the uplink direction and transmit processed tasks that are requested by the DUEs in the downlink direction. To do so, a novel optimization problem is proposed that minimizes the energy at the BS, MEC server, and UUEs by jointly optimizing the transmitter precoding vector at the BS, the uplink power of the UUEs, the computational resources of the MEC server, and the computational task shares in the time-slotted protocol while satisfying the completion-time
threshold for each user’s task. The optimization problem is non-convex, which is approached by using convex approximations followed by an equivalent convex problem that is solved iteratively. The main contributions of this chapter are as follows:

- Compared to a traditional FD network, in the case of a network with UUE and DUE, the task computation and information transmission must be done in a specific order. The transmission and task completion protocol must be designed carefully to demonstrate system efficiency in terms of energy consumption and overall latency using FD communication over HD communication. By efficiently designing a three-time-slot transmission and task completion protocol, we show that the proposed FD scheme can achieve a significant reduction in total energy consumption compared to the HD scheme.

- We consider the problem of minimizing the total weighted energy consumption with the constraint on task completion time for each user’s task. The design parameters are the transmitter precoding vector at the BS, UUE’s uplink power, computational resources at the MEC server, and the shares of computation tasks to be computed at different time slots. The optimization problem is non-convex. Therefore, we propose a solution that solves the optimization problem with significantly lower computational complexity.

- We evaluate the performance of the proposed FD scheme for co-located and non-co-located DUEs and UUEs groups and show that the proposed FD scheme achieves significantly lower energy consumption in the latter case.

The rest of the chapter is organized as follows. The related works are detailed in Section 6.2. Section 6.3 shows the proposed system model. Section 6.4 details the optimization problem. Section 6.5 presents the solution for the optimization problem. The numerical results are presented in Section 6.6. Finally, Section 6.7 summarizes the chapter.

\footnotesize{1For example, for DUE, computation at the MEC server is performed before information transmission while for UUE the order is reversed.}
6.2 Related Work

In this section, we discuss the related work on MEC that is utilized in a variety of networks.

**HD MEC network:** Latency and energy consumption are commonly considered to evaluate the performance of MEC networks. A large body of research considered the problem of designing computation and communication resource allocation for MEC networks with the aim of minimizing latency and/or energy. In [124–126], it has been assumed that the computation task is generated at the user end, and the computation tasks can be offloaded to a BS associated with an MEC server for processing. In [124], joint optimization of computation and communication resources was investigated for an MEC network with a single MEC server. The objective was to minimize the weighted sum energy consumption. For a multi-user network, the joint optimization problem of computation task sharing and offloading time allocation with the aim of minimizing the completion time of the computing users was investigated in [125]. In [126], joint optimization of computation resource, communication resource, and task offloading decisions was considered for an MEC network with multiple MEC servers. The objective function was defined as a weighted sum of the task completion time and energy consumption. In [135], the authors considered the task assignment and communication resource allocation in a multi-user WiFi-based MEC architecture, where the objective focused on minimizing the energy consumption on the mobile terminal while jointly optimizing the offloading decisions and radio resource allocations under the application latency constraint.

**FD MEC network:** Recently, FD has been recognized as one of the key technologies in fifth-generation (5G) networks. FD can enable a higher sum uplink-downlink data rate since it allows simultaneous transmission and reception. Motivated by the advantages of FD over HD, FD was applied to MEC networks in [127–129]. In [127], the authors considered a networking scenario in which the mobile devices offload their task to an access point equipped with an MEC server while the access point serves multiple downlink mobile devices and investigated the relationship between the offloading energy and latency. In [129], the co-existence of a computation user and traditional cellular uplink and downlink users has been considered. The overall spectral efficiency is maximized by determining the most
advantageous mode between FD and HD while satisfying cellular users’ information data rate constraints.

**FD-WPCN MEC network:** MEC has also been considered in the WPCN by utilizing FD transmissions [130, 131, 136]. In [130], an FD MEC-enabled cellular IoT network with wireless power transfer was proposed, where the system consists of an FD-aided heterogeneous cellular network that includes one macro BS (MBS) and multiple small BSs, wireless powered IoT nodes, and ET. The MEC server is integrated with MBS to compute tasks from the IoT nodes. In the transmission mechanism, each IoT node harvests energy from the ET to offload partial computation task bits to the associated SBS. The SBS works in FD mode which receives uplink access from the associated IoT nodes while backhauling the received task bits to the MBS in the same frequency band. Similarly in [131], an FD HAP with an MEC server was utilized to provide computing service and energy to the wireless devices (WDs). More specifically, with a certain time allocation mechanism, HAP transmits downlink energy to charge WDs and receive the uplink task bits from each WD in the same frequency band, simultaneously. The transmit power of HAP, time allocation, local computing frequencies, and transmit power of the WDs are jointly optimized to maximize the sum of computation bits.

**Server-based task generation in an MEC network:** Additionally, edge computing has been applied to multimedia content delivery systems [132], [133]. In this case, the multimedia content, that is cached at the MEC server is pre-processed at the MEC server and then delivered to the user devices. The major difference compared to the traditional MEC systems that are studied widely [124–126] is that in this case, the tasks are generated at the server end instead of the user end. In [132], the authors investigated the broadcast-based delivery of VR content. The task here is the conversion of multimedia content from 2D to 3D. In [133], the authors investigated caching, computing, and the decision to deliver 120° or 360°. In this case, the BS performs a quantization task at the MEC server before delivering the videos.

Contrary to the previous works that are limited to either task generation at the user end or the server end, in this work, we designed an MEC network that simultaneously considers both types of aforementioned task generations to support users with limited computational
resources. A novel energy-efficient transmission and computation resource allocation framework is proposed that intelligently utilizes both FD and HD communication to serve the computational needs of the users.

6.3 Multi-user MEC Network System Model

Assume a wireless communication system exists where a BS integrated with an MEC server provides computing facility to a set $L = \{1, .., L\}$ of $L$ UUEs and a set $K = \{1, .., K\}$ of $K$ DUEs, as depicted in Fig. 6.1. The BS has $N$ antennas, and the users have a single antenna that can be used for transmitting as well as receiving [137]. For the DUEs, the tasks are generated at the edge server; while for the UUEs, the tasks are generated at the device end. The task at each DUE $k \in K$ is given by $\phi_k = (W_k, I_k, O_k)$, where $W_k$ stands for the number of CPU cycles required to compute the task, $I_k$ indicates the task input data size and $O_k$ indicates the task output data size. The task at each UUE $l \in \mathcal{L}$ is given by $\pi_l = (\beta_l, b_l)$, where $b_l$ indicates the task input data size and $\beta_l$ stands for the number of CPU cycles required to compute the task. The calculation method for these task parameters is described in [138]. The tasks are non-splittable. In the next two subsections, we describe the signal model and task completion time of DUEs and UUEs.
6.3.1 Transmission Model

