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Drone Base Station Trajectory Management for Optimal Scheduling in LTE-Based Sparse Delay-Sensitive M2M Networks

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Drone Base Station Trajectory Management for Optimal Scheduling in LTE-Based Sparse Delay-Sensitive M2M Networks

by
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Table of Contents

List of Figures

LIST OF TABLES

LIST OF ACRONYMS

5PSE	5th Percentile Spectrum Efficiency
AP	Ad-hoc Point
ACO	Ant Colony Optimization
AIA	Artificial Immune Algorithm
BSs	Base Stations
BER	Bit Error Rate
BLE	Bluetooth Low-Energy
BSR	Buffer Status Report
PNN	By-Passing of Nodes in NN
CNPC	Control and non-payable Communication
DMR	Deadline Missing Ratio
DoS	Denial of Service
DoD	Device-to-Device
DNN	Directional NN
DDNN	Directional NN algorithm Directed to the next NN
DO	Dissolved Oxygen
DDCS	Dynamic Duty Cycle Selection
EWS	Early Warning Systems
ETA	Estimated Time of Arrival
EPC	Evolved Packet Core
E-UTRAN	Evolved UMTS Terrestrial Radio Access Network
FAA	Federal Aviation Administration
FUSNs	Flying Ubiquitous Sensor Networks
FSO	Free Space Optic
FSOC	Free Space Optical Communications
FeICIC	Further-enhanced Intercell Interference Coordination
GTSP	Generalization version of TSP
GA	Genetic Algorithm
HAPs	High Altitude Platforms
H2H	Human-to-Human
ITS	Intelligent Transportation System
IM	Intensity Modulation
IMAV	International Micro Air Vehicle
IoT	Internet of Things
LoS	Line-of-Sight
LPWAN	Low Power WAN
ML	Machine Learning
M2M	Machine-to-Machine

MTCDs	Machine-Type Communication Devices
MBS	Mobile BS
MLP	Multi-layer Perception
MDURP	Multiple Depot UAV Routing Problem
NN	Nearest Neighbour
PDR	Packet Delivery Ratio
PRR	Packet Reception Rate
PSO	Particle Swarm Optimization
PRB	Physical Resource Blocks
PSC	Public Safety Communications
QoS	Quality of Service
RBL	Request Based Learning
ROS	Robot Operating System
SR	Scheduling Request
SAR	Search and Rescue
SCP	Set Covering Problem
SVM	Support Vector Machine
T-BS	Terrestrial BS
TSP	Travelling Salesman Problem
UABs	Unmanned Aerial Base Stations
UASs	Unmanned Aerial Systems
UAVs	Unmanned Aerial Vehicles
UE	User Equipment
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
WSNs	Wireless Sensor Networks
WSANs	Wireless Sensor/Actuator Networks
WiMAX	Worldwide Interoperability for Microwave Access

LIST OF SYMBOLS

h_j	Vertical placement of the UAV-BSs
k	Scaling factor
R_j	UAV's coverage disk
θ_{opt}	Optimal elevation angle
d_{break}	Propagation distance
h_e	Evaporation duct height
h_t	Transmitter height
h_r	Receiver Height
λ	Wavelength of the Transmission
P	Battery power consumption
C_{ij}	Distance covered from node *i* to node *j*
X_{ij}	Binary Indicator
S	Subtours
V	Vertices
N	Number of MTCDs
D_i	Absolute deadline
D_{imax}	Maximum Deadline
$T_{iBUDGET}$	Packet delay budget
$T_{SR-Period}$	Time spent by a packet in the transmit buffer of the device before a scheduling request (SR)
T	Current time
T_{Uplink}	LTE TDD uplink latency
P_{ij}^k	Probability for ant *k* to go from point i to point *j*
η_{ij}	Heuristic desirability from point i to point *j*
τ_{ij}	Pheromone trails
A	Relative influence of the pheromone trail
B	Heuristic information
N_i^k	Set of points not visited by ant k measured at point i
ρ	Pheromone evaporation
$\Delta\tau_{ij}^k$	Amount of pheromone ant *k* deposited on the arcs visited
C^k	Length of tour
T^k	K ant tour
$G = (N, A)$	Construction graph of TSP

