Link Performance Analysis of Unmanned Aerial Vehicles

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Declaration

It is hereby declared that

1. The thesis submitted is our own original work, while some parts of it have been accepted for publication titled "Application of Unmanned Aerial Vehicles in Wireless Networks: Mobile Edge Computing and Caching," by CRC Press, while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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Abstract

Unmanned Aerial Vehicles (UAVs) play a vital role in the growing technological advancements. Researchers have been trying to utilize UAVs as a replacement to static base stations. However, adjustments need to be made in order to form a seamless wireless connection with ultra-reliability and low latency. In this thesis, we explore the idea of implementing flying base stations in conjunction with MEC architecture. We provide descriptions of Mobile Edge Computing and Caching and their need in achieving a secure connection for time sensitive applications while simultaneously reducing the energy consumption of UAVs. Furthermore, we execute mathematical models for data rate, transmission delay, time consumption and energy consumption using Non-Orthogonal Multiple Access (NOMA) techniques and compare their simulations at different Signal to Noise Ratios (SNRs) for both uplink and downlink transmissions. From our proposed model we derived a numerical result which showed that at SNR 30 dB the total delay is 0.16% more than the processing delay.

Keywords: Caching, energy consumption, mobile edge computing, non-orthogonal multiple access, time consumption and unmanned aerial vehicle.

Dedication

This dissertation is dedicated to our loving parents without whom we would not have become the individuals we are today. They have showered us with their unconditional love and support though all phases of our lives and have constantly motivated us to become better human beings.

Acknowledgement

Firstly, we would like to thank Almighty for His mercy, kindness and guidance towards us. The knowledge we have acquired over the course of these four years is reflected in this thesis. Without His guidance we would not have been able to fruitfully complete our undergraduate thesis work without being deterred from out path. Additionally, it goes without saying that we would not have come this far if it were not for our supervisor, Dr. Saifur Rahman Sabuj, Assistant Professor, Department of Electrical and Electronic Engineering, Brac University. He has introduced us to the field of wireless communication and made us fall in love with it. We will be forever indebted and grateful to him for his constant support, guidance and motivation whenever we were losing hope. Also, we would like to thank all the teachers and staff of the Department of Electrical and Electronic Engineering, Brac University, for always being there for us and helping us achieve our desired goals to their best capabilities. Last but not the least, we would like to thank our parents for always being by our side over the years and encouraging us to follow our dreams even if it meant sacrificing theirs.

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List of Acronyms

A2G	Air-to-Ground
AR	Augmented Reality
AWGN	Additive White Gaussian Noise
BS	Base Station
ETSI	European Telecommunications Standards Institute
GMU	Ground Mobile User
IoT	Internet of Things
ISG	Industry Specific Group
LOS	Line-of-Sight
MEC	Mobile Edge Computing
MIMO	Multiple Input Multiple Output
NOMA	Non-Orthogonal Multiple Access
NLOS	Non-Line-of-Sight
OFDM	Orthogonal Frequency Division Multiplexing
QoE	Quality of Experience
QoS	Quality of Service
RAN	Radio Access Network
SIC	Successive Interference Cancellation

SINR	Signal-to-interference-plus-noise ratio
SNR	Signal-to-Noise Ratio
UAV	Unmanned Aerial Vehicle
URLLC	Ultra-Reliable and Low-Latency Communication
UTM	UAV Traffic Management
VR	Virtual Reality

List of Symbols

r_{UBS}	Received signal at the UAV-BS
h_j	Channel coefficient of j^{th} GMU
x_j	Data of GMU_j with unit energy
P_{GMU}	Transmission power for all GMUs
a_j	Power coefficient of GMU_j
N_p	Zero mean complex AWGN
σ^2	Variance
$SINR_m$	SINR of m^{th} UAV
γ	SNR
R_{sum}^{NOMA-u}	Sum rate of uplink NOMA
s_{GMU}	Signal transmitted at UAV-BS
P_{UBS}	Transmission power coefficient at UAV-BS
y_n	Received signal at n^{th} GMU
h_n	Channel coefficient of n^{th} GMU
$SINR_n$	SINR of n^{th} GMU
R_n^{NOMA-d}	Downlink rate for NOMA

R_{sum}^{NOMA-d}	Sum rate for downlink NOMA
$P_e(LOS)$	Probability function for LOS connection
λ and μ	Environmental dependent constants
θ_e	Angle of elevation
$P_e(NLOS)$	Probability function for NLOS connection
K_e	Path loss
τ	Path loss exponent
y_{LOS}	Excessive loss for LOS link altered by shadowing
y_{NLOS}	Excessive loss for NLOS link altered by shadowing
$\overline{K}_e(N_b, G)$	Average path loss for both LOS and NLOS
$u_{nq,t}(s_{nq,t})$	Uplink rate
$d_{nq,t}(s_{nq,t})$	Downlink rate
$s_{nq,t}$	Index of GMU
$D_{nq,t}^{U}$	Uplink transmission delay
$D_{nq,t}^{D}$	Downlink transmission delay
$\beta_{nq,t} w_{n,t}$	Portion of task sent by GMU, n, to UAV-BS, q, for computing at time, t

$\beta_{nq,t}$	Division parameter
$D_{nq,t}^{E}(\beta_{nq,t})$	Edge computing time
f	Frequency of the CPU
ω	Number of cycle (per bit) required for computing
$D_{nq,t}^{L}(\beta_{nq,t})$	Local computing time
f_n	Frequency of the CPU clock of GMU n
ω_n	Number of cycle (per bit) required for computing by GMU n
$D_{nq,t}(\beta_{nq,t}, s_{nq,t})$	Total processing delay
$D_{nq,t}^{A}(v_{nq,t})$	Wireless access delay
$s_{q,t}$	Number of GMUs linked with UAV-BS q
$v_{nq,t}$	Service sequence variable
$T_{n,t}(\beta_{nq,t}, s_{nq,t}, v_{nq,t})$	Total delay
$E_{n,t}(\beta_{nq,t}, s_{nq,t})$	Energy consumption of GMU n
C	Energy consumption of device operation
ς_n	GMU device chip dependent energy coefficient
$(1-\beta_{nq,t})w_{n,t}$	Local computation task size
$E_{q,t}(\beta_{nq,t}, s_{nq,t})$	Energy consumption of each UAV-BS

C_q	Energy required by UAV to hover
ς	UAV-BS device chip dependent coefficient
$\beta_{nq,t} w_{n,t}$	Edge computation task size

