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Uplink Noma in UAV-Assisted IoT Networks

By

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Uplink Noma in UAV-Assisted IoT Networks

Ali Mrad

ABSTRACT

Non-orthogonal multiple access (NOMA) is one of the promising access technologies to improve spectral efficiency and serve a higher number of users in different internet of things (IoT) systems. This technology proves important in scenarios with time-sensitive services when data has to be collected before a set deadline, otherwise, it is rendered useless, as well as, in scenarios with limited resources and large number of users. Therefore, this thesis explores the potential of NOMA in improving the performance of IoT networks served by unmanned aerial vehicles (UAVs). The first part of the thesis considers the problem of data collection from time-constrained IoT devices through deploying a UAV with uplink NOMA. This problem is formulated to determine an optimized UAV trajectory, IoT devices scheduling, and power allocation in the NOMA clusters that maximize the number of served devices while considering various constraints including the energy and flight duration of the UAV and successive interference cancellation (SIC) in the NOMA cluster. Given the complexity of the problem and the incomplete knowledge about the environment, the problem is divided into two subproblems: the first models the UAV trajectory and the selection of the first device in the NOMA cluster at each time slot as a Markov Decision Process, and uses Proximal Policy Optimization to solve it. The second device is then selected using a heuristic algorithm based on prioritizing devices with higher bit rate requirements and strict deadlines. The second subproblem addresses power allocation inside the NOMA cluster, and is formulated as an optimization problem for maximizing the sum rates of the two selected users. Regarding the second part of the thesis, uplink NOMA with joint-transmission coordinated multi-point (JT-CoMP) is leveraged in a UAV-assisted IoT network. IoT devices with strong channel conditions utilize NOMA to transmit to a single UAV closest to each device, while the IoT device with poor channel conditions utilize JT-CoMP NOMA and transmits to two UAVs. This problem is formulated as an optimization problem to maximize the sum rate of the IoT devices given the NOMA, UAV, and IoT devices constraints. The obtained problem is non-convex mixed-integer non-linear program which is difficult to solve in a straightforward manner, hence alternating optimization technique is used where the original problem is divided into two subproblems. In the first subproblem the positions of the UAVs are optimized to maximize the sum rate of the IoT devices and the second subproblem handles IoT devices transmit power optimization then alternating between the two subproblems is performed to improve the performance. For each subproblem, successive convex approximation is leveraged to get a solution. Then, simulation results are presented to demonstrate the performance gains of the proposed solutions as compared to alternative solution approaches.

Keywords: Non-orthogonal multiple access (NOMA), Deep reinforcement learning (DRL), Internet of things (IoT), Unmanned Aerial Vehicle (UAV), Timely data collection, Joint-Transmission Coordinated Multi-Point (JT-CoMP).

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Chapter One

Introduction

1.1 Motivation

Recent research articles on the internet of things (IoT) shows that the number of IoT devices is expected to exceed one trillion devices by 2022, with the number of interconnected IoT devices expected to reach 75.44 billion by 2025 [1]. IoT introduced a new paradigm where a large number of devices are expected to connect to a network, communicate with each other, and share information. Therefore, different research addressed the integration and enhancement of IoT with the current available networks and applications (such as wearables, buildings, and agriculture) given the different challenges and requirements of the IoT devices [2] [3].

Moreover, IoT devices can operate in different environments and are utilized for various applications in, for example, smart cities, agriculture, and infrastructure; however, these devices have limited capabilities and for many use cases, IoT devices are constrained by, for example, the deadlines and reliability of the data and the available resources. Therefore, data collection is necessary for many IoT applications, especially in remote or inaccessible areas such as forests and rural areas with little or no infrastructure. In particular, energy- and time-efficient data collection is required to guarantee the different constraints of the IoT devices; otherwise, the data collected may lose its value. To this end, UAVs are considered as a promising technology, for timely data collection from IoT devices, due to their flexibility, low cost, ease of deployment, and high mobility [4], [5]. UAV-enabled wireless communications can achieve high throughput because of the high probability of line-of-sight (LOS) between the UAVs and the IoT devices [6]. Moreover, in disaster scenes with affected infrastructure, UAVs can be deployed to provide wireless connectivity [7], [8], or to relay commands from a remote server to certain IoT devices when there is no direct communication link [9], [10]. Other benefits of using UAVs in a network include traffic offloading, improving the user's data rate, and improving the quality of service [11], [12]. All these use-cases highlight the role of UAVs in the next-generation mobile communication network. However, UAV communication is limited by the mobility, flight time, and available energy of the UAV.

Non-orthogonal multiple access (NOMA) is another promising technology for the next generation networks and IoT applications. With NOMA, a large number of users (or devices) can be supported using the same available resources, which is essential for different use cases with a large number of IoT devices and limited resources. Moreover, NOMA transmissions can be further improved by using Coordinated multi-point (CoMP) transmissions where the base stations or UAVs coordinate to further improve the quality of the signal from desired devices or users. Therefore, uplink NOMA in UAV communication can provide flexibility, efficiency, and support a large number of IoT devices while managing the challenges caused by the limited resources of the UAV and the constraints of the IoT devices. Accordingly, in this thesis, we leverage both NOMA techniques and UAVs services as an enabling technology for IoT applications given the constraints of the IoT devices, the UAV deployment and mobility constraints, and the NOMA constraints. We highlight the importance of NOMA aided uplink communication by presenting two UAV aided IoT scenarios with various requirements and comparing against other approaches.

1.2 Thesis Contributions

In this thesis, we consider UAVs providing services to a set of IoT devices with different constraints in an uplink NOMA system. In particular, the first part of this thesis considers a UAV deployed to collect data from time constrained IoT devices using uplink NOMA. We formulate the problem as an optimization problem for maximizing the number of served IoT devices, however the obtained problem is mixed integer non linear program, so we divide it into two subproblems where in the first subproblem we use deep reinforcement learning (DRL) to determine the trajectory of the UAV and one of the devices to serve, then we use a heuristic approach to select the second device. In the second subproblem we perform power allocation to maximize the sum rate of the IoT devices in the NOMA cluster. And we test our solution against four other approaches to highlight it's performance, where we achieve two to three more devices served compared to orthogonal multiple access, 3 times performance gain compared to a greedy approach based on the distance to the UAV, and 6 times performance gain compared to other greedy method based on the IoT devices deadlines.

In the second part of this thesis we consider a novel IoT network scenario with uplink JT-CoMP NOMA, where two UAVs are deployed to serve IoT devices with minimum data rate constraints. In particular the IoT devices with strong channel transmit to the closest UAV, while the device with weak channel, leverage JT-CoMP NOMA to transmit to both UAVs, simultaneously. We formulate the problem as an optimization problem for maximizing the sum rate of the IoT devices and we use alternating optimization and successive convex approximation to handle this problem. Then we highlight the performance of our solution approach by varying the system parameters and comparing with other solution approaches. In particular our approach achieves an increase in the total sum rate of the IoT devices by 2 bps/Hz compared to a heuristic algorithm that uses random locations for the UAVs.

This thesis resulted in two publications where the first (Chapter 3) was published in IEEE International Conference on Communication 2022, and the second article (Chapter 4) is in progress to be submitted for publication.

1.3 Thesis Organization

The rest of this thesis is organized as follows. In chapter 2, we present the basic concepts, features, and challenges of NOMA by comparing against orthogonal multiple access techniques. Moreover, we present reinforcement learning and deep reinforcement learning as one of the promising solutions in communication systems and describe their fundamental components. Then in chapter 3, we study the performance of NOMA aided UAV data collection from time constrained IoT devices and we aim to maximize the number of served devices by optimizing the trajectory of the UAV, the IoT devices scheduling, and their transmit power. Chapter 4 handles UAV positioning and IoT transmit power optimization in a UAV assisted IoT network with JT-CoMP NOMA; we formulate the optimization problem as maximizing the sum rate of the IoT devices given the different constraints of the IoT devices and the UAVs. Finally, in chapter 5, we present the conclusion and some possible future work for uplink NOMA.

Chapter Two

Background Information

In this chapter we present the fundamental concepts that are used in this thesis. We first start by an introduction of non orthogonal multiple access techniques where we present the features, basic concepts, and challenges of NOMA. Then we explain the main concepts of reinforcement learning and deep reinforcement learning (that were used as a solution approaches in Chapter 3 of this thesis) and highlight their growing importance as solution approaches in the next generation cellular systems.

2.1 Non-Orthogonal Multiple Access

NOMA is one of the promising multiple access technologies that is expected to have an important role in the next generation networks. In NOMA, multiple users can be supported by using the same frequency and time resources by differentiating between the different users (or signals) in the power domain or the code domain [13]. In this chapter of the thesis we present the different features of NOMA to highlight its importance for the next generation networks. Then we present a detailed explanation on uplink and downlink NOMA, followed by the challenges of using NOMA techniques.

2.1.1 Features of NOMA

Current research shows that the number of IoT devices is expected to rise rapidly, with different devices having different requirements, resources, and constraints. Therefore, NOMA is currently being researched as an enabling technology to support the large number of devices using the existing resources. The main advantages of NOMA compared to traditional orthogonal multiple access (OMA) includes the following:

- Improved Channel Capacity:
  In [13], the authors show that the channel capacity of NOMA in the additive white Gaussian noise (AWGN) channel outperforms that of OMA for both uplink and downlink test cases. Moreover, in [14] and [15] the authors show that multiple-input multiple-output NOMA (MIMO NOMA) achieves higher channel capacity compared to MIMO OMA, and they highlight the effect of power allocation on the data rate.

- Higher Connectivity:
  In OMA, the number of users that can be supported is limited by the number of available resource blocks. However, in NOMA users are allowed to share the same resources at the same time which can support a larger number of devices.

- User Fairness:
  NOMA can achieve a better user fairness compared to OMA due to the different power allocation policies that can be used in NOMA (for example, more power can be allocated to the user with weak channel compared to OMA techniques). However, there is a trade off between the total throughput in the system and the user fairness. Moreover, some applications such as soil monitoring require low data rates, which can be better supported in NOMA compared to OMA where a dedicated time and frequency slots are allocated (so less resources are wasted especially for applications that do

not require large or dedicated resources).

- Compatibility:

  NOMA can be added on top of the existing multiple access techniques because in NOMA we exploit the power domain. So it does not affect the current technologies that utilize the frequency or time domains.

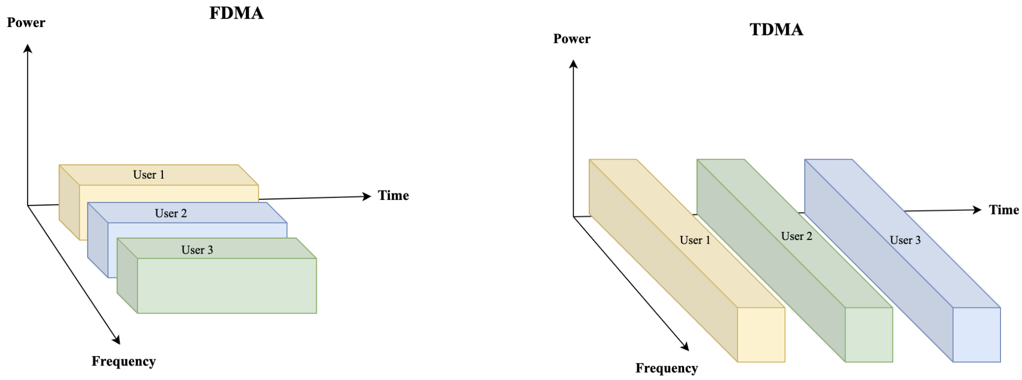
- Low Latency:

  Noma offers lower latency because the transmissions of all the users happen simultaneously rather than specific (scheduled) time slots [16].

2.1.2 NOMA Concepts

All the features of NOMA motivate it's use as the next generation multiple access technology. In wireless communications, multiple access techniques can be divided into: orthogonal multiple access (OMA) and non-orthogonal multiple access (NOMA). In OMA, resources are divided among the users, so for example, in frequency division multiple access (FDMA) as shown in figure 1a, the bandwidth is divided into different frequency bands and each user is assigned certain frequency, hence this allows all the users to transmit at the same time. On the other hand, in TDMA (figure 1b) users are assigned certain time slots where only in these slots they can transmit, however during this period the users can utilize the whole bandwidth available.

Although in OMA, assigning time or frequency resources reduces the interference between the IoT devices, the concept of the internet of things and the demand for more resources that are already scarce are some of the drawbacks of using OMA techniques. To this end, NOMA was proposed as an enhancement of OMA for scenarios with large number of IoT devices and limited resources. As shown in figure 2, devices in NOMA utilize the same frequency and time resources, and differentiating between the devices is in the power domain by varying the transmit powers of the IoT devices or in the code domain by assigning dis-



(a) Frequency Division Multiple Access.

(b) Time Division Multiple Access.

Figure 1: Orthogonal Multiple Access

similar codes to different devices [17].

First for downlink NOMA with two IoT devices only. The base station (or UAV) would select the appropriate users to pair together. Usually selecting the users is based on their channel quality, so ideally we would have a near user with a strong channel and a far user with a weak channel. The base station performs superposition coding so both devices will be served using the same time and frequency resources, however the far user will be assigned a higher transmit power compared to the near user (to improve its channel). The far user will decode the NOMA signal directly. On the other hand, the near user would first decode the signal from the far user. Then perform successive interference cancellation and remove the far user signal from the overall NOMA signal. Note that in downlink NOMA the IoT devices can remove interference only from the devices that has worse channel. So, the transmitted signal by the base station can be expressed as:

$$x = \sum_{i}^{M} \sqrt{P_i x_i} \tag{2.1}$$

And, the message at the receiver side can be expressed as:

$$y = h_f x_f + h_n x_n + 1 \tag{2.2}$$

where h_f is the channel of the far user, h_n is the channel of the near user, x_f is the message of the far user, and x_n is the message of the near user.

The far user message remains the same and interference is present, but the near user decodes the dominant interference from the far user using SIC, so the obtained messages becomes:

$$y = h_n x_n + 1 \tag{2.3}$$

Therefore the signal to noise ration (SNR) of the near user and far user can be expressed as:

$$SNR_{near} = \frac{P_{near}}{N} \tag{2.4}$$

$$SNR_{far} = \frac{P_{far}}{P_{near} + N} \tag{2.5}$$

where N is the noise. Note that both users utilize the full bandwidth. Consequently, the data rate of IoT device i (given that the IoT devices channel quality are sorted in descending order) can be expressed as:

$$R_i = log_2(1 + \frac{P_i \lambda_i}{\sum_{j=1}^{i-1} P_j \lambda_j + N}) \tag{2.6}$$

where N is the total number of IoT device and λ_i is the channel of IoT device i.

Moreover, to perform effective SIC in a M user NOMA cluster, the following constraints should be satisfied:

$$P_i \lambda_i - \sum_{j=1}^{i-1} P_j \lambda_i \geq \eta \tag{2.7}$$

where η is the minimum power difference to distinguish between the different IoT devices.

