Performance Analysis and Optimization of Infrastructure, Aerial and Multi-Hop Ad-Hoc Networks

by

Nadir Adam

Submitted in Partial Fulfillment of the
Requirements for the Degree
Doctor of Philosophy

Supervised by Professor Wendi Heinzelman and Professor Cristiano Tapparello

Department of Electrical and Computer Engineering
Arts, Sciences and Engineering
Edmund A. Hajim School of Engineering and Applied Sciences

University of Rochester
Rochester, New York

2020
To my family.
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Biographical Sketch

The author was born in Wad Madani, Sudan. He attended University of Khartoum and graduated with a Bachelor of Science degree in Electrical and Electronics Engineering in 2009. He began graduate studies in the Department of Electrical Engineering at United Arab Emirates University in 2012 and received a Master of Science degree in 2015. He began graduate studies in the Department of Electrical and Computer Engineering at the University of Rochester in 2015 and received a Master of Science degree in 2017.

The following publications were a result of work conducted during doctoral study:


Acknowledgments

First and foremost, I thank Allah for giving me the opportunity, strength, and ability to complete this research study.

I would like to express my earnest gratitude to my dissertation advisors Professor Wendi Heinzelman and Professor Cristiano Tapparello for their excellent guidance and mentorship that allowed me to finish this dissertation. In particular, I would like to thank them for dedicating their knowledge, experience and time to advise me through research difficulties and provide exceptional feedback and suggestions on my research projects, as well as proofreading my research papers. I would also like to thank Professor Halim Yanikomeroglu for his contribution to the placement optimization of multiple UAV-BSs project.

This dissertation is possible because of the friendship and support of the past and present members of the Wireless Communication and Networking Group (WCNG). A special thanks goes to Utku Demir, Dr. Hoda Ayatollahi, Dr. Colin Funai, and Dr. Sefik Emre Eskimez.

Also, I would also like to express my appreciation to the staff of the Electrical & Computer Engineering Department who have come to my assistance time and time again.

I would like to thank Professor Sandhya Dwarkadas and Professor Gonzalo Mateos for acting as members of my committee, and Professor Ehsan Hoque for acting as Chairperson of the defense.

Finally, I must express my very sincere gratitude to my wonderful family and lovely wife for their love, endless support and continuous encouragement throughout my years of PhD studies.
Abstract

With the increasing availability of wireless networks, the continuous development of new wireless technologies and recent technological advancements in the area of unmanned aerial systems, it is essential to optimize the users’ connection to meet the increased demands in terms of throughput and delay. In conventional infrastructure-based networks, the devices are connected to a central entity that is responsible for coordinating the network. Although infrastructure networks may be available in many situations, infrastructure-less or ad-hoc networks are necessary in situations where infrastructure-based networks are difficult to deploy (e.g., disaster or rural areas) or are inefficient to support connectivity. Therefore analyzing, optimizing, and selecting the best connection, whether it is through an existing infrastructure or an ad-hoc network, is vital for optimizing the users’ performance and meeting the quality of service (QoS) requirements.

My dissertation examines various approaches to optimize network connectivity for both wireless sensor networks and for mobile users. For example, I have used real elephants’ movement data and a multi-sink extension to the epidemic routing with vaccine protocol in Network Simulator (ns-3) to analyze the performance of Wi-Fi infrastructure mode and multi-hop Wi-Fi ad-hoc mode in a real life animal tracking sensor network application called JumboNet. Based on simulation results, Wi-Fi ad-hoc mode with epidemic routing outperforms infrastructure mode Wi-Fi in terms of packet delivery ratio. On the other hand Wi-Fi in infrastructure mode results in a lower delay and energy consumption per packet with the cost of a lower number of delivered packets.

Additionally, I developed an Android application that scans and collects information about the accessibility, quality and attributes of Wi-Fi access points, and cellular base stations. Moreover, the application measures the throughput and delay of the infrastructure networks. Based on the collected
data, about 10% of the scanned locations have only 0-2 Wi-Fi access points (APs), and for more than 20% of the locations, all the available APs are private and inaccessible due to security restrictions. Using an ad-hoc network can allow devices that do not have a direct access to the infrastructure network to be connected through other devices that do have access to the Wi-Fi APs.

In this regard, I developed an Android application that connects a Wi-Fi Direct ad-hoc network to the Internet via a gateway node that is connected to an infrastructure network. The application can be used to evaluate the impact of extending access to the Internet to devices that do not have direct access. Moreover, based on energy consumption models for LTE, Wi-Fi and Wi-Fi Direct, I evaluated the tradeoffs between throughput, delay, and energy consumption of infrastructure and multi-hop ad-hoc networks. Based on the collected data, the throughput of infrastructure and multi-hop ad-hoc networks increases with increasing data size. Furthermore, Wi-Fi Direct multi-hop ad-hoc networks with Wi-Fi connection from the gateway node are more energy efficient when uploading and downloading data compared with a direct cellular connection in some cases.

Furthermore, I investigated the 3D placement problem for multiple unmanned aerial vehicles base stations (UAV-BSs) that maximizes the number of covered users with the same as well as with different QoS requirements. First, I presented a mathematical formulation of the multiple UAV-BSs placement problem, and showed that it is a non-convex optimization problem. Then, I proposed two heuristic algorithms, and I showed that for users with the same as well as with different QoS requirements, the proposed algorithms achieve near optimal performance and outperform the Linear Approximation (LA) state-of-the-art algorithm in terms of the average number of covered users and execution time. Finally, I explored the 3D placement problem for multiple UAV-BSs that maximizes the number of covered ground users both with and without support of multi-hop ad hoc ground networks. First, I presented a mathematical formulation of the single UAV-BS placement problem, then I proposed a heuristic algorithm that maximizes the number of directly and indirectly covered ground users considering users with the same as well as with different quality of service (QoS) requirements. Simulation results show the merits of utilizing the multi-hop capabilities of the ground users in terms of reducing the number of UAV-BSs required to cover the users.
Overall, this dissertation contributes to the design, analysis, and optimization of infrastructure-based, aerial and multi-hop ad-hoc networks in various applications ranging from WSNs to mobile networks. Furthermore, these contributions will give new insights to the design of next generation wireless networks that are able to meet the users’ demands and QoS requirements.
Contributors and Funding Sources

This work was supported by a dissertation committee consisting of Professor Wendi Heinzelman (advisor) from the Department of Electrical and Computer Engineering, Dr. Cristiano Tapparello (co-advisor) from the Department of Electrical and Computer Engineering, Professor Gonzalo Mateos from the Department of Electrical and Computer Engineering, and Professor Sandhya Dwarkadas from the Department of Computer Science. The ns-3 multi-sink extension presented in Chapter 3 was developed by Dr. Cristiano Tapparello. Additionally, the ns-3 code used in Chapter 3 was partially developed by Ibrahim Akbar. The Android application presented in Chapter 4 was partially developed by Dr. Colin Funai. All other work in this dissertation was completed independently by the author.

This work was funded by the National Science Foundation (NSF), Harris RF, Empire State Development’s Division of Science, Technology and Innovation (NYSTAR), University of Rochester Data Science Center of Excellence (CoE), and University of Rochester Center for Emerging and Innovative Sciences (CEIS).
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Chapter 1

Introduction

The technological advancements of smartphones and tablets within the past few years have increased the demands for wireless and mobile networks [1]. According to a recent report by Cisco, 13% of the total IP traffic in 2016 was from smartphones, and this is expected to rise up to 33% and to exceed Personal Computers (PC) traffic by 2021 [2]. Moreover, the growth rates of smartphones, devices that support Machine-to-Machine (M2M) communications, TVs, and tablets are expected to be 49%, 49%, 21%, and 29% by 2021, respectively [2].

In parallel, Wireless Sensor Networks (WSNs) have gained increasing popularity for a range of applications, such as air quality monitoring, water quality monitoring, disaster monitoring, and animal tracking to improve the ecosystem and human life. For instance, there is a high cost associated with providing fencing and mustering for animals, hence, providing situational awareness of the state of the pasture and of the animals is crucial, especially in areas where humans and animals share the same living area [3, 4, 5, 6].

Furthermore, Unmanned Aerial Vehicles (UAVs) have been utilized in recent years to support a wide array of applications such as natural disaster monitoring, emergency situation assistance, and providing coverage in rural or sparsely populated areas [7, 8]. This is due to their cost efficiency, ease of deployment, high relocation flexibility, and the higher probability of establishing a Line-of-sight (LoS) communication between a UAV and the ground users [9, 10].

Due to the increasing availability of these different types of wireless networks and the continuous development of new wireless technologies and protocols, it is vital to analyze and optimize infrastructure networks and multi-hop ad-hoc networks, whether to improve the ecosystem using wireless
sensor networks [11], or to optimize the users’ and network performance in traditional wireless and mobile networks [12].

1.1 Wireless Sensor Networks (WSNs)

Wireless Sensor Networks (WSNs) consist of spatially distributed, autonomous, wireless, networked sensor nodes that are deployed and must remain operational to collect and transfer data from the environment to a base-station [13, 14]. WSNs have gained increasing popularity for a range of applications, such as environmental monitoring [15, 16, 17, 18], monitoring for disasters such as earthquakes, hurricanes and floods [19, 20, 21], health monitoring of civil structures such as bridges and buildings [22, 23, 24], and animal tracking [3, 4, 5, 6].

However, sensor nodes have limited energy in their primary power storage unit, and this energy may be quickly drained if the sensor node remains operational over long periods of time. Therefore, the idea of harvesting ambient energy from the immediate surroundings of the deployed sensors has been explored, to recharge the batteries and to directly power the sensor nodes. This type of WSN is typically referred to as an Energy-Harvesting Wireless Sensor Network (EH-WSN).

1.2 Energy-Harvesting Wireless Sensor Networks (EH-WSNs)

To address the challenge of the limited energy supply when powering sensor nodes with batteries, new WSN platforms that support the harvesting of energy from the immediate surroundings have been developed. These devices are able to capture small amounts of energy that would have been lost as heat, light, sound, vibration or movement within the environment [25]. By recharging the battery with energy harvested from the environment, and by developing energy harvesting aware protocols that support so-called “energy-neutral operation,” theoretically, WSNs could have infinite lifetime.

Several researchers have explored technologies to harvest energy from natural sources such as the sun, wind, and water flow to power the sensor nodes [25], while others have explored man-made sources of energy, such as humans and animals walking, magnetic fields, high frequency vibrations,
and Radio Frequency (RF) fields [26]. In this dissertation, I focus on mechanical energy harvesting
due to its implementation in the JumboNet application.

1.3 Infrastructure-Based Wireless Networks

In conventional infrastructure-based networks, the devices in the network are connected to a cen-
tral entity that is responsible for coordinating the network. Cellular and Wi-Fi networks are the two
most dominant infrastructure-based networks that provide access to the Internet for mobile and wire-
less devices.

1.3.1 Long Term Evolution (LTE)

LTE is a cellular broadband technology defined by the Third Generation Partnership Project
(3GPP). LTE is based on Orthogonal Frequency Division Multiplexing (OFDM) to achieve higher
data rates, better coverage, low latency, improved system capacity, and multi-antenna support [27, 28].

The LTE access network is composed of an eNodeB, which manages radio resources, whereas the
core network is composed of the Mobility Management Entity (MME), the Serving Gateway (S-GW),
and the Packet Data Network Gateway (P-GW) [29]. The MME is responsible for authentication,
security, and storing of users’ position information. The S-GW is responsible for routing and data
forwarding, whereas the outgoing communication with IP and circuit switched networks is handled
by the P-GW. The LTE standard defines a peak rate of 1 Gbps for low mobility and 100 Mbps for high
mobility communication with a coverage area up to several kilometers [30].

1.3.2 IEEE 802.11 (Wi-Fi)

Wireless Fidelity (Wi-Fi) is a protocol defined by the Wi-Fi Alliance that allows devices inside a
Wireless Local Area Network (WLAN) to connect to the Internet when connected to an access point
(AP) using the unlicensed 2.4 GHz and 5 GHz spectrum bands [31, 32]. The latest Wi-Fi 802.11
standard was designed to achieve data rates up to 7 Gbps, and a coverage area in the hundreds of meters [33]. Although Wi-Fi has penetrated most areas in the US, most Wi-Fi access points (APs) do not allow unauthorized devices to connect to them for security reasons.

In the infrastructure mode, the Wi-Fi AP coordinates the network centrally in a virtual star topology [34]. In order to discover active networks, Wi-Fi stations scan the available channels looking for transmitted beacons from access points (APs). Afterwards, the Wi-Fi station authenticates itself with the AP, after which the station can participate in the network [31].

1.4 Ad-Hoc Wireless Networks

In contrast to infrastructure networks, wireless ad-hoc networks, are infrastructure-less networks in which the devices communicate between each other without the need for central control [35]. Furthermore, infrastructure-less networks are necessary in situations where infrastructure-based networks are insufficient to support connectivity or are difficult to deploy, e.g., rural or disaster areas [36].

1.4.1 Wi-Fi Ad-Hoc Mode

In ad-hoc mode, Wi-Fi capable devices can directly communicate with each other, and the management of the ad-hoc network is done through collaboration between the nodes in the network that share responsibility equally [37]. Only single-hop communication is supported, so if devices A and B are not within the transmission range of each other, they cannot talk to each other. Multi-hop communication in ad-hoc mode is not supported due to the lack of routing functions within the Wi-Fi standard [38].

1.4.2 Wi-Fi Direct

One of the promising protocols that is capable of creating ad-hoc networks is Wi-Fi Direct, which can play a major role in providing an Internet connection to devices that are not able or allowed to directly connect to the Internet. Wi-Fi Direct is a protocol defined by the Wi-Fi Alliance to enhance
peer to peer communication over traditional Wi-Fi without the requirement of a fixed infrastructure. The Wi-Fi Direct standard organizes devices into groups, where one device acts as the Group Owner (GO) and embeds soft access point (AP) functionalities such as power management mechanisms similar to an infrastructure-based Wi-Fi network. Moreover, the GO is responsible for group advertisement as well as routing data through its group. All the other devices connect to the GO, and act as Group Members (GMs) [39, 40].

1.5 Networks Supported by Unmanned Aerial Vehicles (UAVs)

In the wireless communication field, aerial base stations or unmanned aerial vehicles base stations (UAV-BSs) have been studied recently as a way of improving the performance of wireless networks in scenarios where we expect a high atypical traffic such as in disaster areas or at temporary events, or scenarios in which the terrestrial network is damaged, unavailable or insufficient to provide the required QoS requirements to the users [41, 42].

Furthermore, utilizing mobility control and adaptive communication can provide good wireless connectivity to the terrestrial network or the ground users [43]. Therefore, the use of UAV-BSs has been proposed to support users that suffer from sever shadowing or experience high interference [44]. Indeed, using UAVs equipped with wireless transceivers has already been proposed to improve the performance of 5G networks [45]. Furthermore, mobile operators like Verizon and AT&T have already conducted trials on using LTE UAV-BSs [46], [47]. Obtaining the best performance from the UAV-BSs is highly dependent on their 3D locations, and hence research on their placement has gained significant interest recently [48].

1.6 Contributions of this Dissertation

Given the increasing number of mobile devices with access to the Internet and the development of different wireless technologies, in addition to the recent technological advancements in the area of unmanned aerial systems, enhancing the network performance by choosing the best connection
and optimizing the locations of UAV-BSs becomes paramount. For instance, both wireless devices in mobile networks and sensor nodes in WSNs may send or receive data via a direct path through infrastructure networks or through an indirect path via one or multiple devices using ad-hoc networks. Finally, optimizing the location of a UAV-BS has a huge impact on its performance.

This dissertation aims to address the analysis and optimization of infrastructure, aerial and multi-hop ad-hoc networks in order to improve the users’ and network performance. The specific contributions of my work include the following:

- I have presented a review of the state-of-the-art in EH-WSNs for environmental monitoring applications including a real life elephant tracking application called JumboNet [49]. This work is described in [50] and part of it is described Section 2.2.