Chapter 1

Introduction

1.1 Introduction

For the flexibility of use in various domains, Unmanned Aerial Vehicles (UAVs) or more commonly termed as drones have been a popular replacement for fixed locational base stations among researchers. With the help of cloud computing UAVs can achieve wide area coverage. Their mobility function allows it to track the movement of the user and cope with data traffic [1]. To further help with effortless wireless communication 5G architecture implements effective computational and caching methods within UAV's system. One of which is Mobile Edge Computing (MEC), a term coined by European Telecommunications Standards Institute (ETSI) [2]. The purpose of mobile edge computing is to bring cloud computing closer to the users, that is, edge computing [3]. It uses real-time analytics and machine intelligence [4] to ensure low latency in the transmission of data among time sensitive programs and simultaneously reduces the energy consumption [5]. Increase in use of applications by consumers that require intensive computing capabilities and storage facilities, made them in need to be offloaded to a cloud for better performance and increased battery life for the user equipment [4]. To make the process more efficient and less expensive for consumers MEC cloud is employed which reduces congestion on mobile networks [3]. Since MEC has large storage capacities, computing resources and network services, along with radio network information and user traffic, service providers can personalize the applications based on that information to further improve the Quality of Service (QoS) and enhance user's Quality of Experience (QoE) [2]. MEC uses caching to temporarily store frequently used data based on its popularity and other additional features. Subsequently UAV enabled caching mitigates the challenges of caching, such as, limited access and coverage [6]. This further ensures the low latency and reliability that MEC promises. Integration of MEC in UAVs diminishes the need for manually piloting the UAVs thus solving the problem of privacy and security issues [7]. Although this allows UAVs to have a higher probability of Line-of-Sight (LOS) communication [1], there are also other factors that needs to be addressed. The issue of air traffic and geofences is resolved by the newly proposed UAV Traffic Management (UTM) framework which uses Ultra-Reliable and Low-Latency Communication (URLLC) to identify, localize, and steer the UAVs and to avoid packet loss that might cause some severe damages [7]. Optimization of bit allocation and trajectory design can further improve UAVs' performance [5]. With uplink and downlink communication using Non-Orthogonal Multiple Access (NOMA) method UAVs can support operations such as video streaming, augmented reality, image processing and the Internet of Things (IoT) [2,3]. They can also provide coverage to remote areas without the use of expensive infrastructure [8].

1.2 Literature Review

Researchers before us has already explored the idea of implementing UAVs as base stations. Their studies have experimented on how the integration of MEC with UAVs helps with its energy efficiency and low latency data transfer. Previous research papers also addressed the privacy and security issues along with the applications that can benefit from UAVs acting as flying, mobile base stations.

In [8] Mozaffari et al introduced UAVs as base stations and explored its advantages as well as its applications in wireless communications. The paper used mathematical models and analytical frameworks to analyse, optimise, and design UAVs and found solutions to its challenges such as three-dimensional deployment, performance analysis, channel modelling, and energy efficiency.

Meanwhile, privacy and security issues were addressed in [9], [10], and [11]. They proposed a strategy to detect and respond to anomalies in UAV's behaviour and network connection. Actions against cyber-attacks and network hijacking were also discussed using simulations which also had low energy consumption.

According to [7] human piloted UAV base stations also poses privacy and security issues, therefore, a UAV Traffic Management (UTM) framework was established which identifies air traffic and geofences and steers UAVs accordingly using Ultra-Reliable and Low-Latency Communication URLLC to avoid packet loss which otherwise can cause severe damages.

MEC was integrated into UAVs to help with factors such as air traffic, geofences, energy consumption, and network congestion. Researchers in their studies [2], [4], [12], and [13] introduced MEC as a cloud computing but closer to the user, that is, to the edge. They elaborated on its definition and performed surveys of MEC on resource management, technological developments, and their future research challenges. The papers also included MEC's usage for applications such as augmented reality, video streaming, and automated cars as well as the future research works and technological advancements involving MEC.

In [1] Yang et al generated algorithms to find out proper placements of UAV base stations for efficient resource allocation based on user traffic and their requirements. A cluster-based algorithm was used to address three subproblems exclusively, which are user association, computation capacity, and location planning.

Zhou et al [5] produced trajectory designs for efficient energy transfers between UAVs and mobile users. With the help of that energy mobile users can offload data into the cloud which can enhance the performance of the programs and improve the battery life of the user equipment.

Wu et al and Bai et al in their respective articles [14] and [15] formulated offloading strategies to optimize energy efficiency for the UAVs since they have limited energy. They combined UAV position optimization algorithm with LSTM-based task prediction algorithm, with an added physical layer security, to produce a three-layered offloading strategy which reduces UAV's energy consumption.

In reports [6], [16], and [17] authors talked about caching, a storage unit for MEC, which is used to temporarily store frequently used data based on content popularity or user's requirements. They proposed a neural-blockchain based, content-centric caching method which will reduce the backhaul pressure and improve user experience.

In UAV enabled wireless communication both uplink and downlink transmission occur. [18] and [19] experiments on how Non-Orthogonal Multiple Access method is superior to Orthogonal Multiple Access for both uplink and downlink transmissions.

Articles [20] and [21] initiated propagation models to predict air-to-ground path loss. These path loss models compensate for the disparity in height between a low-altitude platform and a high-altitude terminal in an urban environment.

1.3 Motivation

Utilizing Unmanned Aerial Vehicles (UAVs) as mobile base stations has already been a popular research topic in the telecommunication industry. However, the purpose of our paper is to explore further each segment of this topic. We were tempted to discover energy efficient methods to implement UAVs as base stations, keeping in mind the security and privacy of the user and the information channel as well as ensuring no network congestion for a faster, low-latency transmission of data from the service provider to the mobile user. We reintroduced Mobile Edge Computing (MEC) architecture and its caching method to attain an improved Quality of Experience (QoE) and Quality of Service (QoS) for the users and the service providers respectively. Unlike past studies we were motivated to use Non-Orthogonal Multiple Access (NOMA) method for both uplink and downlink communications. Using simulations, we derived models for path loss, transmission delays, time consumption, energy consumption, and data rate, and performed comparisons between them at different levels of Signal to Noise Ratios (SNRs).

1.4 Background of Caching and Mobile Edge Computing

1.4.1 Introduction of Caching

Caching at network edge is a recently developed technique used in the 5G mobile network to lower the backhaul rates during the prime hours of communication. Local caches are assigned to pre-fetch the most popular files from the core network during off-peak hours and store them at the edge nodes. In this way, the cache-aided networks bring the files closer to end users and make it easily accessible by them during the prime hours. Caching helps to reduce the pressure of backhaul by effective utilization of the off-peak hours and lowers the network traffic rates. This technique not only brings contents closer to the mobile users, but also makes an excellent use of existing network bandwidth by reducing the server traffic [1].

Caching can be applied in flying Base Stations or UAVs. Requested contents are collected in advance from the central server in case it is not available at the edge and a copy of the content is stored for future use. In contrast, if the requested content was to be retrieved every time from the core network, a slow back-haul link would have caused a significant delay in the communication [7]. By applying caching at the MEC server, the amount of transmitted data that needs to be processed is brought to a minimum, hence, a higher data transmission rate is achieved. This ensures an effective use of bandwidth of the existing network. When caching is done at UAVs, it is important to note that the fronthaul links that connect the UAVs to cloud will have limited capacity due to the fact that UAVs generally have narrow bandwidth. A solution to the bandwidth problem of UAVs could be the implementation of caching technique where the UAVs will be employed to download and cache all the requested content during the low traffic phase or after the UAVs have returned to their designated bases. Caching allows UAVs to channel content to its user who has requested it, thereby significantly reducing the traffic. With appropriate implementation of the technique, UAVs are relieved of data overload, energy consumption of the system is minimized and QoE is enhanced.

1.4.1.1 Advantages

1. Caching minimizes network congestion by pre-fetching data during off-peak hours.
2. It helps to speed up the communication process and achieve better QoE.
3. It escalates the data transmission rate and makes the network more efficient.
4. It conserves power by making efficient use of the prevailing bandwidth
5. Caching in UAVs enables them to track the mobility pattern of the users to effectively serve them.
6. It accelerates the loading process and minimizes the system resources required to load a content.
7. Overall, it utilizes the network infrastructure effectively and reduces cost.