As for uplink NOMA, all IoT devices transmit their data to a base station using same resources but different transmit power levels, then at the base station

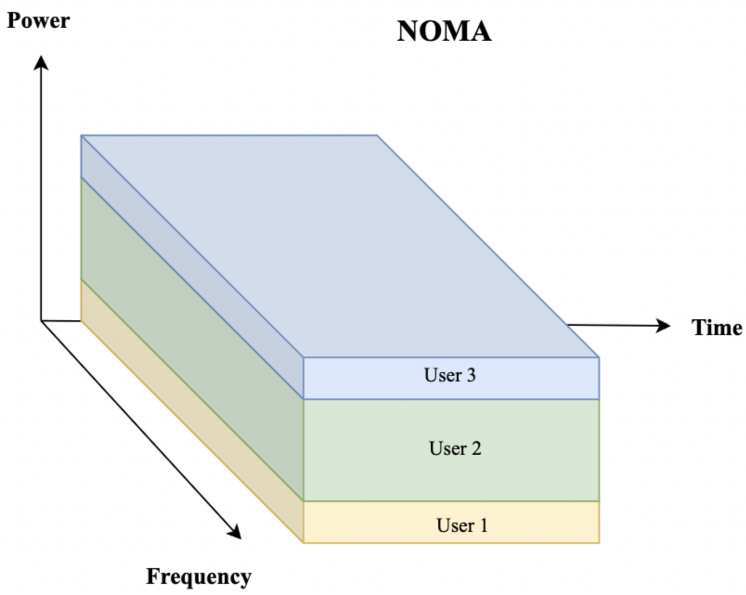


Figure 2: Non-Orthogonal Multiple Access.

SIC is performed to differentiate between the different signals. In this thesis, the UAVs first decode the signal from the near device (which suffer interference from the devices with weaker channel), then it subtracts the strong device signal from the overall NOMA signal. Accordingly, the data rate of a device i in a M NOMA cluster can be expressed as:

$$R_i = log_2 \left(1 + \frac{P_i \lambda_i}{\sum_{j=i+1}^{M} P_j \lambda_j + N} \right) \tag{2.8}$$

Moreover, the following constraints should be satisfied for effective SIC:

$$P_i \lambda_i - \sum_{j=i+1}^{M} P_j \lambda_j \geq \eta \tag{2.9}$$

In this thesis we focus on the power domain NOMA for uplink transmissions.

2.1.3 Challenges of NOMA

Although NOMA provides many advantages in UAV aided IoT networks, different challenges should be considered while using NOMA. The challenges can be summarized as following [18]:

- SIC techniques:

  Recent literature explored different SIC decoding orders based on several metrics. This includes decoding messages from IoT devices based on the channel quality with respect to the UAV or base station (usually, in uplink NOMA users with strong channel are decoded first followed by users with lower channel quality). On the other hand, there is also an SIC decoding orders based on quality of service, and a hybrid SIC order that adapts the decoding order to achieve higher performance [19]. Therefore, the advantages and disadvantages of each SIC decoding order depends on the use case itself which makes it difficult to choose the better decoding order. For example, in a two user system, power domain NOMA is usually preferred because the performance is better than OMA schemes. However the quality of service drops for large number of IoT devices. On the other hand, Cognitive radio NOMA selects the SIC decoding order based on the quality of service requirements of the IoT devices which in return is better for cases where devices can be divided into delay tolerant or delay sensitive devices.

- Power allocation:

  In power domain NOMA, differentiating between the IoT devices is based on the difference in their transmit powers and their channel qualities. Therefore, performing power allocation while ensuring the quality of service constraints and the SIC decoding constraints is not a trivial task especially with a large number of IoT devices in one NOMA cluster. Moreover, the channel quality of the devices depends on the positioning of the UAVs, which consequently affects the transmit power of the IoT devices and increases the complexity of the problem.

- IoT devices paring:

  An important step in NOMA is dividing the IoT devices into clusters that will utilize the same resources. Each NOMA cluster is affected by the constraints of the IoT devices and with larger number of devices in one cluster, the interference from the other devices withing the same cluster increases. Therefore, the process of clustering is not trivial especially with the varying positions of the UAVs. And with time or resource constrained application the complexity can increase.

- Increased complexity:

  Using NOMA scheme increases the complexity of the considered scenario because we should consider the clustering of the IoT devices, then we should perform power allocation for each NOMA cluster in order to guarantee both the requirement of these devices and SIC techniques requirements, given the interference in one cluster and between the different clusters.

- Interference:

  As mentioned earlier, IoT devices within the same NOMA cluster share the same resources which results in interference between these devices that can affect the quality of service. For example, in uplink NOMA the IoT device with the strong channel will experience interference from all the devices that have lower channel quality.

2.2 Reinforcement Learning

In this section, we present the basic concepts of reinforcement learning (RL) methods that were used in the thesis. Moreover, we highlight the general concepts of RL and it's importance in IoT applications with randomness in the environment.

Machine learning methods usually rely on existing data to learn patterns and make inferences. However, in IoT applications this data might not be available or accessible; therefore, reinforcement learning can be utilized to achieve a high performance and to generalise for random test cases. The main difference between RL and other machine learning approaches can be summarized as:

- In RL, there is no supervisor and no labeled data, instead only a reward where the agent learns how to maximize the reward function.
- Time matters in reinforcement learning and the feedback or reward is delayed not instantaneous.
- The actions of the agent affect the data it receives from the environment, as well as the reward it receives.

Reinforcement learning can be defined as a mapping from a set of states to a set of actions with the goal of maximizing the total cumulative reward. As shown in figure 3, the agent takes as an input the current state S_t and reward R_t and then it outputs an action to the environment. Based on the action, the environment then returns the new state S_{t+1} and the reward R_{t+1}. These steps are repeated until the agent converges and learns a good policy. Convergence occurs when the reward function becomes stable so the difference between the current and previous reward becomes negligible. The main components of RL include:

- Policy: which is a mapping from perceived states of the environment to actions that can be taken in those states.
- Reward: numerical values that defines how good and bad values are, where defining the reward depends on the scenario considered. For example, in a scenario that aims to minimize the distance a UAV and an IoT device the reward can be equal to the negative of the distance between them.
- Value function: The value of a state is the total amount of reward an agent can expect to accumulate over the future, starting from that state and following a policy. The agent aims to maximize the discounted sum of rewards. Accordingly the value of a state s following a policy π is:

$$V_{\pi}[s] = E_{\pi}\left[\sum_{j=0}^{T} \gamma^{j} R_{t+j+1} | s = s_t\right] \quad (2.10)$$

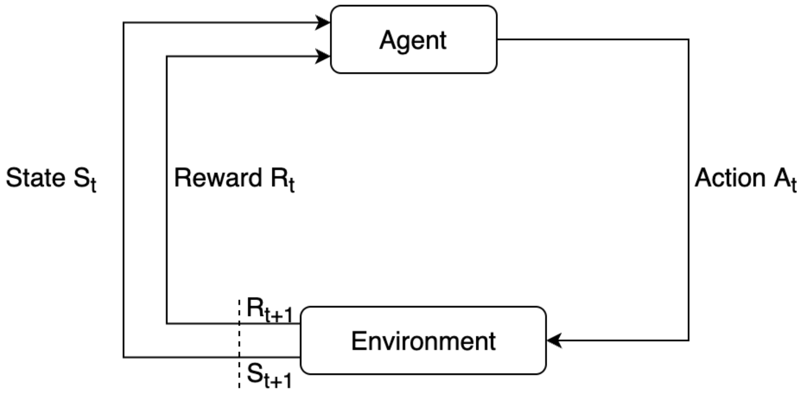


Figure 3: Reinforcement Learning.

where γ is the discount factor and R is the reward. Choosing the value of γ determines the emphasis on the previous states. So, if $\gamma = 0$ then we only focus on the instantaneous state (and reward), and if $\gamma = 1$ then we focus all the previous states.

- Model of environment: It can be divided into model free and model based environments. The model based environments allow inferences to be made about how the environment will behave. On the other hand, model free environments are explicitly trial-and-error learners where the agents learn by interacting with the environment.

The cumulative discounted reward can be defined as:

$$R = \sum_{t=0}^{T} = \gamma^t r_t \tag{2.11}$$

where r_t is the reward at time slot t. Accordingly the goal of the agent is to find the optimal policy π^* that maximizes the expected reward:

$$\pi^* = \text{argmax}_\pi \quad E[R|\pi] \tag{2.12}$$

If we assume Markov property for the environment, then the current state only depends on the previous one (not the total history). So, first we define the problem as a Markov Decision Process (MDP) denoted by a tuple $< S, A, \gamma, R, T >$ where:

- S is the state space, where s_t is the state of the agent at time slot t.
- A is the action space, where a_t is the set of actions the agent can take at time slot t from state s_t.
- γ is the discount faction ($0 \leq \gamma \leq 1$).
- R is the discounted reward function.
- T is the state transition probabilities. It defines the probability of moving to a state $s_t + 1$ given that the agent is in a state s_t and take action a_t $P(s_{t+1}|s_t, a_t)$.

However, this requires complete knowledge of the state transition probabilities which is usually not given. Therefore, deep reinforcement learning (DRL) and neural networks can be used to learn complex policies by approximating value functions. PPO [20] starts by initializing a sampling policy pi and value function. Then it iterates over the number of episodes and then over the number of time slots. And at each time slot the agent observes the current state and outputs the required actions. Then the reward is computed. Followed by the advantage estimate which is the difference between the discounted sum of the rewards and the estimate discounted sum of rewards. Then the we update the loss function and update the policy.

Chapter Three

NOMA-Aided UAV Data Collection from Time-Constrained IoT Devices

3.1 Introduction

With the current deployment of the fifth generation (5G) network, the focus of the research is shifting toward the six generation (6G) network that is expected to enable different use cases and applications that support a massive number of internet of things (IoT) devices. These devices are utilized for various applications in smart cities, remote areas, agriculture, and infrastructure. However, in practice, IoT devices are constrained by the data deadline, data reliability and their maximum transmit power. Therefore, energy- and time-efficient data collection is required to guarantee the different constraints of the IoT devices; otherwise, the data collected may lose its value. To this end, UAVs are being employed in the literature, for timely data collection from IoT devices, due to their flexibility, low cost, ease of deployment, and high mobility [21]. UAVs are also utilized as an energy-efficient data collection mechanism in wireless sensor networks. In [22], Zhan *et al.* jointly optimized the wake-up schedule of the sensor nodes and the trajectory of the UAV to minimize energy consumption. Similarly, the authors in

[23] aim to minimize the maximum energy consumption of a rotary-wing UAV collecting data from a set of IoT devices, given the energy budget of the UAV and the size of data to be collected. UAVs can also provide connectivity in areas with disrupted communications due to disastrous events or absence of infrastructure [24]. All these use-cases highlight the role of UAVs in the next-generation mobile communication network.

Despite the benefits of using UAVs in IoT systems, UAV communication is limited by the mobility, flight time, and available energy of the UAV. Therefore, improving the radio access technology in UAV-based future networks can help address these limitations. Recently, non-orthogonal multiple access (NOMA) emerged as a promising technology for wireless communication and IoTs applications with limited resources. With NOMA, a large number of users (or devices) can be supported using the same available resources. In Uplink NOMA multiple IoT devices use the same resources to transmit to the UAV or base station at the same time. The transmit power of the devices and the channel gain difference are used to differentiate between the signals of these devices. Then, at the receiver side (UAV or base station), successive interference cancellation (SIC) is performed to detect and decode the signals from the different IoT devices. Therefore, the benefits of uplink NOMA combined with the benefits of UAVs can provide flexibility, efficiency, and support a large number of IoT devices while managing the challenges caused by the limited UAV resources and the IoT devices' constraints.

The rest of this chapter is organised as follows: In section 3.1.1 we present the recent literature on NOMA and UAV data collection for time constrained applications. Followed by the system model and the problem formulation in section 3.2. Then in section 3.3 we explain our proposed solution approach to tackle this problem. And we evaluate the performance of our solution by varying the system parameters and comparing against four greedy heuristics in section 3.4. Finally, we present our concluding remarks and future work on this topic in section 3.5.

3.1.1 Related Literature

Recent literature addressed different scenarios where NOMA and UAVs are used for IoT applications. The authors in [25] consider UAV-assisted data collection with NOMA, where the location of the UAV, the grouping of the sensors, and the power control are jointly optimized to maximize the rate of a wireless sensor network. Similarly, in [26], the authors consider a UAV collecting messages transmitted by ground sensors. They aim to maximize the sum rate of the users by optimizing the UAV deployment position and the power control given the transmission power constraints and the quality of service constraints. In [27], the authors consider UAVs collecting data from IoT nodes while NOMA is invoked in uplink transmission. They aim at maximizing the system capacity by jointly optimizing the subchannel assignment, the uplink transmit power of the IoT nodes, and the height of the UAVs. Moreover, the authors in [28] consider integrating NOMA into UAV communication system to collect data from large scale IoT devices within the UAV flight time. They aim at minimizing the total energy consumption of the IoT devices by optimizing the trajectory of the UAV, the transmit power, and the scheduling of the IoT devices. The work in [29] maximized the minimum throughput from the ground nodes for both NOMA and OMA transmission, subject to the energy budget of the ground nodes and the UAV. Their simulations propose that NOMA have higher performance gain than OMA when the ground nodes have enough energy budget. Accordingly, in this chapter, we consider a UAV dispatched to collect data, using Uplink NOMA, from IoT devices placed in a remote area. The IoT devices are constrained by their release time and deadline; hence, the data should be fully collected within this window; otherwise, the devices are not considered served. The UAV is also limited by the available energy and the flight duration. Therefore, we aim to maximize the number of served IoT devices by optimizing the UAV trajectory, the selection of IoT devices in the NOMA cluster and their transmit power.

3.1.2 Contributions

Existing work on UAV data collection with uplink NOMA transmissions considers different scenarios where a UAV (mobile or stationary) is used to collect data from IoT devices. However, using NOMA with energy constrained UAV and time constrained IoT devices remains uncovered in the literature. Thus, this chapter aims at bridging this gap through the following contributions:

- We consider a new scenario where a UAV is deployed to collect data using uplink NOMA from time-constrained IoT devices in a remote area. We aim at maximizing the number of served devices by optimizing the UAV trajectory, the IoT devices selection as part of a NOMA cluster and their power allocation, given the available UAV energy, NOMA SIC constraint, IoT devices release time, deadline, target data required and maximum transmit power. In NOMA, having effective SIC is based on the channel gain difference between the IoT devices, however, the channel gain varies due to the UAV mobility which makes the problem more difficult to solve.

- We use deep reinforcement learning to determine the trajectory of the UAV and select the first IoT device in a NOMA cluster at each time slot. Then, we develop a heuristic algorithm to select the second device in the NOMA cluster based on prioritizing devices with higher bit rate requirements to upload their data before it expires. As for power allocation, we optimize the transmit power of the selected IoT devices to maximize their sum rate.

- We present different simulations of our solution while varying the system parameters and we compare with alternative baseline approaches.