ABSTRACT

Providing connectivity in areas out of reach of the cellular infrastructure is a very active area of research. This connectivity is particularly needed in case of the deployment of machine type communication devices (MTCDs) for critical purposes such as homeland security. In such applications, MTCDs are deployed in areas that are hard to reach using regular communications infrastructure while the collected data is timely critical. Drone-supported communications constitute a new trend in complementing the reach of the terrestrial communication infrastructure. In this study, drones are used as base stations to provide real-time communication services to gather critical data out of a group of MTCDs that are sparsely deployed in a marine environment.

Studying different communication technologies as LTE, WiFi, LPWAN and Free-Space Optical communication (FSOC) incorporated with the drone communications was important in the first phase of this research to identify the best candidate for addressing this need. We have determined the cellular technology, and particularly LTE, to be the most suitable candidate to support such applications. In this case, an LTE base station would be mounted on the drone which will help communicate with the different MTCDs to transmit their data to the network backhaul. We then formulate the problem model mathematically and devise the trajectory planning and scheduling algorithm that decides the drone path and the resulting scheduling.

Based on this formulation, we decided to compare between an Ant Colony Optimization (ACO) based technique that optimizes the drone movement among the sparsely-deployed MTCDs and a Genetic Algorithm (GA) based solution that achieves the same purpose. This optimization is based on minimizing the energy cost of the drone movement while ensuring the data transmission deadline missing is minimized. We present the results of several simulation experiments that validate the different performance aspects of the technique.

CHAPTER 1. INTRODUCTION

1.1 Introduction

In this chapter, an overview about drones along with their applications and challenges is given. We then introduce the problem statement that is addressed through this research, the motivation and the research objectives and contributions as discussed in this thesis.

1.1.1 Drones: An Overview

As defined in [1] and [2], Unmanned Aerial Vehicles (UAVs), commonly known as drones (we will be using the two terms interchangeably throughout this thesis), are aircraft that have no onboard human pilot. The Federal Aviation Administration (FAA) has also defined a UAV as "A device used or intended to be used for flight in the air that has no onboard pilot". Since the start of the twenty-first century, one can notice a fast proliferation of the drones' technologies impacting a wide range of industries and performing critical tasks. Drones' use has been permitted in Hollywood film production by producing high-definition imaging drones [2]. UAVs' sizes vary from large military UAVs of 200 feet to commercial inch-wide UAVs. UAVs' flight height can range from few feet to 17,000 miles. Typical commercial UAVs' design is as illustrated in Figure 1.1.

Figure 1.1 Commercial drone design [2]

Several industrial giants are increasingly relying on the use of drones to provide Internet access for developing countries [3]. The use of drones for providing communications is also expanding to include different applications such as civil applications and public safety communication (PSC) applications.

The study in [4], has predicted a huge increase in the number of drones in the coming years. Hence, some regulations should be set to maintain safety requirements to support this large expansion. Since this expansion might take an international level, international legalization and regulation should be there for drones' manufacturing and usage.

1.1.2 Applications of Drones

Despite the limited application scope of drones at their beginnings, they are now used in a wide range of applications that touch all aspects of life [1]. The predicted extensive use of the drones in the future, however, depends on the possibility of their safe maneuver in specified areas and the removal of stringent legal requirements on their operation. There are still important technical roadblocks that pertain to the reliability and safety issues facing the operation of small drones that are being addressed by many researchers around the world [5].

The applications of drones can be categorized into four domains [6]. The Search and Rescue (SAR) application is one of the main applications where the drones are used to search for any target(s) and help rescuers reach these targets. The second domain includes coverage which is subdivided into area coverage and network coverage. Area coverage primarily deals with monitoring and surveillance applications while in network coverage drones act as communication relays. The third domain is the construction domain which deals with lifting building elements from one place to another. Delivery of goods is the last domain, according to this classification.