1.4.1.2 Disadvantages

1. Caching at UAVs may cause greater consumption of power when compared to caching at BSs due to the finite battery life of UAV/drones.
2. There is a risk of outdated or irrelevant data delivery due to the rapidly evolving content demand.
3. The cache memory itself may have very limited capacity to store data.

4. High cache-miss rates may occur if the stored data is misplaced or lost.
5. Prediction of content popularity is complex and unsteady, so an efficient caching policy needs to be worked out and then applied [22].

1.4.2 Introduction of Mobile Edge Computing

The term MEC is created by the European Telecommunications Standards Institute (ETSI) and the Industry Specification Group (ISG). By definition, it is a cloud computing technology that offers an information technology infrastructure system. It operates within the range of radio access network (RAN) and exists in close proximity with the mobile end users. MEC is capable to work independently with its available local resources. By being in the vicinity of end users, MEC can inspect large volumes of data with exceptionally low latency and high bandwidth and enhanced quality, all while using low-level signaling for information sharing. Implementation of MEC into a system can be favorable for business and events in current times as it enables applications to provide real-time information and facilitates efficient networks and services [12].

1.4.2.1 Advantages

1. MEC reduces network congestion by minimizing data traffic load [3].
2. MEC gives the application providers useful information of the user traffic and network that helps them fix bugs and improve user experience [4].
3. It can also foster real-time analytics and machine-intelligence software [4].
4. There need not be a major architectural change for consumers to enjoy MEC services; existing infrastructure can be modified to implement MEC [3].
5. MEC can also serve queries from devices that require response times of 100ms or below [2].

6. MEC's ability to provide high-speed, real-time and highly localized feedback allows it to serve many practical uses such as Augmented Reality (AR), Virtual Reality (VR), Location Services, Autonomous cars, IoT, data caching and efficient content distribution [2, 3].

1.4.2.2 Disadvantages

1. Application providers may find it difficult to manage multiple clouds and establish coordination between each cloud [4].
2. MEC is susceptible to system overload or system failures, leading to loss of valuable data. This issue can be tackled by offloading some of its data to nearby MECs to relieve burden on a single MEC.
3. Mobile Users are constantly on the move and changing their geographical locations, so the MEC services need to be mobility-aware and coordinate between distant cloud servers.
4. MEC, being a cloud based computing at the edge, possesses risks of probable security issues during data transfer [2].
5. Due to complicated administrative policies, implementation of MECs may be a challenging task [2].

1.4.3 Layering of the UAV Based MEC Architecture

Caching at edge layers promote better execution and optimization of data transfer, especially for large video contents. MEC conducts all the administrations at the edge of the cellular systems, while providing support to its near end users via various cloud centers. The main task of MEC is to provide reliable and low-latency services to its clients by deploying UAVs. MEC, with the help of UAVs, not only improves the QoS but also ensures that the connection is not hampered even in catastrophic events like flood, storm, or earthquakes. This means they can be used for disaster communications, resident monitoring, and ad hoc network/communication arrangements. If need be, MEC can further incorporate other IoT gadgets to improve its clientele's QoE with high-speed communication. With effective utilization of caching, MEC diminishes the computational separation between the source and the servers by restoring location information of near-end users for assisted communication. Caching in a UAV based MEC architecture allows data to be stored on specific servers so that the transmission latency is kept to a minimum. However, the layout of the network is hierarchical so the end users may have to bear the burden of overheads caused due to the maintenance of a continuous connection.

Explanation of the layers

- Mobile computing network forms a hierarchical framework and is visualized to consist of three layers as illustrated in Figure 1 - the Cloud Layer, Edge Layer and the Subscriber Service Layer.

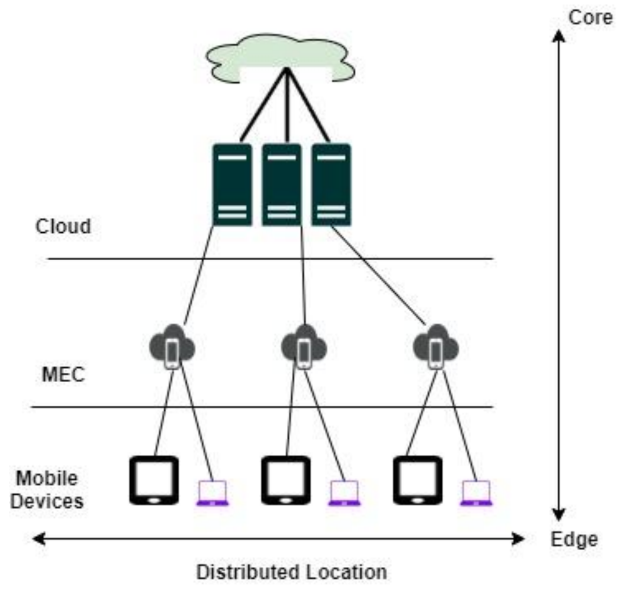

Figure 1: Illustration of MEC and cloud [23].

- The top most layer, aka the cloud, allows for the flow of applications, services and data from end users and back to the main server. This layer is well developed and is situated farthest away from the smart end users and devices.
- The lowest tier, Service subscriber layer, consists of all the widely available computational devices such as laptops, smart phones, television, fridges, vehicles, etc. These smart devices are designated with specific edge nodes [13].
- The MEC layer lies as the intermediary between the cloud and the smart edge devices. As depicted in Figure 1.4.3.1, the MEC layer assembles the information packets produced by the IoT administrations. Here, the packets are locally stored and processed before they reach the centralized core network.
- Every drone is equipped with pre-fetched contents by using caching technique and the content servers are located remotely at the hubs. Each drone is part of a specific cluster, which in turn, is inspected by its top-tier drone. In this way, a multilayer drone network is formed [23]. By using stochastic geometry, that is, by considering nearby group of users as clusters, the performance of a huge MEC network equipped with cache can be examined [14].
- Every MEC server must take into account the storage space required to cache the most trending contents in its cell, and also designate a fractional space for the less popular ones. The computation performance of MEC is improved by cooperative caching i.e offloading some of its data to nearby MEC servers to relieve burden on a single server.
- In a UAV based MEC architecture with a three-layer offloading strategy, for the transmission of subtask k, the required data packets, p, can be divided into two parts, $p = p_1 + p_2$. The information packets which are treated by the IoT devices locally are p_1.

The information packets which are offloaded to the UAV-enabled MEC server for processing are p_2 [14].

1.4.4 Objective of the Thesis

The main aim of this study is to design a network model that will ensure improved energy consumption, decreased latency and efficient processing of data. To ensure this we have incorporated MEC and caching in our UAV-BS architecture. The necessary measures have been identified and addressed in order to achieve this target.

1. Caching is implemented at the UAV-BS to preeminently fetch and store data in order to decrease the backhaul rates.
2. MEC in the UAV-BS helps to reduce traffic, latency, and enhance QoE by analyzing large volumes of data.
3. We have introduced NOMA method for uplink and downlink communication to further enhance the performance of the system and effectively utilize the bandwidth.

1.5 Organization

This dissertation has been broken down into four chapters which consist of all the required information on Caching, MEC, relevant mathematical models and equations, system models and simulation results. Additionally, a comprehensive summary of the entire research work along with future scopes have been discussed.

Chapter 1 Introduction

In this chapter, we have discussed the overview of caching and MEC along with their advantages and disadvantages. We have explained the hierarchical MEC implemented architecture and also discussed our motivation behind following this line of research. Lastly, this chapter consists of an informative overview of previous work done on caching and MEC and the objective of our paper.