3.2 System Model and Problem Formulation

As shown in figure 4, we consider a NOMA-assisted UAV data collection for time constrained IoT devices. A UAV is dispatched to collect data from $\mathcal{M}$

$= \{1, ..., M\}$ IoT devices that are randomly distributed in a remote area, with $q_i = (x_i, y_i)$ representing the coordinates of IoT device i. Each IoT device i has a release time ρ_i and a deadline δ_i, with the randomness of the release time modeled using a uniform distribution. The UAV should collect the data before δ_i expires, otherwise the data loses its value [21]. We denote by P_i the transmit power of IoT device i. Moreover, we use the discrete state model where the time horizon T is divided into $\mathcal{N} = \{1, 2, ...N\}$ intervals of equal size δ_t. The UAV flies at a fixed altitude H above the ground; the position of the UAV is denoted by $q_u = (x_u, y_u)$ and $q_u[n]$ determines the UAV position in the n^{th} time slot. The distance between the UAV and IoT device i at time n is:

$$d_i^u[n] = \sqrt{(x_u[n] - x_i)^2 + (y_u[n] - y_i)^2 + H^2} \quad \forall n \in \mathbb{N} \tag{3.1}$$

Moreover, the UAV has a maximum flight speed V_{max}, so the change in position of the UAV during one time slot is constrained by:

$$||q_u[n] - q_u[n-1]||^2 \leq (V_{max}\delta_t)^2 \tag{3.2}$$

The UAV flies at a height that allows a clear line of sight with the IoT devices [27]. Following the free space model, the channel gain at IoT device i at time slot n is:

$$h_i[n] = \frac{\beta_0}{d_i^u[n]^2} \tag{3.3}$$

where β_0 is the channel gain at reference distance $d_0 = 1$ m.

In figure 4, two users are paired at each time slot and they utilize uplink NOMA to transmit, using the same channel, to the UAV. Moreover, due to the time varying position of the UAV, the channel gain of the users vary from one time slot to another. At the receiver side (i.e. UAV side), successive interference cancellation (SIC) is done according to the descending order of the channel gain at the receiver. Therefore, a binary variable $\alpha_{ij}[n]$ is used to determine the SIC decoding order. $\alpha_{ij}[n]$ is set to 1 if the channel gain of the i^{th} user at time slot n is greater than that of the j^{th} user and it can be expressed as:

$$\alpha_{ij}[n] = \begin{cases} 0, & \text{if } d_i^u \geq d_j^u. \\ 1, & \text{if } d_i^u[n] < d_j^u[n]. \quad \forall n \in N, \forall i, j \in \mathcal{M}, i \neq j \end{cases} \tag{3.4}$$

Equation (3.4) can be rewritten as:

$$\alpha_{ij}[n] \in \{0, 1\}, \tag{3.5}$$

$$\alpha_{ii}[n] = 0, \tag{3.6}$$

$$\alpha_{ij}[n] + \alpha_{ji}[n] = 1, \tag{3.7}$$

$$\alpha_{ij}[n](||q_u[n] - q_i||^2 + H^2) \leq (||q_u[n] - q_j||^2 + H^2), \tag{3.8}$$

where Constraint (3.5) sets $\alpha_{ij}[n]$ to binary. Constraint (3.6) ensures that the signal of device i is not considered interference when decoding the user message. (3.7) ensures that for any two users, one user only is considered a strong user at any time instant when its channel gain is higher than the second user. (3.8) guarantees that $\alpha_{ij}[n]$ is set to 0 if $d_i^u[n] > d_j^u[n]$ and 1 otherwise. Moreover, a binary variable Γ_{ij}^n is introduced to determine if IoT devices i and j are scheduled at time slot n. At each time slot n, we pair one user with a high channel gain with another user with a weak channel gain, so Constraint (3.9) is added to ensure a maximum of two users scheduled at the same time slot as follows:

$$\sum_{i,j \in \mathcal{M}, i \neq j} \Gamma_{ij}^n \leq 1 \quad \forall n \in N \tag{3.9}$$

Accordingly, the data rate of user i scheduled at time slot n in bps/Hz is given by:

$$R_i[n] = log_2 \left(1 + \frac{P_i[n]\lambda_i[n]}{\sum_{j=1}^{M} \alpha_{ij}[n]\Gamma_{ij}^n \lambda_j[n] P_j[n] + 1} \right) \tag{3.10}$$

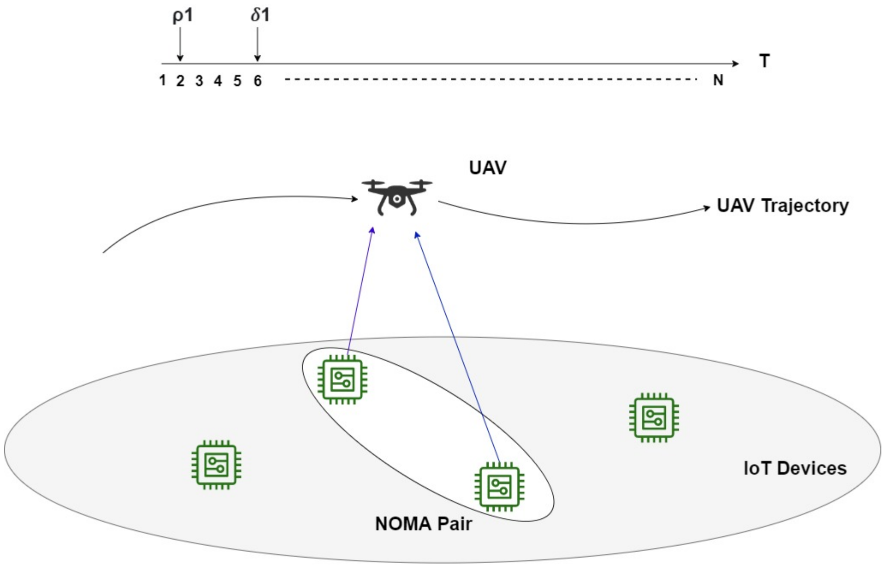


Figure 4: System model: A NOMA pair (2 IoT-devices) transmit to the UAV using the same resources at the same time slot.

where $\lambda_i[n] = (h_i[n]/N_0)$ is the normalized channel gain, N_0 is the noise power and $\sum_{j=1}^{M} \alpha_{ij}[n]\Gamma_{ij}^n h_j[n]P_j[n]$ is the interference from the IoT device with a weaker channel gain that is scheduled at the same time slot n.

Moreover, to ensure effective SIC at the UAV the following power constraint should be satisfied:

$$\Gamma_{ij}^n \left(\frac{P_i[n]\lambda_i[n]}{\alpha_{ij}[n]P_j[n]\lambda_j[n]} \right) \geq \eta \Gamma_{ij}^n \quad \forall i, j \in \mathcal{M}, \forall n \in N \tag{3.11}$$

where η is the minimum power difference required to distinguish between the different users [25].

The service amount S_i in bits/Hz of an IoT device i over the flight trajectory of the UAV is expressed as:

$$S_i = \delta_t \sum_{n=1}^{N} s_i^n \quad \forall i \in \mathcal{M} \tag{3.12}$$

where:

$$s_i^n = \begin{cases} R_i[n] & \text{if } \rho_i \leq n \leq \delta_i. \\ 0, & \text{otherwise.} \quad \forall n \in \mathbb{N}, \forall i \in \mathcal{M} \end{cases} \tag{3.13}$$

We also introduce a binary variable κ_i that indicates if IoT device i was served during the flight time of the UAV. Therefore, the following constraints should be satisfied for κ_i:

$$\kappa_i > \frac{S_i - S_i^{min}}{S_g}, \forall i \in \mathcal{M} \tag{3.14}$$

$$\kappa_i \leq 1 + \frac{S_i - S_i^{min}}{S_g}, \forall i \in \mathcal{M} \tag{3.15}$$

where S_i^{min} is the minimum amount of data that needs to be uploaded by IoT device i (bits/Hz), and S_g is a large constant to ensure the validity of the equations.

Following [23], the power consumed by a rotary wing UAV at time slot n and speed $v_u[n]$ is expressed as:

$$P(v_u[n]) = c_1 \left(1 + \frac{3||v_u[n]||^2}{W_{tip}^2}\right) + P_{hv} \left(\sqrt{1 + \frac{||v_u[n]^4||}{4v_0^4}} - \frac{||v_u[n]^2||}{2v_0^2}\right)^{\frac{1}{2}} + \frac{1}{2} d_0 A s \zeta ||v_u[n]||^3 \tag{3.16}$$

where $v_u[n]$ is the speed of the UAV at time slot n. c_1 represents the blade profile power and P_{hv} is the induced power while UAV is hovering. W_{tip} is the rotator blade tip speed, d_0 is the fuselage drag ratio, v_0 is the mean rotor-induced velocity in hover, A is rotor disc area, ζ is the air density, and s is the rotor solidity. Therefore, the total energy consumed during the UAV flight can be estimated as follows:

$$E_{trj} = \sum_{n=1}^{N} \delta_t P(v_u[n]) \tag{3.17}$$

Accordingly, we formulate the problem as maximizing the number of served IoT devices by optimizing the trajectory of the UAV, the pairing of the IoT devices, scheduling of the IoT devices, and the power allocation, while limiting the total energy consumed by the UAV to a limited energy budget. The NOMA-aided UAV data collection problem $\mathcal{P}$ can then be formulated as:

$$\mathcal{P}: \quad \max_{q_u[n],\Gamma_{ij}^n,P_i[n]} \quad \sum_{i\in\mathcal{M}} \kappa_i \tag{3.18a}$$

subject to:

$$E_{trj} \leq E_{max} \tag{3.18b}$$

$$\sum_{i,j\in\mathcal{M},i\neq j} \Gamma_{ij}^n \leq 1 \quad \forall n \in N \tag{3.18c}$$

$$(3.2), (3.5), (3.6), (3.7), (3.8), (3.11), (3.14), (3.15) \tag{3.18d}$$

$$\kappa_i, \Gamma_{ij}^n \in \{0, 1\}, \forall i \ \forall n \tag{3.18e}$$

where (3.18a) is the objective function that aims at maximizing the number of served IoT-devices. Constraint (3.18b) guarantees that the energy consumed by the UAV is less than its available energy E_{max}. (3.18c) ensures that at each time slot there is a pairing of two different users. (3.18e) sets the variables to binary. Note that the formulated problem ($\mathcal{P}$) is a mixed integer non-convex problem due to the constraints (3.11), (3.14), (3.15), and (3.18b). Hence, it is hard to be solved optimally and we resort to DRL to determine the solution.

3.3 Proposed Solution

Given the complexity of $\mathcal{P}$, we divide it into two subproblems: 1) UAV trajectory and IoT devices scheduling subproblem, and 2) power allocation subproblem.

3.3.1 UAV Trajectory and IoT Devices Scheduling Subproblem

We formulate the first subproblem as a Markov Decision Process (MDP) denoted by a tuple $\langle \mathcal{S}, \mathcal{A}, \gamma, \mathcal{R}, \mathcal{T} \rangle$ where :

- $\mathcal{S}$ is the state space where s_n is the state of the agent at time slot n. The state is a vector that includes the current position of the UAV q_u, the position of the IoT devices q_i, the deadline γ_i of the IoT devices, the amount of consumed energy, the total available energy of the UAV E_{max}, and the percentage of service for each IoT device ($\frac{S_i}{S_i^{min}} * 100$).

- $\mathcal{A}$ is the action space, and $a_n \in \mathcal{A}$ is the action taken by the agent at time slot n. In our problem, the action is the trajectory of the UAV where the UAV can move forward, backward, to the left, to the right, or hover in its current position. The agent also selects the first IoT device in the pair to be served at each time slot, and the speed of the UAV where we discretize the speed into different values.

- γ is the discount factor ($0 \leq \gamma \leq 1$).

- $\mathcal{R}$ is the discounted reward function where the agent receives a step reward of 1 whenever a device is served. $\mathcal{R}$ is defined as $\mathcal{R} = \sum_{n=1}^{N} \gamma^{n-1} r^n$, where r^n is the step reward at time slot n.

- $\mathcal{T}$ is the state transition probabilities. It denotes the probability of the agent taking an action a in a state s and moving to a state s', $Pr(s_{n+1} = s' \mid s_n = s, a_n = a)$.

For DRL, we use proximal policy optimization (PPO) to develop our agent and learn the UAV trajectory and the scheduling of the first IoT device as shown in Algorithm 1. In PPO, the agent first initializes random sampling policy π and value function. Then for each iteration, the agent observes the state at each time slot n and selects an action a_n. Next, we move the UAV if there is enough available energy and if it stays inside the area of interest. Based on the agent action, a list of devices with low channel gain is formed and the one with the most urgent data is selected (Algorithm 2). The latter criterion is based on the remaining data required by the device ($S^i_{min} - S_i$) divided by the remaining time

Algorithm 1 Proximal Policy Optimization Proposed Solution

Input: N, Learning Rate,γ,ϵ, Adam Optimizer Parameters, NOMA Parameters.

Output: UAV Trajectory and IoT Devices Scheduling.

Initialize sampling policy π with random parameter θ
Initialize value function with random parameter ϕ
for *Iteration = 0,1,...* **do**
  while $n < N$ **do**
    Observe a State s_n.
    Select the first IoT device to serve, the trajectory and the speed of the UAV a_n.
    Check available energy.
    if UAV outside the allowed area **then**
      Cancel the movement of the UAV.
    end if
    SecondIoTDevice = Algorithm2()
    Perform power Allocation for the selected devices.
    Compute the reward r^n.
  end while
  Compute the advantage estimate for all epochs.
  Use ADAM optimizer to optimize the surrogate loss function.
  Update policy: $\pi_{\theta_{old}} \leftarrow \pi_\theta$
end for

Algorithm 2 Second Device Selection

Input: M, λ, S, S_{min}, ρ α, δ, CurrentTimeSlot

Output: SecondIoT

Initialize SecondIoT $\leftarrow$ *-1, temp* $\leftarrow$ *0*
$arr, idx \leftarrow$ Sort all IoT devices and their indices in the descending order of λ.
for $i \in idx[M/2.....M]$ **do**
  if $S_i < S^i_{min}$ **and** $\rho_i \leq$ *CurrentTimeSlot* $< \delta_i$ **then**
    $Curr = (S^i_{min} - S_i)/(\delta_i - \textit{CurrentTimeSlot})$.
    if Curr $>$ temp **then**
      $temp = Curr$
      $SecondIoT = i$
    end if
  end if
end for

in which the device is active ($\delta_i -$ current time step t). After the selection of the two devices, power allocation is performed as presented in the second subproblem. The reward is calculated at the end of each time slot. If the service amount of a selected device exceeds the minimum amount of data, a positive reward of 1 is given. Finally, PPO computes the estimated advantage function and optimizes the surrogate loss function (via Adam optimizer).