- I have used real elephants’ movement data and a multi-sink extension to ns-3 to evaluate the performance of Wi-Fi and Wi-Fi ad-hoc with epidemic routing in JumboNet [49]. This work is described in [51] and in detail in Chapter 3.

- I have developed an Android application that collects information about the accessibility, quality and attributes of Wi-Fi access points, in addition to cellular base stations. Moreover, the application measures the throughput and delay of both infrastructure networks. This work is described in [52] and in detail in Chapter 4.

- I have developed an Android application that connects an ad-hoc network to the Internet via a gateway node that is connected to an infrastructure network. Furthermore, the application shows the performance of extending access to the Internet to devices that do not have direct access. Moreover, based on energy consumption models for LTE, Wi-Fi and Wi-Fi Direct, I have evaluated the tradeoffs between throughput, delay, and energy consumption of infrastructure and multi-hop ad-hoc networks. This work is presented in [53] and explained in Chapter 5.

- I have proposed two heuristic algorithms to optimize the location of multiple UAV-BSs to maximize the number of covered users, and I have shown that for users with the same as well as with different QoS requirements, the proposed algorithms achieve near optimal performance
and outperform the Linear Approximation (LA) state-of-the-art algorithm in terms of the average number of covered users and execution time. This work is presented in [54] and explained in Chapter 6.

- I have proposed a heuristic algorithm that takes into account the multi-hop capabilities of the ground users and reduces the required number of UAV-BSs to provide coverage for all users. This work is presented in [55] and explained in Chapter 7.

Overall, this dissertation contributes to the design, analysis, and optimization of infrastructure-based, aerial and multi-hop ad-hoc networks in various applications ranging from WSNs to mobile networks. Furthermore, these contributions give new insights to the design of next generation wireless networks that are able to meet the users’ demands and QoS requirements.

This dissertation is organized as follows. Chapter 2 provides related work on energy harvesting in Wireless Sensor Networks (WSNs), wireless networks for wildlife monitoring, wireless infrastructure networks performance evaluation as well as wireless networks optimization using unmanned aerial vehicles (UAVs). Chapter 3 evaluates the performance of direct Wi-Fi and Wi-Fi ad-hoc with various epidemic routing protocols for movement pattern analysis and real time monitoring of the elephants’ locations in JumboNet. In Chapter 4, I evaluate the accessibility and the quality of wireless networks, and I provide analysis of the infrastructure network in terms of the upload and download speeds. Chapter 5, presents an Android application that creates multi-hop ad-hoc networks using Wi-Fi Direct and either Wi-Fi or LTE cellular connection from a gateway node to the Internet. Chapter 6 presents a mathematical formulation of the multiple UAV-BS placement problem, and shows heuristic algorithms that solve the problem and optimize the locations of the UAV-BSs. In Chapter 7, I present a heuristic algorithm that optimizes the locations of multiple UAV-BSs while taking into account the multi-hop capabilities of the ground users. Finally, Chapter 8 presents an overview of my contributions to the development and optimization of wireless and mobile networks, as well as suggestions for future work.
Chapter 2

Related Work

In this chapter, I provide an overview of the previous work in mechanical energy harvesting, animal tracking using wireless networks, a background on the performance evaluation and analysis of infrastructure-based and ad-hoc networks, and UAV placement optimization in wireless networks.

2.1 Mechanical Energy Harvesting

Due to the piezoelectric materials’ properties, piezoelectric energy harvesting devices are known to generate energy at higher voltages without any external voltage supply. For instance, lead zirconate titanate (PZT) is known for its high energy conversion rate, while polyvinylidene fluoride (PVDF) is known for its high mechanical strength [56]. Other advantages piezoelectric harvesters offer in WSNs include their easiness to model due to their simple structure, low cost, and absence of electromagnetic interference [56, 57, 58]. On the other hand, piezoelectric devices require energy harvesting circuits in order to regulate the output power leading to energy losses, thereby affecting the overall efficiency of the energy harvesting system [56]. Moreover, it is difficult to integrate piezoelectric devices into a small system [57, 58].

There are a number of systems that have been developed using piezoelectric devices. For example, in [59], an underground piezoelectric energy harvester used in an agricultural application was shown to provide encouraging capabilities in harvesting above ground accelerations from a four wheeler center pivot irrigation system. Moreover, energy harvesting from the vibrations of roads caused by automobiles is another promising technique for powering wireless sensor nodes. This approach has
been used for monitoring car exhaust fumes (air quality measurements) or measuring traffic flow (disaster traffic management) [60, 61, 62]. Additionally, harvesting energy from vibrations has been used for disaster relief operations [63], where experimental results show that a mechanical vibration energy harvesting system can provide sustainable energy for operation. A high vibrational acceleration, wide range frequency band, and an adaptive resonant frequency tracker are the main requirements to design a high performance vibration energy harvesting system.

Energy can also be harvested from water current depending on the water flow rate, either from water flow with greater pressure (turbulent) or flow at a constant velocity. The energy derived from flowing water is mainly kinetic. Kinetic energy is obtained as a result of pressure fluctuations or by applying pressure to the flowing water using mechanical devices and must be converted into electrical energy. While water flow energy harvesting has not been explored extensively in WSNs, some research has explored how to harvest energy from flowing water. Most of these works used different techniques to harvest kinetic energy. For example, [64] used a fluttering flag to harvest kinetic energy from a turbulent flowing water to electrical energy using a piezoceramic transducer; [65] used a shear mode piezoelectric energy harvester to harness energy from pressurized water flow; [66] harvested energy using a micro-turbine from a water distribution system in different bypass pipes; and [67] used an electromagnetic vibration generator to harvest energy from the periodic movement of a magnet within a coil box.

2.2 Wireless Networks For Wildlife Monitoring

Wireless networks have been used to track and gather information about different animal species with projects such as TurtleNet for studying the Gopher tortoise [68], ZebraNet for tracking Zebras [69], tracking sheeps [70], and tracking Cervus elaphus (a type of deer) in their environment to keep them from becoming an endangered species [71], [72]. The animals’ habits, behaviors and habitat conditions can help researchers provide the basis for the effective protection, sustainable use, and scientific management of wildlife resources [71], [72], [73].

To gather the required information, a wireless device is typically attached to the animal, and
Global Positioning System (GPS) is usually used to find the animal’s location [74]. Afterwards, the location and auxiliary sensor data is transmitted to a base station either directly using Wi-Fi, cellular or satellite communication [75], or through multi-hop ad-hoc networks [69]. While satellite communication is considered a possible solution [75], the considerable additional cost and energy consumption of such a connection make it impractical for large scale deployments [51].

As a solution to the expensive cost of using satellite communication, energy harvesting can be used to recharge the batteries of the wireless device and extend its lifetime. For instance, the ZebraNet and TurtleNet projects use solar power [68], [69], while thermal energy harvesting is used in [70] to recharge their system batteries.

2.3 Wireless Infrastructure Networks Performance Evaluation

Several studies have been carried out in the literature to evaluate the availability and performance of various wireless technologies, as summarized in Table 2.1.

2.3.1 Wi-Fi Networks Performance Evaluation

An experimental evaluation of Wi-Fi in terms of the coverage, loss rate, and throughput was presented in [76, 77, 78, 79]. Furthermore, the authors in [80, 81, 82, 83] investigated the throughput, power, and energy consumption per bit of different modern smartphones when using Wi-Fi. Moreover, based on the work in [81], an energy consumption model for Wi-Fi was obtained and presented in [84].

An experiment to observe the impact of buildings on a wireless network, focusing on its performance as a function of physical distance and channel overlap was conducted in [85]. The authors also used a spectrum analyzer for a week to continuously monitor the wireless network in an office building, and found the average RSSI indoors to be 20 dB higher compared to the average RSSI recorded outdoors. A symbolic space modeling and analysis based on Wi-Fi network data was presented in [86]. The authors’ aim was to use the Wi-Fi network usage patterns to characterize the physical space. For instance, in libraries, the usage percentage of the Wi-Fi network would be high as
most people use wireless devices.

### 2.3.2 Cellular Networks Performance Evaluation

The authors in [87] analyzed cellular connectivity and quality of three cellular network providers in Trondheim, Norway. First, the authors have developed an Android application that collects parameters such as GPS coordinates, signal strength indicator (RSSI) and round trip delay. Based on the their results, a higher signal strength slightly improves the round-trip delay. In contrast, in the EDGE network, the round-trip delay is highly correlated with the received signal strength.

Similarly, the achieved data rates and power consumption of LTE were investigated in [88, 89]. Based on the experimental results, the authors proposed an LTE energy consumption model based on the received and transmitted powers in addition to the data rate. Similarly, the energy consumption of LTE was investigated in [90], in which the authors have found that the energy consumption to download data varies with the network quality.

### 2.3.3 Wi-Fi & Cellular Networks Performance Evaluation

An experimental evaluation of the accessibility and amount of data transferred from and to the Internet on 3G and Wi-Fi access points is conducted for both driving and walking speeds in [91, 92, 93]. Similarly, Paris Wi-Fi and 3G connectivity were studied in [33] to evaluate the potential of Wi-Fi offloading using 82 Km of the bus routes of the city. The authors have obtained 92% 3G cellular coverage, and 99% Wi-Fi coverage using Wireless Internet Service Providers (WISPs) access points.

The throughput and power consumption of different wireless technologies such as Bluetooth, Wi-Fi Direct, 3G, and 4G were studied in [94, 95, 96, 97, 98, 99, 100, 101]. For power measurements, the authors in [98] used iperf to generate and shape data, and Labview was used on a laptop to configure the Agilent E3631A power supply to provide the current. On the other hand, for power measurements, the authors in [101] connected a Monsoon power meter to the device and ran data transfers. Furthermore, for traffic measurements, the traffic was recorded using tcpdump via the Android API.
The authors in [102] developed an Android application that continuously sends and receives data, and then recorded the percentage of available battery, amount of transferred data, and elapsed time when using Bluetooth, Wi-Fi and 3G. The measurement experiments were performed on an HTC Desire HD phone running Android 2.3 operating system.

The authors also proposed a simple linear energy consumption model based on the percentage of consumed battery, when transferring $x$ amount of data in GB, or when using the technology for $z$ amount of hours. Furthermore, the authors presented the benefits of their proposed protocol of collaborative downloading by combining together different wireless technologies.

The authors in [102] have found that in 3G, almost 60% of the total energy is wasted as tail energy (energy consumed in high-power state after completion of data transfer), while on the other hand, the ramp energy (energy consumed in switching to high-power state before transfer) is relatively small (14%) compared to the total energy. Finally, it was concluded from [94, 102, 98, 101] that Wi-Fi Direct is the most energy efficient technology followed by Bluetooth, 3G, and 4G.

### 2.4 Wi-Fi Direct Ad-Hoc Networks Performance Evaluation

The authors in [106] conducted a measurements-based study of opportunistic communication that implements a store, carry, and forward paradigm in single and multi-hop wireless networks using Bluetooth, Wi-Fi, and Wi-Fi Direct. Based on practical measurements, the authors have found that mutli-hop networks using Wi-Fi Direct exhibit larger overhead and shorter data transfer delays compared to multi-hop Wi-Fi ad-hoc networks. For instance, the delay to transfer 20 MB of data through a 3-hop Wi-Fi Direct network was about 5.6 seconds, while it was about 6 seconds for a 3-hop Wi-Fi ad-hoc network. Similarly, the performance of a multi-hop Wi-Fi Direct network was evaluated in [107] using 4 Android Nexus 7 devices. The authors measured the network throughput and packet loss rate by varying offered load using Iperf. Their experimental results showed that the throughput decreases with the number of hops, as expected.

Although the research conducted in [106, 107] is related to our work in terms of obtaining experimental results of multi-hop Wi-Fi Direct networks, the authors’ focus in [106] was on the ad-hoc
networks themselves, and on techniques to overcome the 2-hop Wi-Fi Direct limitation, while the authors in [107] proposed and evaluated a multi-hop Wi-Fi Direct protocol that uses IPv6.

To the best of our knowledge, none of the previous work examined how extending access to the Internet to devices that do not have a direct access affects the network performance in terms of throughput, delay, and energy consumption.

Table 2.1: Throughput and energy consumption measurements for various wireless technologies.

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2.5 Wireless Networks Optimization Using Unmanned Aerial Vehicles (UAVs)

Due to recent technological advancements in the area of unmanned aerial systems, equipping an unmanned aerial vehicle (UAV) with a base station (BS) has been proposed to augment terrestrial base stations and to enhance the performance of 5G and beyond-5G networks.

The authors in [108, 109, 110] addressed the problem of locating multiple UAVs in ad-hoc networks to improve the network connectivity and achieve load balancing. The problem was formulated as facility location problem [109, 110] and a combinational optimization problem [108]. Additionally, different methods were proposed to solve the optimization problem and cover all ground users.

Moreover, the authors in [111, 112] addressed the problem of providing full connectivity of disconnected mobile ground nodes and proposed a heuristic algorithm that finds the minimum number and locations of multiple UAVs dynamically. Moreover, the authors assumed the nodes are organized into clusters and at least one node in each cluster should be in the range of at least one UAV. Afterwards, the problem was formulated as an extension of the Facility Location Problem (FLP), which is a non-convex minimization problem. Then, the authors used deterministic annealing clustering algorithm to find the minimum number of UAVs and their locations. Finally, the proposed algorithm is compared with an idealized grid algorithm and K-means clustering algorithm to determine optimality of the solution.

The authors of [113] proposed an algorithm to minimize the number of UAV-BSs needed to provide wireless coverage for a group of distributed terminals on the ground, ensuring that each node is within the communication range of at least one UAV-BS. The authors formulated the UAVs placement problem as a geometric disk cover problem whose objective is to cover a set of \( K \) nodes with a minimum number of disks with a certain radius. The authors proposed a polynomial-time algorithm that places the UAV-BSs sequentially, starting from the perimeter of the area boundary in an inward spiral manner until all the ground nodes are covered. Based on simulation results, the proposed algorithm showed better performance compared to similar heuristic algorithms in terms of the number of required UAV-BSs and time complexity, in addition to a near-optimal performance.
The authors in [114, 115] addressed the problem of finding the minimum number of UAV-BSs and their placement to provide coverage of users with some target quality of service. Moreover, the authors proposed a heuristic algorithm based on particle swarm optimization to find the minimum number of UAV-BSs and their 3D placement positions with different user densities and arbitrary locations. The authors extended their work in [116] to address the problem of maximizing the number of covered users with different quality of service requirements by optimally placing a single UAV-BS. The authors modeled the placement problem as a multiple circles placement problem and proposed an optimal algorithm that utilizes an exhaustive search (ES) over a 1-D parameter in a closed region. Furthermore, the authors also propose a maximal weighted area (MWA) algorithm to tackle the placement problem. Simulation results show that the proposed MWA algorithm achieves comparable performance to the ES algorithm with significant complexity reduction.

The placement problem of multiple UAV-BSs to maximize the number of covered users with the same QoS requirements was studied in [117]. The UAV-BS placement problem was modeled as a circle placement problem, and the authors proposed a successive deployment method based on linear approximation and a K-means clustering technique to solve the placement problem. Simulation results demonstrate that the proposed circle placement methods achieve higher user coverage probability than the benchmark circle placement theory (CPT).

The research conducted in [115, 116, 117] is related to our work in terms of placing either a single UAV-BS for users with different QoS requirements [115], or placing multiple UAV-BSs for users with the same QoS requirements [117]. However, in this dissertation, I tackle the complex combination of these problems by optimizing the locations of multiple UAV-BSs to maximize the number of covered users with different QoS requirements taking into account the multi-hop capabilities of the ground users.
Chapter 3

Performance Evaluation of Wi-Fi vs. Wi-Fi Ad-Hoc with Epidemic Routing in JumboNet

3.1 Introduction

In many parts of Asia, elephants and humans coexist, which causes deaths on both sides. For instance, in Sri Lanka there are a high number of deaths among elephants and people due to the human-elephant conflict. According to the Department of Wild Life in Sri Lanka, the total elephant population in Sri Lanka stood at 5,879 in 2011 but, since then, an average of more than 200 elephants and more than 70 people have been killed annually as a result of conflicts between elephants and humans [118]. The search for effective measures to deal with Human–Elephant Conflicts (HEC) is one of the most significant challenges for elephant conservation globally, which lead the authors in [119] to propose the JumboNet application for tracking elephants.