The study in [7], drones were described for temporarily recovering communications networks and for medicine and post disaster delivery purposes. Drones have also been used in different natural disaster management applications through different arrangements such as integrating them with Wireless Sensor Networks (WSN). These applications may be classified along the lines of monitoring, forecast and early warning systems (EWS), disaster information fusion and sharing, standalone communication systems and search and rescue missions [8]. There are several challenges facing these disaster management applications. The main of which have been identified as coverage, mobility and connectivity, robustness and reliability, security, privacy and safety, interoperability and quality of service (QoS) [8].

Drones are also used in maritime unmanned tasks and missions [9]. This includes sea-border patrolling, search and rescue (SAR) applications, marine oil spill clean-up and environmental monitoring.

The work in [10] discusses novel technologies for UAVs' search and rescue (SAR) applications. Drones in their context scan for the Bluetooth low-energy (BLE) signals emitted by missing people's smartphones. The use of the BLE technology reduces the time and the cost of the operation. The study finds that LPWAN communication technology could be an effective alternative for the BLE if it was supported by the smartphones.

Swarms of drones will soon be involved in numerous applications that span civil and military purposes. Each of these applications involves requirements that are potentially different from those of the other applications. However, for applications that require the drones to exchange large amounts of data, high data-rate communication means would be needed. Free-space optical communications (FSOC) present a strong contender for such communications as opposed to RF-based communications [11]. FSOC is a line-of-sight (LOS) technology that operates at wavelengths of 850 nm, 1300 nm and 1550 nm [12]. FSOC data rate ranges from 1-2 Gbps and covers a distance that varies between 1-3 km [13]. FSOC links are not requiring any spectrum allocation or FCC license [14]. In addition, FSOC does not need any additional infrastructure. It can be installed easily with low cost of installation and maintenance, with no cabling involved [15].

In [16], LoRa is considered suitable for long-range low power wireless sensor/actuator networks (WSANs) till now. UAVs can be deployed as WSANs for localization and tracking applications. The QoS was the main metric for all the work cited in this study.

1.1.3 Drone Communications

Communications nowadays rely on backbone networks without planning for aerial communications systems which could replace the terrestrial communication systems in case of any disastrous situations [17] i.e. for PSC purposes. PSC is one of the key uses of communication systems in 5G and beyond. PSC applications come at the top of the list of applications need drone communication coverage.

The studies in [1]-[4] and [34] mainly investigate the use of drones in different classes of applications under different conditions such as the terrestrial and maritime environments. The common factor among these applications is the need to communicate between the drones, from one side, and fixed locations, from the other side. We notice that such communications are performed using different technologies. Moreover, the drones could assume different roles in the communication process depending on the application needs and conditions.

As far as communication coverage is concerned, the utilization of drones has been classified into three main cases, namely, drone-aided ubiquitous coverage, drone-aided relaying and drone-aided information dissemination [18]. The focus in this case is on the networking architecture and channel characteristics. As shown in Figure 1.2, the network architecture is proposed where the additional control and non-payload communication (CNPC) is an additional link with “more stringent latency and security requirements for supporting safety-critical functions”.

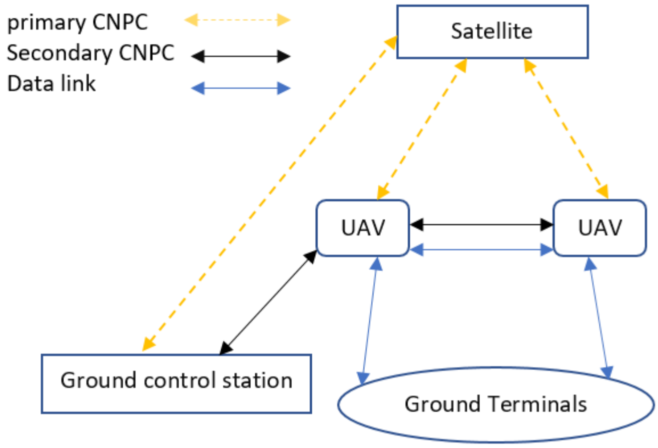

Figure 1.2 Networking Architecture of UAV-aided wireless communications [18]

In [19], the authors focus on the importance of having a wireless communication to assist the drones' flight. So, the drones need both wireless communication with a pilot on the ground and communication with a payload, like a camera or sensor. A frequency spectrum is needed to grant this communication. This spectrum is identified based on the drone type, the flight characteristics and the payload. For the short-range communication, WiFi is used. However, to avoid the interference due to the flight height, the WiFi frequency should be used within the line of sight of the pilot. For long-distance flying drones, the low frequency will not be applicable, as for instance, in the Netherlands it is expected that a part of the 7 GHz band will be used for this purpose.