Chapter 2 System Model

Here we have divided the chapter into multiple subsections where we discuss our proposed system model, path loss model and provide all necessary computational equations and derivations.

Chapter 3 Simulation Results and Discussion

This chapter discusses the simulation results that have been obtained through calculations on MATLAB. Data rate, transmission delay and energy consumption have been measured in terms of SNR and part of task being completed.

Chapter 4 Conclusion and Future Scope

We end the thesis with this chapter which provides the summary of our established model and its implications. Finally, we discuss the future work that can be done to further improve our proposed system model to ensure even lower energy consumption and latency.

Chapter 2

System Model

2.1 Network Model

From Figure 2 it can be seen that we will be using UAVs as aerial BS which will have uninterrupted connectivity with ground mobile users (GMUs). We will implement Non-Orthogonal Multiple Access (NOMA) method for both uplink and downlink communication. Depending on the channel strength of each user, successive interference cancellation (SIC) is assigned. For NOMA method, during uplink, the GMUs use the same frequency and time slot, but different power levels while communicating with the UAV-BS. The same is seen for downlink when UAV-BS communicates with GMUs using the same frequency and time slot but different power levels.

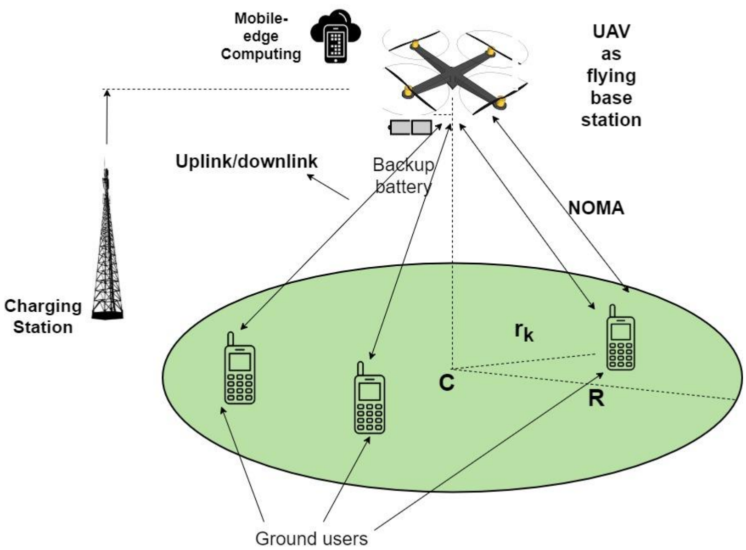

Figure 2: Illustration of proposed system model [23].

2.2 Mathematical Models

2.2.1 Model of NOMA

In our uplink NOMA network, every GMU will transmit signals to the UAV-BS. Assuming that the UAV-BS sends power allocation coefficients to the GMUs and that the uplink and downlink paths are reciprocal of one another, we can write the received signal at the UAV-BS as:

$$r_{UBS} = \sum_{j=1}^{M} h_j \sqrt{a_j P_{GMU}}\, x_j + N_p \tag{1}$$

Where the channel coefficient of the j^{th} GMU is h_j, the data of GMU_j with unit energy is x_j, the greatest transmission power expected to be same for all GMUs is P_{GMU}, the power coefficient allocated for GMU j subjected to $\sum_{j=1}^{M} a_j = 1$ and $a_1 \geq a_2 \geq .... \geq a_M$ is a_j and as there is no loss of generality the channel gains are assumed to follow the order $|h_1|^2 \leq |h_2|^2 \leq ... \leq |h_M|^2$, and N_p is the zero mean complex additive white Gaussian noise (AWGN) which has a variance of σ^2, therefore, $N_p \in \mathrm{CN}(0, \sigma^2)$.

The signal-to-interference-plus-noise ratio (SINR) for the m^{th} UAV can be written as (2) from the breakdown of the above expression [18]:

$$SINR_m = \frac{a_m \gamma |h_m|^2}{\gamma \sum_{j=1}^{m-1} a_j |h_j|^2 + 1} \tag{2}$$

where $\gamma = P_{GMU} / \sigma^2$, γ is the signal-to-interference-plus-noise ratio (SNR) and for the first GMU, we can express:

$$SINR_1 = a_1 \gamma |h_1|^2 \tag{3}$$

For the sum rate analysis of uplink NOMA network, we write it for the first UAV and the rest (2 to M) UAVs as a summation as:

$$
\begin{aligned}
R_{sum}^{NOMA-u} &= \sum_{m=1}^{M}\left(1+SINR_m\right) \\
&= \log_2\left(1+a_1\gamma\left|h_1\right|^2\right)+\sum_{m=2}^{M}\log_2\left(1+\frac{a_m\gamma\left|h_m\right|^2}{\gamma\sum_{j=1}^{m-1}a_j\left|h_j\right|^2+1}\right) \\
&= \log_2\left(1+\gamma\sum_{m=1}^{M}a_m\left|h_m\right|^2\right)
\end{aligned}
\tag{4}
$$

Taking into account the downlink NOMA network, the signal transmitted at the UAV-BS is written as:

$$
s_{GMU} = \sum_{j=1}^{N}\sqrt{a_j P_{UBS}}\,x_j \tag{5}
$$

Where the transmission power coefficient at the UAV-BS is P_{UBS}. The received signal at the n^{th} GMU is written as:

$$
y_n = h_n s_{GMU} + N_n = h_n\sum_{j=1}^{N}\sqrt{a_j P_{UBS}}\,x_j + N_n \tag{6}
$$

Where the channel coefficient of the n^{th} GMU is h_n and the zero mean complex AWGN is N_n with variance of σ^2, which means, $N_n \in \mathrm{CN}\left(0,\sigma^2\right)$.

The SINR can be written as (7) after carrying out SINR analysis of the n^{th} GMU to find the k^{th} GMU, $k < n$ and $k \neq N$:

$$
SINR_{k\to n} = \frac{a_k\gamma\left|h_n\right|^2}{\gamma\left|h_n\right|^2\sum_{j=k+1}^{M}a_j+1} \tag{7}
$$

where $\gamma = P_{UBS} / \sigma^2$ is the SNR. To obtain the necessary data of the n^{th} GMU, SIC will be carried out for the signal of GMU $k < n$. Hence, the SINR of the n^{th} GMU is expressed as:

$$SINR_n = \frac{a_n \gamma |h_n|^2}{\gamma |h_n|^2 \sum_{j=n+1}^{M} a_j + 1} \tag{8}$$

The SINR of the N^{th} GMU is given by:

$$SINR_N = a_N \gamma |h_N|^2 \tag{9}$$

Now, we can write the downlink rate of NOMA for the n^{th} GMU as:

$$\begin{aligned} R_n^{NOMA-d} &= \log_2 (1 + SINR_n) \\ &= \log_2 \left(1 + \frac{a_n \gamma |h_n|^2}{\gamma |h_n|^2 \sum_{j=n+1}^{N} a_j + 1} \right) \end{aligned} \tag{10}$$

Therefore, the sum rate for downlink NOMA is expressed as:

$$\begin{aligned} R_{sum}^{NOMA-d} &= \sum_{n=1}^{N} (1 + SINR_n) \\ &= \sum_{n=1}^{N-1} \log_2 \left(1 + \frac{a_n \gamma |h_n|^2}{\gamma |h_n|^2 \sum_{j=n+1}^{N} a_j + 1} \right) + \log_2 \left(1 + a_N \gamma |h_N|^2 \right) \\ &= \sum_{n=1}^{N-1} \log_2 \left(1 + \frac{a_n}{\sum_{j=n+1}^{N} a_j + 1/\gamma |h_n|^2} \right) + \log_2 \left(1 + a_N \gamma |h_N|^2 \right) \end{aligned} \tag{11}$$

2.2.2 Path Loss Model

According to our chosen Air to Ground (A2G) channel [19, 20], the GMU, as shown in Figure 3, can have two types of links with the UAV-BS. It can be Line-of-Sight (LOS) or strong Non-Line-of-Sight (NLOS). Depending on environmental factors like the height of buildings, density of the buildings and the distance between the UAV-BS and GMU, a model based on probability is made. We obtain the elevation angle by taking into account all of the mentioned factors. Here, the result of small scale fading has been purposely ignored because it is more likely to have LOS or strong NLOS link rather than to have weak multipath [21].