Recent studies on wild elephants have shown that, on average, Asian elephants travel 3.2 km per day in herds, while lone males travel 3.6 km per day and up to 8.9 km per day in musth [120]. Typically, elephants visit a water source at least once a day and, depending on the particular natural environment, can come in the vicinity of other elephants at ponds and other locations on several occasions [121]. Hence, the elephants can be represented as a sparse mobile ad-hoc network or a delay tolerant network.

A kinetic energy harvester prototype that uses magnetic levitation and ferro fluid bearings to generate energy from an elephant’s movements was presented in [119]. The proposed harvester is composed of one moving magnet, two stationary magnets, a polycarbonate tube, and two coils. Through
experimentally validated analytical and simulation models of the energy harvester, and measurements of the elephant movement, the proposed prototype was found to be able to generate 88.91 J per day. This energy was able to power a mounted tracking unit (tag), which transmits the elephant’s location to a remote monitoring center at least 24 times a day.

The JumboNet QoS metrics include the delay to receive the location data, the wireless device energy consumption, and the location data packet delivery ratio of different wireless technologies. Due to the highly negative impacts of the Human–Elephant Conflicts (HEC), and the need to mitigate its effects, the best wireless technology must be used to maximize the application performance based on the QoS metrics, whether it is through infrastructure networks or via multi-hop ad-hoc networks.

Given the above, in this chapter I discuss and evaluate the performance of direct Wi-Fi and Wi-Fi ad-hoc with various epidemic routing protocols for movement pattern analysis and real time monitoring of the elephants’ locations in JumboNet.

3.2 Routing Protocols in JumboNet

In this section, I provide a brief description of some of the routing protocols implemented to allow multi-hop communication using Wi-Fi ad-hoc in JumboNet. In particular, I describe spray and wait, epidemic routing, and epidemic routing with vaccine protocols.

3.2.1 Spray and Wait

The authors in [122] proposed the “Spray and Wait” protocol, in which the node spreads message copies in the network until an adequate number of copies are disseminated, at which point the node switches to direct transmission, whereby the node only sends the packet directly to the sink once in range. There are many techniques for spraying message copies in the network. Regarding the system implementation, I focus on source spraying, in which, each source node starts with L message copies, and forwards them to the first L encountered nodes. In our simulation, I implement the source spray and wait protocol, in which the source node sends its packets to all nodes it encounters, then these nodes cannot forward these packets unless they are in transmission range of a sink.
3.2.2 Epidemic Routing

Epidemic routing has been proposed as a viable approach for routing data in networks where there is no direct connection between the source and the destination at the time of data generation. Epidemic routing is a store-and-forward protocol, where all the generated and received data are first stored in a buffer and then disseminated to any other node as soon as it is within transmission range. The protocol relies on mutual packet exchange between mobile nodes, and considers that one of the nodes will eventually reach the destination [123].

3.2.3 Epidemic Routing with Vaccine

In some situations, the traditional epidemic routing protocol can result in buffer overflow and energy waste that results from storing and exchanging messages that have already been delivered to the destination. Hence, many approaches have been proposed to overcome this issue, such as limiting the time the messages are forwarded [124], limiting the hop count [124], optimizing beaconing rate [125, 126], using explicit notification via vaccine [127], and immunity [128].

The different elements required for the epidemic routing operation are described in detail in [129]. In what follows, I provide a brief overview of each component for completeness, in addition to a description of all the parameters that I can control.

Beacon Mechanism

The epidemic routing ns-3 implementation uses an automatic beaconing mechanism, where each node automatically broadcasts a control packet that contains information about the sender. This beacon packet is used to notify nearby nodes of the presence of a node so that the summary vector exchange with vaccine can be performed.

Summary Vector Exchange with Vaccine

The summary vector exchange with vaccine mechanism represents the core of the epidemic routing protocol. According to this mechanism, when two nodes meet (i.e., one of the nodes receives a
beacon from the other) they first determine which packets each node is missing, and then exchange those packets so that at the end of the process both nodes have the same set of packets.

The main objective of the summary vector exchange is to avoid the transmission of packets that are already present in the other node. At the same time, the nodes will exchange a vaccine packet that lists all packets known to have been delivered to the sink, which ensures that packets that already reached the destination are not propagated further throughout the network. The summary vector exchange with vaccine is shown in Figure 3.1.

According to this mechanism, when two nodes meet, the nodes with the smaller node identifier (node A, in Figure 3.1) sends its vaccine vector denoted as $VV_A$ to the other node (node B). After receiving $VV_A$, node B first uses the packet IDs contained in $VV_A$ to generate the vaccine vector $VV_B$ by determining the set of packets for which it has the vaccine but that are not present in $VV_A$, and then updates its packet and vaccine queues accordingly (i.e., it removes from its packet queue the packets for which it received the vaccine and adds the missing vaccines to its own queue). Vector $VV_B$ is then sent back to node A, which uses the vector to update its own packet and vaccine queues. At this point, node A follows the traditional epidemic routing protocol and sends to node B its summary vector ($SV_A$), which includes all the packets in A’s packet queue. After receiving $SV_A$, node B compares the packet IDs contained in the vector with the packet IDs present in its own buffer, and determines both the packets that it needs to send to node A and the packets that it needs to receive from node A, $SV_B$. After this, node B first sends to node A the missing packets and then the summary vector $SV_B$, which is used by node A to send the packets that node B is missing. At the end of this five-way handshake, both nodes have the same set of packets, unless they moved out of connectivity range before the process could be completed.

**Epidemic Buffer**

Each node is equipped with a buffer to store its own data, in addition to accepted data from other nodes. Two parameters can be tuned to control the buffer size, $QueueLength$, which determines the maximum size of this queue, and $QueueEntryExpireTime$, which determines the maximum time a packet can live in the epidemic queue since it was generated at the source.
CHAPTER 3. PERFORMANCE EVALUATION OF WI-FI VS. WI-FI AD-HOC WITH EPIDEMIC ROUTING IN JUMBONET

Figure 3.1: Summary vector exchange with vaccine scheme.

Vaccine Buffer

An extra buffer is needed when implementing the vaccine with epidemic routing. This buffer is required to store the IDs of the packets already received by any sink. Vaccine buffer size can be tuned using VaccineQueueLength that determines the maximum size of this queue, and VaccineEntryExpireTime that determines the maximum time a vaccine can live in the vaccine queue since generated at the destination.

Hop Count

The HopCount field determines the maximum number of exchanges each packet encounters beyond the source before it is dropped, and it was introduced to work as a time to live (TTL) field in IP packets, to limit the number of packet exchanges in the network [123].

Host Recent Period

HostRecentPeriod contains the time in seconds in which hosts cannot re-exchange summary vectors. This value can be tuned based on the probability of acquiring new messages in a certain period of time.

3.3 Multi-Sink Extension

In real time monitoring, tracking data must reach the destination within a specific delay bound; this can either be done by increasing the nodes’ transmission power or by adding more sinks to increase
the probability of a node being in the vicinity of one of the sinks. For direct delivery, spray and wait, and epidemic routing without vaccine, the extension of these protocols to the case of multiple sinks is straightforward. The nodes simply deliver the packets to any of the sinks.

On the other hand, in order to support the delivery of the packets to multiple sinks, the epidemic routing with vaccine extension allows us to directly specify the list of sinks as a protocol parameter. This list is used by the protocol to establish separate point to point connections between the sinks so that, as soon as one of the sinks receives a data packet from one of the nodes, the corresponding vaccine entry can be added to the vaccine buffer of all the other sinks. This extension allows for a further reduction of the traffic generated by the network by avoiding the delivery of the same packet to different sinks, as well as by spreading the vaccine of a packet through multiple generation points (i.e., each sink).

3.4 Simulation Results

In this section, I study the performance of different delay-tolerant routing protocols in single and multiple sinks networks by simulating the scenario where the nodes move according to the wild elephants’ movement data provided by the Centre for Conservation and Research, Sri Lanka [130], and shown in Figure 3.2, and compare it to two direct delivery approaches: one in which the nodes can only buffer 1 packet and the second one in which the nodes can buffer the data until they are delivered. In the implementation, the transmission power is varied from 0 dBm to 14 dBm, which translates to a transmission range from 6 Km to 30 Km, respectively, based on the free space propagation model [131].

I provide analysis on the achievable packet delivery ratio, average delay and the energy consumption per received packet. In order to evaluate the performance of the protocols, I consider two applications: movement patterns analysis and real time tracking.
Figure 3.2: Wild elephants’ movements recorded in Sri Lanka for 24 tagged elephants and the locations of the sinks. Each line represents the movement of a herd of elephants over the course of 10 days.

3.4.1 Movement Patterns Analysis

When studying animals’ grazing habits and movement patterns, obtaining as much information about all the elephants’ locations as possible will provide better analysis and helps in developing future mobility models. For this scenario, packet delivery ratio is the most important metric.

Regarding the system implementation, I simulate the scenario in which each herd leader generates its location information once every hour for a total of 24 times per day, which is feasible using the energy harvested from the elephant movement as described in [119]. I set the interval between beacons to be 60 minutes, which is the same as the location generation rate, and I set the time in which the elephants do not re-exchange the summary vectors also to 60 minutes to limit the energy consumption. Moreover, based on the information in [119], I set the size of the position updates to be 32 bytes. I assume the nodes have limited buffer size and can only store half the maximum number of packets in the network.
Table 3.1: Movement pattern analysis parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of elephants</td>
<td>24</td>
</tr>
<tr>
<td>Number of packets per node over simulation time</td>
<td>24 packets</td>
</tr>
<tr>
<td>Packet size</td>
<td>32 Bytes</td>
</tr>
<tr>
<td>Hop Count</td>
<td>6</td>
</tr>
<tr>
<td>Maximum epidemic buffer occupancy</td>
<td>288 packets</td>
</tr>
<tr>
<td>Maximum vaccine buffer occupancy</td>
<td>576 IDs</td>
</tr>
<tr>
<td>Maximum Tx Current</td>
<td>23.5 mA</td>
</tr>
<tr>
<td>Rx Current</td>
<td>5.5 mA</td>
</tr>
<tr>
<td>Idle Current</td>
<td>0.12 µA</td>
</tr>
<tr>
<td>Rx Sensitivity</td>
<td>-107 dBm</td>
</tr>
<tr>
<td>Interval between sending packets</td>
<td>60 minutes</td>
</tr>
<tr>
<td>Beacon Interval</td>
<td>60 minutes</td>
</tr>
<tr>
<td>Host Recent Period</td>
<td>60 minutes</td>
</tr>
<tr>
<td>Queue Entry Expire Time</td>
<td>10 days</td>
</tr>
<tr>
<td>Vaccine Queue Entry Expire Time</td>
<td>10 days</td>
</tr>
<tr>
<td>Simulation time</td>
<td>10 days</td>
</tr>
</tbody>
</table>

Figure 3.3 shows the packet delivery ratio (PDR), delay, and energy consumption per received packet as a function of the transmission power for a single sink network with nodes with limited buffer size. As shown in Figure 3.3(a), increasing the transmission power allows the nodes to connect to additional nodes, which increases the packet delivery ratio. In the case of the epidemic routing with vaccine protocol, a 100% PDR can be achieved using 4 dBm transmit power compared to about 10 dBm needed in the spray and wait protocol. Even with the maximum transmission power of 14 dBm, direct delivery with/without buffer achieves only about 95% PDR. It is clear that having a buffer increases the PDR for direct delivery. While increasing the transmission power results in a higher PDR and a lower delay, it increases the energy consumption of the nodes and hence requires more harvested energy to operate. Depending on the energy and delay constraints, different transmission powers can be used.

The average delay per received packet for the movement patterns analysis is shown in Figure 3.3(b). For epidemic routing with/without vaccine and the spray and wait protocols, the average delay per received packet rises when using 4 dBm compared to 3 dBm as a higher number of packets are received...
Figure 3.3: PDR, delay and energy consumption per received packet for the movement patterns analysis in a single sink architecture.
that could not be received with a lower transmission power, although these additional packets are received with a high delay that increases the average delay. Due to the elephants’ movement patterns, the delay of the direct delivery with buffer varies with the transmit power. For instance, for a transmit power of 8 dBm, all the packets are received instantly while for 9 dBm, more packets are received with a high delay, which increases the average delay. A direct delivery without buffer approach has the lowest delay and energy consumption per received packet; however, this corresponds to a low packet delivery ratio as shown in Figure 3.3(a).

In order to limit the energy consumption of the nodes, installing more sinks enables nodes to decrease their transmission power while still achieving a high PDR. Since the sinks’ locations are a crucial parameter to the protocols’ performance and to maximize the benefit of multiple sinks, their positions and order were determined after extensive simulations, and are shown in Figure 3.2.

Figure 3.4 shows the effect of increasing the number of sinks on the PDR, delay and energy consumption per received packet when the nodes use 4 dBm as their transmission power. At this transmission power, only one sink is needed to achieve a 100% PDR for the epidemic routing with vaccine protocol, 4 sinks for the spray and wait protocol and 7 sinks for the two direct delivery approaches. Having a buffer results in a higher PDR in direct delivery, as shown in Figure 3.4(a).

Figure 3.4(b) shows that increasing the number of sinks decreases the average delay per received packet from more than 30 hours when using 1 sink to about 45 minutes when using 7 sinks. From Figure 3.4(c), it is clear that for a multi-sink architecture, the epidemic routing with vaccine protocol has the lowest energy consumption per received packet compared to the epidemic routing without vaccine and the spray and wait protocol, as the vaccine disseminates more efficiently through the network.

Figure 3.5 shows the transmission power required to achieve at least a 90% PDR and the corresponding delay and energy consumption per received packet for both single sink and multiple sinks architectures. We see from Figure 3.5(a) that the epidemic routing with/without vaccine protocols require the least transmission power of 4 dBm for one sink and 0 dBm when 7 sinks are installed. Figures 3.5(b) and 3.5(c) show the trade-offs between the average delay and the energy consumption per received packet. For instance, for a 2 sinks architecture, the source spray and wait protocol has
Figure 3.4: Effect of number of sinks on PDR, average delay and energy consumption per received packet at 4 dBm transmit power for the movement pattern analysis.
Figure 3.5: Required transmission power, the corresponding average delay and energy consumption per received packet to achieve 90% PDR for the movement pattern analysis in a single sink architecture.
Table 3.2: Real time tracking parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interval between sending packets</td>
<td>60 minutes</td>
</tr>
<tr>
<td>Beacon Interval</td>
<td>10 minutes</td>
</tr>
<tr>
<td>Host Recent Period</td>
<td>10 minutes</td>
</tr>
<tr>
<td>Queue Entry Expire Time</td>
<td>60 minutes</td>
</tr>
<tr>
<td>Simulation Time</td>
<td>10 days</td>
</tr>
</tbody>
</table>

a lower delay compared to the epidemic routing with/without vaccine protocols at the expense of requiring a higher transmission power that results in an increase in the energy consumption per received packet. As shown in Figure 3.5(c), using a low transmission power of 0 dBm with 7 sinks results in a lower energy consumption per received packet compared to using 4 dBm in a single sink network, which demonstrates the benefits of the multi-sink architecture.

### 3.4.2 Real Time Tracking

In real time tracking applications, the current locations of the elephants are considered to be the most important data, as this will help avoid any human-animal conflict. Therefore, packets must be delivered to the sink within a predetermined bound for the location information to be of value. Regarding the system implementation of real time tracking, the nodes keep generating packets every hour for the entire simulation time, and any location information older than 1 hour is discarded from the node’s queue, hence I consider only epidemic routing without vaccine. Table 3.2 shows the parameters used for real time tracking. The beacon interval and the host recent period decrease from 1 hour as used for the movement patterns analysis to 10 minutes to receive the elephants’ locations more frequently.