1.1.4 Drones' Challenges and Opportunities

As discussed in [20] the opportunities of using drone-cell communications include the following:

1- Drone cells are useful in scenarios that need agility and resiliency of wireless networks.
2- Drone cells can help prevent unexpected congestion in the network as it may provide additional coverage in case of a natural disaster.

3- Mobility of drone cells enables them to serve users with high mobility and data rate demand thus reducing the handover done through terrestrial base stations.

However, an efficient design of drone base stations is one of the challenges. Determining their mechanics as size, aerodynamics, and the maximum takeoff weight is very crucial. A drone-BS is defined by [21] as a low altitude UAV equipped with transceivers to assist wireless networks. So, the drone-cell configurations can vary from drone relay, small drone-BS and macro drone-BS. FSO and mmWave are considered promising technologies for high rate and low spectrum cost.

The study in [2] has presented some of the challenges encountered by the drones and solutions for them were also provided. So, for example, the jamming and spoofing issues, which hits the drone's security challenge, could be solved by collaborating with the drones manufacturer to encrypt the signals. Flying over prohibited zones, on the other hand, might be solved by creating no-fly zones.

Drones have some licensing challenges, where the Federal Aviation Administration (FAA) has launched B4UFLY application to inform people of the drone uses and regulations [22]. Another challenge facing the massive deployment of drones is their usage without jeopardizing cellular services [3].

1.2 Problem Statement and Research Objectives

Homeland security or coastal safety precautions require the deployment of monitoring machine-type communication devices (MTCDs) at sea. The purpose is to monitor and report hostile movements (e.g. activities of smugglers or enemy troops) or catastrophic natural phenomena such as tsunamis. These MTCDs, which are sparsely deployed, thus detect specific events and generate real-time data that need to be transmitted under stringent delay requirements. The regular terrestrial network range does not cover such areas in the sea that are usually far away from shores. For this purpose and given that we are dealing with critical timely data, drones present themselves as flying alternatives to terrestrial fixed base stations to augment the terrestrial networks and provide the required coverage.

Therefore, a drone can be used as a base station that flies to the location of the MTCD that has data to transmit, according to a certain scheme. The requirement is to ensure that the used drone can tend to the delay needs of these MTCDs that are deployed according to a certain pattern with specified distances in between.
Therefore, the UAV trajectory should be optimized such that the transmission deadlines of the different MTCDs are fulfilled. In addition, the power consumed in such drone movement is optimized with the purpose of maximizing the battery of the drone. This is done via ensuring that the distance traveled by the drone as it collects the MTCDs' data is minimized.

The objectives of this research can therefore be summarized in the following:

- Studying the use of drones in different roles in communication services using different technologies
- Studying the optimization techniques most suitable for addressing the trajectory planning subject to specific transmission constraints
- Utilizing the most suitable optimization technique as the core of the scheduling technique for drone-mounted base stations using LTE-based cellular communications

1.3 Motivation

It is important to direct the scientific research to serve the society and address citizens' needs. Egypt has large coastal line that requires constant monitoring. The study in this thesis can be applied to serve/monitor Egypt's marine environment such as the Suez Canal and other maritime areas along its coastal line. The use of modern technologies such as drone communications can prove invaluable to securing areas that are difficult to reach and monitor by regular communications means.

1.4 Thesis Contributions and Organization

The contributions of this research can be summarized as follows:

- Investigating and classifying the use of drones in different roles in communication services
- Investigating the most suitable optimization scheme to use for optimal path planning for the purpose delivery of communication services by a flying drone-mounted base station
- Formulating the problem of optimal drone trajectory planning subject to specific MTCD data transmission constraints
- Devising an optimal drone-based LTE scheduling technique that minimizes the deadline missing ratio of MTCD data transmission.