The overall task computation of the UUEs and DUEs can be completed in three time slots: In the first time slot, the DUEs’ tasks $\phi_k$, $\forall k \in K$ are computed at the edge-server, while each UUE sends a share of its task input bits $((1 - \delta_l)b_l)$ of $\pi_l$, $\forall l \in L$ to the BS in HD mode, where $\delta_l$ corresponds to the share of computation task of UUE $l$ and $0 \leq \delta_l \leq 1$. In the second time slot, FD transmission is adopted. Each UUE sends the rest of its input bits $\delta_l b_l$, while the BS sends shares of output task bits $(\alpha_k O_k)$ of $\phi_k$, $\forall k \in K$ simultaneously, where $\alpha_k$ corresponds to the share of computation task of DUE $k$ and $0 \leq \alpha_k \leq 1$. In the third time slot, after BS receives input of all the task bits of $\pi_l$ of each UUE $l$ in the first two time slots, it computes the tasks $\pi_l$, $\forall l \in L$. Simultaneously, the BS sends the rest of the output task bits $((1 - \alpha_k)O_k)$ of $\phi_k$, $\forall k \in K$ in HD mode. The overall task completion procedure is depicted in Fig. 6.2.

The downlink channel between BS and DUE $k$ can be written as:

$$h_k = \frac{h_k'}{(H^2 + \|B - D_k\|^2)^{\frac{2}{\epsilon}}},$$

(6.1)

where $h_k$ and $h_k' \in \mathbb{C}^{(N \times 1)}$. Each element of $h_k'$ is a random variable with zero mean and unit variance, and $\epsilon$ is the path loss exponent which is taken as $\epsilon = 2$. $H$ and $B = (B^x, B^y)$

---

2We assume that the tasks are requested by the DUEs before the start of the timeline and the processed task results for the UUEs are offloaded after the end of the timeline, with insignificant time delays.
are the height and location of the BS, respectively. \( \mathbf{D}_k = (D_x^k, D_y^k) \) is the location of the DUE \( k \). Similarly, the uplink channel between UUE \( l \) and BS can be written as:

\[
\mathbf{g}_l = \frac{\mathbf{g}'_l}{(H^2 + \|\mathbf{B} - \mathbf{U}_l\|^2)^{\frac{1}{2}}}, \tag{6.2}
\]

where \( \mathbf{g}_l \) and \( \mathbf{g}'_l \in \mathbb{C}^{(N \times 1)} \). Each element of \( \mathbf{g}'_l \) is a random variable with zero mean and unit variance. \( \mathbf{D}_k = (D_x^k, D_y^k) \) is the location of the DUE \( k \).

The received signal at the BS in the first time slot can be expressed as:

\[
y_{HD}^{BS} = \sum_{l=1}^{L} P_{l_{HD}} \bar{g}_l x_l + \mathbf{n}'_{BS}, \tag{6.3}
\]

where \( P_{l_{HD}}, \) and \( \bar{x}_l \) with \( E\{|\bar{x}_l|^2\} = 1 \) are the transmit power of UUE \( l \) in HD mode, and message of UUE \( l \), respectively. \( \mathbf{n}'_{BS} \in \mathcal{CN}(0, \sigma_{BS}^2 \mathbf{I}) \) represents the additive white Gaussian noise (AWGN) at the BS. For the UUEs, the BS adopts minimum mean square error and successive interference cancellation (MMSE-SIC) receiving technique to maximize the received signal-to-interference and noise ratio (SINR) of UUE \( l \). For simplicity, we assume the decoding order follows the UUE index, \( i.e., \ l = 1, 2, \ldots, L \). Thus, the resulting SINR in decoding UUE \( l \)'s information can be expressed as:

\[
\gamma_{l_{HD}} = P_{l_{HD}}^2 \mathbf{g}_l^H \left( \sum_{j > l} P_{j_{HD}}^2 \mathbf{g}_l \mathbf{g}_j^H + \sigma_{BS}^2 \mathbf{I} \right)^{-1} \mathbf{g}_l. \tag{6.4}
\]

For the downlink transmission during the second time slot, the downlink signals are precoded at the BS prior to being transmitted to the DUEs. Therefore, the received signal at the DUE \( k \) can be expressed as:

\[
y_k^{FD} = \mathbf{h}_k^H \mathbf{w}_k x_k + \sum_{i=1, i \neq k}^{K} \mathbf{h}_i^H \mathbf{w}_i x_i + \sum_{l=1}^{L} P_l \bar{g}_{l,k} x_l + n_k, \tag{6.5}
\]

where \( \mathbf{w}_k \in \mathbb{C}^{N \times 1} \) is the beamforming vector of DUE \( k \) in FD mode. \( \bar{g}_{l,k} = \frac{g_0}{d_{l,k}^{1/2}} \in \mathbb{C} \) is the channel between UUE \( l \) to DUE \( k \), wherein \( g_0 \) is the channel gain at a reference distance of 1 meter, and \( d_{l,k} \) is the distance between UUE \( l \) and DUE \( k \). \( P_l \) is the transmit power of UUE.
l in FD mode, $x_k$ with $E\{|x_k|^2\} = 1$ is the signal intended to DUE $k$, $x_l$ with $E\{|x_l|^2\} = 1$ is the signal from UUE $l$ to BS, and $n_k \in CN(0, \sigma_k^2)$ represents the AWGN at the DUE $k$. The term $P_l\bar{g}_{l,k}x_l$ represents the co-channel interference (CCI) from UUE $l$ to DUE $k$.

The received signal at the BS in the second time slot can be expressed as:

$$y_{BS}^{fd} = \sum_{l=1}^{L} P_l g_l x_l + \sqrt{\sigma_{SI}} K \sum_{k=1}^{K} G^H w_k x_k + n_{BS}^{\prime}, \quad (6.6)$$

where $G \in \mathbb{C}^{N \times N}$ is the self-interference (SI) channel from transmit antennas to the receive antennas at the BS, and $0 \leq \sigma_{SI} \leq 1$ is used to model the SI propagation. Therefore, $G^H w_k x_k$ represents the residual SI signal received at the BS after real-time cancellation in the analog and digital domains. $n_{BS} \in CN(0, \sigma_{BS}^2 I)$ represents the AWGN at the BS. Therefore, the uplink SINR at the BS and downlink SINR at DUE $k$ can be expressed as:

$$\gamma_l^{fd} = P_l^2 g_l^H \times \left( \sum_{j > l} P_j^2 g_j^H + \sigma_{SI} \sum_{k=1}^{K} G^H w_k w_k^H G + \sigma_{BS}^2 I \right)^{-1} g_l, \quad (6.7)$$

and

$$\gamma_k^{fd} = \frac{|h_k^H w_k|^2}{\sum_{i=1, i\neq k}^{K} |h_k^H w_i|^2 + \sum_{l=1}^{L} P_l^2 |\bar{g}_{l,k}|^2 + \sigma_d^2}, \quad (6.8)$$

respectively.