Figure 3.6 shows the packet delivery ratio, delay and energy consumption per received packet for the real time tracking in JumboNet. It can be seen from Figure 3.6(a) that the epidemic routing protocol achieves a higher packet delivery ratio than the other protocols. For transmit powers below 8 dBm, and due to the lower packet delivery ratio, the average delay of the spray and wait protocol is lower than that for epidemic routing. On the other hand, for higher transmission powers, the PDR
Figure 3.6: PDR, average delay and energy consumption per received packet for real time tracking in a single sink architecture.
of the epidemic routing and the spray and wait protocols are close, and the epidemic routing protocol has a lower average delay and a lower energy consumption compared to the spray and wait protocol, as shown in Figures 3.6(b) and 3.6(c).

Figure 3.7 shows the effects of the number of sinks on the PDR, delay and energy consumption per received packet. As shown previously, adding more sinks increases the PDR. Due to the delay constraints, to achieve a 100% PDR in a real time tracking application, a higher transmission power must be used compared to the movement patterns analysis.

From Figure 3.7, I can conclude that for a large number of sinks, a direct delivery approach is superior to delay tolerant routing protocols in term of delay and energy consumption per received packet as shown in Figures 3.7(b) and 3.7(c).

Figure 3.8 shows the required transmission power to achieve at least a 90% PDR within an hour from generation. For the same transmission power, epidemic routing has the highest delay and the lowest energy consumption compared to the spray and wait protocol. Furthermore, due to the delay constraint, using a large size buffer does not have much affect on the direct delivery approach as shown in Figure 3.8(a).

In a single sink network, epidemic routing can achieve more than 90% PDR with only 6 dBm transmission power compared to 9 dBm when implementing the spray and wait protocol. The trade-off between the lower energy consumption of the epidemic routing at 6 dBm and the lower average delay of the spray and wait protocol at 9 dBm is clear from Figures 3.8(b) and 3.8(c).

Figure 3.9 shows the minimum value of the hop count parameter of epidemic routing (HopCount) to reach a 90% PDR for real time tracking. It is clear that as the number of sinks increases and/or high transmit powers are used, the required hop count decreases until it reaches a hop count of 1. At this point, direct delivery is a better approach due to its lower energy consumption.
Figure 3.7: Effect of number of sinks on PDR, average delay and energy consumption per received packet at 4 dBm transmit power for real time tracking.
Figure 3.8: Required transmission power, the corresponding average delay and energy consumption per received packet to achieve 90% PDR for real time tracking in a single sink architecture.
CHAPTER 3. PERFORMANCE EVALUATION OF WI-FI VS. WI-FI AD-HOC WITH EPIDEMIC ROUTING IN JUMBONET

3.5 Conclusions

In this chapter, I evaluated the performance of Wi-Fi and Wi-Fi Ad-Hoc with different delay-tolerant routing protocols in the elephant tracking JumboNet application, for both single base station and multiple base stations architectures. For a single base station network, the multi-hop Wi-Fi ad-hoc with epidemic routing protocol network outperforms the ad-hoc network implementing the spray and wait and the Wi-Fi infrastructure network approaches in terms of PDR. On the contrary, if enough base stations are installed, or if the nodes can afford a high transmission power, a direct delivery approach using the infrastructure network would be most efficient to implement as the nodes consume the lowest energy and the packets experience the shortest delay compared to other approaches. A trade-off between the cost of adding a new base station versus the gain in terms of a packet delivery ratio, delay, and the energy consumption must be considered.

Figure 3.9: Minimum required hop count in epidemic routing (HopCount) to achieve 90% PDR for real time tracking in a single and multiple sinks architecture.
Chapter 4

Availability and Performance Analysis of Infrastructure Networks

4.1 Introduction

Given the increasing number of mobile devices with access to the Internet and the development of different wireless technologies, choosing the best network to optimize certain parameters becomes paramount. For instance, both wireless devices in mobile networks and sensor nodes in WSNs may send data via a direct path through infrastructure such as Wi-Fi or cellular networks or through an indirect path via one or multiple devices using ad-hoc protocols such as Wi-Fi Direct.

In this chapter, I evaluate the accessibility and the quality of wireless networks around the University of Rochester in Rochester, NY. The system evaluation focuses on the AP received signal level and on the number of total/open access points. In addition, I provide analysis of the infrastructure network in terms of the upload and download speeds.

4.2 System Architecture

In this section, I provide a brief description of the developed data collection application that collects data about the available wireless networks. Our Android applications can be downloaded from [132].

I have developed an Android application that collects information about the accessibility, quality and attributes of Wi-Fi access points. The application utilizes the built in scanning functionality of
Android OS to obtain information about the Wi-Fi connection, including:

- Scan time;
- GPS coordinates of the device;
- AP SSID, BSSID, and signal strength;
- Wi-Fi frequency range and channel bandwidth and
- Security, authentication, and encryption capabilities.

Based on this data, for each geographical location I have then extracted the following extra information:

- Number of open and total access points and
- Maximum, average, and minimum AP signal strength.

In addition, after connecting to a Wi-Fi network, I obtain the upload and download speeds by transferring an 8 MByte file to and from an Internet server to allow the TCP window to reach its maximum size.

For cellular networks, I record the following information:

- Scan time;
- GPS coordinates of the device;
- Number of cellular base stations and
- Reference Signal Received Power (RSRP).

The Reference Signal Received Power represents the average received power of the cellular tower reference signal and is used for cell selection, re-selection, and handover.
4.3 Performance Evaluation

In this section, I present the Wi-Fi and cellular network coverage around the University of Rochester in the Rochester, NY. Using the application described in Section 4.2, I have gathered data about Wi-Fi access points using 3 off-the-shelf Android devices running Android 6.0 OS. In addition, I present the Wi-Fi infrastructure networks throughput in terms of the upload and download speeds.

4.3.1 Wi-Fi & Cellular Coverage

Figure 4.1(a) shows a heat map of the received signal strength of a cellular network using the data collected over the period of 7 days. The data collection campaign was carried out by students carrying Android tablets.

In Figure 4.1(a), the red and blue colors indicate high and low cellular reference signal received power values, respectively. Here, I have averaged the recorded signal level for the same location. The maximum recorded cellular signal strength was $-69$ dBm recorded outdoors, which suggests the existence of a nearby cellular base station. On the other hand, the minimum recorded signal was $-128$ dBm. To put these values into perspective, the reporting range of RSRP is defined from $-140$ dBm to $-44$ dBm with 1 dB resolution [133].

Similarly, Figure 4.1(b) shows a heat map of the average Wi-Fi received signal strength. The maximum average recorded Wi-Fi signal strength was $-45$ dBm obtained when connected to a home access point in which the Android device was meters away from the access point. On the other hand, a Wi-Fi signal of only $-94$ dBm was recorded when riding a car in the freeway, which is expected as no access points are installed in this area.

A summary of selected Wi-Fi and cellular recorded data is shown in Table 4.1.

These results show that, for optimizing the next generation wireless networks, a hybrid architecture must be considered to benefit from both the cellular and Wi-Fi networks coverage areas and their intrinsic capabilities for indoor and outdoor communications.

A histogram of the total and open number of available access points scanned at each location is shown in Figure 4.2. From this figure, I can see that the maximum number of APs was 66 recorded
Figure 4.1: Average Cellular Reference Signal Received Power and Average Wi-Fi Received Signal Strength.
Table 4.1: Summary of selected Wi-Fi and cellular recorded data

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Wi-Fi</strong></td>
<td></td>
</tr>
<tr>
<td>Average number of access points per location</td>
<td>15</td>
</tr>
<tr>
<td>Minimum RSSI</td>
<td>−94 dBm</td>
</tr>
<tr>
<td>Average RSSI</td>
<td>−77 dBm</td>
</tr>
<tr>
<td>Maximum RSSI</td>
<td>−45 dBm</td>
</tr>
<tr>
<td><strong>Cellular</strong></td>
<td></td>
</tr>
<tr>
<td>Average number of base stations per location</td>
<td>6</td>
</tr>
<tr>
<td>Minimum RSRP</td>
<td>−128 dBm</td>
</tr>
<tr>
<td>Average RSRP</td>
<td>−100 dBm</td>
</tr>
<tr>
<td>Maximum RSRP</td>
<td>−69 dBm</td>
</tr>
</tbody>
</table>

near College Town, which is an area full of stores and restaurants. Furthermore, the average number of scanned APs was 15, which suggests a high accessibility of Wi-Fi APs in this area. However, about 10% of the locations have only 0-2 Wi-Fi APs, and for more than 20% of the locations, all of the available access points are private and inaccessible due to security restrictions.

I note that an increasing number of ISPs started utilizing Wi-Fi hotspots to offload data from the cellular network in order to optimize the spectrum [134]. Hence, I expect to see an increase in the number of open Wi-Fi APs in the near future.

### 4.3.2 RSSI Level vs. Download and Upload Speeds

In this section, I present the average download and upload speeds with respect to the received signal strength and frequency range for Wi-Fi.

Figure 4.3 shows the average download and upload speeds with respect to the RSSI for the 2.4 GHz and 5.8 GHz frequencies. It is worth noting that these results are obtained through extensive experiments (over 1000 runs).

It is clear from Figure 4.3 that for the same received signal level, a higher bandwidth results in higher download speeds on average. Moreover, the average download speed on the range −64 dBm to −53 dBm RSSI for the 2.4 GHz frequency was about 14.64 Mbps, while for the same RSSI range, the 5.8 GHz Wi-Fi reached an average download speed of about 27.78 Mbps, which is almost double
Figure 4.2: Probability mass function of the number of APs scanned per location.

Figure 4.3: Average download and upload speeds with respect to the received signal strength indicator (RSSI).
the download speed for the 2.4 GHz frequency. This is due to the higher number of channels, larger bandwidth in the 5 GHz frequency Wi-Fi, in addition to the higher interference from other devices in the 2.4 GHz frequency Wi-Fi compared to the 5 GHz.

On the other hand, a higher frequency doesn’t necessarily result in higher upload speeds, as the average upload speeds were about 6.89 and 6.24 Mbps for the 2.4 GHz and 5.8 GHz, respectively. This may be due to Internet traffic and server limitations. Based on these results, I can conclude that, on average, the 5.8 GHz frequency Wi-Fi results in a higher download speed compared to the 2.4 GHz Wi-Fi regardless of the received signal strength (RSSI).

4.4 Conclusions

In this chapter, I evaluated the accessibility, quality in terms of upload and download speeds, and attributes of Wi-Fi access points and cellular base stations of wireless infrastructure networks around the University of Rochester in Rochester by developing an Android application that can be downloaded from [132] and used by others to map Wi-Fi and cellular coverage in their area. Experimental results show that Wi-Fi and cellular networks cover almost the entire movement route. Nevertheless, and due to security restrictions, open and accessible Wi-Fi networks are not as available as private Wi-Fi networks. Furthermore, due to the asymmetric connection between the mobile device and the access point, the Wi-Fi upload speed is much smaller compared to the download speed.

Due to the increasing availability of mobile devices with embedded ad-hoc protocols such as Wi-Fi Direct, another method of connecting devices to the Internet via multi-hop networks becomes available. Hence, it is essential to find the best connection whether it is through infrastructure networks or via multi-hop ad-hoc networks, which is discussed in detail in the next chapter.
Chapter 5

Performance Evaluation of Wi-Fi Direct Multi-Hop Ad-Hoc Networks

5.1 Introduction

Over the years, several protocols have been proposed to be used for ad-hoc communication such as IEEE 802.11s, ZigBee, and Wi-Fi Direct. For instance, the IEEE 802.11s standard was designed on top of the IEEE 802.11 family to create a wireless mesh network to overcome limitations of single hop communications [135]. On the other hand, ZigBee was developed as a low data rate, short range communication standard for wireless sensor networks [136]. A promising protocol that is capable of creating wireless ad-hoc networks is Wi-Fi Direct, which can play a major role in connecting devices to the Internet when they do not have direct access through a cellular network or a Wi-Fi AP.

In this chapter, I show how extending access to the Internet to devices that might not otherwise have a direct connection through multi-hop ad-hoc connections affects the overall network performance. In particular, I present an Android application that creates multi-hop ad-hoc networks using Wi-Fi Direct and either Wi-Fi or LTE cellular connection from a gateway node to the Internet. I use the collected data from the application to provide an empirical performance evaluation of providing Internet connectivity through multi-hop Wi-Fi Direct networks in terms of the upload and download speeds, in addition to the network delay, compared to Wi-Fi and LTE cellular connections. Furthermore, based on existing energy consumption models for Wi-Fi, Wi-Fi Direct, and LTE, I present the total energy consumption of the multi-hop ad-hoc networks, and analyze tradeoffs between using a direct connection via the infrastructure networks and Wi-Fi Direct multi-hop ad-hoc networks.
5.2 Wi-Fi Direct

To create a Wi-Fi Direct group, the first step is the device discovery process, which consists of scan and find phases. During the scan phase, the device scans the Wi-Fi social channels for a predetermined time duration to collect information about all the available devices. Subsequently, during the find phase, a device in the search state sends probe requests and waits for a probe response from a device in the listen state on the same channel to start the group formation phase [36]. After the device discovery, each device broadcasts an intent value based on the number of neighbors and the Received Signal Strength Indicator (RSSI), and the device with the highest intent value is selected as a GO, and uses Dynamic Host Configuration Protocol (DHCP) to assign IP addresses to the GMs [137].

In each group, a peer-to-peer (P2P) client is a device that supports the Wi-Fi Direct protocol, whereas devices that support only traditional Wi-Fi but do not support the Wi-Fi Direct protocol are referred to as legacy clients (LCs), which see the group owner as a traditional Wi-Fi access point. Both legacy clients and P2P clients can coexist in the same group [138].

It is worth noting that Wi-Fi Direct was originally designed to allow communication between devices in a single group and does not inherently allow inter-group communication due to routing conflicts, as I will discuss in detail in Section 5.3.

5.3 Android Application Implementation

In this section, I provide a description of the functionalities required to create an ad-hoc network using Wi-Fi Direct, and to evaluate the performance of providing access to the Internet through the ad-hoc network.

Android 4.0 (API level 14) or later devices are able to connect to each other directly via Wi-Fi without the need of an intermediate access point [139]. Moreover, the WifiP2pManager class provides methods that support the interaction with the Wi-Fi hardware, and allows devices to discover, connect, and disconnect from peers [140].

In order to obtain the performance of multi-hop ad-hoc networks, I have developed an Android
application that uses Wi-Fi Direct to create an ad-hoc network. I note that, as discussed in [140], creating multi-hop Wi-Fi Direct networks using Android devices is not straightforward.

### 5.3.1 1-Hop Ad-Hoc Network

For a 1-hop ad-hoc network, the network consists of a client device (acting as a Wi-Fi Direct group member, GM) and a gateway device (acting as a Wi-Fi Direct group owner, GO), as shown in Figure 5.1(a). The application works as follows: the peer discovery process is initiated by the client and the gateway devices every 3 minutes. When the gateway is discovered by the client, the client device sends a connection invitation to the gateway to form a Wi-Fi Direct group. After this, the client device starts sending data to the gateway, which is responsible for uploading the data to the Internet server. Subsequently, the gateway device starts downloading data from the Internet server and thereafter transfers it to the client through the P2P interface.
For clarity, the solid lines in Figure 5.1 show the download route, while the dotted lines represent the upload route.

### 5.3.2 2-Hop Ad-Hoc Network

In a 2-hop ad-hoc network, the network consists of a client device (acting as a Wi-Fi Direct group member $GM_1$), a relay device (acting as a Wi-Fi Direct group owner, $GO$) and a gateway device (acting as a Wi-Fi Direct group member $GM_2$), as shown in Figure 5.1(b). Similar to subsection 5.3.1, after the Wi-Fi direct group is formed, the client device sends the data through the relay device to the gateway, which is responsible for uploading the data to the Internet server. Similarly, the gateway device downloads data from the Internet server and sends it to the client through the relay device. It is important to note that for 1-hop and 2-hop ad-hoc networks, all the communication can be routed through the devices’ P2P interfaces.