The rest of this thesis is organized as follows. In Chapter 2, a novel classification of drone communications is introduced. The necessary background and literature review for the trajectory planning technique that we propose in this research is also covered in this chapter. In Chapter 3, the ACO trajectory planning and scheduling technique is discussed. In Chapter 4, the evaluation results of the ACO technique are presented. This is done under different operating conditions. In addition, the results of comparing the ACO technique to another GA technique from the literature are presented. The thesis is concluded in Chapter 5.

CHAPTER 2. BACKGROUND AND DRONE COMMUNICATIONS CLASSIFICATION

2.1 Introduction

In this chapter, we present a novel classification of drone communications from a technological perspective. We therefore categorize studies performed about using drones in communication tasks along the lines of used technology and the drones' role in the communication process.

We then provide a review about the marine environment, UAV-Marine environment communications, Machine-to-Machine (M2M) communications, UAV-Trajectory management and the traveling salesman problem (TSP) related papers. These issues form the basis for our ACO technique that we present in Chapter 3 and evaluate in Chapter 4.

2.2 UAVs Communication Techniques

Many studies have dealt with drone communications using different communication techniques and standards. The most widely used technologies are the cellular technology (particularly LTE), WiFi, low power WAN (LPWAN), and Free Space Optical Communications (FSOC).

2.2.1 Cellular/LTE

The UAV needs essential communication links towards its operator for various reasons. For example, such communication links are important for piloting the UAV itself, wireless relay services, and real-time update of telemetry data. For these reasons cellular network is considered for providing connectivity for UAV infrastructure [23].

The 4G cellular network technology is considered one of the best candidate to improve the public safety communication (PSC) as it sustains real-time "mission critical communication" by its "interference coordination and coverage range extension" capabilities[24]. LTE technology has quality-of-service(QoS) management, congestion control capability, interference management and adaptive modulation and carrier aggregation [25].

2.2.2 WiFi

Some of the recent studies, however, addressed the problem of using drones over a WiFi network. The study in [22] for example, stated that the drones are more vulnerable of cyber-attacks being over a WiFi network. De-authentication attacks and GPS spoofing are the two main focus of [22] to present the disadvantages of using unencrypted WiFi.

The study in [26] also introduces the drones' usage as a rogue access point to prove the feasibility of hijacking the WiFi home networks by using the Man-in-the-Middle type attack on APs and connected client devices. This flying WiFi-sniffing machine is a cheap solution. Therefore, the study concludes that a set of regulations are needed to prevent attacks on the existing networks.

2.2.3 LPWAN

The Low Power Wide-Area Network (LPWAN) technology is an emering technology for IoT as in [27]. LPWAN technology is defined in [28] as a network technology which was developed for low power M2M communication over the Internet of Things (IoT). LPWAN technologies are considered quite promising for IoT applications since they provide low-power and long-range connectivity solutions [29] which are the communication features crucially needed by IoT applications, in general.

The study in [30] focuses on the technology diversity for the IoT applications, which includes LPWANs. LPWANs are characterized by "low power consumption, affordable cost, high communication range, and the capability to handle massive deployments of infrequently transmitting devices". SIGFOX and LoRaWAN are two emerging LPWAN solutions. Both technologies operate on ALOHA-based channel access with frequency hopping.

2.2.4 FSO

Free-space optical (FSO) is a "wireless communication system that uses an optical carrier to transfer information through free space" [12]. The FSO communication is established when the transmitter modulates the data into an optical carrier to be transmitted to the receiver through an optical channel. The study in [12] determined that the simplest modulation technique is the intensity modulation (IM) where the "source data is modulated on the intensity of light". Then, the transmitter directs the light source, Laser, towards the receiver. The receiver focuses the light beam directed on to its photodetector to have the optical signal converted to an electrical signal. With the aid of a bandpass filter, the received signal gets rid of the background noise. The sent signal is then restored after some amplification and filtering [12].