In the third time slot, the signal transmitted from the BS can be expressed as:

$$\hat{y}_k^{hd} = h_k^H w_k^{hd} \bar{x}_k + \sum_{i=1, i\neq k}^{K} h_k^H w_i^{hd} \bar{x}_i + n_k^{\prime}, \quad (6.9)$$

where $n_k^{\prime} \in CN(0, \sigma_k^2 I)$ represents the AWGN at the DUE $k$, and $\bar{x}_k$ with $E\{|\bar{x}_k|^2\} = 1$ is the signal intended to DUE $k$. The SINR at the DUE $k$ can be expressed as:

$$\gamma_k^{hd} = \frac{|h_k^H w_k^{hd}|^2}{\sum_{i=1, i\neq k}^{K} |h_k^H w_i^{hd}|^2 + \sigma_k^2}, \quad (6.10)$$
6.3.2 Task Completion Delay and Energy Analysis

At the first time slot, the BS is required to compute all the DUEs’ tasks. The total computation CPU cycle is $\sum_{k=1}^{K} W_k$. Let $F_1$ be the MEC server’s computation power allocated to compute the tasks $\phi_k$, $k \in K$ at the first time slot. The total processing power at the MEC server is $F$, and $F_1$ should not exceed $F$, i.e., $F_1 \leq F$. Then, the computation delay at the MEC can be expressed as:

$$T_{1}^{MEC} = \frac{\sum_{k=1}^{K} W_k}{F_1}. \quad (6.11)$$

BS’s computational power consumption can be expressed as $p_l = \gamma_c F_1^3$, where $\gamma_c$ denotes a constant related to the processor hardware architecture [139]. Therefore, the computation energy at the BS to compute the tasks $\phi_k$, $k \in K$ is $\gamma_c F_1^2 \sum_{k=1}^{K} W_k$.

The UUE $l$ offloads $(1 - \delta_l) b_l$ bits in the first time slot and $\delta_l b_l$ bits in the second time slot. The delay in transmitting $(1 - \delta_l) b_l$ bits in the uplink can be expressed as:

$$\tau_{l,BS}^{HD} = \frac{(1 - \delta_l) b_l}{B \log(1 + \gamma_{l}^{HD})}, \quad (6.12)$$

where $B$ is the total bandwidth of the link. The total communication energy consumption at UUE $l$ in the first time slot is $P_{l}^{HD} \tau_{l,BS}^{HD}$. Also, the total duration of the first time slot is $\tau_1 = \max \left( \max_{l \in \mathcal{L}} \tau_{l,BS}^{HD}, T_{1}^{MEC} \right)$.

At the second time slot, BS transmits $\alpha_k O_k$ bits to each DUE $k$, and each UUE $l$ transmits $\delta_l b_l$ bits to the BS in FD mode. Therefore, the duration of second-time slot can be expressed as:

$$\tau_2 = \frac{\delta_l b_l}{B \log(1 + \gamma_{l}^{FD})} = \frac{\alpha_k O_k}{B \log(1 + \gamma_{k}^{FD})}, \quad (6.13)$$

and the communication energy consumption at UUE $l$ and BS are $P_{l}^{2} \tau_2$ and $||w_k||^2 \tau_2$, respectively.

At the third time slot, the BS is required to compute all the UUEs’ tasks. The total computation CPU cycle is $\sum_{l=1}^{L} \beta_l$. Let $F_2$ be the MEC’s computation power allocated to compute the tasks $\pi_l$, $l \in \mathcal{L}$ at the third time slot. The total processing power at the MEC
server is $F$, and $F_2$ should not exceed $F$, i.e., $F_2 \leq F$. Then, the computation delay at the MEC can be expressed as:

$$T_2^{MEC} = \sum_{l=1}^{L} \frac{\beta_l}{F_2}$$

(6.14)

The computation energy at the BS to compute the tasks $\pi_l$, $l \in L$ is $\gamma_c F_2^2 \sum_{l=1}^{L} \beta_l^2$. At the same time slot, BS transmits $(1 - \alpha_k)O_k$ bits to the DUE $k$ in HD mode. Therefore, the delay in transmitting $(1 - \alpha_k)O_k$ bits in the downlink in HD mode can be expressed as:

$$\tau_{HD,k,BS} = \frac{(1 - \alpha_k)O_k}{B \log(1 + \gamma_{hd})}.$$  

(6.15)

Therefore, the total duration of the third time slot is $\tau_3 = \max(\max_{k \in K} \tau_{HD,k,BS}^k, T_2^{MEC})$. The communication energy consumption at the BS in this time slot is $||w_{hd}^k||^2 \tau_{HD,k,BS}^k$. Finally, the overall completion time can be expressed as:

$$\mathcal{T} = \tau_1 + \tau_2 + \tau_3,$$

(6.16)

and the overall energy consumption at the BS and total $L$ UUEs can be written as

$$\gamma_c F_1^2 \sum_{k=1}^{K} W_k + \gamma_c F_2^2 \sum_{l=1}^{L} \beta_l^2 + \sum_{k=1}^{K} ||w_{hd}^k||^2 \tau_{HD,k,BS}^k + \sum_{l=1}^{L} \gamma_c F_2^2 \sum_{k=1}^{K} ||w_{hd}^k||^2 \tau_{HD,k,BS}^k + \sum_{l=1}^{L} P_l^2 \tau_{HD,l,BS}^l + \sum_{l=1}^{L} P_l^2 \tau_2,$$

respectively.

### 6.4 Energy Minimization Problem Formulation

In this work, we aim to minimize total energy consumption by considering the following optimization variables: Deciding the precoding vectors $w_k$ and $w_{hd}^k$ at the BS and the transmit powers $P_l$ and $P_{hd}^l$ at the UUEs, shares of tasks $\delta_l$ and $\alpha_k$ in the HD and FD modes, and MEC server’s computing resource allocations $F_1$ and $F_2$. Formally, the optimization
problem is formulated as:

\[
\min_{W, W^{hd}, P, P^{hd}, F, \alpha, \delta} \left( \gamma_1 F_1^2 \sum_{k=1}^{K} W_k + \gamma_2 F_2^2 \sum_{l=1}^{L} \beta_l^2 + \sum_{k=1}^{K} ||w^{hd}_k||^2 \tau_{k,BS} + \sum_{k=1}^{K} ||w_k||^2 \tau_2 \right) \\
+ \sum_{l=1}^{L} P^{hd}_l \tau_{l,BS} + \sum_{l=1}^{L} \beta_l^2 \tau_2 \right)
\]

s.t. \[ T \leq T^{th} \] (6.17a)

\[ F_1, F_2 \leq F \] (6.17b)