### 5.3.3 3-Hop Ad-Hoc Network

In a 3-hop ad-hoc network, the network is organized into two Wi-Fi Direct groups, in which each group consists of one $GM$ and one $GO$, and the two $GOS$ are connected to each other to relay information between the two groups.

However, creating a 3-hop ad-hoc network using Wi-Fi Direct is not straightforward compared to 1-hop and 2-hop networks, since the stock Android OS implementation of the protocol assigns the same IP address: 192.168.49.1 to the Wi-Fi Direct GOs in different groups, therefore not allowing a connection between two GOs due to routing conflicts [106, 140].

To overcome this obstacle, I have created legacy client (LC) interfaces in both relay nodes, alongside their primary $GO_1$ and $GO_2$ P2P interfaces, and connect this additional interface to the P2P interfaces of the other device (i.e., $GO_1$ and $GO_2$), as shown in Figure 5.1(c).

Moreover, to send data from the client device $GM_1$ to the gateway $GM_2$, and due to limitations imposed by the Android operating system, the client cannot reach the gateway directly; therefore, I have specified the LC interface of Relay 2 as the destination address. When Relay 2 receives the data
from the client device through Relay 1, it will act as a relay and transfer the data from its legacy client interface to its GO P2P interface and finally to the gateway, which is responsible for uploading the data to the Internet server.

Similarly, to send data from the gateway $GM_2$ to the client device $GM_1$, the LC interface of Relay 1 needs to be specified as the destination address. After the gateway device downloads the data from the Internet server, it will send it to the client device through Relay 1, and when Relay 1 receives the data, it will act as a relay and transfer the data from its LC interface to its GO P2P interface and finally to the client device.

Finally, for 1-hop, 2-hop, and 3-hop Wi-Fi Direct networks, the Android application records the total time from when the client device starts sending data until all the data is received by the Internet server through the gateway device to calculate the upload speed. Similarly, the application records the time since the gateway device requests the data from the Internet server, until all of the data is received by the client device, to calculate the download speed.

It is worth noting that, although the roles of the client and gateway in Figure 5.1(a) can be reversed, i.e., the client becomes the GO and the gateway becomes the GM, based on our experimental results, the difference in Wi-Fi Direct speed between the $GM - GO$ and $GO - GM$ connections is small (less than 5%); hence, I expect similar performance of the multi-hop ad-hoc networks. In our analysis, I refer to the average speeds of the client-gateway and gateway-client links of 1-hop, 2-hop, and 3-hop Wi-Fi Direct ad-hoc networks as the Wi-Fi Direct speed.

Furthermore, although the 2-hop ad-hoc system can be created with a $GM$ connected to a relay node acting as $GO_1$ on its P2P interface, and with its LC interface connected to another group owner $GO_2$, our focus is primarily on networks that use solely the P2P interfaces, unless it is necessary as in the 3-hop ad-hoc network discussed in Section 5.3.3.
5.4 Energy Consumption Models

In this section, I present a description of the total energy consumption model used in our analysis.

Since the devices do not transmit/receive data simultaneously, the total energy consumption $E_{Tx}$ to send $s$ bits of information via $h$ number of Wi-Fi Direct hops and a Wi-Fi/LTE network from the gateway node is given as:

$$E_{Tx}^t = ((E_{tx}^{P2P} + E_{rx}^{P2P})h + E_{tx}^{WiFi/LTE})s$$  \hspace{1cm} (5.1)$$

where $E_{tx}^{P2P}$, $E_{rx}^{P2P}$ represent the energy consumption per bit to transmit/receive data via Wi-Fi Direct, and $E_{tx}^{WiFi/LTE}$ is defined as the energy consumption per bit to send data via Wi-Fi or LTE.

Similarly, the total energy consumption $E_{Rx}^t$ to receive $s$ bits of information via Wi-Fi or LTE, and then through $h$ Wi-Fi Direct hops is given as:

$$E_{Rx}^t = (E_{rx}^{WiFi/LTE} + (E_{tx}^{P2P} + E_{rx}^{P2P})h)s$$ \hspace{1cm} (5.2)$$

where $E_{tx}^{P2P}$, $E_{rx}^{P2P}$ represent the energy consumption per bit to transmit/receive data via Wi-Fi Direct, and $E_{rx}^{WiFi/LTE}$ is defined as the energy consumption per bit to receive data via Wi-Fi or LTE.

In order to obtain the values of $E_{tx}^{P2P}$, $E_{rx}^{P2P}$, $E_{tx}^{WiFi}$, and $E_{rx}^{WiFi}$, I have used the energy consumption models presented in [104] due to the fact that the Wi-Fi Direct multi-hop ad-hoc networks considered in this paper were created using the same devices as in [104].

On the other hand, to obtain the values of $E_{tx}^{LTE}$ and $E_{rx}^{LTE}$, I have used the ratio in energy consumption between LTE and Wi-Fi obtained from [105], to find approximate values for the LTE energy consumption for our devices.

Based on the energy consumption models developed in [104, 105], the energy consumption per bit for transmitting/receiving 10 MB of data using LTE, Wi-Fi and Wi-Fi Direct is presented in Table 5.1.

Finally, it is worth noting that both these models consider only the energy consumption from data transfer and ignore the overhead of scanning and connecting phases before transmission starts for the infrastructure and the ad-hoc networks. Hence, I expect the total energy consumption to be somewhat
higher than our model for both infrastructure and multi-hop ad-hoc networks.

<table>
<thead>
<tr>
<th>Technology</th>
<th>Transmit ($\mu$J/bit)</th>
<th>Receive ($\mu$J/bit)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LTE</td>
<td>0.76</td>
<td>0.48</td>
</tr>
<tr>
<td>Wi-Fi</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>Wi-Fi Direct</td>
<td>0.03</td>
<td>0.03</td>
</tr>
</tbody>
</table>

5.5 Simulation Results

In this section, I present the effect of data size on the 1-hop, 2-hop, and 3-hop Wi-Fi Direct network speeds. In addition, I provide a comparison in terms of the average upload and download speeds and delay to upload/download 1 MB and 10 MB of data using TCP for a direct 802.11g Wi-Fi connection, a direct LTE connection, and 1-hop, 2-hop and 3-hop ad-hoc Wi-Fi Direct networks with Wi-Fi and LTE connections from the gateway. Finally, I analyze the client and total energy consumption based on the energy models developed in [104, 105].

It is worth noting that the nominal data rates of Wi-Fi 802.11g and LTE are 54 Mbps and 100 Mbps, respectively. Furthermore, the average throughput of the infrastructure and multi-hop ad-hoc networks was measured over 200 runs in different locations.

5.5.1 Throughput of Infrastructure Networks and Multi-Hop Ad-Hoc Networks vs. Data Size

Figure 5.2 shows the average Wi-Fi speeds for uploading and downloading 1MB, 2MB, 5MB, and 10 MB of data, as well as the average Wi-Fi Direct client-gateway and gateway-client speeds for 1-hop, 2-hop and 3-hop ad-hoc networks.

It is clear from Figure 5.2 that the average Wi-Fi and Wi-Fi Direct speeds increase with increasing the data size, which may be due to the TCP slow start. For instance, the 1-hop, 2-hop, and 3-hop Wi-Fi Direct speeds to transfer 10 MB of data are 28.8 Mbps, 24.6 Mbps, and 15.7 Mbps, respectively.
CHAPTER 5. PERFORMANCE EVALUATION OF WI-FI DIRECT MULTI-HOP AD-HOC NETWORKS

On the other hand, the 1-hop, 2-hop, and 3-hop Wi-Fi Direct speeds to transfer 1 MB of data are 14.3 Mbps, 12.9 Mbps, and 9.8 Mbps, respectively.

Moreover, for all data sizes, Wi-Fi Direct has a lower speed compared with downloading data via the Wi-Fi Network. For instance, transferring 10 MB of data using Wi-Fi Direct reaches a speed of 28.8 Mbps compared to about 37 Mbps to download the same amount of data from the Internet server using the Wi-Fi network.

Furthermore, due to the asymmetric connection between the gateway and the access point, the Wi-Fi upload speed is much smaller compared to the download speed.

Moreover, Figure 5.2 shows that the throughput of the client-gateway and gateway-client ad-hoc links decreases by adding more hops for all sizes of data, as expected.

Figures 5.3 and 5.4 show the total upload and download speeds of 1-hop, 2-hop, and 3-hop ad-hoc networks with Wi-Fi as the connection to the Internet for transferring 1 MB and 10 MB of data.

Figure 5.3 shows that the average speed to upload 1 MB of data via the direct Wi-Fi connection to the Internet server is about 2.8 Mbps. Furthermore, the 1-hop, 2-hop, and 3-hop Wi-Fi upload speeds are about 2.1 Mbps, 2.0 Mbps, and 1.9 Mbps, respectively.

On the other hand, uploading 10 MB of data via the Direct, 1-hop, 2-hop, and 3-hop ad-hoc
CHAPTER 5. PERFORMANCE EVALUATION OF WI-FI DIRECT MULTI-HOP AD-HOC NETWORKS

Figure 5.3: Average upload speeds for direct Wi-Fi, 1-hop, 2-hop, and 3-hop Wi-Fi Direct ad-hoc networks with Wi-Fi connection from the Gateway node for 1 MB and 10 MB of data (Measured).

Figure 5.4: Average download speeds for direct Wi-Fi, 1-hop, 2-hop, and 3-hop Wi-Fi Direct ad-hoc networks with Wi-Fi connection from the Gateway node for 1 MB and 10 MB of data (Measured).

Figure 5.5: Average upload speeds for direct LTE, 1-hop, 2-hop, and 3-hop Wi-Fi Direct ad-hoc networks with LTE connection from the Gateway node for 1 MB and 10 MB of data (Measured).

Figure 5.6: Average download speeds for direct LTE, 1-hop, 2-hop, and 3-hop Wi-Fi Direct ad-hoc networks with LTE connection from the Gateway node for 1 MB and 10 MB of data (Measured).
networks with Wi-Fi network as the gateway to the Internet reached 7.5 Mbps, 5.4 Mbps, 5.4 Mbps, and 4.9 Mbps upload speeds, which are higher speeds compared to the ad-hoc networks uploading 1 MB of data.

Figure 5.4 shows that the average speed to download 1 MB of data via the direct Wi-Fi connection to the Internet server is about 18 Mbps. Furthermore, the 1-hop, 2-hop, and 3-hop Wi-Fi download speeds are about 7 Mbps, 5.9 Mbps, and 5.8 Mbps, respectively. On the other hand, downloading 10 MB of data via the Direct, 1-hop, 2-hop, and 3-hop ad-hoc networks with Wi-Fi network as the gateway to the Internet reached 37 Mbps, 19 Mbps, 18 Mbps, and 12 Mbps download speeds, which are higher speeds compared to downloading 1 MB of data using the ad-hoc networks.

Furthermore, similar trends regarding the effect of data size and number of hops on the throughput of the multi-hop ad-hoc networks with LTE connection from the gateway node are observed in Figures 5.5 and 5.6.

Lastly, it is clear from Figures 5.3, 5.4, 5.5 and 5.6 that for delay-tolerant applications, infrastructure networks as well as multi-hop ad-hoc networks are more efficient transferring/receiving larger data sizes.

### 5.5.2 Delay of Wi-Fi and Multi-Hop Ad-Hoc Networks vs. Data Size

In this section, I present the network delay to upload and download 1 MB and 10 MB of data using 1-hop, 2-hop, and 3-hop Wi-Fi Direct multi-hop ad-hoc networks with Wi-Fi or LTE connection from the gateway node.

It is clear from Figures 5.7 and 5.8 that the average upload and download delays increase with increasing the data size and number of hops, as expected.

For instance, the direct Wi-Fi, 1-hop, 2-hop, and 3-hop Wi-Fi Direct networks delay to upload 10 MB of data are 11 s, 14.8 s, 14.8 s, and 16.5 s, respectively. On the other hand, the direct Wi-Fi, 1-hop, 2-hop, and 3-hop Wi-Fi Direct delay to transfer 1 MB of data are 2.9 s, 3.8 s, 3.9 s, and 4.2 s, respectively, as shown in Figure 5.7.

Furthermore, due to the asymmetric connection between the gateway and the access point, the
Wi-Fi download delay is much smaller compared to the upload delay.

Lastly, similar trends regarding the effect of data size and number of hops on the delay of the multi-hop ad-hoc networks with LTE connection from the gateway node are observed in Figures 5.9 and 5.10.

### 5.5.3 Throughput of Wi-Fi vs. Cellular Multi-hop Ad-Hoc Networks

In this section, I present a comparison of throughput to upload and download 10 MB of data between a direct Wi-Fi connection, a direct LTE connection, and 1-hop, 2-hop and 3-hop ad-hoc networks with Wi-Fi and LTE connections from the gateway node.

Figure 5.11 shows that the average speed to upload 10 MB of data via a direct LTE connection to the Internet server was about 6.3 Mbps, while the average upload speed of the direct Wi-Fi network was higher and reached an average of about 7.5 Mbps. Furthermore, the 1-hop, 2-hop, and 3-hop LTE upload speeds were about 5.3 Mbps, 5.2 Mbps, and 4.5 Mbps, respectively. Similarly, the 1-hop, 2-hop, and 3-hop ad-hoc networks with Wi-Fi network as the gateway to the Internet reached slightly higher upload speeds compared to the ad-hoc networks with LTE as the Internet gateway technology. Specifically, the 1-hop, 2-hop, and 3-hop Wi-Fi upload speeds were about 5.4 Mbps, 5.4 Mbps, and 4.9 Mbps, respectively.

As shown in Figure 5.12, the average download speed of the direct LTE connection was about 42 Mbps. Moreover, using the Wi-Fi network results in an average download speed of about 37 Mbps, which is comparable to the LTE connection average download speed. Moreover, the download speed for 1-hop, 2-hop, and 3-hop ad-hoc LTE networks reached an average of about 23 Mbps, 21 Mbps, and 16.1 Mbps, respectively. Furthermore, the 1-hop, 2-hop, and 3-hop Wi-Fi download speeds were about 20 Mbps, 18 Mbps, and 12 Mbps, respectively.

Based on these experimental results, the upload speeds of the direct Wi-Fi connection were higher compared to the LTE network. On the other hand, the LTE cellular network results in the highest download speeds compared to Wi-Fi and multi-hop ad-hoc networks.
CHAPTER 5. PERFORMANCE EVALUATION OF WI-FI DIRECT MULTI-HOP AD-HOC NETWORKS

Figure 5.7: Average upload delay for direct Wi-Fi, 1-hop, 2-hop, and 3-hop Wi-Fi Direct ad-hoc networks with Wi-Fi connection from the Gateway node for 1 MB and 10 MB of data (Measured).

Figure 5.8: Average download delay for direct Wi-Fi, 1-hop, 2-hop, and 3-hop Wi-Fi Direct ad-hoc networks with Wi-Fi connection from the Gateway node for 1 MB and 10 MB of data (Measured).

Figure 5.9: Average upload delay for direct LTE, 1-hop, 2-hop, and 3-hop Wi-Fi Direct ad-hoc networks with LTE connection from the Gateway node for 1 MB and 10 MB of data (Measured).

Figure 5.10: Average download delay for direct LTE, 1-hop, 2-hop, and 3-hop Wi-Fi Direct ad-hoc networks with LTE connection from the Gateway node for 1 MB and 10 MB of data (Measured).
CHAPTER 5. PERFORMANCE EVALUATION OF WI-FI DIRECT MULTI-HOP AD-HOC NETWORKS

5.5.4 Energy Consumption of LTE, Wi-Fi and Multi-hop Ad-Hoc Networks

In Figures 5.13, 5.14 and 5.15, I plot the energy to upload (Figure 5.13) and download (Figure 5.14) 10 MB of data for different numbers of hops and the energy at the client node (Figure 5.15) using the energy consumption models discussed in Section 5.4 with the parameters shown in Table 5.1.