3.3.2 Power Allocation Subproblem

Let R_s and R_w be the data rates of the strong/near user and the weak/far user, respectively. Given the current position of the UAV and the two selected IoT devices at each time slot (from the previous subproblem), this subproblem determines the channel gain at the current time slot and performs power allocation to maximize the sum rates of the two users and achieve the most gain, given the maximum transmit power constraints for the IoT devices and the effective SIC constraint. Therefore, we formulate the problem as follows:

$$\max_{P_s, P_w} \quad R_s + R_w \tag{3.19}$$

subject to:

$$P_s \lambda_s / (P_w \lambda_w) \geq \eta$$

$$P_s \leq P_{max}$$

$$P_w \leq P_{max}$$

Equation (3.19) can be rewritten as:

$$\begin{aligned} R_s + R_w &= log_2\left(1 + \frac{P_s \lambda_s}{P_w \lambda_w + 1}\right) + log_2(1 + P_w \lambda_w) \\ &= log_2(P_w \lambda_w + 1 + P_s \lambda_s) - log_2(P_w \lambda_w + 1) + log_2(1 + P_w \lambda_w) \\ &= log_2(P_w \lambda_w + P_s \lambda_s + 1) \end{aligned} \tag{3.20}$$

Maximizing (3.20) is equivalent to maximizing the sum of the powers of the strong user and the weak user. Therefore, we can rewrite (3.19) as follows:

$$\max_{P_s, P_w} \quad P_s + P_w \tag{3.21}$$

subject to:

$$P_s \lambda_s \geq \eta P_w \lambda_w$$

$$P_s \leq P_{total}$$

$$P_w \leq P_{total}$$

The obtained problem (3.21) is a linear problem, so we use Python *revised simplex* method to solve this problem.

3.4 Performance Results and Analysis

In this section, we study the performance of our solution approach under various circumstances and compare it with 4 baseline methods. In our simulations, we consider 15 IoT devices that are randomly distributed. The total number of time slots is 90 with each time slot set to 1. For the UAV, it flies at a fixed altitude of 100 meters with a maximum speed of 50 m/s. Since the agent selects the speed of the UAV, the values are discretized to [0, 30, 50] m/s. Further, the parameters used for the energy consumption model of the UAV are present in table 3.1 [29]. For the wireless channel, we set $\beta_0 = -50$ dB, $N_0 = -110$ dBm/hz, and $\eta = 5$ dB. For the DRL, we use 3 layers with the activation functions *Tanh* and *Softmax*. The number of variables in the hidden layer is 64 and *Adam* optimizer is used to minimize the loss function. The learning rate is set to 0.002, $\gamma = 0.99$, and the clip parameter is 0.2. The remaining parameters are presented in each subsection of the results. Moreover, all the simulation results are generated using Python and PyTorch and they are averaged over 100 data samples to ensure consistency.

For the training of the DRL agent, we consider a geographical area of size

Parameter	Value
UAV Max Speed (V_{max})	50 m/s
Blade Profile Power (c_1)	79.86
Induced Power while Hovering (P_{hv})	88.63
Rotor Blade tip Speed (W_{tip})	120
Fuselage Drag Ratio (d_0)	0.6
Mean Rotor Induced Velocity in Hover (v_0)	4.03
Rotor Disc Area (A)	0.503
Air Density (ζ)	1.225
Rotor Solidity (s)	0.05

Table 3.1: UAV energy parameters

$1.5 \times 1.5\ km^2$ where the IoT devices are randomly distributed. The available energy of the UAV is set to 20 Kilo-joules (kJ), and the minimum amount of data required by the IoT devices is 10 bits/Hz. The initial location of the UAV is set to the center of the considered area.

As shown in figure 5. the cumulative reward (number of served IoT devices) increases with the increase of the number of iterations and it starts to converge before reaching 1000 iterations. At the beginning of the learning, the agent wastes resources by moving the UAV randomly and depleting the available energy, while the IoT devices are not properly scheduled. With training, the number of served devices increases (reward increases), which indicates that the agent starts adapting to the randomness in the release time of the IoT devices and learns how to move the UAV given the deadline constraints of the IoT devices, the effective SIC constraints, and the UAV available energy.

To validate the performance of our proposed solution, we develop four methods to compare with:

- *Orthogonal Multiple Access (OMA)*: we use DRL with time division multiple access to determine the trajectory of the UAV and the selection of one IoT device only.

- *NOMA Stationary UAV*: The UAV is placed at the center of the area, and DRL is used to select the devices in the NOMA cluster at each time slot.

Algorithm 3 NOMA Greedy Algorithms

Input: $q_u[0]$, V_{max}, q_i, S_i^{min},ρ_i, δ_i, E_{max}, NOMA parameters

Output: UAV Trajectory and Served IoT Devices

for $t = 0, 1, ..., T$ **do**
  if Energy Consumed $> E_{max}$ **then**
    return
  end if
  Deadline-based approach: Sort all IoT devices in the increasing order of their deadline.
  Distance-based approach: Sort all IoT devices in the increasing order of their distance.
  if No IoT devices are active at time t **then**
    Move the UAV to the IoT device that will first become active.
    Update energy consumed
  else
    Deadline-based approach: Select the first active IoT device with the shortest deadline.
    Distance-based approach: Select the first active IoT device with the shortest distance to the UAV.
    Update location of the UAV.
    Update energy consumed.
    SecondIoTDevice = Algorithm2()
    Perform power allocation for the selected devices.
    Update service amount of the selected devices.
  end if
end for

- *NOMA Greedy Distance*: The UAV moves to and selects the closest IoT device in each time slot as shown in Algorithm 3.
- *NOMA Greedy Deadline*: The UAV moves to and selects the devices with the shortest deadline in each time slot as shown in Algorithm 3.

3.4.1 Effect of the Area Size

In figure 6, the UAV available energy is 30 kJ, the maximum transmit power of the IoT devices is 1 mW, and the minimum amount of required data $S_i^{min} = 10$ bits/Hz for all the devices. We compare the number of served IoT devices using

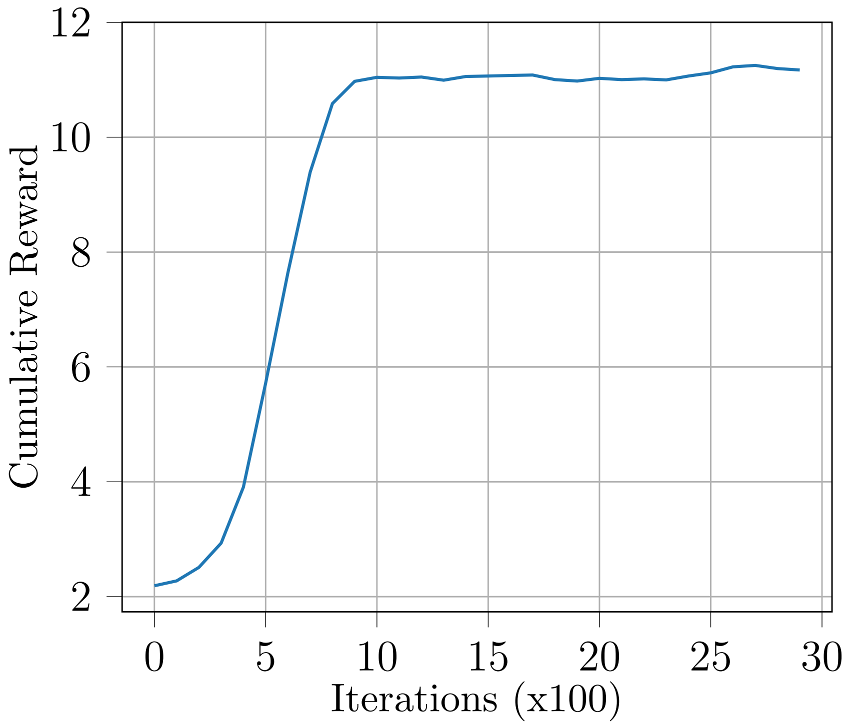


Figure 5: DRL convergence.

each approach while varying the size of the considered area. Accordingly, the increase in the size of the area leads to a decrease in the number of served devices for all the approaches. However, our proposed solution (NOMA with mobile UAV) provides better performance compared to the other approaches for all the considered test cases. Compared to NOMA with stationary UAV, our method yields an increase in performance by 1 to 2 served devices. The gain compared to OMA is clear, where an increase in 2 to 3 served devices is present. Moreover, the advantages of using DRL for UAV trajectory and selection of IoT devices are present compared to the greedy approaches, where our algorithm serves 6 to 7 more devices compared to the greedy distance and greedy deadline when the size of the area is between 500×500 m^2 and 2×2 km^2. This is mainly because greedy methods waste the UAV available energy and have a bad scheduling of the IoT devices. However, the greedy approach based on the distance performs better than the one based on the deadline, because the selection of the IoT devices that are closer to the UAV results in higher data rates. Further, with a small area size ($< 1.5 \times 1.5$ km^2), the performance of stationary UAV with NOMA is better

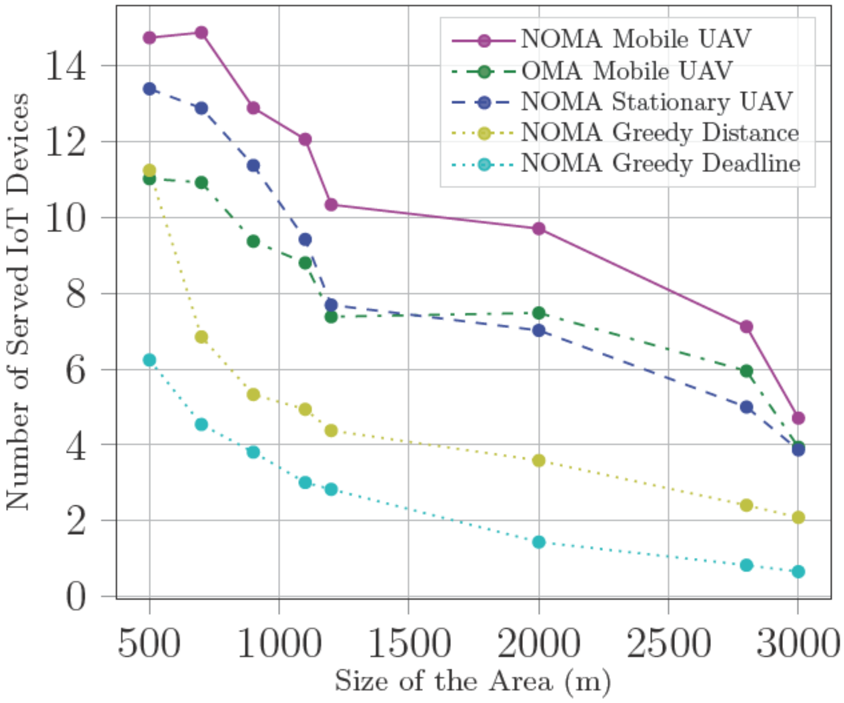


Figure 6: Effect of the area size.

than that of mobile UAV with OMA; however, with the increase in the size of the area, OMA becomes better due to the mobility of the UAV. For the very large areas the difference in performance becomes negligible for all the methods due to the lack of available resources (UAV energy) and the deadline constraints of the IoT devices.

3.4.2 Effect of the UAV Available Energy

In figure 7, the IoT devices are distributed in an area of size 1000×1000 m^2 with their maximum transmit power set to 1 mW and S_i^{min} set to 15 bits/Hz. We examine the effect of the UAV available energy on the performance (number of served devices) of each algorithm. In general, the increase in the UAV available energy yields better gain for all the approaches used, because the UAV has more resources to serve more devices. First, we notice that with low available energy, the performance of OMA is slightly better than NOMA, mainly because with OMA only 1 device is being served, so no interference is present and the data rate of the selected IoT device is high, thus less time is required to serve this

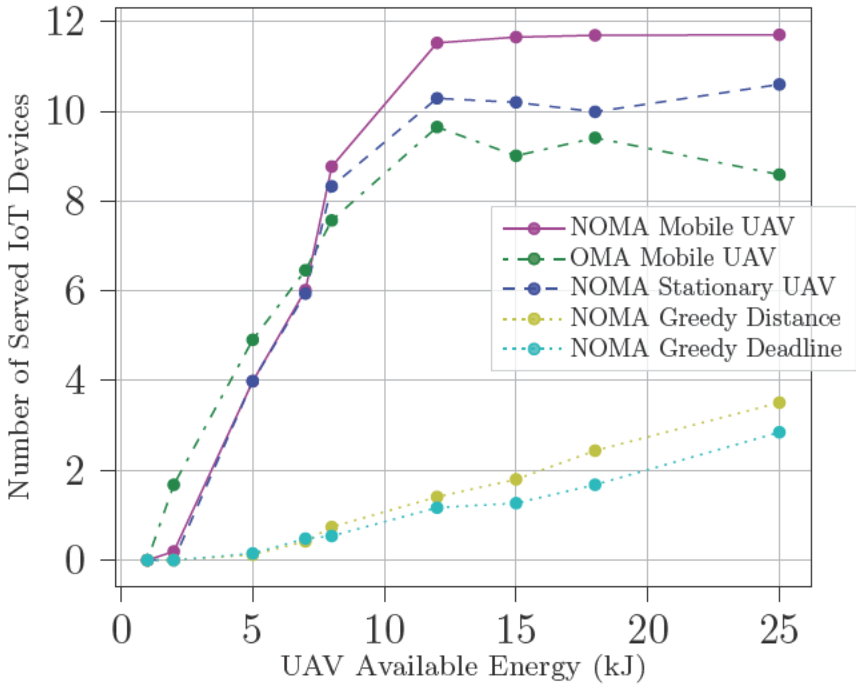


Figure 7: Effect of UAV available energy.

device. However, with enough energy ($E_{max} \geq 8$ kJ) the performance of NOMA with stationary UAV or mobile UAV outperforms that of OMA, where mobile UAV with NOMA achieves a gain of 2 to 3 served devices compared to OMA. We also observe that our method achieves higher performance gain compared to the greedy methods (6 to 7 more devices are served using our proposed algorithm when $E_{max} = 25$ kJ) because the greedy approaches are somehow unaware of the objective of maximizing the total number of served devices. Further, figure 7 shows that the distance-based greedy method achieves better performance than the deadline-based greedy method because in the deadline-based method the UAV wastes more time and energy to fly to the IoT devices with strict deadlines.

3.4.3 Effect of the Maximum Transmit Power of the IoT Devices

In figure 8, we consider an 1.8×1.8 km^2 area with UAV available energy set to 30 kJ and the minimum amount of required data for the IoT devices $S_i^{min} = 30$ bits/Hz. First, we observe that increasing the maximum transmit power of the

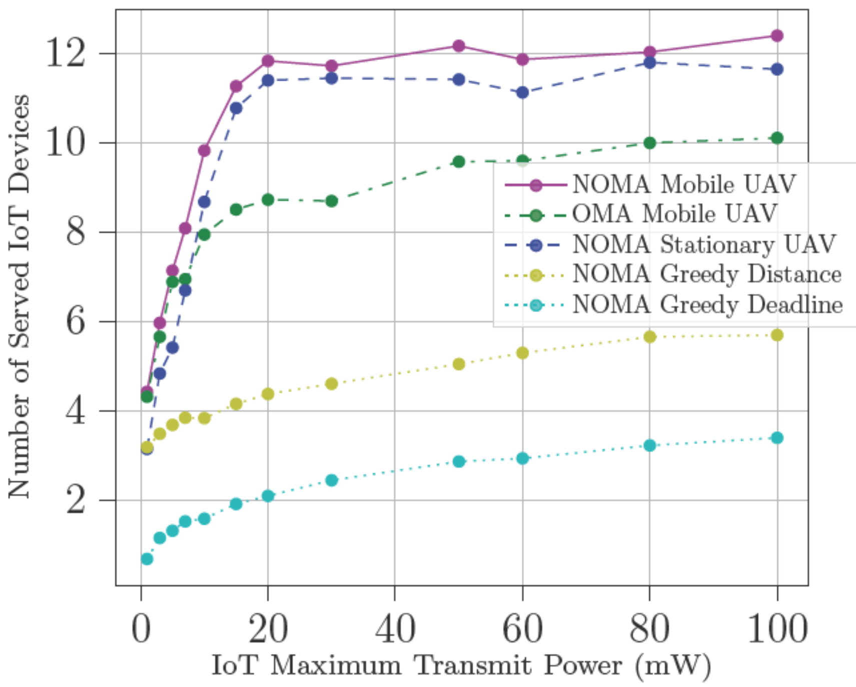


Figure 8: Effect of IoT devices maximum transmit power.