\[ 0 \leq \alpha_k, \delta_l \leq 1, \forall k \in K, \forall l \in L \] (6.17c)

where \( W = (w_1, w_2, ..., w_K) \), \( W^{hd} = (w_1^{hd}, w_2^{hd}, ..., w_K^{hd}) \), \( P = (P_1, P_2, ..., P_L) \), \( P^{hd} = (P_1^{hd}, P_2^{hd}, ..., P_L^{hd}) \), \( F = (F_1, F_2) \), \( \alpha = (\alpha_1, \alpha_2, ..., \alpha_K) \), and \( \delta = (\delta_1, \delta_2, ..., \delta_K) \). The constraint (6.17b) ensures the tasks are completed within a time threshold \( T^{th} \). The problem (6.17) is non-concave mainly due to the multi-user and co-channel interference terms in (6.4), (6.7), (6.8), and (6.9) that cause objective function (6.17a) and constraint (6.17b) to be non-concave functions. Following, we approach the problem by introducing some slack variables and reformulate the problem as follows:
\[
\min_{\mathbf{W}, \mathbf{W}^{hd}, \mathbf{P}, \mathbf{P}^{hd}, \mathbf{F}, \alpha, \delta, \mathbf{u}, \mathbf{v}, \mathbf{V}} \left( \gamma_C F_1^2 \sum_{k=1}^{K} W_k + \gamma_C F_2^2 \sum_{l=1}^{L} \beta_l^2 + \sum_{k=1}^{K} \frac{||w_{hd}^k||^2}{v_k} + \sum_{k=1}^{K} \frac{||w_k||^2}{V_2} \right)
\]
\[+ \sum_{l=1}^{L} \frac{P_{hd}^2}{u_l} + \sum_{k=1}^{K} \frac{P_l^2}{u_l} \right)
\]  

\text{s.t.} \quad C1: V_1 + \frac{1}{V_2} + V_3 \leq T^{th}  \quad (6.18b) 

\[C2: \frac{\sum_{k=1}^{K} W_k}{F_1} \leq V_1 \quad (6.18c)\]

\[C3: \frac{(1 - \delta_l)b_l}{B} \leq \frac{\log(1 + \gamma_{hd})}{u_l}, \ \forall l \in \mathcal{L} \quad (6.18d)\]

\[C4: \frac{1}{u_l} \leq V_1, \ \forall l \in \mathcal{L} \quad (6.18e)\]

\[C5: \frac{\delta_l b_l}{B} \leq \frac{\log(1 + \gamma_{fd})}{V_2}, \ \forall l \in \mathcal{L} \quad (6.18f)\]

\[C6: \frac{\alpha_k O_k}{B} \leq \frac{\log(1 + \gamma_{fd})}{V_2}, \ \forall k \in \mathcal{K} \quad (6.18g)\]

\[C7: \frac{\sum_{l=1}^{L} \beta_l}{F_2} \leq V_3 \quad (6.18h)\]

\[C8: \frac{(1 - \alpha_k)O_k}{B} \leq \frac{\log(1 + \gamma_{hd})}{v_k}, \ \forall k \in \mathcal{K} \quad (6.18i)\]

\[C9: \frac{1}{v_k} \leq V_3, \ \forall k \in \mathcal{K} \quad (6.18j)\]

\[C10: v_k > 0, u_l > 0, \forall k \in \mathcal{K}, \forall l \in \mathcal{L} \quad (6.18k)\]

\[C11: V_1 > 0, V_2 > 0, V_3 > 0 \quad (6.18l)\]

\[C12: (6.17c), (6.17d) \]

where \(v_k, u_l, V_1, V_2\) and \(V_3\) are the slack variables, \(\mathbf{V} = (V_1, V_2, V_3), \mathbf{u} = (u_1, u_2, ..., u_L)\), and \(\mathbf{v} = (v_1, v_2, ..., v_K)\). The constraints \(C3, C5, C6,\) and \(C8\) are non-convex. Therefore, the optimization problem is difficult to solve optimally in practice. Next, we present a sub-optimal solution to the problem by convexifying each non-convex constraint and optimizing each optimization variable iteratively until convergence.
6.5 Proposed Solution To The Energy Minimization Problem

In this section, we first show the procedure to convexify the non-convex constraints \( C_3, C_5, C_6, \) and \( C_8 \). Followed by the formulation of the proposed approximated convex problem that is equivalent to the problem (6.18). Next, we propose an iterative algorithm to solve the approximated convex problem. Last, we discuss the complexity and convergence analysis of the solution. Note that the proposed solution is mainly based on an inner approximation framework [140] under which the non-convex parts are completely exposed.

6.5.1 Convex Approximation of Constraint \( C_6 \)

For equivalent convex approximation of constraint \( C_6 \), we first introduce the approximation of function \( \Xi(\gamma, t) = \log(1 + \gamma)/t \) at a feasible point \( \gamma(\kappa), t(\kappa) \) as follows:

\[
\Xi(\gamma, t) \geq A^{(\kappa)} - B^{(\kappa)} \frac{1}{\gamma} - C^{(\kappa)} t \\
\forall \gamma > 0, \gamma^{(\kappa)} > 0, t, 0, t^{(\kappa)} > 0
\] (6.19)

where

\[
A^{(\kappa)} = 2\Xi(\gamma^{(\kappa)}, t^{(\kappa)}) + \frac{\gamma^{(\kappa)}}{t^{(\kappa)}(\gamma^{(\kappa)} + 1)} \\
B^{(\kappa)} = \frac{\gamma^{(\kappa)}^2}{t^{(\kappa)}(\gamma^{(\kappa)} + 1)}, C^{(\kappa)} = \frac{\Xi(\gamma^{(\kappa)}, t^{(\kappa)})}{t^{(\kappa)}}
\]

The proof of (6.19) is provided in [141]. According to [142], for \( \bar{w}_k = e^{-j\arg(h_k w_k)} w_k \) with \( j = \sqrt{-1} \), it is given that \( |h_k^H w_k| = |h_k^H \bar{w}_k| = \Re \{h_k^H \bar{w}_k\} \geq 0 \) and \( |h_k^H w_k| = |h_k^H \bar{w}_k|, \forall k' \neq k \in K \). Let, \( \Pi_k(X) = \sum_{i=1, i \neq k}^K \Re \{h_i^H w_i\}^2 + \sum_{l=1}^L P_l |\hat{g}_{k,l}^2| + \sigma_d^2 \), where \( X = (W, P) \). The expression \( \gamma^{fd}_k = \frac{|h_k^H w_k|^2}{\Pi_k} \) can be equivalently replaced by:

\[
\gamma^{fd}_k = \frac{\Re \{h_k^H w_k\}^2}{\Pi_k}, \forall k \in K
\] (6.20)

with the following conditions:

\[
\Re \{h_k^H w_k\} > 0, \forall k \in K
\] (6.21)
Then, using the approximation in (6.19), right-hand side of constraint C6 at a feasible point $(X^{(\kappa)}, V_2^{(\kappa)})$ is lower bounded as follows:

$$
\frac{\log(1 + \gamma_k^d(X))}{V_2} \geq A_k^{(\kappa)} - B_k^{(\kappa)} \frac{\Pi_k(X)}{R\{h_k^H w_k\}^2} - C_k^{(\kappa)} V_2
$$

$$
= R_k^{D,(\kappa)}(X, V_2) \quad (6.22)
$$

where:

$$
A_k^{(\kappa)} = 2\log(1 + \frac{\gamma_k^d(X)}{V_2^{(\kappa)}}) + \frac{\gamma_k^d(X)}{V_2^{(\kappa)}(\gamma_k^d(X) + 1)},
$$

$$
B_k^{(\kappa)} = \frac{\gamma_k^d(X)^2}{V_2^{(\kappa)}(\gamma_k^d(X) + 1)},
$$

$$
C_k^{(\kappa)} = \frac{\log(1 + \gamma_k^d(X))}{V_2^{(\kappa)}},
$$

Also, as in [141], to further expose the hidden convexity of the right-hand side in (6.22), the following inequality is utilized

$$
||z||^2 \geq 2R\{z^H z\} - ||z^{(\kappa)}||^2
$$

(6.23)

where $\forall ||z||, ||z^{(\kappa)}|| \in \mathbb{C}^N$, and $||z||^2$ is the convex function. As a result, (6.22) can be rewritten as:

$$
\frac{\log(1 + \gamma_k^d(X))}{V_2} \geq A_k^{(\kappa)} - B_k^{(\kappa)} \frac{\Pi_k(X)}{\theta_k^{(\kappa)}(w_k)} - C_k^{(\kappa)} V_2
$$

$$
= R_k^{D,(\kappa)}(X, V_2) \quad (6.24)
$$

over the trust region:

$$
2R\{h_k^H w_k\} - R\{h_k^H w_k^{(\kappa)}\} > 0, \forall k \in \mathcal{K}, \quad (6.25)
$$
where:

\[ \theta_k^{(\kappa)}(w_k) = \mathcal{R}\{h_k^H w_k^{(\kappa)}\} \left(2\mathcal{R}\{h_k^H w_k\} - \mathcal{R}\{h_k^H w_k^{(\kappa)}\}\right) \]

It follows from (6.24) that \( R_{k}^{D,(\kappa)}(X, V_2) \) is a concave function which satisfies the following condition:

\[ R_{k}^{D,(\kappa)}(X^{(\kappa)}, V_2^{(\kappa)}) = \log(1 + \gamma^{fd}_k(X^{(\kappa)})) \]

Finally, the constraint C6 can be iteratively replaced by the following constraint:

\[ R_{k}^{D,(\kappa)}(X, V_2) \geq \frac{\alpha_k O_k}{B}, \forall k \in \mathcal{K}. \quad (6.27) \]

### 6.5.2 Convex Approximation of Constraint C5

The right-hand side of constraint C5 is lower bounded at the feasible point \((X^{(\kappa)}, V_2^{(\kappa)})\) as:

\[ \frac{\log(1 + \gamma^{fd}_l)}{V_2} \geq \bar{A}_l^{(\kappa)} + \tilde{B}_l^{(\kappa)} P_l - \frac{\Phi_l(X)}{V_2^{(\kappa)}} - \tilde{C}_l^{(\kappa)} V_2 \]

\[ = R_{l}^{U,(\kappa)}(X, V_2), \quad (6.28) \]

where:

\[ \bar{A}_l^{(\kappa)} = \frac{2 \log(1 + \gamma^{fd}_l(X^{(\kappa)})) - \gamma^{fd}_l(X^{(\kappa)})}{V_2^{(\kappa)}}, \tilde{B}_l^{(\kappa)} = \frac{2 \gamma^{fd}_l(X^{(\kappa)})}{P_l V_2^{(\kappa)}}, \tilde{C}_l^{(\kappa)} = \frac{\log(1 + \gamma^{fd}_l(X^{(\kappa)}))}{V_2^{(\kappa)^2}}, \]

\[ \Phi_l^{(\kappa)}(X) = P_l^2 g_l^H \Theta_l^{(\kappa)} g_l + \sum_{j > l} P_j^2 g_j^H \Theta_l^{(\kappa)} g_j + \sigma_{SI} \sum_{k=1}^K w_k^H G \Theta_l^{(\kappa)} G^H w_k + \sigma^2 \text{Tr}(\Theta_l^{(\kappa)}), \]

\[ \Theta_l^{(\kappa)} = \left( \sum_{j > l} (P_j^{(\kappa)})^2 g_j g_j^H + \sigma_{SI} \sum_{k=1}^K G^H w_k^{(\kappa)} (w_k^{(\kappa)})^H G \right) \]

\[ + \sigma^2 I \right) - \left( (P_l^{(\kappa)})^2 g_l g_l^H + \sum_{j > l} (P_j^{(\kappa)})^2 g_j g_j^H + \sigma_{SI} \sum_{k=1}^K G^H w_k^{(\kappa)} (w_k^{(\kappa)})^H G + \sigma^2 I \right) - \succeq 0. \]
Note that $R^U_t(X, V_2)$ is a concave function which satisfies the following condition:

$$R^U_t(X, V_2) = \frac{\log(1 + \gamma^{fd}_t(X^{(\kappa)}))}{V_2^{(\kappa)}}. \quad (6.29)$$

Therefore, the constraint $C_5$ can be iteratively replaced by the following constraint:

$$R^U_t(X, V_2) \geq \delta B, \forall l \in L. \quad (6.30)$$

6.5.3 Convex Approximation of Constraint $C_8$

We follow the similar approximation approach of constraint $C_6$ to convexify constraint $C_8$. Let, $\Lambda_k(Y) = \sum_{i=1, i \neq k}^K R\{h_i^Hw_{i \kappa}^{hd}\}^2 + \sigma_d^2$, where $Y = (W^{hd}, D^{hd})$. Similar to (6.20), the expression $\gamma_k^{hd} = \frac{|h_k^Hw_{k \kappa}^{hd}|^2}{\Lambda_k}$ can be replaced by:

$$\gamma_k^{hd} = \frac{R\{h_k^Hw_{k \kappa}^{hd}\}^2}{\Lambda_k}, \quad \forall k \in K \quad (6.31)$$

with the following conditions:

$$R\{h_k^Hw_{k \kappa}^{hd}\} > 0, \quad \forall k \in K. \quad (6.32)$$

The right-hand side of constraint $C_8$ is lower bounded at the feasible point $(Y^{(\kappa)}, v_k^{(\kappa)})$ as:

$$\frac{\log(1 + \gamma_k^{hd}(Y))}{v_k} \geq Y_k^{(\kappa)} - \psi_k^{(\kappa)} \Lambda_k(Y) = \frac{Y_k^{(\kappa)}}{\lambda_k^{(\kappa)}} - \Omega_k^{(\kappa)}v_k$$

$$= S_k^{D_k^{(\kappa)}}(Y, v_k) \quad (6.33)$$

over the trust region:

$$2R\{h_k^Hw_{k \kappa}^{hd}\} - R\{h_k^Hw_{k \kappa}^{hd(\kappa)}\} > 0, \forall k \in K, \quad (6.34)$$
where:

\[
\Upsilon_k^{(\kappa)} = \frac{2\log(1 + \gamma_k^{hd}(Y^{(\kappa)}))}{v_k^{(\kappa)}} + \frac{\gamma_k^{hd}(Y^{(\kappa)})}{v_k^{(\kappa)}(\gamma_k^{hd}(Y^{(\kappa)}) + 1)},
\]

\[
\Psi_k^{(\kappa)} = \frac{\gamma_k^{hd}(Y^{(\kappa)})^2}{v_k^{(\kappa)}(\gamma_k^{hd}(Y^{(\kappa)}) + 1)}, \Omega_k^{(\kappa)} = \frac{\log(1 + \gamma_k^{hd}(Y^{(\kappa)}))}{v_k^{(\kappa)i}},
\]

\[
\chi_k^{(\kappa)}(w_k^{hd}) = \mathcal{R}\{h_k^H w_k^{hd}\} \times (2\mathcal{R}\{h_k^H w_k^{hd}\} - \mathcal{R}\{h_k^H w_k^{hd}\}).
\]

It follows from (6.33) that \(S_k^{D,(\kappa)}(Y, v_k)\) is a concave function which satisfies the following condition:

\[
S_k^{D,(\kappa)}(Y^{(\kappa)}, v_k^{(\kappa)}) = \frac{\log(1 + \gamma_k^{hd}(Y^{(\kappa)}))}{v_k^{(\kappa)}}, \quad (6.35)
\]

Thus, the constraint \(C_8\) can be iteratively replaced by the following constraint:

\[
S_k^{D,(\kappa)}(Y, v_k) \geq \frac{(1 - \alpha_k)O_k}{B}, \forall k \in \mathcal{K}. \quad (6.36)
\]

6.5.4 Convex Approximation of Constraint \(C_3\)

The constraint \(C_3\) is approximated in the same way as the constraint \(C_5\). Similar to (6.28), the right-hand side of the constraint \(C_3\) is lower bounded at the feasible point \((Y^{(\kappa)}, u_l^{(\kappa)})\) as:

\[
\frac{\log(1 + \gamma_l^{hd})}{u_l^{(\kappa)}} \geq \Upsilon_l^{(\kappa)} + \Psi_l^{(\kappa)} P_l - \frac{\Gamma_l(Y)}{u_l^{(\kappa)}} - \Omega_l^{(\kappa)} u_l
\]

\[
= S_l^{U,(\kappa)}(Y, u_l), \quad (6.37)
\]
where:

\[
\tilde{\Upsilon}_l^{(\kappa)} = \frac{2 \log(1 + \gamma_l^{hd}(Y^{(\kappa)})) - \gamma_l^{hd}(Y^{(\kappa)})}{u_l^{(\kappa)}}, \quad \bar{\Phi}_l^{(\kappa)} = \frac{2 \gamma_l^{hd}(Y^{(\kappa)})}{P_l^{hd(\kappa)} u_l^{(\kappa)}}, \quad \bar{\Omega}_l^{(\kappa)} = \frac{\log(1 + \gamma_l^{hd}(Y^{(\kappa)}))}{u_l^{(\kappa)^2}},
\]

\[
\Gamma_l^{(\kappa)}(Y) = P_l^{hd} g_l^H \bar{\Theta}_l^{(\kappa)} g_l + \sum_{j > l} P_j^{hd} g_j^H \bar{\Theta}_l^{(\kappa)} g_j + \sigma^2 \text{Tr}(\bar{\Theta}_l^{(\kappa)}),
\]

\[
\bar{\Theta}_l^{(\kappa)} = \left( \sum_{j > l} (P_j^{hd(\kappa)})^2 g_j g_j^H + \sigma^2 I \right)^{-1} - \left( (P_l^{hd(\kappa)})^2 g_l g_l^H + \sum_{j > l} (P_j^{hd(\kappa)})^2 g_j g_j^H + \sigma^2 I \right)^{-1} \geq 0.
\]

Moreover, \( S_l^{U,(\kappa)}(Y, u_l) \) is a concave function which satisfies the following condition:

\[
S_l^{U,(\kappa)}(Y, u_l) = \frac{\log(1 + \gamma_l^{hd}(Y^{(\kappa)}))}{u_l^{(\kappa)}}.
\]

As a result, the constraint \( C3 \) can be iteratively replaced by the following constraint:

\[
S_l^{U,(\kappa)}(Y, u_l) \geq \frac{(1 - \delta_l) b_l}{B}, \forall l \in L.
\]

### 6.5.5 Equivalent Convex Optimization Problem and Algorithm

After considering the convex approximations of all the non-convex constraints. Problem (6.18) can be equivalently replaced by the following convex optimization problem which is solved at the \( \kappa^{th} \) iteration according to:

\[
\min_{W, W_l^{hd}, P, P_l^{hd}, F, \alpha, \delta, u_v, V} \left( \sum_{k=1}^{K} W_k + \gamma_c F_1^2 \sum_{k=1}^{K} \beta_l^2 + \sum_{k=1}^{K} \frac{||w_k^{hd}||^2}{u_k} + \sum_{k=1}^{K} \frac{||w_k||^2}{V_2} 
\]

\[
+ \sum_{l=1}^{L} \frac{P_l^{hd2}}{u_l} + \sum_{l=1}^{L} \frac{P_l^{2}}{V_2} \right)
\]

s.t. \( C1, C2, C4, C7, C9, C10, C11, C12, (6.21), (6.25), (6.27), (6.30), (6.32), (6.34), (6.36), (6.39) \)
Note that the problem (6.40) can be iteratively solved using the convex optimization solvers such as CVX until the convergence of the objective function (6.40a). Therefore, we propose an iterative algorithm to minimize the total energy of the system in the problem (6.40) which is summarized in Algorithm 1.