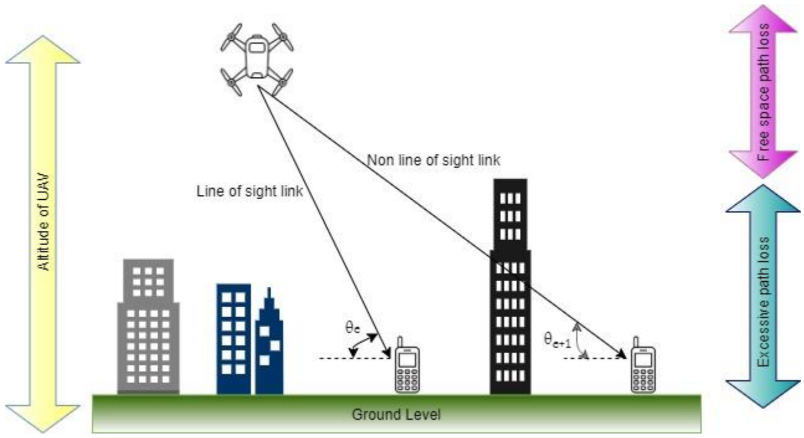

Figure 3: Example of UAV path loss model [19].

We can write the probability function for LOS connection between the GMU and UAV-BS as [20]:

$$P_e(LOS) = \frac{1}{1 + \lambda \exp(-\mu[\theta_e - \lambda])} \tag{12}$$

where λ and μ are the constants that depend of the state of the environment such as rural, sub-urban, dense urban etc., respectively and θ_e is the angle of elevation. The probability function for a GMU with strong NLOS connection with the UAV-BS can be written as:

$$P_e(NLOS) = 1 - P_e(LOS) \tag{13}$$

Two distinct scattering environments can be seen from Figure 3 between the GMU and the UAV-BS. They are: low scattering and reflection close to the UAV and high scattering due to man-made barriers close to the GMU. The addition of the free space path loss and the excessive losses make up the overall path loss. For NLOS links, this is higher because there is excessive loss due to the reflection of transmitted signals as well as shadowing by obstructions in the coverage areas.

For our proposed A2G channel between the UAV-BS and e^{th} GMU, the path loss, K_e is defined as [24]:

$$K_e = \begin{cases} 10\tau \log(Y_e) + y_{LOS}, & LOS\ link \\ 10\tau \log(Y_e) + y_{NLOS}, & NLOS\ link \end{cases} \tag{14}$$

where τ defines the path loss exponent and the excessive losses for LOS and NLOS links altered by shadowing are y_{LOS} and y_{NLOS} respectively. Both segments of this function follow normal distribution and their mean and variance are calculated using the angle of elevation as well as the environmental factors. Normally, it is impossible to find out the type of link (LOS/NLOS) the GMU had with the UAV-BS unless we have both their locations using a terrestrial map. The average path loss taking into account both the probabilities of LOS and NLOS connections is $\overline{K}_e(N_b, G)$. It is calculated as:

$$\overline{K}_e(N_b, G) = P_e(LOS)K_e(LOS) + P_e(NLOS)K_e(NLOS) \tag{15}$$

2.2.2.2 Transmission Delay

We can rearrange the uplink and downlink rate equation from (4) and (11) as:

$$u_{nq,t}(s_{nq,t}) = s_{nq,t} \log_2\left(1 + \gamma \sum_{n=1}^{N} a_n |h_n|^2\right) \tag{16}$$

$$d_{nq,t}(s_{nq,t}) = s_{nq,t} \sum_{n=1}^{N-1} \log_2\left(1 + \frac{a_n}{\sum_{j=n+1}^{N} a_j + 1/\gamma |h_n|^2}\right) + \log_2\left(1 + a_N \gamma |h_N|^2\right) \tag{17}$$

where $s_{nq,t}$ is the index of the GMU. When $s_{nq,t} = 1$, GMU n is connected to the UAV-BS q at time t; otherwise $s_{nq,t} = 0$. Hence we write the uplink and downlink transmission delay as the following [25]:

$$D_{nq,t}^{U} = \frac{\beta_{nq,t} w_{n,t}}{u_{nq,t}\left(s_{nq,t}\right)}$$
$$= \frac{\beta_{nq,t} w_{n,t}}{\log_2\left(1+\gamma\sum_{n=1}^{N} a_n |h_n|^2\right)} \tag{18}$$

$$D_{nq,t}^{D} = \frac{\beta_{nq,t} w_{n,t}}{d_{mq,t}\left(s_{mq,t}\right)}$$
$$= \frac{\beta_{nq,t} w_{n,t}}{\sum_{n=1}^{N-1}\log_2\left(1+\frac{a_n}{\sum_{j=n+1}^{N} a_j + 1/\gamma |h_n|^2}\right) + \log_2\left(1 + a_N \gamma |h_N|^2\right)} \tag{19}$$

here, $\beta_{nq,t} w_{n,t}$ is the portion of the task that GMU n sends to UAV q for computing at each time instant t where the division parameter is $\beta_{nq,t} \in [0,1]$.

2.2.2.3 Computing Model

We can divide computing model into two segments which are edge computing and local computing. When the UAV-BS jointly carries out the task of the GMU n, this is known as edge computing. When the task is carried out by the GMU itself.

2.2.2.3.1 Edge computing model: For a data size of $\beta_{nq,t} w_{n,t}$, offloaded by GMU n to UAV-BS q, the time taken by UAV-BS q to compute the task is:

$$D_{nq,t}^{E}(\beta_{nq,t}) = \frac{\omega \beta_{nq,t} w_{n,t}}{f} \tag{20}$$

where f is the frequency of the central processing unit (CPU) which is assumed to be equal for all UAV-BSs. The number of cycles (per bit) required for processing is ω.

2.2.2.3.2 Local computing model: For a data size of $(1-\beta_{nq,t})w_{n,t}$, the time taken by GMU n to process the task locally is:

$$D^{L}_{nq,t}(\beta_{nq,t}) = \frac{\omega_n\left(1-\beta_{nq,t}\right)w_{n,t}}{f_n} \tag{21}$$

where f_n is the frequency of the CPU clock of GMU n and the number of cycles (per bit) required for computing the data is ω_n.