IoT devices helps in improving the performance of all the approaches because more resources are available to the IoT devices. Moreover, we notice that the performance difference between NOMA stationary UAV and NOMA mobile UAV is similar; however, compared to time division multiple access, NOMA has a gain of 2 to 3 served devices with enough transmit power. Furthermore, using NOMA with DRL for UAV trajectory yields a 3× performance gain compared to the trajectory based on distance (NOMA Greedy Distance) and a 6× gain compared to the one based on the deadline of IoT devices (NOMA Greedy Deadline). Our proposed algorithm achieves 20% to 30% gain (with enough transmit power) compared to OMA. Moreover, using DRL to determine the UAV trajectory and selection of the first IoT device leads to a significant improvement compared to the greedy heuristics.

3.5 Conclusion

This chapter studied uplink NOMA for UAV data collection from time-constrained IoT devices. The problem is formulated as an optimization problem for maximizing the number of served devices, but due to its complexity, we used DRL to determine the trajectory of the UAV and the selection of the first IoT devices in the NOMA cluster. The second IoT device is selected based on prioritizing devices with higher bit rate requirements to upload their data before it expires. Power allocation is then optimized to maximize the sum rate of the selected IoT devices. Simulation results show the advantages of our proposed method against four alternative methods. Mainly, NOMA achieves an improvement of $10\% - 30\%$ more served devices compared to OMA. Future works can investigate using multiple UAVs and planing their trajectories to avoid collisions and maximize the number of served IoT devices. Further, future work can also consider pairing more than 2 devices in one NOMA cluster.

Chapter Four

UAV Assisted Joint Transmission in Uplink NOMA Systems

4.1 Introduction

Non-orthogonal multiple access (NOMA) is regarded as one of the enabling technologies in the next generation networks. Compared to orthogonal multiple access (OMA) techniques, in NOMA multiple users or IoT devices transmit their data at the same time using the same resources by varying the transmit power of these devices. In particular, the users use different power levels to transmit to the receiver at the same time using the same resources, then successive interference cancellation is done at the receivers side to decode these signals [30]. Therefore in NOMA we have an improved spectral efficiency, improved fairness between the users (especially users with weak channels), and massive connectivity compared to OMA [31]. However, the drawbacks of using NOMA is the interference from the other devices within the same NOMA cluster, and the increasing complexity of SIC with the increase of the number of devices to serve [32]. A good candidate to overcome the previous challenges is using joint transmission coordinated multi-point transmission (JT-CoMP) scheme with the NOMA scheme where IoT devices can transmit to multiple UAVs, simultaneously. CoMP scheme was first proposed as an improvement for LTE-A [33], and it can enhance the channel of the cell edge users and increase the cell coverage. Therefore, with such scheme, the users in the network can be divided into cell center users and cell edge users, where the cell edge users (users with weak channel) transmit to more than one base station or unmanned aerial vehicles (UAVs) mounted base stations. At the receiver side, coordination is performed to improve the signal from cell edge users.

Moreover, UAVs have different application and use cases in the literature to aid the current networks and to provide services in areas that lack infrastructure such as forests and remote areas. The flexibility of the UAVs and their ease of deployment can improve the wireless connectivity and improve the channel of users with weak channel; UAVs can also be used to collect data from IoT devices and to relay data between far away targets [5] [34]. All these test cases emphasize the importance of integrating UAVs with the current and future networks. However, UAVs are subject to different constraints (such as movement and energy constraints) that should be taken into consideration.

4.1.1 Related Literature

Recent literature addressed different use cases where a NOMA aided UAV is used to provide different services for users (or IoT devices). The authors in [35], optimize the location of the UAV and power allocation in the NOMA cluster to improve the performance of the NOMA aided UAV networks. Similarly, in [36], the authors propose using NOMA to increase the capability of accommodating users in a network. They use a UAV to assist the base station and they formulate the problem as maximizing the sum rate by jointly optimizing the trajectory of the UAV and the NOMA decoding order. In [37], a multi-UAV system is considered to serve IoT devices via uplink NOMA; the height of the UAVs, the IoT devices transmit power and subchannel assignments are optimized in order to maximize the system capacity. And, the authors in [38] analyse the performance of NOMA with an imperfect channel state information between the UAV and the users; they optimize the scheduling of the users and power allocation to maximize the energy efficiency.

Moreover, integrating CoMP transmissions with NOMA is also being researched to improve the performance of traditional NOMA techniques. The authors in [39], utilize JT-CoMP NOMA transmissions to help the users with high channel gain in a multiple base stations network, mainly because these users experience high inter cell interference. On the other hand, in [40] the authors utilize CoMP transmissions with cooperative NOMA to improve the channel of the cell edge users because these users has a low channel quality with respect to the base station (due to the large distance between them). In [41], a novel NOMA scheme is proposed using JT-CoMP NOMA following an opportunistic strategy. Compared to traditional JT-CoMP NOMA scheme, it achieves higher capacity and reduces the superposition coding (SC) decoding complexity under high signal to interference scenarios. Moreover, in [42], the authors deploy a UAV in a two cell system where one of the cells is damaged. The UAV position is optimized to reduce the interference by leveraging the interference cancellation techniques in CoMP NOMA. Further, in [43], the authors study the performance of JT-CoMP uplink NOMA in a two cell network where the cell edge users transmit to both base stations simultaneously. They aim to minimize the total transmit power by optimizing the precoding scheme power allocation subject to the signal to interference plus noise ratio. A similar system model was considered in [44], where JT-CoMP NOMA and intelligent reflecting surfaces (IRS) are used to improve the performance of the cell edge user. A joint power allocation and phase shift optimization problem is formulated to minimize the uplink power. Furthermore, the authors in [45], consider a multiple base station scenario where each base station serves a near user then all the base stations collaborate to serve a far user via CoMP NOMA. A stochastic geometry approach is presented to gain insights on the outage probabilities and ergodic rates.

All these scenarios and use cases highlight the importance of CoMP, NOMA, and UAVs in the next generation networks and for the scenarios with a large number of IoT devices. Therefore, in this chapter, we consider two UAVs deployed to serve IoT devices in a network. The devices with strong channel leverage NOMA only, meanwhile the devices with weak channel leverage JT-CoMP NOMA to transmit to both UAVs. We formulate the problem as maximizing the sum rate of the IoT devices by optimizing the positioning of the UAVs and power allocation in the NOMA clusters given the constraints of the IoT devices, UAVs constraints, and NOMA constraints.

4.1.2 Contributions

Existing work on JT-CoMP NOMA mainly addressed use cases with a terrestrial base station or with downlink transmissions. However, the problem of UAV assisted JT-CoMP uplink NOMA transmissions from IoT devices with target data rate constraints remains uncovered in the literature. Therefore, the main contributions of this chapter can be summarized as follows:

- We consider a new scenario where two UAVs are deployed to serve constrained IoT devices. We formulate the problem as maximizing the sum rate of the devices by optimizing the positioning of the UAVs and the transmit power of the IoT devices.
- Given the complexity of the obtained problem, we leverage alternating optimization to handle it, where the original optimization problem is divided into UAV positioning subproblem and power allocation subproblem, then we alternate between them to improve the performance. For each subproblem, we use successive convex approximation to generate a solution.
- We highlight the performance of our solution approach by varying the system parameters and comparing with baseline methods.

The rest of this chapter is organized as follows. Section 4.2, we presents the system model of our problem and the problem formulation, followed by the proposed solution approach in section 4.3 and the analysis of the performance in section 4.4. Finally, we present our concluding remarks in section 4.5.

4.2 System Model and Problem Formulation

As shown in figure 9, we examine uplink non-orthogonal multiple access with joint-transmission coordinated multi-point (JT-CoMP) in a UAV-assisted network. In particular, we consider two UAVs, two near IoT devices and one far IoT device, where the UAVs are deployed to ensure that these devices achieve a minimum required data rate. The near IoT devices send their data only to one UAV closest to these devices, on the other hand, the far IoT device sends data to both UAVs simultaneously through JT-CoMP NOMA transmission. The three devices utilize NOMA to send their data to the UAV using the same resources at the same time; then, at each UAV, the signals are decoded and removed from the overall signal in the descending order of the channel gain using successive interference cancellation (SIC) technique.

We denote by $\mathcal{U} = \{1, 2\}$ the indices of the UAVs and $\mathcal{M} = \{1, 2, 3\}$ the indices of the IoT devices. $Q_u = (x_u, y_u)$ represents the planar position of the UAV u, $q_i = (x_i, y_i)$ denotes the position of the IoT device i, and P_i is the transmit power of IoT device i. We denote by X and Y the size of the area considered, and we assume that the UAVs fly at a fixed altitude H that allows a clear line of sight with the IoT devices. The distance between a UAV u and IoT device i can be expressed as:

$$d_{i,u} = \sqrt{H^2 + ||Q_u - q_i||^2} \quad \forall i \in \mathcal{M}, \forall u \in \mathcal{U} \tag{4.1}$$

Moreover, the channel gain at IoT device i, following the free space model, is:

$$h_{i,u} = \frac{\beta_0}{d_{i,u}^2} \quad \forall u \in \mathcal{U} \tag{4.2}$$

where β_0 is the channel gain at reference distance $d_0 = 1$ m. Accordingly, the received signal at UAV u from the IoT devices is:

$$y_u = \sum_{i=1,}^{M} h_{i,u}\sqrt{P_i}x_i + N_0 \tag{4.3}$$

where x_i is the signal from the IoT device i and N_0 is the additive white Gaussian noise.

Then we introduce the following binary variables that indicate to which UAV the IoT devices are connected, and to indicate if the devices have a strong channel gain or a weak channel gain. First we introduce a binary variable α_i^u that indicates if a device i is connected to UAV u. Accordingly, the following constraints are introduced:

$$\alpha_i^u \in \{0, 1\} \quad \forall i \forall u \tag{4.4}$$

$$\sum_{i}^{\mathcal{M}} \alpha_i^u = 2, \quad \forall u \in \mathcal{U} \tag{4.5}$$

$$1 \leq \sum_{u}^{\mathcal{U}} \alpha_i^u \leq 2 \quad \forall i \in \mathcal{M} \tag{4.6}$$

where (4.5) ensures that each UAV has two devices connected to it; and (4.6) ensures that each device should be connected to at least one UAV or a maximum of two UAVs (for the case of joint transmission).

Moreover, we use a binary variable β_i^u that indicates if device i has a strong channel with respect to UAV u. Accordingly:

$$\beta_i^u \in \{0, 1\} \quad \forall i \forall u \tag{4.7}$$

$$\beta_i^u \leq \alpha_i^u \tag{4.8}$$

$$\sum_{u} \alpha_i^u \beta_i^u \leq 1 \tag{4.9}$$

$$\alpha_i^u \geq 1 - \sum_{u} \beta_i^u \quad \forall i \in \mathcal{M}, \forall u \in \mathcal{U} \tag{4.10}$$

$$\sum_{i} \beta_i^u = 1 \quad \forall u \in \mathcal{U} \tag{4.11}$$

$$d_{i,u}\beta_i^u \leq d_{j,u} \quad \forall j \in \mathcal{M}, j \neq i \tag{4.12}$$

where constraint (4.7) sets the variable β_i^u to binary, (4.8) ensures that devices that are not connected to the UAV can not be considered strong devices. Constraint (4.9) ensures that if IoT device i is a strong user with UAV u, it cannot be associated with other UAVs. (4.10) guarantees that the user with weak channel should connect to both UAVs. Constraint (4.11) guarantees that only one UAV can only have one strong user, and (4.12) ensures that the device closest to the UAV is considered the strong user (i.e. the user with high channel gain).

Note that the UAVs decode the signal from the near users first that will suffer from interference form the other devices. Then, for the far user, the UAV decodes and removes the signal from the IoT devices closest to them. Then maximum ratio combining (MRC) is used to process the signal to both UAVs from the far device. Therefore the data rate of a user i can be expressed as:

$$R_i = \log\left(1 + \sum_{u} \alpha_{i,u} \frac{P_i \lambda_{i,u}}{\sum_{j=1, i\neq j}^{\mathcal{M}} (1 - \beta_j^u) P_j \lambda_{j,u} + 1}\right) \tag{4.13}$$

where $\lambda_{i,u} = (h_{i,u}/N_0)$ is the normalized channel gain. Therefore, in Fig 9, the data rate of user 1 connected to UAV 1 and has a strong channel is:

$$R_1 = \log\left(1 + \frac{P_1 \lambda_{1,1}}{\lambda_{2,1} P_2 + \lambda_{3,1} P_3 + 1}\right) \tag{4.14}$$

Similarly, the data rate of IoT device 3 connected to UAV 2 (and has a strong channel) is:

$$R_3 = \log\left(1 + \frac{P_3 \lambda_{3,2}}{\lambda_{2,2} P_2 + \lambda_{1,2} P_1 + 1}\right) \tag{4.15}$$

Then, for IoT device 2 the data rate can be expressed as:

$$R_2 = \log\left(1 + \frac{P_2 \lambda_{2,1}}{P_3 \lambda_{3,1} + 1} + \frac{P_2 \lambda_{2,2}}{P_1 \lambda_{1,2} + 1}\right) \tag{4.16}$$

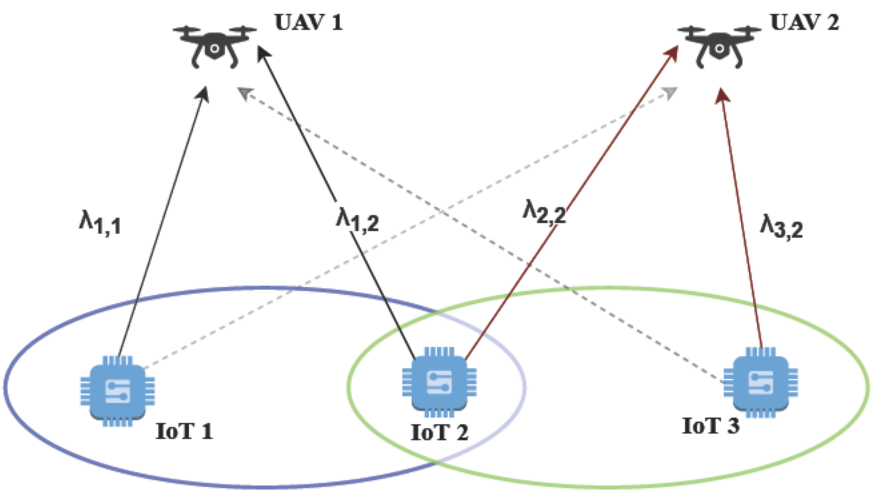


Figure 9: System model: JT-CoMP NOMA.