**Algorithm 3 Proposed Solution for Total Energy Minimization**

**Initialization:** Set tolerance $\rho$, iteration $\kappa = 0$ and initial values of $P^{(0)}$, $P^{hd(0)}$, $W^{(0)}$, $W^{hd(0)}$, $F^{(0)}$, $\alpha^{(0)}$, $\delta^{(0)}$, $u^{(0)}$, $v^{(0)}$, and $V^{(0)}$

1. **Repeat**
2. Solve (6.40), to obtain the optimal solution of $P^*$, $P^{hd*}$, $W^*$, $W^{hd*}$, $F^*$, $\alpha^*$, $\delta^*$, $u^*$, $v^*$, and $V^*$
3. Update $P^{(\kappa+1)} = P^*$, $P^{hd(\kappa+1)} = P^{hd*}$, $W^{(\kappa+1)} = W^*$, $W^{hd(\kappa+1)} = W^{hd*}$, $F^{(\kappa+1)} = F^*$, $\alpha^{(\kappa+1)} = \alpha^*$, $\delta^{(\kappa+1)} = \delta^*$, $u^{(\kappa+1)} = u^*$, $v^{(\kappa+1)} = v^*$, $V^{(\kappa+1)} = V^*$.
4. Set $\kappa = \kappa + 1$
5. **Until** convergence

The algorithm comprises two main parts as follows: Initialization, where the initial feasible values of all the optimization variables in the problem (6.40) are set including the tolerance and iteration variables; Iterative loop (steps 1 – 5), where the problem (6.40) is solved through convex solver and optimization variables are updated in a loop until the difference between two successive values of the objective function (6.40a) is less than the tolerance $\rho$.

### 6.5.6 Complexity and Convergence Analysis

#### 6.5.6.1 Complexity Analysis

The computational complexity in each iteration of Algorithm 3 is dominated by the step 2, where the convex problem (6.40) is solved to obtain an optimal solution of the optimization variables. Moreover, problem (6.40) includes $(9K + 5L + 8)$ linear and quadratic constraints,
and \((2NK + 4L + 2K + 4)\) variables. Therefore, the total computational complexity required to solve the problem (6.40) is \(O((9K + 5L + 8)^{2.5}((2NK + 4L + 2K + 4)^2 + 9K + 5L + 8))\) [143].

6.5.6.2 Convergence Analysis

The convergence of Algorithm 3 depends on the convergence of the convex program in step 2, where the optimal point is obtained satisfying the Karush-Kuhn-Tucker (KKT) conditions [77]. Also, the Algorithm 3 utilizes the inner approximation method to find the optimal solution of the convex problem (6.40). This implies that the feasible set \(G = \{P, P^{hd}, W, W^{hd}, F, \alpha, \delta, u, v, \text{ and } V\} \) at iteration \(\kappa\) of the considered problem is also feasible at iteration \((\kappa + 1)\) i.e., \(G^{(\kappa + 1)} \subseteq G^{(\kappa)}\) [140]. According to [144], KKT invex condition is satisfied when \(\kappa \to \infty\). Thus, in every subsequent iteration, the optimal solution is monotonically improved toward the KKT point but for practicality, the algorithm improves the solution till the condition \(E_T^{(\kappa)} - E_T^{(\kappa + 1)} \leq \rho\) is satisfied, where \(E_T\) corresponds to the total energy of the system.

6.6 Performance Evaluation of the Proposed Solution

In this section, the performance of the proposed transmission scheme is evaluated through numerical simulations. The simulation parameters, unless mentioned otherwise, are as follows: \(b_l, I_k\) and \(O_k\) uniformly distributed in \([200, 400]\) kbits, \(\beta_l\), and \(W_k\) uniformly distributed in \([500, 1500]\) CPU cycles, \(\gamma_c = 10^{-30}, \sigma_{SI} = 10^{-15}, F = 20\) GHz, \(B = 50\) MHz, \(g_0 = 1.42 \times 10^{-2}, H = 10\) meters, \(T_{th} = 1, K = 10, L = 10, N = 20\) and \(\sigma_{BS}^2 = \sigma_k^2 = -169\) dBm, \(\forall k \in K\). Also, we uniformly generated the UUEs and DUEs in a circular coverage area with a 100 meter radius as shown in Fig. 6.3.

To show the performance comparisons, the proposed transmission scheme is compared with the following benchmark scheme:

- **Half Duplex** The overall task is completed in two time-slots. In the first time-slot, each UUE offloads all the respective task bits \(b_l\), while the task for each DUE is computed at the MEC server simultaneously. After these operations are completed, in the second time-slot, the BS sends the output task bits of size \(O_k\) to each DUE \(k\), while the task for each UUE \(l\) is computed at the MEC server.
Note that the proposed scheme can operate in an HD mode similar to the benchmark scheme discussed above when task share variables are set to 0 i.e., $\alpha_k = 0, \forall k \in K$, and $\delta_l = 0, \forall l \in L$.

In Fig. 6.4, we analyze the performance of the proposed FD scheme and benchmark HD scheme in terms of the total energy consumption of the system when the total number of users i.e., $K + L$, increases from 4 to 20. Note that in Fig. 6.4, we utilized an equal number of UUEs and DUEs, where the location of each UUE and DUE were incrementally acquired from the generated users in Fig. 6.3. For example, the locations of UUEs and DUEs with
Figure 6.5: Total energy consumption of the system versus the self-interference power

\( K + L = 4 \) in Fig. 6.4 correspond to the UUE #01 and UUE #02, and DUE #01 and DUE #02 in Fig. 6.3, respectively. It can be seen that the total energy increases with an increase in the total number of users in both transmission schemes because each additional pair of UUE and DUE augments communication and computation overheads that lead to more energy consumption. The proposed FD scheme outperforms the HD scheme by \( 6.6 \times \) on average, and at most \( 11.6 \times \) when the total number of users is set to 20. This is because the HD scheme significantly increases the time delay in both the time slots and also the transmission powers in both uplink and downlink, compared to the proposed FD scheme, to accommodate the increasing number of users. Moreover, we found that the energy benefit of utilizing the FD in the proposed scheme becomes incrementally significant after a certain total number of users (8 in our results). The reason deals with the constraint \( C_1 \) that causes both the HD and FD schemes to restrict the transmission powers till the total time delay is equal to the threshold, and once the time delay threshold is reached, both the schemes increase the transmission powers to accommodate more users, where proposed FD scheme has an edge over HD scheme because it supports the bi-directional communication of UUE and DUE in the same time slot through interference cancellations.

Following, the dependency of total energy consumption on the self-interference power \( \sigma_{SI} \) in the proposed FD scheme is shown in Fig. 6.5, where \( K = L = 2 \). It can be seen that total energy increases with an increase in the self-interference power and this is because the BS
increases DL power to suppress the interference and increase the downlink SNR of each DUE to successfully transmit corresponding DL task bits. The total energy is also calculated using the HD scheme with the same user setup which is also shown in Fig. 6.5. The comparison between HD and the proposed scheme shows that the HD scheme can perform marginally better than the FD scheme when self-interference power is very high.