2.2.2.4 Time Consumption Model

In our proposed model, the maximum time between the local computing time and edge computing time, since the tasks can be processed by both the GMU and the UAV-BS simultaneously, will be the total time required for task completion. To be able to effectively carry out the task of GMU n by both the GMU and the UAV-BS q, the total time required can be expressed as:

$$D_{nq,t}(\beta_{nq,t}, s_{nq,t}) = \max\left\{D^{U}_{nq,t}(\beta_{nq,t}, s_{nq,t}) + D^{E}_{nq,t}(\beta_{nq,t}) + D^{D}_{nq,t}(\beta_{nq,t}, s_{nq,t}), D^{L}_{nq,t}(\beta_{nq,t})\right\} \tag{22}$$

where $D^{L}_{nq,t}(\beta_{nq,t})$ is the local computing time and $D^{E}_{nq,t}(\beta_{nq,t})$ is the edge computing time.

There will be a wireless access delay as each GMU will have to wait for service. For GMU n linked with UAV-BS q, the access delay is:

$$D^{A}_{nq,t}(v_{nq,t}) = \sum_{n'\in V_n} D^{D}_{n'q,t}(s_{n'q,t}, \beta_{n'q,t}) \tag{23}$$

where $|s_{q,t}|$ represents the absolute value of $s_{q,t}$ which is the number of GMUs that are linked with UAV-BS q, $v_{nq,t}$ is the service sequence variable which follows $1 \le v_{nq,t} \le |s_{q,t}|$ and $V_n = \left\{n' \middle| v_{n'q,t} < v_{nq,t}\right\}$ is the cluster of GMUs that are server by UAV q before GMU n. The access delay and the processing delay, which makes up the total delay for computing a task is written as:

$$T_{n,t}(\beta_{nq,t}, s_{nq,t}, v_{nq,t}) = D^{A}_{nq,t}(v_{nq,t}) + D_{nq,t}(\beta_{nq,t}, s_{nq,t}) \tag{24}$$

2.2.2.5 Energy Consumption Model

The total energy consumption of the GMU is make up of device operating energy consumption, data transmission energy consumption and data computing energy consumption. The energy necessary for the device to operate any application is the device operating energy consumption. For GMU n, this is expressed as:

$$E_{n,t}\left(\beta_{nq,t}, s_{nq,t}\right) = C + \varsigma_n \left(f_n\right)^2 \left(1-\beta_{nq,t}\right) w_{n,t} + P_{GMU} D_{nq,t}^U \left(\beta_{nq,t}, s_{nq,t}\right) \tag{25}$$

where C is the energy consumption of device operation, and energy coefficient depending on GMU n's device chip is ς_n. For GMU n computing a task of size $\left(1-\beta_{nq,t}\right)w_{n,t}$, at its local place, the energy consumption is $\varsigma_n\left(f_n\right)^2\left(1-\beta_{nq,t}\right)w_{n,t}$ and for it to be transmitted to UAV-BS q, the energy consumption is $P_{GMU} D_{nq,t}^U\left(\beta_{nq,t}, s_{nq,t}\right)$.

Similarly, we can express the energy consumption of each UAV-BS which is:

$$E_{q,t}\left(\beta_{nq,t}, s_{nq,t}\right) = C_q + \varsigma\left(f\right)^2 \beta_{nq,t} w_{n,t} + P_{UAV} D_{nq,t}^D \left(\beta_{nq,t}, s_{nq,t}\right) \tag{26}$$

where C_q is the energy required for the UAV to hover and the energy consumption coefficient depending on the chip of the UAV-BS is ς. For UAV-BS q, to compute a task of size $\beta_{nq,t} w_{n,t}$ which has been offloaded by GMU n, the energy consumption is $\varsigma\left(f\right)^2\beta_{nq,t} w_{n,t}$. $P_{UAV} D_{nq,t}^D\left(\beta_{nq,t}, s_{nq,t}\right)$ is the energy required to transmit the computed task from UAV-BS q to GMU n.

Chapter 3

Simulation Results and Discussion

3.1 Introduction

In this section, we investigate the performance of our proposed system model numerically via simulations using MATLAB. We consider four GMUs 100m, 80m, 150m and 50m apart from each other. Power coefficients are 0.2, 0.3, 0.3, and 0.2, respectively. The height of the UAV-BS is 300m from the GMUs. We consider the following simulation parameters: $\tau = 2$, $y_{LOS} = 1.6$ dB, $y_{NLOS} = 23$ dB, $\lambda = 12.087$, and $\mu = 0.1139$.

3.2 Plots and Explanation

Figure 4 shows the relationship between the data rate and SNR. Here we see that there is an exponential increase in data rate for both uplink and downlink transmission with increasing SNR. Below 30dB SNR approximately, the data rate is almost zero but beyond that the data rate increases significantly. At a closer look we see that the data rate is slightly higher for downlink transmission than uplink transmission.

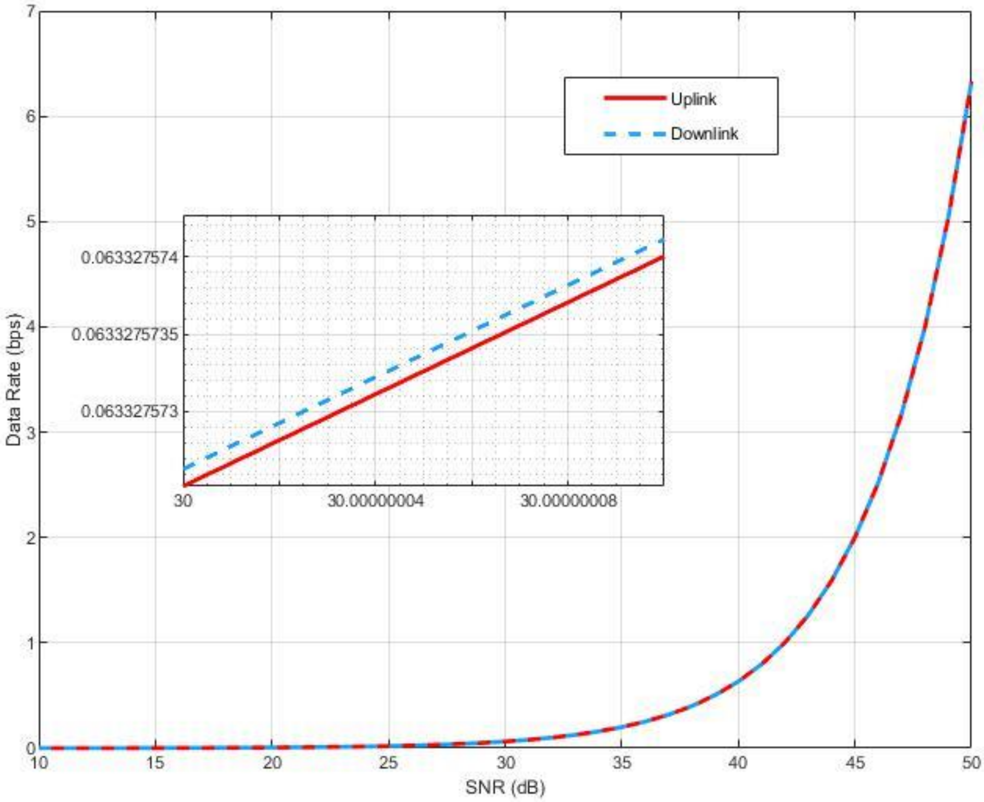

Figure 4: Comparison of the Data Rate (bps) and SNR (dB).