Figure 5.13 shows that the total energy consumption of the direct upload Wi-Fi connection to the Internet server is about 24 J, while the total energy consumption of the LTE network is about 60.7 J. Furthermore, the 1-hop, 2-hop, and 3-hop energy consumption are about 28.8 J, 33.6 J, and 38.4 J, respectively. On the other hand, the 1-hop, 2-hop, and 3-hop ad-hoc networks with LTE network as the connection to the Internet consumed much higher energy consumption of about 65.5 J, 70.3 J, and 75.1 J, respectively.

As shown in Figure 5.14, the total energy consumption to download data from the Internet server through direct Wi-Fi and multi-hop ad-hoc networks using a Wi-Fi connection to the Internet was the same as the energy consumption to upload data to the Internet.

On the other hand, using a direct LTE network results in a higher energy consumption of about 38.8 J. Moreover, the total energy consumption for 1-hop, 2-hop, and 3-hop ad-hoc networks with
Figure 5.13: Total energy in J to upload 10 MB of data for direct Wi-Fi, direct LTE, 1-hop, 2-hop, and 3-hop Wi-Fi Direct ad-hoc networks with Wi-Fi and LTE connections from the Gateway node (Model).

Figure 5.14: Total energy in J to download 10 MB of data for direct Wi-Fi, direct LTE, 1-hop, 2-hop, and 3-hop Wi-Fi Direct ad-hoc networks with Wi-Fi and LTE connections from the Gateway node (Model).

LTE connection to the Internet are about 43.6 J, 48.4 J, and 53.2 J, respectively.

It is worth noting that due to the higher energy per bit to upload data using LTE compared to Wi-Fi, and the comparatively lower Wi-Fi Direct energy per bit (refer to Table 5.1), Wi-Fi Direct multi-hop ad-hoc networks with Wi-Fi connection from the gateway node are more energy efficient when uploading data compared with a direct LTE connection up to 7 hops, as shown by the solid horizontal line in Figure 5.13. After this point, the direct LTE connection becomes more energy efficient. Similarly, multi-hop ad-hoc networks with Wi-Fi connection from the gateway node are more energy efficient when downloading data compared with a direct LTE connection up to 3 hops, as shown by the solid horizontal line in Figure 5.14.

It is clear from Figures 5.13 and 5.14 that the total energy consumption of the network increases by adding more hops. On the other hand, from the client prescriptive, using Wi-Fi Direct results in the lowest energy consumption compared to direct LTE and Wi-Fi, as shown in Figure 5.15.
5.6 Conclusions

In this chapter, I have developed an Android application to create ad-hoc networks using Wi-Fi Direct. Based on experimental results, extending access to the Internet through 1-hop, 2-hop, and 3-hop Wi-Fi Direct networks is viable at the expense of a decrease in upload and download speeds. Moreover, it was shown that multi-hop ad-hoc networks are more efficient when transferring larger data sizes compared to smaller data sizes. Lastly, using multi-hop ad-hoc networks with Wi-Fi connection from the gateway node is sometimes more energy-efficient than using a direct LTE connection, and multi-hop ad-hoc networks are always more energy-efficient for the client node than transmitting directly through either Wi-Fi or LTE.

In this chapter, the Wi-Fi APs and cellular base station locations were fixed. Implementing ground mobile base stations as well as flying base stations can potentially improve the performance of wireless networks. Hence, in the next chapter, I explore the optimization of the locations of Unmanned Aerial Vehicles Base Stations (UAV-BSs) that provide base station support to ground nodes.
Chapter 6

Placement Optimization of Multiple UAV Base Stations

6.1 Introduction

Due to recent technological advancements in the area of unmanned aerial systems, equipping an unmanned aerial vehicle (UAV) with a base station (BS) has been proposed to augment terrestrial base stations and to enhance the performance of 5G and beyond-5G networks.

Furthermore, utilizing mobility control and adaptive communication can provide good wireless connectivity to the terrestrial network or the ground nodes [43]. Therefore, the use of UAV-BSs has been proposed to support users that suffer from sever shadowing or experience high interference [44]. Indeed, using UAVs equipped with wireless transceivers has already been proposed to improve the performance of 5G networks [45]. Furthermore, mobile operators like Verizon and AT&T have already conducted trials on using LTE UAV-BSs [46], [47]. Moreover, on-board radio access nodes (UxNB) that provide connectivity to end users is a study item in 3GPP release-17 [141].

Obtaining the best performance from the UAV-BSs is highly dependent on their 3D locations, and hence research on their placement has gained significant interest recently [48]. In this chapter, I explore the UAV-BS location optimization problem considering users with both the same and different quality of service (QoS) requirements.
CHAPTER 6. PLACEMENT OPTIMIZATION OF MULTIPLE UAV BASE STATIONS

6.2 System Model

I consider a target area with two sets of users demanding either the same or different QoS requirements, and the aim is to find the optimal locations of multiple UAV-BSs that maximizes the number of covered users while achieving the required QoS requirements for each set. In this section, I begin by presenting the path loss model and then derive the mathematical formulation for the single and multiple UAV-BSs placement problems. Finally, I present heuristic algorithms for solving the multiple UAV-BSs placement problem.

6.2.1 Path Loss Model

I consider a target area with a set of users $U$, where each user $i$ of the set $U_k$ demands a unique QoS requirement $k$ from 1 to $K$ where

$$\bigcup_{k=1}^{K} U_k = U. \quad (6.1)$$

As discussed in [115], the total probabilistic mean path loss between a UAV-BS at location $(x_D, y_D)$ and at height $h$, and a ground node is given by

$$L(h, r_{ik}) = \frac{A}{1 + a \exp(-b(\frac{180}{\pi})(\theta_{ik} - a))} + 20\log \frac{r_{ik}}{\cos(\theta_{ik})} + B, \quad (6.2)$$

where $A = \eta_{LoS} - \eta_{NLoS}$, $B = 20 \log(\frac{4\pi f_c}{c}) + \eta_{NLoS}$, and $\eta_{LoS}$ and $\eta_{NLoS}$ are the average additional losses for LoS and NLoS, respectively. Furthermore, $f_c$ is the carrier frequency, $a$ and $b$ are the S-curve parameters which only depend on the environment, and $r_{ik}$ is the distance between the UAV-BS center and user $i$ of the set $U_k$, and is given by

$$r_{ik} = \sqrt{(x_{ik} - x_D)^2 + (y_{ik} - y_D)^2}. \quad (6.3)$$

As shown in [115], the user $i$ of the set $U_k$ is covered if its probabilistic mean signal-to-noise ratio (SNR) exceeds a predefined threshold $\gamma^k_{\text{th}}$ (dB), which can be written as

$$\gamma(h, r_{ik})[\text{dB}] \geq \gamma^k_{\text{th}}, \quad (6.4)$$
where
\[
\gamma(h, r_{ik})[\text{dB}] = P_t - L(h, r_{ik}) - P_n, \quad (6.5)
\]
and \(P_t, P_n\) are the transmit power of the UAV-BS, and the noise power at the ground node, both in dBW, respectively.

Furthermore, as shown in [116], for users with the same QoS requirements, the coverage region of a single UAV-BS is a circular disk with radius \(R_k(h) = r|_{L(h, r_{ik}) = L_{th}^k}\), where
\[
L_{th}^k = P_t - P_n - \gamma_{th}^k. \quad (6.6)
\]

On the other hand, for users with different QoS requirements, the coverage region forms a set of circular discs with center \((x_D, y_D)\) and radii
\[
\{R_k(h)\}_{k=1}^K
\]

Moreover, it was shown in [142] that the optimal elevation angle that maximizes the coverage radius depends only on the environment as shown in Table 6.1. This angle can be formulated as
\[
\theta^* = \tan^{-1} \frac{h^*_k}{R^*_k}. \quad (6.7)
\]
Hence, for a given environment, the maximum coverage radius \(R^*_k\) can be obtained by solving (6.2), and since the optimal elevation angle is already known based on the environment (as shown in Table 6.1), the optimal altitude \(h^*_k\) can be calculated using (6.7).

<table>
<thead>
<tr>
<th>Environment</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Suburban</td>
<td>20.34°</td>
</tr>
<tr>
<td>Urban</td>
<td>42.44°</td>
</tr>
<tr>
<td>Dense Urban</td>
<td>54.62°</td>
</tr>
<tr>
<td>High-Rise Urban</td>
<td>75.52°</td>
</tr>
</tbody>
</table>

Finally, (6.7) shows an interesting relationship between the UAV-BS height, its maximum cov-
average radius, and the path loss. For instance, the higher the location of the UAV-BS, the larger its coverage radius, but this also results in a larger distance and a higher path loss between the UAV-BS and the ground nodes.

6.2.2 Single UAV-BS Placement Problem Formulation

In this section, I present a brief description of the placement formulation of one UAV-BS, as discussed in [116]. As shown in Section 6.2.1, the user $i$ of the set $U_k$ is covered if it is located within $R_k(h)$ of the horizontal location $(x_D, y_D)$ of the UAV-BS.

Hence, the optimization problem of maximizing the number of covered users using a single UAV-BS can be formulated as a mixed integer non-linear problem (MINLP) as shown in (6.8):

$$\text{maximize} \sum_{k=1}^{K} \sum_{i \in U_k} u_{ik},$$

subject to

$$\sqrt{(x_{ik} - x_D)^2 + (y_{ik} - y_D)^2} \leq R_k(h) + M(1 - u_{ik})$$

$$\forall i \in U_k, k = 1, 2, ..., K$$

$$u_{ik} \in \{0, 1\}, \forall i \in U_k, k = 1, 2, ..., K,$$

where $u_{ik} \in \{0, 1\}$ is a binary variable such that $u_{ik} = 1$ if the user $i$ of the set $U_k$ is within the coverage region of the UAV-BS and $u_{ik} = 0$, otherwise. Moreover, $M$ is a constant chosen large enough that the first constraint of the optimization problem above is trivially satisfied when $u_{ik} = 0$.

6.2.3 Multiple UAV-BS Placement Problem Formulation

I formulate the general problem of placing $m$ UAV-BSs simultaneously to maximize the number of covered users with different QoS requirements, where each user $i$ of the set $U_k$ is covered by at least one UAV-BS, as follows:
maximize  \( \sum_{k=1}^{K} \sum_{i \in U_k} \left( \sum_{n=1}^{m} u_{ikn} - \sum_{n<j} u_{ikn} \cdot u_{ijk} + \ldots + (-1)^{m+1} \prod_{n=1}^{m} u_{ikn} \right) \), \hspace{1cm} (6.9) \\
subject to \\
\sqrt{(x_{ik} - x_{D1})^2 + (y_{ik} - y_{D1})^2} \leq R_k(h_1) + M (1 - u_{ik1}) \\
\sqrt{(x_{ik} - x_{D2})^2 + (y_{ik} - y_{D2})^2} \leq R_k(h_2) + M (1 - u_{ik2}) \\
\hspace{1cm} \forall i \in U_k, k = 1, 2, \ldots, K \\
u_{ik1}, \ldots, u_{ikm} \in 0, 1, \forall i \in U_k, k = 1, 2, \ldots, K.

In particular, for two UAV-BSs, this reduces to

\[ \text{maximize} \sum_{k=1}^{K} \sum_{i \in U_k} u_{ik1} + u_{ik2} - u_{ik1} \cdot u_{ik2}, \] \hspace{1cm} (6.10) \\
subject to \\
\sqrt{(x_{ik} - x_{D1})^2 + (y_{ik} - y_{D1})^2} \leq R_k(h_1) + M (1 - u_{ik1}) \\
\sqrt{(x_{ik} - x_{D2})^2 + (y_{ik} - y_{D2})^2} \leq R_k(h_2) + M (1 - u_{ik2}) \\
\hspace{1cm} \forall i \in U_k, k = 1, 2, \ldots, K \\
u_{ik1}, u_{ik2} \in 0, 1, \forall i \in U_k, k = 1, 2, \ldots, K,

where \((x_{D1}, y_{D1}, h_1)\) and \((x_{D2}, y_{D2}, h_2)\) are the 3D locations of the first and second UAV-BSs, respectively. Also \(u_{ik}\) and \(z_{ik}\) are binary variables such that \(u_{ik1} = 1\) if the user is within the coverage
region of the first UAV-BS and $u_{ik2} = 1$ if the user is within the coverage region of the second UAV-BS. Moreover, $M$ is a constant chosen large enough that the constraints of (6.10) are satisfied when $u_{ik1}$ or $u_{ik2} = 0$.

### 6.2.4 Heuristic Algorithms

The problem described by (6.10) is a non-convex optimization problem, hence, in the following, I present the proposed heuristic algorithms to solve the multiple UAV-BS placement problem.

#### Sequential Exhaustive Search (SES)

I first propose a Sequential Exhaustive Search (SES) algorithm that optimally places the first UAV-BS according to (6.8), then deploys the UAV-BSs in a successive manner, providing the best location once the covered nodes are removed.

The SES algorithm performs an exhaustive search for the optimal altitude ($h_o$) of the first UAV-BS in the closed region $[h_1, h_K]$, where $h_1$ and $h_K$ are the optimal altitudes corresponding to the smallest and largest path loss thresholds, respectively. The corresponding coverage radius of the first UAV-BS is calculated using (6.7). Then, (6.8) is solved to obtain the optimal $(x_D, y_D)$ location of the first UAV-BS. Afterwards, all the users that are covered by the first UAV-BS are removed from the set of users, and the algorithm is run again.

Algorithm 1 presents pseudo-code for the SES algorithm.

#### Sequential Maximal Weighted Area (SMWA)

If the users in the set $U_k$ are uniformly distributed over the region with density $\lambda_k$, the average number of covered users $N_{avg}(h)$ is given by (6.11):

$$N_{avg}(h) = \pi \sum_{k=1}^{K} \lambda_k R_k^2.$$  

(6.11)

Since the aim is to obtain the maximum number of covered users, it is necessary to find the optimal altitude $h_o$ of (6.11), which can be computed by equating its first derivative with respect to $h$
Algorithm 1 SES Algorithm

Input
Ground nodes’ locations set \((S)\);
Total number of nodes \(= N\);
Maximum number of UAV-BSs \(= m\);

Initialization
Number of deployed UAV-BSs \((n) = 1\);
Number of covered nodes at each height \((N_h) = 0\);
Maximum number of covered nodes by a single UAV-BS \((M_n) = 0\);
Optimal UAV-BS location \(x^*_n = 0\) and \(y^*_n = 0\);

while \((N > 0 \&\& n \leq m)\) do
  
  Solve (6.2) to find \(h_1\) and \(h_K\)
  
  for \(h = h_1\) to \(h_K\) do
    
    Solve (6.7) to find \(R_k(h)\);
    
    Solve (6.8) to find \(x_D, y_D, u_i\);
    
    \(N_h = \sum_{i=1}^{N} u_i\); if \(N_h > M_n\) then
      
      \(M_n = N_h\);
      
      \(x^*_D = x_D\) and \(y^*_D = y_D\);
    end
  end

  Remove the covered nodes’ locations from \(S\)
  
  \(N = N - M_n\);
  
  \(n = n + 1\);
  
  \(M_n = 0\);
end

\[ \frac{\partial}{\partial h} \sum_{k=1}^{K} \lambda_k R_k^2(h) = 0, \] \hspace{1cm} (6.12)

which, as formulated in [116], yields

\[ \sum_{k=1}^{K} \frac{2 \lambda_k X_k(h) R_k(h)^2}{R_k(h)^2 + h^2 + h X_k(h)} = 0, \] \hspace{1cm} (6.13)

where

\[ X_k(h) = \frac{9 \ln(10) A_0 b}{\pi} \frac{R_k(h) \exp(-b(\frac{180}{\pi}) \tan^{-1}(\frac{h}{R_k(h)}) - a)}{(1 + a \exp(-b(\frac{180}{\pi}) \tan^{-1}(\frac{h}{R_k(h)}) - a))^2} - h. \] \hspace{1cm} (6.14)

After finding the optimal altitude \(h_o\) by solving (6.13), (6.8) is solved to find the optimal \((x_D, y_D)\)
location of the first UAV-BS. After removing the already covered users, the process is repeated to deploy the next UAV-BS.