Then we formulate the problem as maximizing the sum of the data rates of the IoT devices by optimizing the position of the UAVs, and the transmit power of the IoT devices. The problem $\mathcal{P}$ can then be formulated as:

$$\mathcal{P}: \quad \max_{P_i, q_u} \quad \sum_i R_i \tag{4.17a}$$

subject to

$$0 \leq P_i \leq P_{max} \quad \forall i \in \mathcal{M} \tag{4.17b}$$

$$0 \leq x_u \leq X \quad \forall u \in \mathcal{U} \tag{4.17c}$$

$$0 \leq y_u \leq Y \quad \forall u \in \mathcal{U} \tag{4.17d}$$

$$(4.5), (4.6), (4.8), (4.9), (4.10), (4.11), (4.12) \tag{4.17e}$$

$$R_i \geq R_i^{min} \quad \forall i \in \mathcal{M} \tag{4.17f}$$

$$\alpha_i^u, \beta_i^u \in \{0, 1\} \quad \forall i, \forall u \tag{4.17g}$$

where Constraint (4.17b) ensures that the transmit power of all IoT devices is less than or equal the maximum transmit power. Constraints (4.17c) and (4.17d) guarantee that the UAVs are deployed within the area considered. And (4.17f) ensures the minimum rate required for each IoT device i. (4.17g) sets the variables to binary.

4.3 Proposed Solution

The obtained problem ($\mathcal{P}$) is mixed integer non linear (MINLP) which is NP hard and hence difficult to solve, therefore we divide the problem into two subproblems where in the first subproblem we determine the positioning of the UAVs using successive convex approximation (SCA), then in the second subproblem we determine the transmit power of the IoT devices using also SCA. Then we alternate between the two subproblem to improve the performance. Given the varying positions of the UAVs, there are three possibilities for determining which IoT device is considered weak. Therefore, to determine the best association, we compare these possibilities against each other and select the one that maximizes the performance.

4.3.1 UAV Positioning Subproblem

To solve the UAV positioning subproblem, we first solve the power allocation subproblem to get the initial transmit power of the IoT devices. Using these values, we get the UAVs positions, and then alternate between the two subproblems until convergence. So the UAV positioning subproblem can be formulated as maximizing the sum rate by optimizing the positions of the UAVs. However, we introduce a new variable μ_i to make the data rate a constraint and remove it from the objective. Hence the optimization problem for the UAV positioning subproblem is formulated as:

$$\mathcal{P}1: \quad \max_{Q_u} \quad \sum_i \mu i \tag{4.18a}$$

subject to

$$R_i \geq \mu_i \tag{4.18b}$$

$$0 \leq x_u \leq X \quad \forall u \in \mathcal{U} \tag{4.18c}$$

$$0 \leq y_u \leq Y \quad \forall u \in \mathcal{U} \tag{4.18d}$$

$$\mu_i \geq R_i^{min} \quad \forall i \in \mathcal{M} \tag{4.18e}$$

The data rate of the first strong IoT devices can be expressed as:

$$R_1 = \log\left(1 + \frac{P_1 \lambda_{1,1}}{\lambda_{2,1} P_2 + \lambda_{3,1} P_3 + 1}\right) \tag{4.19}$$

Therefore, we introduce new variables z_1 and $v1$, with the following constraints:

$$log(1 + e^{z_1 - v_1}) \geq \mu_1 \tag{4.20}$$

$$cP_1 \frac{1}{H^2 + ||Q_1 - q_1||^2} \geq e^{z_1} \tag{4.21}$$

$$cP_2 \frac{1}{H^2 + ||Q_1 - q_2||^2} + cP_3 \frac{1}{H^2 + ||Q_1 - q_3||^2} + 1 \leq e^{v_1} \tag{4.22}$$

where $c = \beta_0 / N_0$. Constraint (4.20) can the be rewritten as:

$$1 + e^{z_1 - v_1} \geq e^{\mu_1} \tag{4.23}$$

Then we use first order Taylor approximation to transform the constraint into a convex constraint:

$$1 + e^{\bar{z_1} - \bar{v_1}}(1 + z_1 - v_1 - \bar{z_1} + \bar{v_1}) \geq e^{\mu_1} \tag{4.24}$$

Similarly, we rewrite constraint (4.21) and use first order Taylor approximation as:

$$\frac{1}{cP_1}H^2 + \frac{1}{cP_1}||Q_1 - q_1||^2 \leq e^{-\bar{z}_1}(\bar{z}_1 - z_1 + 1) \tag{4.25}$$

Moreover, for constraint (4.22), we introduce new variables s and y as:

$$H^2 + ||Q_1 - q_2||^2 \geq s_{1,2} \tag{4.26}$$

$$H^2 + ||Q_1 - q_3||^2 \geq s_{1,3} \tag{4.27}$$

$$c\frac{P_2}{s_{1,2}} \leq y_{1,2} \tag{4.28}$$

$$c\frac{P_3}{s_{1,3}} \leq y_{1,3} \tag{4.29}$$

Hence constraint (4.22) can be replaced by:

$$1 + y_{1,2} + y_{1,3} \leq e^{v_1} \tag{4.30}$$

Moreover, constraints (4.28) and (4.29) can be replaced by the following constraints, respectively:

$$c(1 + P_2)^2 + (y_{1,2} - s_{1,2})^2 \leq c(1 - P_2)^2 + (y_{1,2} + s_{1,2})^2 \tag{4.31}$$

$$cP_3^2 + (y_{1,3} - s_{1,3})^2 \leq cP_3^2 + (y_{1,3} + s_{1,3})^2 \tag{4.32}$$

However constraints (4.26), (4.27), (4.31), (4.32), and (4.30) are still non convex, therefore we use first order Taylor approximation, accordingly:

$$H^2 + ||\bar{Q}_1 - q_2||^2 + 2(\bar{Q}_1 - q_2)^T(Q_1 - \bar{Q}_1) \geq s_{1,2} \tag{4.33}$$

$$H^2 + ||\bar{Q_1} - q_3||^2 + 2(\bar{Q_1} - q_3)^T(Q_1 - \bar{Q_1}) \geq s_{1,3} \tag{4.34}$$

$$c(1+P_2)^2 + (y_{1,2} - s_{1,2})^2 \leq c(1-P_2)^2 + 2(\bar{y_{1,2}} + \bar{s_{1,2}})(y_{1,2} + s_{1,2}) - (\bar{y_{1,2}} + \bar{s_{1,2}})^2 \tag{4.35}$$

$$cP_3^2 + (y_{1,3} - s_{1,3})^2 \leq cP_3^2 + 2(\bar{y_{1,3}} + \bar{s_{1,3}})(y_{1,3} + s_{1,3}) - (\bar{y_{1,3}} + \bar{s_{1,3}})^2 \tag{4.36}$$

$$1 + y_{1,2} + y_{1,3} \leq e^{\bar{v_1}}(v_1 - \bar{v_1} + 1) \tag{4.37}$$

Similarly, the data rate of the third IoT device can be expressed as:

$$R_3 = \log\left(1 + \frac{P_3\lambda_{3,2}}{\lambda_{2,2}P_2 + \lambda_{1,2}P_1 + 1}\right) \tag{4.38}$$

Then we introduce the following constraints:

$$log(1 + e^{z_2 - v_2}) \geq \mu_3 \tag{4.39}$$

$$cP_3\frac{1}{H^2 + ||Q_2 - q_3||^2} \geq e^{z_2} \tag{4.40}$$

$$cP_2\frac{1}{H^2 + ||Q_2 - q_2||^2} + cP_1\frac{1}{H^2 + ||Q_2 - q_1||^2} + 1 \leq e^{v_2} \tag{4.41}$$

Similar to the constraints of the first IoT device, the above constraints related to the third IoT device are convexified as follows:

$$1 + e^{\bar{z_2} - \bar{v_2}}(1 + z_2 - v_2 - \bar{z_2} + \bar{v_2}) \geq e^{\mu_3} \tag{4.42}$$

$$\frac{1}{cP_3}H^2 + \frac{1}{cP_3}||Q_2 - q_3||^2 \leq e^{-\bar{z_2}}(\bar{z_2} - z_2 + 1) \tag{4.43}$$

$$H^2 + ||\bar{Q_2} - q_2||^2 + 2(\bar{Q_2} - q_2)^T(Q_2 - \bar{Q_2}) \geq s_{2,2} \tag{4.44}$$

$$H^2 + ||\bar{Q_2} - q_1||^2 + 2(\bar{Q_2} - q_1)^T(Q_2 - \bar{Q_2}) \geq s_{2,1} \tag{4.45}$$

$$c(1+P_2)^2 + (y_{2,2} - s_{2,2})^2 \leq c(1-P_2)^2 + 2(\bar{y_{2,2}} + \bar{s_{2,2}})(y_{2,2} + s_{2,2}) - (\bar{y_{2,2}} + \bar{s_{2,2}})^2 \tag{4.46}$$

$$cP_3^2 + (y_{2,1} - s_{2,1})^2 \leq cP_3^2 + 2(\bar{y_{2,1}} + \bar{s_{2,1}})(y_{2,1} + s_{2,1}) - (\bar{y_{2,1}} + \bar{s_{2,1}})^2 \tag{4.47}$$

$$1 + y_{2,2} + y_{2,1} \leq e^{\bar{v_2}}(v_2 - \bar{v_2} + 1) \tag{4.48}$$

Now for the far IoT device that utilizes JT-CoMP uplink NOMA to transmit to both UAVs, the data rate can be expressed as:

$$R_2 = \log\left(1 + \frac{P_2\lambda_{2,1}}{P_3\lambda_{3,1} + 1} + \frac{P_2\lambda_{2,2}}{P_1\lambda_{1,2} + 1}\right) \tag{4.49}$$

Hence we introduce the following constraints:

$$1 + e^{z_3 - v_3} + e^{z_4 - v_4} \geq e^{\mu_2} \tag{4.50}$$

To transform this constraint into an convex constraint we perform first order Taylor approximation for the two terms $e^{z_3 - v_3}$ and $e^{z_4 - v_4}$:

$$1 + e^{\bar{z_3} - \bar{v_3}}(1 + z_3 - v_3 - \bar{z_3} + \bar{v_3}) + e^{\bar{z_4} - \bar{v_4}}(1 + z_4 - v_4 - \bar{z_4} + \bar{v_4}) \geq e^{\mu_2} \tag{4.51}$$

Then for the first term $e^{z_3 - v_3}$ we need the following constraints:

$$\frac{1}{cP_2}H^2 + \frac{1}{cP_2}||Q_1 - q_2||^2 \leq e^{-\bar{z_3}}(\bar{z_3} - z_3 + 1) \tag{4.52}$$

$$1 + y_{1,3} \leq e^{\bar{v_3}}(v_3 - \bar{v_3} + 1) \tag{4.53}$$

Similarly the following constraints are required for $e^{z_4 - v_4}$

$$\frac{1}{cP_2}H^2 + \frac{1}{cP_2}||Q_2 - q_2||^2 \leq e^{-\bar{z_4}}(\bar{z_4} - z_4 + 1) \tag{4.54}$$

$$1 + y_{1,2} \leq e^{\bar{v_4}}(v_4 - \bar{v_4} + 1) \tag{4.55}$$

Therefore, the UAV positioning subproblem can be rewritten as:

$$\mathcal{P}1: \quad \max_{z_i, v_i, Q_u, s, y} \quad \sum_i \mu i \tag{4.56a}$$

subject to

$$0 \leq x_u \leq X \quad \forall u \in \mathcal{U} \tag{4.56b}$$

$$0 \leq y_u \leq Y \quad \forall u \in \mathcal{U} \tag{4.56c}$$

$$\mu_i \geq R_i^{min} \quad \forall i \in \mathcal{M} \tag{4.56d}$$

$$(4.24), (4.25), (4.33), (4.34), (4.35), (4.36), (4.37), (4.42).$$

$$(4.43), (4.44), (4.45), (4.46), (4.47), (4.48), (4.51), (4.52).$$

$$(4.53), (4.54), (4.55).$$

4.3.2 Power Allocation Subproblem

Maximizing the sum rate of the IoT devices is non convex. Therefore we start by defining the following exponential slack variables for the users with strong channel:

$$e^{x_1} = \lambda_{2,1}P_2 + \lambda_{3,1}P_3 + 1 + P_1\lambda_{1,1} \tag{4.57}$$

$$e^{y_1} = \lambda_{2,1}P_2 + \lambda_{3,1}P_3 + 1 \tag{4.58}$$

$$e^{x_3} = \lambda_{2,2}P_2 + \lambda_{1,2}P_1 + 1 + P_3\lambda_{3,2} \tag{4.59}$$

$$e^{y_3} = \lambda_{2,2}P_2 + \lambda_{1,2}P_1 + 1 \tag{4.60}$$

As for the users with weak channel that transmits to both UAVs:

$$e^{x_2} = P_3P_1\lambda_{1,2}\lambda_{3,1} + P_3\lambda_{3,1} + P_1\lambda_{1,2} + 1 + P_2P_1\lambda_{1,2}\lambda_{2,1} + P_2\lambda_{2,1} + P_2P_3\lambda_{3,1}\lambda_{2,2} + P_2\lambda_{2,2} \tag{4.61}$$

$$e^{y_2} = P_3P_1\lambda_{1,2}\lambda_{3,1} + P_3\lambda_{3,1} + P_1\lambda_{1,2} + 1 \tag{4.62}$$

Equation (4.61) is non-convex due to the multiplication of the transmit powers of the users. Therefore, we introduce three auxiliary variables A, B, and C. Accordingly, the following constraints are introduced:

$$P_3P_1 \geq A^2 \tag{4.63}$$

$$P_2P_1 \geq B^2 \tag{4.64}$$

$$P_2P_3 \geq C^2 \tag{4.65}$$

Therefore, equation (4.61) can be rewritten as:

$$e^{x_2} = A^2\lambda_{1,2}\lambda_{3,1} + P_3\lambda_{3,1} + P_1\lambda_{1,2} + 1 + B^2\lambda_{1,2}\lambda_{2,1} + P_2\lambda_{2,1} + C^2\lambda_{3,1}\lambda_{2,2} + P_2\lambda_{2,2} \tag{4.66}$$