The transmission delay versus SNR graph from Figure 5 shows a negative relation between the two; as SNR increases, the transmission delay decreases linearly for both uplink and downlink transmission though the decrease is slightly greater for downlink transmission.

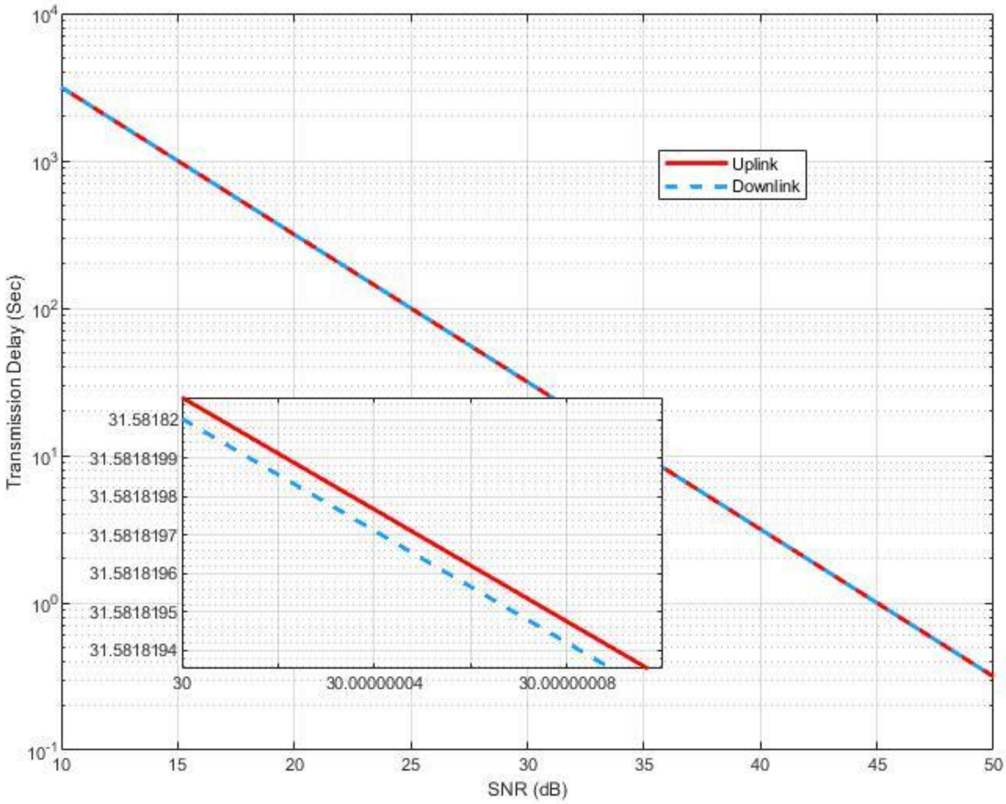

Figure 5: Comparison of the Transmission Delay (sec) and SNR (dB).

The relationship between the overall delay and the SNR is depicted in Figure 6. We also see a negative linear relationship here; as SNR increases, the total delay and the processing delay decreases. The total delay is always greater than the processing delay. At 30 dB SNR, the total delay is 0.16% more than the processing delay.

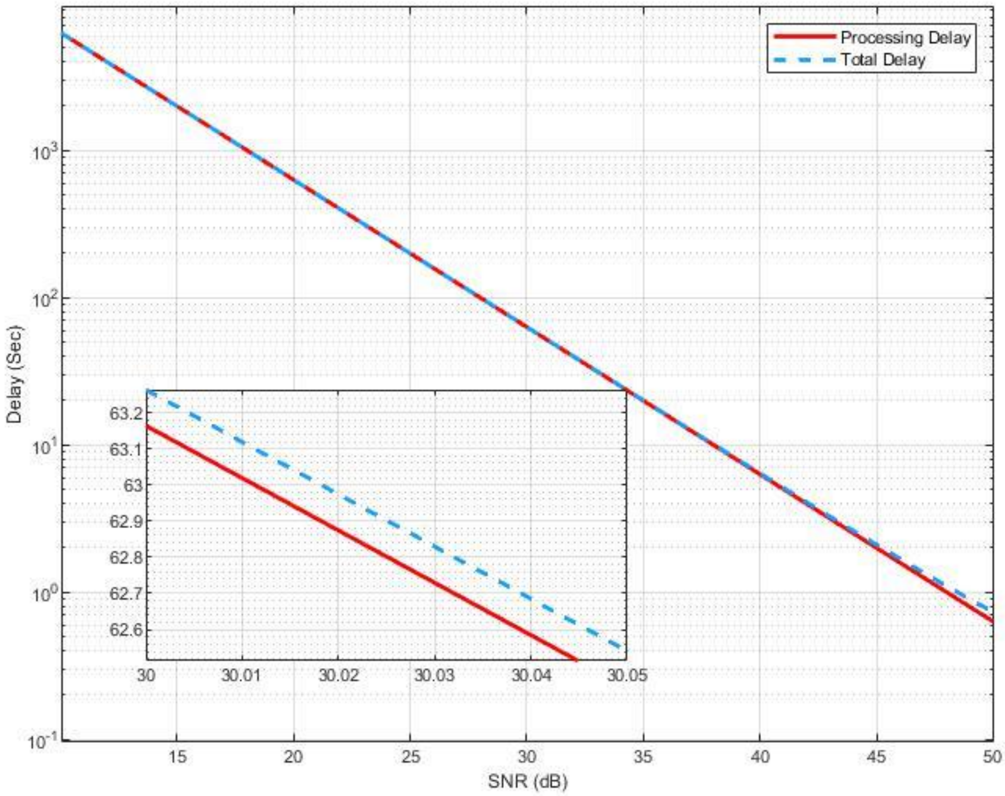

Figure 6: Comparison of the Delay (sec) and SNR (dB).

The effect on energy consumption due to change in SNR is seen from Figure 7. The energy consumption for both the GMU and the UAV-BS decreases linearly with increasing SNR until it levels off at high SNR (approximately 46dB). Further we see that the UAV-BS consumes more energy than GMU at all SNRs. When compared at 30dB SNR, it can be seen that the UAV-BS consumes 90% more energy than the GMU.