Algorithm 2 presents pseudo-code for the SMWA algorithm.

It is worth noting that these SES and SMWA algorithms are appropriately modified versions of the algorithms proposed in [116] to find the locations of multiple UAV-BSs instead of a single UAV-BS.

Algorithm 2 SMWA Algorithm

**Input**
- Ground nodes’ locations set ($S$);
- Total number of nodes = $N$;
- Maximum number of UAV-BSs = $m$;

**Initialization**
- Number of deployed UAV-BSs ($n$) = 1;
- Maximum number of covered nodes by a single UAV-BS ($M_n$) = 0;
- Optimal UAV-BS location $x_{D_n}^* = 0$ and $y_{D_n}^* = 0$;

**while** ($N > 0$ && $n \leq m$) **do**
- Solve (6.14) to obtain $h_o$;
- Solve (6.8) to find $x_D$, $y_D$, $u_i$;
- $x_{D_n}^* = x_D$ and $y_{D_n}^* = y_D$;
- $M_n = \sum_{i=1}^{N} u_i$;
- Remove the covered nodes’ locations from $S$;
- $N = N - M_n$;
- $n = n + 1$;
- $M_n = 0$;

**end**

### 6.3 Benchmark Algorithms

In this section, I provide a brief description of the benchmark algorithms I implemented to compare with the proposed algorithms.

#### 6.3.1 Brute-Force Solution

The Brute-Force solution is a simple but inefficient solution that uses exhaustive search of all the possible locations ($x_D$, $y_D$, $h$) to find the optimal UAV-BSs positions that cover the maximum number of nodes.
6.3.2 Deployment Method with Linear Approximation (LA)

The authors in [117] proposed the LA algorithm to cover the maximum number of ground nodes with the same QoS requirements based on successive deployment of the UAV-BSs.

The LA algorithm solves (6.8) to place the first UAV-BS. Then, the algorithm converts the non-convex constraints of placing the next UAV-BSs into various linear constraints, where each constraint represents a feasible regions to deploy the next UAV-BS so that there will be no interference with the other UAV-BSs, as presented below:

\[
\begin{align*}
\text{maximize} & \quad \sum_{i \in U} u_i, \\
\text{subject to} & \quad \sqrt{(x_{Dm} - x_{D(m-1)})^2 + (y_{Dm} - y_{D(m-1)})^2} \leq R + M (1 - u_i) \\
& \quad y_{Dm} \geq y_{D(m-1)} + 2R \\
& \quad y_{Dm} \leq y_{D(m-1)} - 2R \\
& \quad x_{Dm} \geq x_{D(m-1)} + 2R \\
& \quad x_{Dm} \leq x_{D(m-1)} - 2R,
\end{align*}
\]

where \((x_{Dm}, y_{Dm})\) represents the center of the \(m^{th}\) UAV-BS and \((x_{D(m-1)}, y_{D(m-1)})\) represents the center of the previously deployed UAV-BS, \(R\) is the UAV-BS coverage radius, and \(m\) is the number of UAV-BSs.

Since in each UAV-BS deployment there are 4 different feasible regions, in this paper, I present the results of the regions that succeeded in achieving the maximum number of covered nodes compared to the other available regions of deployment.
6.4 Results

In this section, I present the simulation results of the proposed algorithms in terms of the average number of covered users compared to the state-of-the-art LA algorithm, and the optimal solution for users with the same and different QoS requirements. Furthermore, I present a comparison between the SES and SMWA algorithms in terms of the probability of coverage and total execution time for users with different QoS requirements.

Since the optimization problem (6.8) is non-convex, I use MOSEK with CVX [143, 144, 145] to obtain the UAV-BSs locations in Algorithms 1 and 2. In particular, MOSEK implements the branch and cut method to solve the optimization problem. Furthermore, at each branching node, MOSEK relaxes the conic constraints and converts the underlying subproblem to a Second Order Cone Problem (SOCP), which is a convex optimization problem that can be solved using the primal-dual interior-point method [115].

For users with the same QoS requirements, I assume their SNR threshold is $\gamma_1 = 20$ dB which corresponds to an optimal UAV-BS radius and height of 707 and 646 meters, respectively. On the other hand, for users with different QoS requirements, I assume I have two set of users with densities $\lambda_1$ and $\lambda_2$, and the SNR thresholds for the two sets are $\gamma_1 = 20$ dB and $\gamma_2 = 17$ dB. This corresponds to an optimal UAV-BS radius and height in the range of [707,998], [604,919] meters, respectively.

The rest of the parameters used in the simulations are shown in Table 6.2.

6.4.1 Users with the Same QoS Requirements

Figure 6.1 shows the average number of covered users vs. the number of UAV-BSs, for the proposed algorithms (SES and SMWA), LA, and the optimal solution.

It is clear from Figure 6.1 that for the different algorithms, the average number of covered users increases as I deploy more UAV-BSs, as expected. Moreover, the proposed algorithms achieve the same as or outperform the LA algorithm, and achieve comparable performance to the optimal brute force solution in terms of the average number of covered users.

Since the proposed algorithm SES and the LA algorithm solve the same optimization problem
for placing the first UAV-BS, they have identical performance for 1 UAV-BS. However, the SES algorithm outperforms the LA algorithm in placing 2, 3, and 4 UAV-BSs in terms of the average number of covered users.

It is also clear from Figure 6.1 that the SMWA and SES algorithms have similar performance. This is due to the fact that for nodes with the same QoS requirements, the two algorithms will have the same optimal height.

### 6.4.2 Users with Different QoS Requirements

Figure 6.2 shows the average number of covered users vs. number of UAV-BSs, for the proposed algorithms (SES and SMWA), LA, and the optimal solution for different QoS requirements.

It is clear from Figure 6.2 that the proposed algorithms outperform the LA algorithm in deploying single or multiple UAV-BSs. This is due to the fact that the proposed algorithms take into account the different QoS requirements of the users unlike the LA algorithm. Moreover, the proposed algorithms achieve comparable performance to the optimal brute force solution in terms of the average number of covered users.

It is clear from Figure 6.2 that for the LA, SMWA, and SES algorithms, the average number of

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Number of Nodes</td>
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</tr>
<tr>
<td>Area</td>
<td>3 km * 3 km</td>
</tr>
<tr>
<td>Environment</td>
<td>Urban area</td>
</tr>
<tr>
<td>S-curve parameter $a$</td>
<td>9.61</td>
</tr>
<tr>
<td>S-curve parameter $b$</td>
<td>0.16</td>
</tr>
<tr>
<td>Average additional losses for $LoS$ ($\eta_{LoS}$)</td>
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</tr>
<tr>
<td>Average additional losses for $NLoS$ ($\eta_{NLoS}$)</td>
<td>20</td>
</tr>
<tr>
<td>Frequency ($f_c$)</td>
<td>2 GHz</td>
</tr>
<tr>
<td>Transmission power ($P_t$)</td>
<td>0 dBW</td>
</tr>
<tr>
<td>Noise Power ($P_n$)</td>
<td>−120 dBW</td>
</tr>
<tr>
<td>Set 1 density ($\lambda_1$)</td>
<td>5 users/km$^2$</td>
</tr>
<tr>
<td>Set 2 density ($\lambda_2$)</td>
<td>5 users/km$^2$</td>
</tr>
<tr>
<td>SNR threshold of $\lambda_1$ ($\gamma_1$)</td>
<td>20 dB</td>
</tr>
<tr>
<td>SNR threshold of $\lambda_2$ ($\gamma_2$)</td>
<td>17 dB</td>
</tr>
</tbody>
</table>
covered users increases as I deploy more UAV-BSs, as expected. Moreover, the SMWA and SES algorithms have comparable performances in terms of the average number of covered users for 1 UAV-BS and 2 UAV-BSs. Moreover, the SES algorithm covers more than 76% and 82% of the nodes using 3 UAV-BSs and 4 UAV-BSs, respectively. This percentage drops to about 70% and 71% of the nodes using the SMWA algorithm, respectively. This is due to the uniform distribution assumption of the SMWA algorithm, and as more nodes are covered, this assumption will no longer be valid.

6.4.3 Effect of QoS on the Performance

Figure 6.3 presents the average number of covered users with the same and different QoS requirements for the LA, SMWA, and SES algorithms using 1, 2, 3 and 4 UAV-BSs.

Since the LA algorithm does not consider the difference in QoS requirements of the users, its performance is the same for both situations. On the other hand, the proposed SMWA and SES algorithms take advantage of the different QoS requirements which allow the UAV-BSs to cover a larger radius to serve users with lower QoS requirements, as shown clearly in Figure 6.3.
Figure 6.2: Average number of covered users with different QoS requirements vs. number of UAV-BSs for the LA, SMWA, and SES algorithms, and the optimal solution (found through a brute force search).

### 6.4.4 Probability of Coverage

Figure 6.4 shows the probability of a certain number of covered users for the LA, SMWA and SES algorithms. It is clear from Figure 6.4 that for the LA, SMWA and SES algorithms, the probability of coverage decreases as the number of covered nodes increases. Moreover, the SES algorithm achieves higher performance compared to the LA and SMWA algorithms. This is due to the fact that the SMWA algorithm assumes the nodes are uniformly distributed, and this assumption will no longer be valid by removing the covered nodes, as discussed earlier. Furthermore, since the LA algorithm does not take into account the different QoS requirements, in addition to its constraints, it performs worse than the SES algorithm.

### 6.4.5 Execution Time

Figure 6.5 shows the total execution time vs. number of UAV-BSs, for the LA, SES and SMWA algorithms. It is clear from Figure 6.5 that the execution time of the SMWA algorithm is much less than the SES and LA algorithms. This is expected since the SES and LA algorithms perform an exhaustive search for the optimal height in a closed region, while on the other hand the SMWA does
not since it assumes the nodes are uniformly distributed. Moreover, the LA and SES algorithms have comparable execution times for placing 1 UAV-BS and 2 UAV-BSs. On the other hand, for 3 UAV-BSs and 4 UAV-BSs, and since the number of non-covered nodes of the LA algorithm is much higher than the SES algorithm, the LA algorithm has a higher execution time.

The total execution time of the SES algorithm is highly dependent on the number of ground nodes, as its complexity is $O(2^n n^{3.5} \log(\epsilon^{-1}))$ [116]. For instance, it took about 60 seconds to obtain the first UAV-BS location, but only about an additional 35 and 20 seconds to obtain the location of the second and third UAV-BSs, respectively, as the covered nodes were removed resulting in fewer nodes.
In this chapter, I discussed the placement optimization of multiple unmanned aerial vehicles to maximize the number of covered users with the same and different QoS requirements. First, I formulated the optimization problem as a non-convex optimization problem and presented two heuristic algorithms (SES and SMWA) to obtain the locations of multiple UAV-BSs. Simulation results showed that the SES and SMWA proposed algorithms outperform the state-of-the-art LA algorithm in terms of the average number of covered users for users with the same and different QoS requirements, and achieved near optimal performance for users with the same QoS requirements. Finally, for users with different QoS requirements, I presented a trade-off between the SES and SMWA algorithms based on their achieved probability of coverage, average number of covered users, and total execution time.

The work presented in this chapter assumes nodes need to be in direct communication with one of the UAV-BSs to be covered. However, exploiting the existence of multi-hop ad hoc networks, it is possible to have ground nodes communicate via multi-hop to other ground nodes in direct communication with a UAV-BS to increase the coverage of the network. I explore the extension of UAV-based...
Figure 6.5: Total execution time vs. number of UAV-BSs for the LA, SMWA and SES algorithms.

networks with multi-hop ad hoc networks in the next chapter.
Chapter 7

Utilizing Ground Nodes with Multi-Hop Capabilities to Extend the Range of UAV-BSs

7.1 Introduction

Based on the advancements of using UAV-BSs in next generation wireless networks as well as the benefits of utilizing multi-hop ad-hoc networks to extend the network coverage, in this chapter, I build on the work of the prior chapter and propose an algorithm that optimizes the placement of multiple UAV-BSs to maximize the aggregate number of directly covered nodes (via UAV-Ground links) as well as the indirectly covered nodes (via a Ground-Ground multi-hop ad-hoc network), for nodes with the same as well as different QoS requirements.

7.2 System Model

In our analysis, I consider a target area with a set of nodes $U$, where each node $i$ of the set $U_k$ demands a unique QoS requirement $k$ from 1 to $K$ where

$$\bigcup_{k=1}^{K} U_k = U.$$  \hspace{1cm} (7.1)

Our aim is to find the optimal locations of the UAV-BSs that maximizes the number of covered nodes while achieving the required QoS requirements for each set, given the ground nodes are able to form multi-hop connections to ground nodes that are directly connected to a UAV-BS.
7.2.1 Nodes Distribution

In this chapter, I consider two types of node distributions: uniform distribution and beta distribution.

Uniform Distribution

The probability density function of the uniform distribution, for \( a \leq z \leq b \), is given in (7.2).

\[
p(z) = \frac{1}{b - a}, \tag{7.2}
\]

where \( z \) represents either the \( x \) or \( y \) coordinates of the ground node and \( a \) and \( b \) represents the area bounds.

Beta Distribution

The probability density function of the beta distribution, for \( 0 \leq x \leq 1 \), shape parameters \( 0 \leq (\alpha, \beta) \), and \( \Gamma(l) \) represents the gamma function, is given in (7.3) [146].

\[
p(z) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} z^{(\alpha-1)}(1 - z)^{\beta-1}, \tag{7.3}
\]

where again \( z \) represents either the \( x \) or \( y \) coordinates of the ground node. It is worth noting that the uniform distribution on the interval \([0, 1]\) is a special case of the Beta distribution with \( \alpha = \beta = 1 \).

Figure 7.1 shows an example of nodes distributed uniformly and according to the beta distribution with parameters \( \alpha = 5 \) and \( \beta = 5 \).

7.2.2 UAV-BS to Ground Path Loss Model

As described in Section 6.2.1, the total probabilistic mean path loss between a UAV-BS at location \((x_D, y_D)\) and at height \( h \), and a ground node located at an elevation angle \( \theta_{ik} \) is given as
CHAPTER 7. UTILIZING GROUND NODES WITH MULTI-HOP CAPABILITIES TO EXTEND THE RANGE OF UAV-BSS

Figure 7.1: An example of 100 nodes distributed uniformly 7.1(a) and according to the beta distribution 7.1(b) in a 3 km x 3 km area.

\[ L(h, r_{ik}) = \frac{A}{1 + a \exp(-b(\frac{180}{\pi})(\theta_{ik} - a))} + 20 \log_\frac{r_{ik}}{\cos(\theta_{ik})} + B, \]  
(7.4)

where \( A = \eta_{\text{LoS}} - \eta_{\text{NLoS}} \), \( B = 20 \log(\frac{4\pi f_c}{c}) + \eta_{\text{LoS}} \), and \( \eta_{\text{LoS}} \) and \( \eta_{\text{NLoS}} \) are the average additional losses for LoS and NLoS, respectively. Furthermore, \( f_c \) is the carrier frequency, \( a \) and \( b \) are the S-curve parameters which only depend on the environment, and \( r_{ik} \) is the distance between the UAV-BS center and node \( i \) of the set \( U_k \), and is given as

\[ r_{ik} = \sqrt{(x_{ik} - x_D)^2 + (y_{ik} - y_D)^2}. \]  
(7.5)

7.2.3 Ground to Ground Path Loss Model

For the ground to ground communication between the nodes, I assume and implement the free space path loss model, in which the path loss can be given as:

\[ P_L[\text{dB}] = 20 \log(\frac{4\pi d f_c}{c}), \]  
(7.6)

where \( d \) is the distance between the nodes, \( f_c \) is the carrier frequency and \( c \) is the speed of light. To ensure the QoS requirements of the indirectly covered nodes are met, the maximum path loss between
a directly covered node and an indirectly covered node must not exceed the value presented in (7.7).

\[ P_L[dB] = P_{tm} - P_n - \gamma_{th} \]  

(7.7)

where \( P_{tm} \) is the transmit power of the directly covered node, and \( P_n \) is the noise power at the indirectly covered ground node.