Similarly, for equation (4.62), the approximation of the product of the transmit power is done by introducing a new auxiliary variable D. Accordingly we rewrite (4.62) as follows:

$$e^{y_2} = D\lambda_{1,2}\lambda_{3,1} + P_3\lambda_{3,1} + P_1\lambda_{1,2} + 1 \tag{4.67}$$

with the variable D satisfying the following constraints:

$$\left(\frac{P_3}{b}\right)^2 + (P_1 b)^2 \leq 2D \tag{4.68}$$

where:

$$b = \sqrt{\frac{P_3^{[r]}}{P_1^{[r]}}} \tag{4.69}$$

where $P_3^{[r]}$ and $P_1^{[r]}$ are the values of P_3 and P_1 in the rth iteration, respectively. Now we formulate the optimization problem as maximizing the sum rate of all the IoT devices:

$$\mathcal{P}2: \quad \max_{P_i, x_i, y_i, A, B, C, D} \quad \sum_i x_i - y_i \tag{4.70a}$$

subject to

$$0 \leq P_i \leq P_{max} \quad \forall i \in \mathcal{M} \tag{4.70b}$$

$$x_i - y_i \geq R_i^{min} \quad \forall i \in \mathcal{M} \tag{4.70c}$$

$$\lambda_{2,1}P_2 + \lambda_{3,1}P_3 + 1 + P_1\lambda_{1,1} \geq e^{x_1} \tag{4.70d}$$

$$\lambda_{2,1}P_2 + \lambda_{3,1}P_3 + 1 \leq e^{y_1} \tag{4.70e}$$

$$\lambda_{2,2}P_2 + \lambda_{1,2}P_1 + 1 + P_3\lambda_{3,2} \geq e^{x_3} \tag{4.70f}$$

$$\lambda_{2,2}P_2 + \lambda_{1,2}P_1 + 1 \leq e^{y_3} \tag{4.70g}$$

$$A^2\lambda_{1,2}\lambda_{3,1} + P_3\lambda_{3,1} + P_1\lambda_{1,2} + 1 +$$

$$B^2\lambda_{1,2}\lambda_{2,1} + P_2\lambda_{2,1} + C^2\lambda_{3,1}\lambda_{2,2} + P_2\lambda_{2,2} \geq e^{x_2} \tag{4.70h}$$

$$D\lambda_{1,2}\lambda_{3,1} + P_3\lambda_{3,1} + P_1\lambda_{1,2} + 1 \leq e^{y_2} \tag{4.70i}$$

(4.63)(4.64)(4.65)(4.68)

The optimization problem $\mathcal{P}1$ is still non convex due to the constraints (4.71e), (4.70g), (4.70i). Therefore we use first order Taylor approximation to linearize the constraints. Therefore, $e^{y_1} = e^{\bar{y_1}}(y_1 - \bar{y_1} + 1)$, $e^{y_2} = e^{\bar{y_2}}(y_2 - \bar{y_2} + 1)$, and $e^{y_3} = e^{\bar{y_3}}(y_3 - \bar{y_3} + 1)$, around the points $\bar{y_1}$, $\bar{y_2}$, and $\bar{y_3}$ respectively.

Moreover, we also perform first order Taylor approximation for A^2, B^2, and C^2. Therefore, $A^2 = \bar{A}^2 + 2\bar{A}(A - \bar{A})$, $B^2 = \bar{B}^2 + 2\bar{B}(B - \bar{B})$, and $C^2 = \bar{C}^2 + 2\bar{C}(C - \bar{C})$ around the points $\bar{A}$, $\bar{B}$, and $\bar{C}$ respectively.

Consequently, $\mathcal{P}2$ can be rewritten as:

$$\mathcal{P}2: \quad \max_{P_i,x_i,y_i,A,B,C,D} \quad \sum_i x_i - y_i \tag{4.71a}$$

subject to

$$0 \leq P_i \leq P_{max} \quad \forall i \in \mathcal{M} \tag{4.71b}$$

$$x_i - y_i \geq R_i^{min} \quad \forall i \in \mathcal{M} \tag{4.71c}$$

$$\lambda_{2,1}P_2 + \lambda_{3,1}P_3 + 1 + P_1\lambda_{1,1} \geq e^{x_1} \tag{4.71d}$$

$$\lambda_{2,1}P_2 + \lambda_{3,1}P_3 + 1 \leq e^{\bar{y_1}}(y_1 - \bar{y_1} + 1) \tag{4.71e}$$

$$\lambda_{2,2}P_2 + \lambda_{1,2}P_1 + 1 + P_3\lambda_{3,2} \geq e^{x_3} \tag{4.71f}$$

$$\lambda_{2,2}P_2 + \lambda_{1,2}P_1 + 1 \leq e^{\bar{y_3}}(y_3 - \bar{y_3} + 1) \tag{4.71g}$$

$$\begin{aligned}&(\bar{A}^2 + 2\bar{A}(A - \bar{A}))\lambda_{1,2}\lambda_{3,1} + P_3\lambda_{3,1} + P_1\lambda_{1,2} + \\ &1 + (\bar{B}^2 + 2\bar{B}(B - \bar{B}))\lambda_{1,2}\lambda_{2,1} + P_2\lambda_{2,1} + \\ &(\bar{C}^2 + 2\bar{C}(C - \bar{C}))\lambda_{3,1}\lambda_{2,2} + P_2\lambda_{2,2} \geq e^{x_2}\end{aligned} \tag{4.71h}$$

$$D\lambda_{1,2}\lambda_{3,1} + P_3\lambda_{3,1} + P_1\lambda_{1,2} + 1 \leq e^{\bar{y_2}}(y_2 - \bar{y_2} + 1) \tag{4.71i}$$

(4.63)(4.64)(4.65)(4.68)

The obtained optimization problem is convex, hence we use successive convex approximation to solve it.

4.4 Performance Results and Analysis

In this section we analyse the performance of our solution approach by varying the system parameters and comparing with baseline approaches. We consider two UAVs deployed to ensure minimum data rate requirements of three IoT devices that are randomly placed in a 1000×1000 m^2 area. The maximum transmit power of the devices is set to 10 milliwatt (mW) and the minimum data rate required by all the IoT devices is set to 1 bps/Hz. We assume that the UAVs hover over a fixed altitude of 100 meters, and for the wireless channel, we set the channel gain at reference distance $d_0 = 1m$ to -50 dB, and the power spectral density of noise to -110 dBm/hz. The remaining parameters are presented in each subsection of the results. Moreover, we use CVX and MATLAB to solve the optimization problem.

Given the different possibilities for the deployment positions of the two UAVs, the channel quality of the IoT devices can vary and hence the IoT device with weak channel to both UAVs also varies. Accordingly, in the simulations, we first determine the best IoT devices to UAVs associations by comparing the 3 options for the IoT device with weak channel. For example, consider a simple scenario where $q_1 = (400, 800)$, $q_2 = (50, 300)$, and $q_3 = (750, 100)$. If we assume that the IoT device with weak channel is IoT 1 then the sum rate will be 8.44 bps/Hz. Similarly, if IoT 2 is considered weak the sum rate will be 9.3 bps/Hz and if IoT 3 is considered weak the sum rate is 7.1 bps/Hz. Consequently, we select IoT device 2 as the weak device in order to maximize the performance.

4.4.1 Solution Approach Convergence

In figure 10, we present the convergence of the alternating optimization proposed solution with the increasing number of iterations averaged over different realizations. It is clear that with more iterations, alternating between the power allocation and UAV positioning subproblems increases the total sum rate of the IoT devices from 5.1 bps/Hz to 9.3 bps/Hz. We also notice that the algorithm converges around 9.3 bps/Hz after 8 iterations.

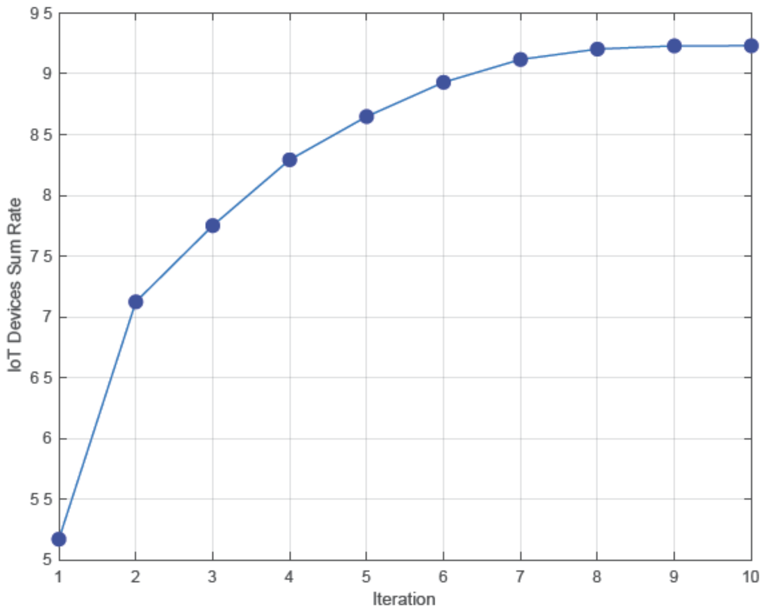
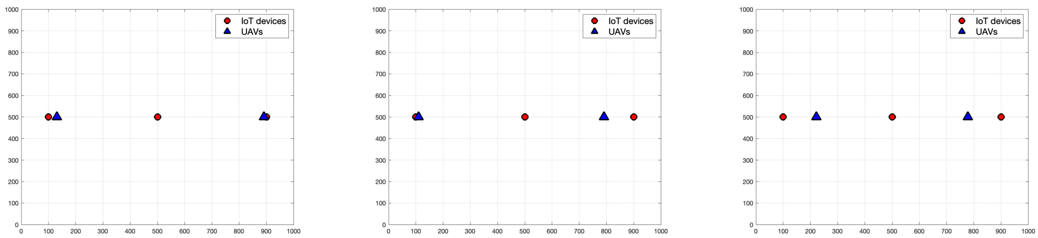


Figure 10: The convergence of the proposed solution of alternating optimization

4.4.2 Effect of Far IoT Device Minimum Rate

We then compare the effect of the minimum required rate of the weak (far) IoT device on the positioning of the UAVs. First, we place the IoT device at fixed positions $q_1 = (100, 500)$, $q_2 = (500, 500)$, and $q_3 = (900, 500)$, with the maximum transmit power of these device set to 23 dBm. Then we compare the positions of the two UAVs when the minimum rate of all the devices is set to 1 bps/Hz and when the minimum rate of the weak IoT device is increased to 3 bps/Hz while that of the strong devices remaining 1 bps/Hz.

Accordingly, in figure 11a where the minimum required rate for all the devices can be easily achieved, the UAVs position converge around the IoT devices that are considered near users. This is expected because such positions can maximize the sum rate of these two near users while minimizing the interference from IoT device 1 to UAV 2 and from IoT device 3 to UAV 1. Similarly, the interference from IoT device 2 at each UAV is also reduced because of the distance between this IoT device and the UAVs. On the other hand, in figure 11b, where a higher



(a) $R_2^{min} = 1bps/Hz$ (b) $R_2^{min} = 3bps/Hz$ (c) $R_2^{min} = 5bps/Hz$

Figure 11: Effect of minimum required rate on the UAVs positions

data is required by the far IoT device, we notice that one of the two UAVs moves toward the middle device until the minimum required rate is achieved. However, the other UAV moves further from the far IoT device to decrease the interference from this UAV and improves the overall performance of all the IoT devices in the system. Increasing the minimum rate required to 5 bps/Hz, we notice in figure 11c, that both UAVs move toward the far IoT device to achieve the minimum rate required by this device.

In figure 12, we further investigate the effect of varying the minimum data rate requirements of the far IoT device on the distance between this device and both UAVs. Starting with a minimum rate value of 0 bps/Hz, the UAVs move to a position directly above the near devices because the highest data rate for these two devices can be achieved at these positions; hence this results in the farthest distance from the IoT device with weak channel to both UAVs. Increasing the required rate leads to a decrease in the distance of one or both UAVs to the far IoT device because moving closer to this device will allow them to serve it by achieving the minimum rate required. For example, when the minimum rate is set to 3 bps/Hz the distance from the far IoT device to the first UAV is approximately 390 meters and 310 meters from the second UAV. For high values of minimum rate (≥ 5) both UAVs move toward the far IoT device to achieve its requirements while considering the minimum required rates for both devices with strong channel quality.

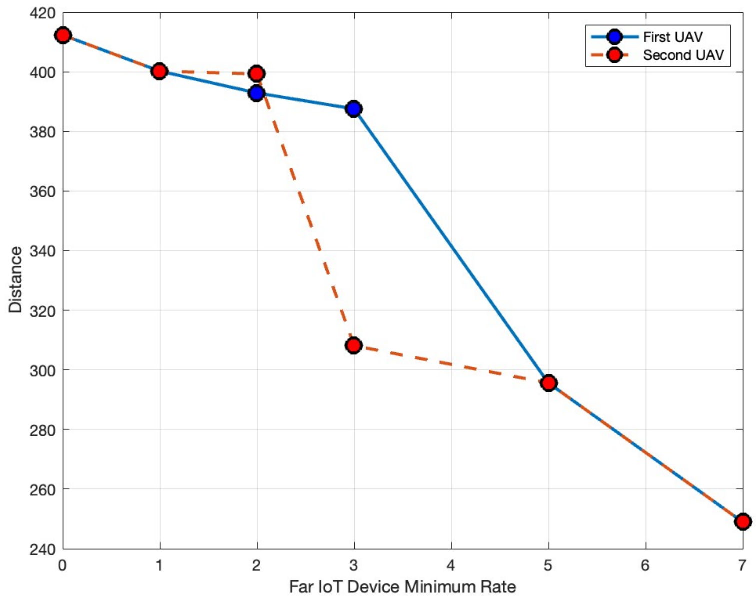


Figure 12: Effect of far IoT device minimum rate on UAVs positioning

4.4.3 Effect of IoT Devices Maximum Transmit Power

In this section, we analyse the effect of the maximum transmit power of the IoT devices on the total sum rate of all devices. We compare our solution approach against a heuristic algorithm that generates 200 random locations for the UAVs, then selects the position that maximizes the total sum rate. We also compare with the another approach that select a sub optimal weak IoT device (i.e. sub optimal UAVs-to-IoT devices association) that helps in showing the effect of far IoT device selection on the total performance.