Swarms of drones will soon be involved in numerous applications that span civil and military purposes. Each of these applications involves requirements that are potentially different from those of other applications. However, for applications that require the drones to exchange large amounts of data, high data-rate communication means would be needed. Free-space optical communication presents a strong contender for such communications as opposed to RF-based communication [11]. FSOC is a line-of-sight (LOS) technology that operates at wavelengths of 850 nm, 1300 nm and 1550 nm [12]. FSOC data rate ranges from 1-2 Gbps and covers a distance that varies between 1-3 km [13]. FSOC links are not requiring any spectrum allocation or FCC license [14]. In addition, FSO does not need any additional infrastructure. It can be installed easily with low cost of installation and maintenance, with no cabling involved [15].

2.3 Classification of Drone Communications: A Technological Perspective

In this section, we introduce our novel classification of drone communications. This classification divides the communication process, where drones are involved, based on the used technology and the role of the drone in the communication process. We cover 4 technologies, as discussed in Section 2.2, and we classify the roles of the drones into, communication providers, communication consumers and relays. Figure 2.1 illustrates this classification.

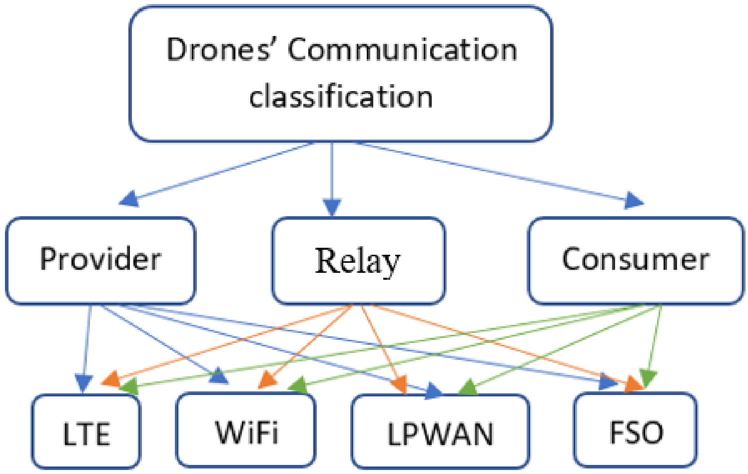

Figure 2.1 Our Proposed Drones' Classification

2.3.1 Drones as Communication Providers

According to this category, drones are used to provide communication services to other entities. This is usually done when the fixed infrastructure is not accessible either due to distance, damage or inadequacy. We study the literature that pertains to this category along the 4 technology lines as we previously stated.

2.3.1.1 Cellular

Using a stochastic geometry-based network planning approach, the study in [31] finds the optimal placements for on demand UAV-BSs (BSs mounted on UAVs) for a cellular network densification application. The UAV's horizontal location is found through a strategic horizontal placement algorithm where the terrestrial BSs (T-BSs) locations, possible horizontal UAV-BSs locations and the desired number of UAV-BSs are inputted such that the algorithm maximizes the network spatial regularity, output. For the vertical placement of the UAV-BSs, the height is calculated as follows.

$$h_j = k \times R_j \tan(\theta_{opt}) \tag{2.1}$$

where $0 < k \leq 1$ is a scaling factor used to reduce the interference, θ_{opt} is the optimal elevation angle and R_j is the radius of the UAV's coverage disk. The results presented in the paper showed that using the strategic

horizontal algorithm improves the spatial regularity of the network and results in the best SINR.
However, the results exhibit some changes when adding the power/energy consumptions to the constraints. This is mainly due to the persistent repositioning of the UAVs which is not studied from the energy consumption point of view due to high computational complexity.

In paper [32], the authors studied the mounting of LTE femtocell BSs on drones to cover unreachable area which may result due to the saturated existing wireless infrastructure. The paper bases the study on the use and comparison of two types of drones. The drone of type 1 has an average carrier speed of 15.0 m/s, a carrier power usage of 5.0 A, a carrier power capacity of 2.0 Ah and a carrier battery voltage of 14.3 V. While, the more expensive type drone has an average speed of 12.0 m/s, a power usage of 13.0 A, a power capacity of 17.33 Ah and a carrier battery voltage of 22.2 V. The results showed that with the two drones type, only 400 drones are needed to have a coverage of 99%, to cover a suburban area of 6.85 Km^2 as compared to 1100 drones that used with the first drones type. As time passes, both drone types cannot sustain the same users' coverage percentage. However, the use of two drone types converges to 10% coverage over 24-hour period as compared to only 3.5% in case of using the first drone type alone. As would normally be expected, the authors also found that the flying height of the drones increases the user coverage. This is due the fact that when the drone is getting higher, it will experience less obstructions and users will be on LOS of the BSs. However, the drone's power consumption will suffer since it will need an extra 0.5A for a 15-meter height increase.