### 7.2.4 Single UAV-BS Placement Problem Formulation For Directly Covered Nodes

As described in Section 6.2.2, the UAV-BS placement problem for directly covered nodes is given as

\[
\text{maximize} \quad \sum_{k=1}^{K} \sum_{i \in U_k} u_{ik}, \\
\text{subject to} \quad \sqrt{(x_{ik} - x_D)^2 + (y_{ik} - y_D)^2} \leq R_k(h) + M(1 - u_{ik})
\]

(7.8)

\[ \forall i \in U_k, k = 1, 2, \ldots, K \]

\[ u_{ik} \in \{0, 1\}, \forall i \in U_k, k = 1, 2, \ldots, K, \]

where \( u_{ik} \in \{0, 1\} \) is a binary variable such that \( u_{ik} = 1 \) if the node \( i \) of the set \( U_k \) is within the coverage region of the UAV-BS and \( u_{ik} = 0 \), otherwise. Moreover, \( M \) is a constant chosen large enough that the first constraint of the optimization problem above is trivially satisfied when \( u_{ik} = 0 \).

### 7.2.5 Heuristic Algorithm

For a given environment and a path loss threshold \( L_{th}^k \), the maximum coverage radius \( R^*_k \) can be obtained by solving (6.2), and since the optimal elevation angle is already known based on the environment (as shown in Table 6.1), the optimal altitude \( h^*_k \) can be calculated using (6.7).
Furthermore, for nodes with different QoS requirements and path loss thresholds between $L_{th}^1$ and $L_{th}^K$, the optimal altitude ($h_o$) of the UAV-BS for the directly covered nodes will be in the range $[h_1, h_K]$ as proven in [142]. Therefore, solving (6.8) results in the optimal UAV-BS placement for the directly covered nodes.

On the other hand, when taking into account nodes that are 1-hop and 2-hop from the directly covered nodes, I propose a heuristic algorithm that performs an exhaustive search for the optimal altitude ($h_o$) of the UAV-BS in the closed region $[h_1^*, h_K^*]$, where $h_1^*$ and $h_K^*$ are some values smaller and larger than the optimal altitudes $[h_1, h_K]$. This change is to accommodate the fact that the optimal height when considering ground nodes with multi-hop capabilities might be outside the range $[h_1, h_K]$.

For each height in the closed region $[h_1^*, h_K^*]$, Algorithm 1 finds the corresponding coverage radius and obtains the 2D location of the UAV-BS and the indices of the directly covered ground nodes. Afterwards, and based on the distances between the directly covered nodes and the rest of the ground nodes, the algorithm finds the indices of the directly and indirectly covered nodes.

After finding the optimal placement of the first UAV-BS, the directly and indirectly covered nodes are excluded from the location set and the process is repeated to find the location of the next UAV-BS until all the ground nodes are covered.

Algorithm 3 presents pseudo-code for our proposed heuristic algorithm.

### 7.3 Results

In this section, I present the simulation results of our proposed algorithm in terms of the average number of directly and indirectly covered nodes for nodes with the same and different QoS requirements, and for nodes with random distribution as well as with Beta distribution with parameters $\alpha = 5$ and $\beta = 5$. I assume 100 nodes are distributed in a 10 km x 10 km or 3 km x 3 km or 1.5 km x 1.5 km area.

For nodes with the same QoS requirements, I assume their SNR threshold is $\gamma_1 = 20$ dB. On the other hand, for nodes with different QoS requirements, I assume I have two set of nodes with densities
Algorithm 3 Algorithm 1

Input
Ground nodes’ locations set \((S)\);
Total number of nodes \(N\);
Ground nodes’ connection range = \(d_m\);
Maximum number of UAV-BSs = \(m\);

Initialization
Number of deployed UAV-BSs \((n) = 1\);
Number of directly covered nodes at each height \((N_n) = 0\);
Number of directly and indirectly covered nodes at each height \((N_m) = 0\);
Maximum number of directly covered nodes by a UAV-BS \((M_n) = 0\);
Maximum number of directly and indirectly covered nodes by a UAV-BS \((M_m) = 0\);
Optimal UAV-BS location without considering multi-hop capability \(x^*_D = 0\) and \(y^*_D = 0\);
Optimal UAV-BS location considering multi-hop capability \(x^*_Dm = 0\) and \(y^*_Dm = 0\);
Connectivity matrix \(c = 0\);

Main
Calculate the distance between the nodes matrix \(x\);

\[ \text{if } x_{ij} > d_m \text{ then} \]
| \(c_{ij} = 0\); |
\[ \text{else} \]
| \(c_{ij} = 1\); |
\[ \text{end} \]
\[ \text{while } (N > 0 \& \& n \leq m) \text{ do} \]
\[ \text{for } h = h^*_1 \text{ to } h^*_K \text{ do} \]
| Solve (6.7) to find \(R_k(h)\); |
| Solve (6.8) to find \(x_D, y_D, u_i\); |
| \(N_n = \sum_{i=1}^{N} u_i\); |
| \text{if } \(N_n > M_n\) then \]
| \(M_n = N_n\); |
| \(x^*_D = x_D\) and \(y^*_D = y_D\); |
| \text{end} \]
| Find the indices of the directly covered nodes \(ii = \text{find}(u > 0);\) |
| Find the indices of the directly and indirectly covered nodes \(\text{find}(c(ii,:) == 1);\) |
| Find the unique indices of the directly and indirectly covered nodes \(B\); |
| \(N_m = \text{size}(B);\) |
| \text{if } \(N_m > M_m\) then \]
| \(M_m = N_m\); |
| \(x^*_Dm = x_D\) and \(y^*_Dm = y_D\); |
| \text{end} \]
| Remove the covered nodes locations from \(S\); |
| \(N = N - N_m;\) |
| \(n = n + 1;\) |
| \(M_n = 0;\) |
| \text{end} \]
TABLE 7.1: SIMULATION PARAMETERS.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
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</thead>
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<tr>
<td>Total number of nodes</td>
<td>100</td>
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<tr>
<td>Area</td>
<td>3 km x 3 km or 1.5 km x 1.5 km or 10 km x 10 km</td>
</tr>
<tr>
<td>Environment</td>
<td>Urban area</td>
</tr>
<tr>
<td>S-curve parameter $a$</td>
<td>9.61</td>
</tr>
<tr>
<td>S-curve parameter $b$</td>
<td>0.16</td>
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</tr>
<tr>
<td>Average additional losses for NLoS ($\eta_{\text{NLoS}}$)</td>
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</tr>
<tr>
<td>Frequency ($f_c$)</td>
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</tr>
<tr>
<td>UAV-BS transmission power ($P_t$)</td>
<td>0 dBW</td>
</tr>
<tr>
<td>Noise Power ($P_n$)</td>
<td>$-120$ dBW</td>
</tr>
<tr>
<td>Set 1 density ($\lambda_1$)</td>
<td>5 nodes/km$^2$ (sparse) or 22 nodes/km$^2$ (dense)</td>
</tr>
<tr>
<td>Set 2 density ($\lambda_2$)</td>
<td>5 nodes/km$^2$ (sparse) or 22 nodes/km$^2$ (dense)</td>
</tr>
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<td>SNR threshold of $\lambda_1$ ($\gamma_1$)</td>
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</tr>
<tr>
<td>SNR threshold of $\lambda_2$ ($\gamma_2$)</td>
<td>17 dB</td>
</tr>
<tr>
<td>Beta distribution parameter $\alpha$</td>
<td>5</td>
</tr>
<tr>
<td>Beta distribution parameter $\beta$</td>
<td>5</td>
</tr>
</tbody>
</table>

$\lambda_1$ and $\lambda_2$, and the SNR thresholds for the two sets are $\gamma_1 = 20$ dB and $\gamma_2 = 17$ dB. The rest of the parameters used in our simulations are shown in Table 7.1.

Figure 7.2 shows the effect of the ground nodes’ transmission powers on the percentage of directly, 1-Hop, and 2-Hop covered nodes for nodes that are distributed according to the uniform and beta distributions in both a 3 km x 3 km area and a 1.5 km x 1.5 km area. It is clear from Figure 7.2 that, as expected, increasing the ground nodes’ transmission powers will increase the percentage of covered nodes. Moreover, when the ground nodes’ transmission power is 30 dBm, all the nodes can be covered with a single UAV-BS.

Furthermore, it is clear from Figure 7.2 that for ground nodes that are distributed according to the beta distribution, the percentage of covered nodes is higher compared to if the nodes are uniformly distributed. This is expected, as with the beta distribution and our parameters selection, the nodes will be concentrated around the area’s center.

Figure 7.3 shows the required number of UAV-BSs to ensure the QoS requirements are met for all ground nodes. It is clear from Figure 7.3 that utilizing the multi-hop capabilities of the ground
nodes decreases the required number of UAV-BSs. For instance, using a 12 dBm transmission power at the ground nodes decreases the required number of UAV-BSs from 3, 5, and 5 to 2, 4, and 4 for nodes with different QoS requirements in a dense area, same QoS requirements in a sparse area, and for nodes with different QoS requirements in a sparse area, respectively. Furthermore, all the ground nodes can be covered with a single UAV-BS using a 30 dBm transmission power at the ground nodes.

Moreover, for nodes with different QoS requirements, the percentage of covered nodes is higher compared to nodes with the same QoS requirements, as shown in Figures 7.2(a) and 7.2(b). This is expected as for nodes with different QoS requirements, the maximum distance allowed between the directly and indirectly covered nodes with lower QoS requirements is higher compared to nodes with
Figure 7.3: Required number of UAV-BSs to ensure QoS requirements for all ground nodes in a dense (1.5 km x 1.5 km) and sparse (3 km x 3 km) areas.

higher QoS requirements.

Finally, it is clear from Figures 7.2(a) and 7.2(c), that distributing the same number of ground nodes in a smaller area results in a higher percentage of covered nodes, as expected.

Figure 7.4 shows the effect of the number of ground nodes for uniformly and beta distributed nodes with the same as well as different QoS requirements assuming one UAV-BS. I assume the ground nodes use 21 dBm as their transmission power. It is clear from Figure 7.4(a) that increasing the number of nodes has a minimal effect on the percentage of covered nodes for nodes that are uniformly distributed. On the other hand, increasing the number of nodes that are beta distributed will increase the percentage of covered nodes due to the fact that more nodes will be concentrated in a certain area. Furthermore, increasing the number of nodes in a certain area increases the probability of having nodes connecting to other ground nodes via multi-hop. This is clear as the percentage of 1-hop and 2-hop covered nodes increases as the number of nodes increases, as shown in Figures 7.4(b) and 7.4(c).

Figure 7.5 shows the effect of the ground nodes’ transmission power and the number of UAV-BSs on the percentage of 2-hop covered nodes in a 10 km x 10 km area. It is clear from Figure 7.5
CHAPTER 7. UTILIZING GROUND NODES WITH MULTI-HOP CAPABILITIES TO EXTEND THE RANGE OF UAV-BSS

Figure 7.4: Percentage of directly, 1-hop, and 2-hop covered nodes with the same and different QoS requirements, uniform and beta distributions. Transmit power is set at 21 dBm and nodes are distributed in a 3 km x 3 km area.
that increasing the transmission power and the number of UAV-BSs will increase the percentage of covered nodes, as expected. Due to the large area, using a 12 dBm transmission power and 5 UAV-BSs will result in about 30% and 60% of covered nodes for nodes distributed uniformly and according to the beta distribution, respectively.
On the other hand, increasing the transmission power to 30 dBm will result in about 80% and 90% of covered nodes for nodes distributed uniformly and requiring the same and different QoS, respectively. Furthermore, using 5 UAV-BSs and 30 dBm will cover about 99% of the beta distributed ground nodes.

Finally, 5 UAV-BSs is required to cover 30% of the uniformly distributed nodes using a 12 dBm transmission power, while with 30 dBm, the same covered nodes percentage can be achieved with only 1 UAV-BS. Similarly, using 5 UAV-BSs covers 60% of the beta distributed nodes with 12 dBm, while for 30 dBm, 1 UAV-BS already covers more than 80% of the nodes. These results show the trade-off between the number of UAV-BSs and the transmission power of the ground nodes.

### 7.4 Conclusions

In this chapter, I discussed the placement optimization of multiple UAV-BSs to maximize the number of covered nodes with the same as well as with different QoS requirements when ground nodes have multi-hop capability to extend the reach of the UAV-BSs. I built on the single UAV-BS formulation problem described in Chapter 6 to propose a heuristic algorithm that optimizes the placement of multiple UAV-BSs while taking into account the multi-hop capabilities of the ground nodes. Simulation results showed the merits of utilizing the multi-hop capabilities of the ground nodes in terms of reducing the number of UAV-BSs required to cover the nodes. Furthermore, a tradeoff between the number of UAV-BSs and the transmission power of the ground nodes required to ensure the QoS requirements of all nodes was presented.
Chapter 8

Conclusions and Future Work

8.1 Conclusions

In this dissertation, I have evaluated the performance of infrastructure and multi-hop ad-hoc networks. The contributions of this research are summarized below.

- I have presented a state-of-the-art review of EH-WSNs for environmental monitoring applications including an elephant tracking application called JumboNet [49].

- I have used real elephants’ movement data from the JumboNet project and an ns3 multi-sink extension to the epidemic routing with vaccine protocol to analyze the performance of Wi-Fi infrastructure mode and multi-hop Wi-Fi ad-hoc mode in JumboNet [49].

- I have developed an Android application that records information about the accessibility, quality and attributes of Wi-Fi APs, in addition to cellular base stations. Moreover, the application measures and records the throughput and delay of the infrastructure networks. The developed Android application can be downloaded from [132] and used by others to map Wi-Fi and cellular coverage in their area.

- I have developed an Android application that connects an ad-hoc network to the Internet via a gateway node that is connected to an infrastructure network. The application shows the impact of extending access to the Internet to devices that does not have direct access. Moreover, based on energy consumption models for LTE, Wi-Fi and Wi-Fi Direct, I have evaluated the tradeoffs
between throughput, delay, and energy consumption of infrastructure and multi-hop ad-hoc networks.

- I have proposed two heuristic algorithms to optimize the location of multiple UAV-BSs to maximize the number of covered users, and I have shown that for users with the same as well as with different QoS requirements, the proposed algorithms achieved near optimal performance and outperformed the Linear Approximation (LA) state-of-the-art algorithm in terms of the average number of covered users and execution time.

- I have proposed a heuristic algorithm that takes into account the multi-hop capabilities of the ground users and reduces the required number of UAV-BSs to provide coverage for all users.

### 8.2 Future Work

In order to improve the performance of wireless networks, several directions can be pursued as future research.

- In Chapter 5 of this dissertation, the linear network has only one flow between the client and the gateway or vice versa. The impacts of extending this assumption to multiple flows in the network can be explored in future work.

- In Chapters 6 and 7 of this dissertation, I assumed a high noise power to balance out the assumption of no co-channel interference in the system model. The impacts of co-channel interference as well as more realistic channel models for the multi-hop network can be explored in future work.

- In a hybrid ground-aerial base stations network, the wireless network benefits from both the typically higher processing capabilities of ground base stations and the mobility convenience of the UAVs. Hence, in order to further improve the wireless network performance, more research can be applied to the placement optimization of both the ground and aerial base stations.
• In this dissertation, the ground nodes can connect to their assigned UAV-BS directly or indirectly via multi-hop connections. A possible future research direction would be to optimize the placement of UAV-BSs while ensuring they are in the communication range of each other to ensure full connectivity of the network.

• An important future direction in the design of next-generation wireless networks is the implementation of deep learning, artificial intelligence (AI), and big data to study and optimize different aspects of the wireless network such as network management and resource sharing.

• Finally, the impacts of security on the design, analysis, and optimization of infrastructure, aerial and multi-hop ad-hoc networks in wireless sensor networks and mobile networks can be explored in future work.
Bibliography