Moreover, Fig. 6.6 shows the total energy consumption of HD and proposed FD schemes calculated when the total number of BS antennas varied between 5 and 25, where we considered $K = L = 2$. It is easy to see that increasing the number of antennas enhances the energy consumption of the overall system in both schemes. However, the increase in energy is more significant in the HD scheme and as the total number of antennas increases the benefit of the proposed FD scheme over the HD scheme is more pronounced ($13 \times$ on average). Thus, in Massive MIMO systems, the proposed FD scheme can provide significantly lower power consumption at both BS and users than the HD scheme which is more beneficial in supporting low-power user equipment.

Next, the dependency of the time delay of the first-time slot $\tau_1$, the third-time slot $\tau_3$, and the overall completion time $T$ on the total processing power of the MEC server $F$ in the proposed FD scheme is shown in Fig. 6.7, where $K = L = 2$.$^3$ It can be seen that the

$^3$Note that the time delay in the second time slot depends on the FD communication which is found to
Figure 6.7: Time delay of first-time slot $\tau_1$, third-time slot $\tau_3$ and overall completion time $T$ versus the total processing power of the MEC server $F$.

time delay decreases with the increase in the total processing power of the MEC server in all cases. We noticed that increasing $F$ by 0.2 KHz decreases the $T$ by 55 milli-seconds, $\tau_1$ by 25 milli-seconds and $\tau_3$ by 29 milliseconds, on average. This is because increasing $F$ allows the MEC server to allocate more processing power to the users. Accordingly, the Algorithm 3 reduces values of $V_1$ and $V_3$ in constraints $C2$ and $C7$ of the convex problem (6.40) during the optimization process which results in the reduction of $\tau_1$, $\tau_3$ and eventually $T$. Also, we found that the time delays in the first-time slot and third-time slot come from the computation time delays of the MEC server serving the computation tasks of UUEs and DUEs because the communication time delays in both time slots are significantly lower than the computation time delays. Note that the reduction in time delays helps the MEC server to allocate less time to serve users at the cost of higher processing power and/or energy consumption required for the task computations which is beneficial when a large sum of users request for the computation services from the MEC server.

In addition, we also considered evaluating the performance of the proposed FD scheme for two different cases of UUEs and DUEs locations. First, when the group of UUEs is co-located with the group of DUEs in the coverage area of the BS. Second, when the group of UUEs and the group of DUEs are located with a large separation distance between them.
To achieve this, for both cases, we generated 5 DUEs and 5 UUEs in a circular coverage area with a 100-meter radius. For the first case, the DUEs and UUEs are co-located on the east side of the BS as shown in Fig. (6.8a). For the second case, all the UUEs are located on the west side of the BS, while all the DUEs are located on the east side of the BS, to achieve significant distance between two user groups as shown in Fig. (6.8b). Then, the total energy of the system is calculated using the proposed-FD scheme for different total numbers of users. It can be seen that the non-co-located UUEs and DUEs case achieves significantly lower (8.9× on average) energy consumption with an increase in users compared to the co-located UUEs and DUEs case. This is because the co-located UUEs and DUEs increase CCI which causes the BS and users to increase power and duration of time slots to cope with the task bit requirements, resulting in increased energy consumption. Therefore, with the proper scheduling of UUE and DUE pairs in the proposed-FD scheme, more performance gains can be achieved. However, user scheduling will be covered in future work.

6.7 Summary

We have considered a network in which a BS equipped with an FD transmission capability and an MEC server for task computation, provides computing services to multiple DUEs and UUEs. We have designed a time-slotted transmission protocol that achieves significantly better energy efficiency compared to the HD scheme. We have studied the problem of
minimizing the total weighted energy at the UUE and the server by jointly optimizing the
transmitter precoding vector at the BS, UUE's uplink power, computational resource at the
MEC server, and the shares of computation tasks to be computed at different time-slots.
We have shown that the proposed FD strategy reduces the total energy consumption by
6.6× on average compared to the HD scheme. It is also shown that the energy benefits of
the proposed FD scheme over the HD scheme increase significantly when more computing
users are incorporated into the network. Also, the locations of the computing users play
an important role in optimizing the network resource allocations, and in support, we have
shown that the large separation between the uplink and downlink computing user groups
benefits the proposed FD scheme to increase the energy efficiency of the overall network.
Finally, our transmission scheme, results, and analysis can be utilized to efficiently design
the MEC network that provides computing facilities to uplink and downlink users.
Chapter 7
Conclusion and Future Work

In this work, we considered various communication links to study novel research problems in a multi-UAV communication network supported by a primary BS that is imagined to monitor the air and soil medium environment in large agricultural fields to maximize crop yields.

We investigated the effects of the UAV’s 3D position on the antenna correlation and channel capacity performance of different multi-antenna system configurations by analyzing multi-antenna channels in the A2A link between two UAVs. Then, for the A2A link in a MIMO system, we proposed a novel direction estimation method that achieves good prediction accuracy. The results indicated that the proposed direction estimation method can be directly applied in UAV-based massive MIMO networks to efficiently select directional transmission beams with limited complexities on the aerial nodes.

We proposed a UAV-based FD multi-user communication network that serves multiple FD users on the ground and designed a novel resource allocation optimization problem. The problem is found to be non-convex which is hard to solve optimally. Therefore, a joint sub-optimal solution is proposed that improves the FD communication rate performance compared to the baseline algorithms.

We investigated the wireless channel characteristics between UAV and UG nodes using in-field outdoor measurements. The path loss and fading in the A2UG and UG2A channels are obtained at various altitudes and elevation angles, demonstrating the effect of soil depth, soil moisture, UAV 3D location, and UAV antenna position on signal propagation. A novel path loss model is proposed which provides low estimation errors compared to the prior model in the literature. The small-scale fading distribution is analyzed at UAV and UG nodes that follow the Rician distribution. The Rician-K parameter is calculated which is found to be significantly dependent on the UAV’s altitude, elevation angle, and antenna position. Also,
it is shown that the Gaussian function provides more accurate estimates of the Rician-K at various UAV 3D positions compared to the A2G exponential model. Moreover, the empirical findings and models are applied to a UAV-based IoUT network to find an energy-efficient data collection strategy while satisfying the sensor data collection requirements. The numerical results demonstrate that the proposed scheme saves a considerable amount of energy on the SNs compared to baseline schemes.

Last, we considered a network where several uplink and downlink computing users receive computing services from a BS with FD transmission capability and an MEC server. We developed a time-slotted transmission protocol that achieves much higher energy efficiency compared to the HD scheme. A novel joint optimization problem is proposed and solved that minimizes the total energy consumption of the network by optimizing the computation and communication resources of the network. The performance of the proposed scheme is analyzed for co-located and non-co-located downlink and uplink computing users which shows that the computing users’ locations are critical in optimizing network resource allocations.

The findings and analysis in this work could be used to improve communication between different types of nodes in aerial and ground networks. We intend to expand our analysis in the A2UG work to include more soil types and moisture levels in the future.
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