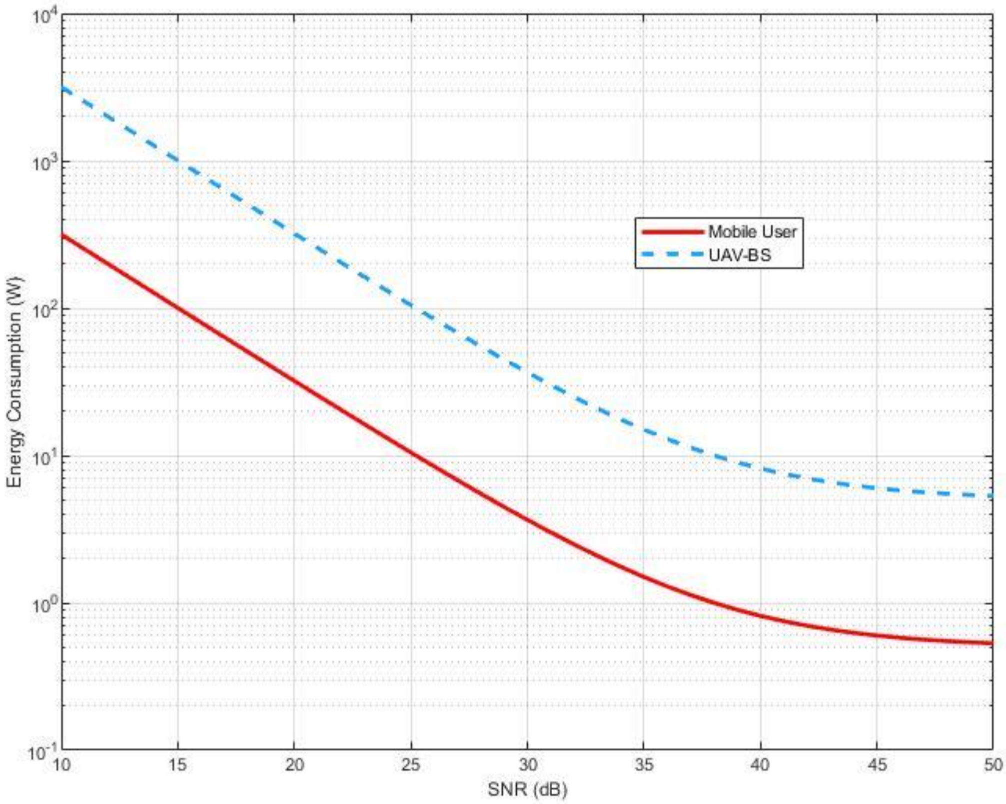

Figure 7: Comparison of the Energy Consumption (W) and SNR (dB).

Finally, Figure 8 shows the effect on energy consumption due increase in the part of task completed ($\beta_{nq,t}$). We can see that the initial in energy consumption is very rapid and then slows down but continues to increase till the entire task is completed and almost levels off. This is true for both GMU and UAV-BS, though the energy consumed by the UAV-BS is greater than the GMU at all times. At 40% task completion, the energy consumption of the UAV-BS is 90% greater than that of the GMU.

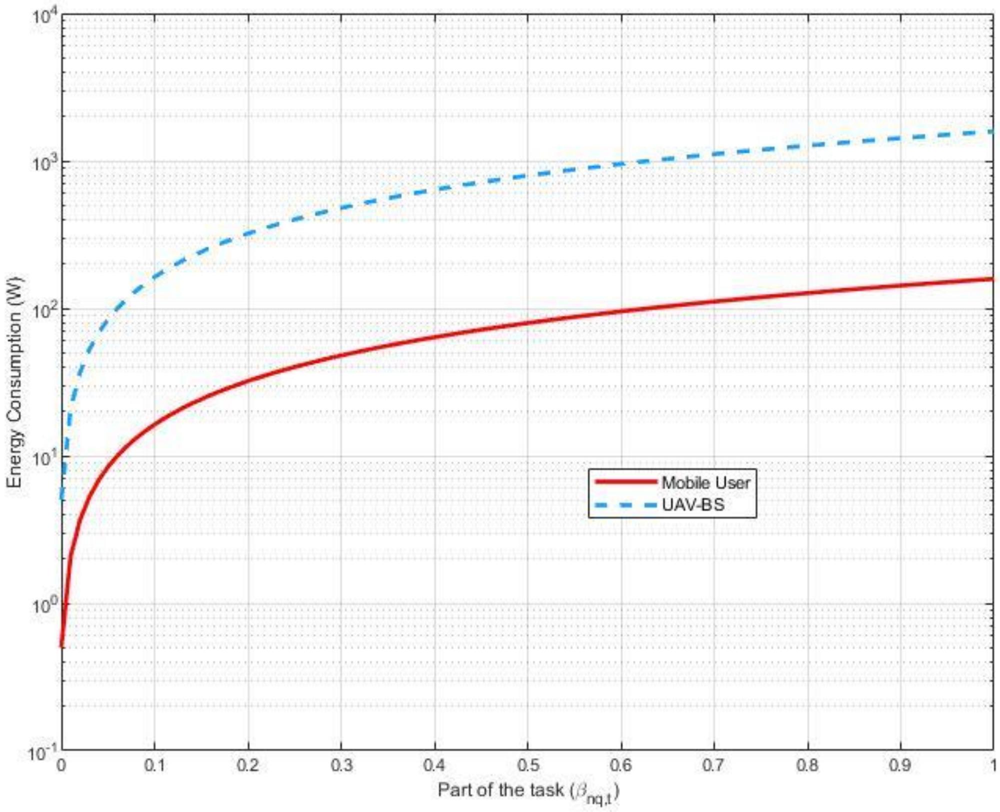

Figure 8: Comparison of the Energy Consumption (W) and Part of the Task ($\beta_{nq,t}$).

Chapter 4

Conclusion and Future Work

4.1 Conclusion

To have the ability of making the analyst more comfortable for research, Unmanned Aerial Vehicle (UAV) is being used as a flying base station instead of the conventional ground base station. As a flying base station it is more effective as it can cover a larger area than fixed locational base station. For making reliable communication and to decrease latency in wireless network communication, MEC has been applied along with the UAV in 5G Mobile networks. Here, we have used Non-Orthogonal Multiple Access (NOMA) for both Uplink and Downlink transmission which gives a far better experience to the users as well as saving energy and reducing problems like transmission delay. Besides, having a lot of advantages it has some drawbacks too which have been briefly mentioned in this thesis. From the overall simulation results, we can see that UAV-BS consumes a total of 90% more energy than the GMU when the SNR is 30 dB and task completion is 40%. Not only that, at 30 dB SNR range, total delay shows 0.16% more than the processing delay. We have briefly discussed UAV-BS along with MEC's comfort and weak zone as well as suggested a possible systemic model with mathematical results. Finally, by going through this paper it can be said that UAV-BS adds to a dependent, more cost effective, practical and on-demand wireless communication.

4.2 Future Work

To make wireless network communication more fruitful, employing UAV as base station is more than essential in the current time. This paper has discussed and showed how we can improve the performances of UAV and though there is some lacking, in future they can be improved by further investigation which have not been mentioned in our work. There is a huge opportunity to explore further into our proposed system model for future developments, some of which are mentioned below:

i. To get better transmission rate, transmit antenna selection techniques will be applied which includes using a secondary transmitter in order to get a better outage probability for downlink communication [26].

ii. In order to increase energy efficiency and throughput, optimization techniques such as optimal power with constraints, OPWC, and optimal power without constraints, OPWOC, can be applied both of which have shown much greater efficiency, especially OPWC shows great performance for high data rate and high path loss exponents [27].

iii. Additionally, energy harvesting techniques can be applied to the cognitive radio network by means of a two-slope path loss model which can help to improve the energy consumption of the UAV-BS [28].

iv. Also, by using a stochastic geometry approach we can analyze the energy efficiency of the UAV-BS and look further into the energy efficiency of the system. In order to design an efficient system we must consider ideal channel probability and transmission schedule probability and then derive the energy efficiency [29].

v. For our model, we have considered AWGN channel but the analysis can also be performed using a Nakagami-m fading channel as that shows a lower probability of error when MIMO-OFDM is used [30].

vi. Using an OFDM based communication for a Nakagami fading channel shows improved bit error rate for decode and forward scheme compared to amplify and forward scheme which can be investigated in our system model [31].

vii. Lastly, further investigation can be done on our proposed model in order to solve problems like latency and energy efficiency. By implementing an algorithm that optimizes the transmission power of ultra-reliable and low latency communication (URLLC) users and massive machine-type services (mMTC) users it is possible to improve the aforementioned issues [32].

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