The study in [33] introduced a load balancing framework between LTE-U UABSs and WiFi access points (APs). It discusses maximizing the capacity of LTE-Unlicensed technology for UABSs while minimizing the interference affecting WiFi networks. The bandwidth scarcity led the authors to resort to utilizing unlicensed frequency bands (LTE-U) for public safety networks (PSNs). However, the challenge lies in deploying the heterogeneous network without jeopardizing the WiFi APs users' performance. To address this, the authors developed a regret-based learning (RBL) dynamic duty cycle selection (DDCS) technique to configure LTE-U transmission gaps for them to show that both LTE-U and WiFi can coexist in the unlicensed band thus achieving satisfactory throughput. This is done without reducing the LTE-U radio access technology (RAT) or the WiFi RAT performances.

2.3.1.2 WiFi

In [34] a flying communication server is presented. It consists of a drone equipped with a single board computer (Raspberry Pi) implemented in a WiFi base station, a web server and a WebRTC server. The proposed application is to offer a wireless network function shared by rescue teams in a disastrous situation. The system requirements include having a 50-meter WiFi distance, the minimum video stream frame rate defined is 5fps and the ability of five rescue teams to use the channel simultaneously. The paper verifies the performance of the flying communication server according to the quality of the effective area video sharing and the text chat. Further work should be done to improve the performance when dealing with real time communications.

The study in [35], investigates the use of drones to provide high-speed WiFi wireless infrastructure. In this case drones are used to serve a military environment by using a wireless mesh network. The drone in this environment communicates events that occur in the field via collecting real-time data through an attached camera. The range of coverage is 200 m. The supported throughput is 160 Mbps and the video transmission coverage is almost 120 m.

2.3.1.3 LPWAN

The study in [36] consider a point-to-point communication model where a drone is flying over a number of nodes to collect data using the LoRaWAN communication protocol. The ALOHA transmission policy is modified to introduce an efficient time-scheduled transmission mechanism to eliminate potential packet collisions. The authors developed an algorithm to reduce the packet collisions. Simulation results show that a single drone can collect the data of an entire day of an area of more than 1500 × 1500 m2 that has 80 nodes, without packet collisions.

The authors in [37] propose a multi-technology opportunistic platform for environmental data gathering. It’s opportunistic in such a way that the nodes collect a wide range of data to a fixed station for analysis purposes. This is done through multi-technology communications that include both long range and short-range communication technologies, LoRa and WiFi. Both technologies are used opportunistically to gather data to the server. Increasing the number of LoRa sinks increases the channel occupancy and reduces the transmission delay. This reduction is done through the proposed MAC protocol which manages the medium access of each data gathering unit.

2.3.1.4 FSO

The study in [38] introduced an energy-efficient wireless transmission FSO model using laser and LED optical links for collecting sensory data from an unreachable environment. The model can be viewed as a UAV drops some mission-specific sensors to collect some sensory data and transmit back to the UAV using FSO links. The authors pinpoint the 4-phase operational flow of the model. The first phase, namely, the pre-initialization phase, specifies the sink node/UAV by hard-coding within the sensor nodes’ software stack. The second phase is the spreading phase where the sensor nodes are dropped from the UAV. The third phase is the ground initialization which takes place once sensors hit the ground where they start calibrating the FSO model. Finally, the operational phase where the sensors start collecting data and transmitting them using FSO. The suggested model is tested practically to study its applicability.