As shown in figure 13, increasing the maximum transmit power of the IoT devices results in an increase in the total sum rate of the IoT devices for all the solution approaches, because more resources are available for these devices. In our proposed solution approach the sum rate increases from 10.4 bps/Hz at a maximum transmit power of 10 milliwatt to a 12.5 bps/Hz at 50 milliwatt, and for a transmit power of 150 milliwatt we are able to acheive approximately 14 bps/Hz. Moreover, our proposed solution approach yields approximately an increase (in the sum rate) of 2 bps/Hz compared to the random positioning of the UAVs and 3 bps/Hz compared to the approach that selects a different IoT

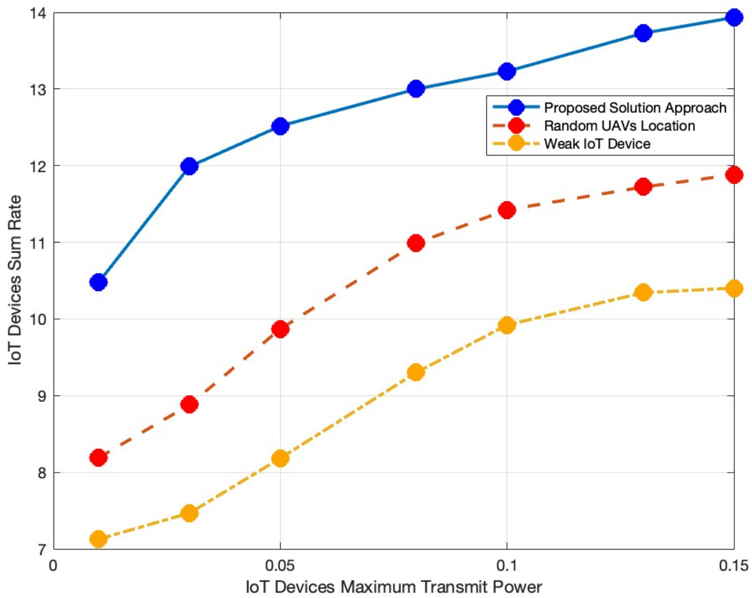


Figure 13: Effect of IoT devices maximum transmit power

device as weak device. Furthermore, comparing the three approaches shows the importance of selecting the appropriate weak IoT device, because a sub optimal assignment will lead to a decrease in the performance due to the high interference between the IoT devices.

4.5 Conclusion

In this chapter, we investigate the performance of joint-transmission coordinated multipoint (JT-CoMP) uplink non-orthogonal multiple access (NOMA) in a unmanned aerial vehicles (UAVs) aided network. Specifically, two UAVs are deployed to serve IoT devices in a network where the devices with weak channel leverage JT-CoMP NOMA to transmit to both UAVs simultaneously. We aim to maximize the sum rate of all the devices while considering the different constraints, so we use alternating optimization on two subproblems that handle UAVs positions and IoT devices transmit power respectively. The output of one subproblem is the input for the other, and for each subproblem, we use successive convex approximation to get a solution. Simulation results show the performance of our solution approach compared to other baseline approaches where we achieve an increase of 2 bps/Hz compared to the random UAVs location approach and 3 bps/Hz compared to a method that selects a non optimal weak IoT device.

Chapter Five

Conclusions and Future Work

In conclusion, in this thesis we analyzed the performance of uplink NOMA in a UAV aided network for constrained IoT applications. We motivated the use of NOMA by presenting two scenarios that highlights its performance and we discussed the challenges and different solution approaches to tackle each problem.

In the first part of the thesis, we leverage Non-orthogonal multiple access and the mobility of UAVs to collect data from time constrained IoT devices. We aim to maximize the number of served devices by optimizing the UAV trajectory, IoT device scheduling, and power allocation. Given the complexity of the obtained problem we divide it into UAV trajectory and IoT device paring subproblem and power allocation subproblem. The first subproblem is solved using deep reinforcement learning that determines the UAV trajectory and one of the IoT devices. Then we use a heuristic algorithm do determine the second IoT device to select and pair with the first one. The Second subproblem is power allocation for the paired devices where we formulate it as an optimization problem for maximizing the sum rate in the NOMA cluster. Our suggested solution approach achieves higher performance compared to other greedy methods and compared to orthogonal multiple access technique.

Then in the second part of this thesis, we leverage JT-CoMP NOMA and UAVs to ensure minimum data rate requirements of the IoT devices. We aim to maximize the sum rate of the devices by optimizing UAV positions, IoT association and transmit power. The obtained problem is MINLP so we divide the it into UAV trajectory and IoT association subproblem and power allocation subproblem. The output of one subproblem is the input for the other. And we alternate between the two until the solution converges. We highlight the performance of our solution approach by varying the system parameters and comparing with baseline approaches.

Indeed, NOMA is a promising technology for the next generation networks. For a future work we are considering the use of multi-agent deep reinforcement learning to control the trajectories of multiple UAVs in the same scenarios discussed in chapters 3 and 4. Another possible direction is to consider pairing a large number of IoT devices together where a clustering technique can be developed to determine which IoT device form a NOMA cluster. It is also interesting to study the performance of uplink cooperative NOMA that is being recently studied and researched in different IoT use cases.

Bibliography

[1] K. O. M. Salih, T. A. Rashid, D. Radovanovic, and N. Bacanin, "A comprehensive survey on the internet of things with the industrial marketplace," *Sensors*, vol. 22, no. 3, p. 730, 2022.

[2] S. Kumar, P. Tiwari, and M. Zymbler, "Internet of things is a revolutionary approach for future technology enhancement: a review," *Journal of Big data*, vol. 6, no. 1, pp. 1–21, 2019.

[3] M. Noura, M. Atiquzzaman, and M. Gaedke, "Interoperability in internet of things: Taxonomies and open challenges," *Mobile networks and applications*, vol. 24, no. 3, pp. 796–809, 2019.

[4] D. Ebrahimi, S. Sharafeddine, P.-H. Ho, and C. Assi, "Uav-aided projection-based compressive data gathering in wireless sensor networks," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 1893–1905, 2019.

[5] M. Samir, S. Sharafeddine, C. M. Assi, T. M. Nguyen, and A. Ghrayeb, "Uav trajectory planning for data collection from time-constrained iot devices," *IEEE Transactions on Wireless Communications*, vol. 19, no. 1, pp. 34–46, 2019.

[6] Z. Yang, C. Pan, K. Wang, and M. Shikh-Bahaei, "Energy efficient resource allocation in uav-enabled mobile edge computing networks," *IEEE Transactions on Wireless Communications*, vol. 18, no. 9, pp. 4576–4589, 2019.

[7] J. Lyu, Y. Zeng, R. Zhang, and T. J. Lim, "Placement optimization of uav-mounted mobile base stations," *IEEE Communications Letters*, vol. 21, no. 3, pp. 604–607, 2017.

[8] S. Sharafeddine and R. Islambouli, "On-demand deployment of multiple aerial base stations for traffic offloading and network recovery," *Computer Networks*, vol. 156, pp. 52–61, 2019.

[9] H. Ren, C. Pan, K. Wang, W. Xu, M. Elkashlan and A. Nallanathan, "Joint Transmit Power and Placement Optimization for URLLC-Enabled UAV Relay Systems," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 7, pp. 8003–8007, 2020.

[10] N. Abbas, A. Mrad, A. Ghazleh, and S. Sharafeddine, "Uav-based relay system for iot networks with strict reliability and latency requirements," *IEEE Networking Letters*, vol. 3, no. 3, pp. 110–113, 2021.

[11] J. J. Nielsen and P. Popovski, "Latency Analysis of Systems with Multiple Interfaces for Ultra-Reliable M2M Communication," *in Proceedings of the 17th International Workshop on Signal Processing Advances in Wireless Communications*, pp. 1–6, 2016.

[12] X. Xi, X. Cao, P. Yang, J. Chen, T. Quek and D. Wu, "Joint User Association and UAV Location Optimization for UAV-Aided Communications," *IEEE Wireless Communications Letters*, vol. 8, no. 6, pp. 1688–1691, 2019.

[13] L. Dai, B. Wang, Y. Yuan, S. Han, I. Chih-Lin, and Z. Wang, "Non-orthogonal multiple access for 5g: solutions, challenges, opportunities, and future research trends," *IEEE Communications Magazine*, vol. 53, no. 9, pp. 74–81, 2015.

[14] Y. Liu, G. Pan, H. Zhang, and M. Song, "On the capacity comparison between mimo-noma and mimo-oma," *IEEE Access*, vol. 4, pp. 2123–2129, 2016.

[15] M. Zeng, A. Yadav, O. A. Dobre, G. I. Tsiropoulos, and H. V. Poor, "Capacity comparison between mimo-noma and mimo-oma with multiple users in a cluster," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 10, pp. 2413–2424, 2017.

[16] Z. Ding, Y. Liu, J. Choi, Q. Sun, M. Elkashlan, I. Chih-Lin, and H. V. Poor, "Application of non-orthogonal multiple access in lte and 5g networks," *IEEE Communications Magazine*, vol. 55, no. 2, pp. 185–191, 2017.

[17] K. K. Vaigandla and D. N. Venu, "A survey on future generation wireless communications-5g: Multiple access techniques, physical layer security, beamforming approach," *Journal of Information and Computational Science*, vol. 11, no. 9, pp. 449–474, 2021.

[18] W. K. New, C. Y. Leow, K. Navaie, Y. Sun, and Z. Ding, "Application of noma for cellular-connected uavs: Opportunities and challenges," *Science China Information Sciences*, vol. 64, no. 4, pp. 1–14, 2021.

[19] Z. Ding, R. Schober, and H. V. Poor, "Unveiling the importance of sic in noma systems—part 1: State of the art and recent findings," *IEEE Communications Letters*, vol. 24, no. 11, pp. 2373–2377, 2020.

[20] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov, "Proximal policy optimization algorithms," *arXiv preprint arXiv:1707.06347*, 2017.

[21] M. Samir, S. Sharafeddine, C. M. Assi, T. M. Nguyen, and A. Ghrayeb, "UAV trajectory planning for data collection from time-constrained IoT devices," *IEEE Transactions on Wireless Communications*, vol. 19, no. 1, pp. 34–46, 2020.

[22] C. Zhan, Y. Zeng, and R. Zhang, "Energy-efficient data collection in UAV enabled wireless sensor network," *IEEE Wireless Communications Letters*, vol. 7, no. 3, pp. 328–331, 2018.

[23] C. Zhan and H. Lai, "Energy minimization in Internet-of-Things system based on rotary-wing UAV," *IEEE Wireless Communications Letters*, vol. 8, no. 5, pp. 1341–1344, 2019.

[24] S. K. Singh, K. Agrawal, K. Singh, C. -P. Li and W. -J. Huang, "On UAV Selection and Position-Based Throughput Maximization in multi-UAV Relaying Networks," *IEEE Access*, vol. 8, pp. 144039–144050, 2020.

[25] W. Chen, S. Zhao, R. Zhang, Y. Chen, and L. Yang, "UAV-assisted data collection with nonorthogonal multiple access," *IEEE Internet of Things Journal*, vol. 8, no. 1, pp. 501–511, 2021.

[26] J. Lu, Y. Wang, T. Liu, Z. Zhuang, X. Zhou, F. Shu, and Z. Han, "UAV-enabled uplink non-orthogonal multiple access system: Joint deployment and power control," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 9, pp. 10090–10102, 2020.

[27] R. Duan, J. Wang, C. Jiang, H. Yao, Y. Ren, and Y. Qian, "Resource allocation for multi-UAV aided IoT NOMA uplink transmission systems," *IEEE Internet of Things Journal*, vol. 6, no. 4, pp. 7025–7037, 2019.

[28] J. Zhao, Y. Wang, Z. Fei, X. Wang, and Z. Miao, "NOMA-aided UAV data collection system: Trajectory optimization and communication design," *IEEE Access*, vol. 8, pp. 155843–155858, 2020.

[29] X. Mu, Y. Liu, L. Guo, J. Lin, and Z. Ding, "Energy-constrained UAV data collection systems: NOMA and OMA," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 7, pp. 6898–6912, 2021.

[30] M. S. Ali, H. Tabassum, and E. Hossain, "Dynamic user clustering and power allocation for uplink and downlink non-orthogonal multiple access (noma) systems," *IEEE access*, vol. 4, pp. 6325–6343, 2016.

[31] L. Dai, B. Wang, Z. Ding, Z. Wang, S. Chen, and L. Hanzo, "A survey of non-orthogonal multiple access for 5g," *IEEE communications surveys & tutorials*, vol. 20, no. 3, pp. 2294–2323, 2018.

[32] E. Hossain and Y. Al-Eryani, "Large-scale noma: Promises for massive machine-type communication," *arXiv preprint arXiv:1901.07106*, 2019.

[33] R. Irmer, H. Droste, P. Marsch, M. Grieger, G. Fettweis, S. Brueck, H.-P. Mayer, L. Thiele, and V. Jungnickel, "Coordinated multipoint: Concepts, performance, and field trial results," *IEEE Communications Magazine*, vol. 49, no. 2, pp. 102–111, 2011.

[34] M. Samir, D. Ebrahimi, C. Assi, S. Sharafeddine, and A. Ghrayeb, "Leveraging uavs for coverage in cell-free vehicular networks: A deep reinforcement learning approach," *IEEE Transactions on Mobile Computing*, vol. 20, no. 9, pp. 2835–2847, 2020.

[35] X. Liu, J. Wang, N. Zhao, Y. Chen, S. Zhang, Z. Ding, and F. R. Yu, "Placement and power allocation for noma-uav networks," *IEEE Wireless Communications Letters*, vol. 8, no. 3, pp. 965–968, 2019.

[36] N. Zhao, X. Pang, Z. Li, Y. Chen, F. Li, Z. Ding, and M.-S. Alouini, "Joint trajectory and precoding optimization for uav-assisted noma networks," *IEEE Transactions on Communications*, vol. 67, no. 5, pp. 3723–3735, 2019.

[37] R. Duan, J. Wang, C. Jiang, H. Yao, Y. Ren, and Y. Qian, "Resource allocation for multi-uav aided iot noma uplink transmission systems," *IEEE Internet of Things Journal*, vol. 6, no. 4, pp. 7025–7037, 2019.

[38] H. Zhang, J. Zhang, and K. Long, "Energy efficiency optimization for noma uav network with imperfect csi," *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 12, pp. 2798–2809, 2020.

[39] M. S. Ali, E. Hossain, A. Al-Dweik, and D. I. Kim, "Downlink power allocation for comp-noma in multi-cell networks," *IEEE Transactions on Communications*, vol. 66, no. 9, pp. 3982–3998, 2018.

[40] M. Elhattab, M. A. Arfaoui, and C. Assi, "A joint comp c-noma for enhanced cellular system performance," *IEEE Communications Letters*, vol. 24, no. 9, pp. 1919–1923, 2020.

[41] Y. Tian, S. Lu, A. Nix, and M. Beach, "A novel opportunistic noma in downlink coordinated multi-point networks," in *2015 IEEE 82nd Vehicular Technology Conference (VTC2015-Fall)*, pp. 1–5, IEEE, 2015.

[42] A. Kilzi, J. Farah, C. A. Nour, and C. Douillard, "Analysis of drone placement strategies for complete interference cancellation in two-cell noma comp systems," *IEEE Access*, vol. 8, pp. 179055–179069, 2020.

[43] H. Wang, S.-H. Leung, and R. Song, "Precoding design for two-cell mimo-noma uplink with comp reception," *IEEE Communications Letters*, vol. 22, no. 12, pp. 2607–2610, 2018.

[44] H. Wang, C. Liu, Z. Shi, Y. Fu, and R. Song, "Power minimization for two-cell irs-aided noma systems with joint detection," *IEEE Communications Letters*, vol. 25, no. 5, pp. 1635–1639, 2020.

[45] Y. Sun, Z. Ding, X. Dai, and O. A. Dobre, "On the performance of network noma in uplink comp systems: A stochastic geometry approach," *IEEE Transactions on Communications*, vol. 67, no. 7, pp. 5084–5098, 2019.