As communication backhauls are moving from terrestrial one to flying vehicles, the need for high rate links emerged. The study in [39], revised the challenges FSO communications faced between a swarm of UAVs and between High Altitude Platforms (HAPs). As per previous works revised by [39], the ground-to-UAV FSO links were tested for three different wavelength (0.85 ηm, 1.55 ηm and 10 ηm) for different link distances (4 km and 8 km). Results supported the three wavelengths for FSO links.

2.3.2 Drones as Communication Consumer

In this category, the drones act as end users from communications perspective. This is usually the case when the drone is engaged in some application such as search and rescue, goods delivery or military operations. In this case, the drone requires to communicate with a source of communication to receive guidance or to deliver data that it has collected from the field.

2.3.2.1 Cellular

The study in [40] analyzes different supervised machine learning (ML) algorithms can be used to identify the airborne users (UAVs) and normal ground users (UEs) in the network based on LTE radio measurements. In this scenario, the airborne data is collected by attaching an Andriod smart phone underneath the UAV. The three main ML classifiers' algorithms used were the Support Vector Machines (SVM), Multi-Layer perceptron (MLP) and the Bayesian classifier. The classifiers will evaluate the radio measurements and set a "positive" if the user is an airborne and a "negative" if not. The Bayesian estimator provides reasonable separation of the data, and can be tuned by changing the a priori probability of the data. It is indicated that the Bayesian estimator is more insensitive to the distribution or size of the training set. The SVM estimator also provides good results with lower specificity and higher sensibility. The MLP, however, showed high dependency with the training set distribution. It also was outperformed by the other two algorithms. The advantages of the MLP was made clear through the study where using the MLP method will save the BS storage cost since can be trained without the need of storing all the previous examples learned in its memory.

The work in [41] investigated the use of 4G LTE outdoors macro cells and indoor femto cells for UAV based building surveillance networks. The main target was using camera mounted on UAVs for a video streaming application. The throughput for the macro UEs (outdoor UAVs) is 600kbps when stationary. However, the throughput drops to 2/3rd of the previous value when the UAV is mobile. The performance gets better when increasing the UAV speed as the number of microcells increases. The throughput for the femto UEs (stationary Indoor UAVs) increases with the increase of the number of femtocells. This increase is linear when the number of floors equals to 1 and exponential for 2 and 3 floors.

The work in [42], studies the radio channel between UAV and LTE cellular network. The path loss regression line is gathered from scenarios done on the UAV flying at different heights operating on a 800 MHz LTE network. They presented three main causes for signal-to-interference level degradation which are expanded radio horizon at higher levels, LOS clearing and decreased obstruction of the first Fresnel zone.

2.3.2.2 WiFi

The study in [43] introduces the award-winning design of an autonomous quadrotor multi-robot architecture in order to take part in the indoor challenge of the international micro air vehicles (IMAV) 2013 [44]. This multi-robot architecture mainly consists of low-cost AR Drone 2.0 platforms [45], their ground computers and WiFi links within the Robot Operating System (ROS) middleware [46]. Each drone is expected to navigate and avoid any other drones or obstacles. Despite the apparent robustness of the design, its dependence on WiFi communication links limits its practical prospects as well as the number of drones hovering simultaneously due to limited WiFi bandwidth.

In [47], drones were used in an indoor application specifically transferring products in a warehouse. The main challenge in this application is the strong wireless network interference in indoor environment. This may affect the drone’s control performance. Therefore, the study’s objective is reducing this interference to achieve a better controllability of drones’ position. The authors in [47] conducted two experiments one using the same WiFi channel of two drones (high interference) another using different WiFi channels of two drones (low interference). However, using different WiFi channels between the two-drone resulted in a better overall performance. The controllability of both drones showed improvement due to the reduction in interference. The study also showed that after altering the drones’ WiFi channel to different a frequency, the wireless network interference is reduced and thus achieving the study’s objective.

2.3.2.3 LPWAN

The study in this journal article [16], LoRa is declared to be suitable for long-range low power wireless sensor/ actuator networks (WSANs) till now. UAVs can be deployed as WSANs for localization and tracking applications. The QoS was the main metric for all the papers cited in this journal.

The study in [48] expects the use of the LPWAN communications to spread among major countries around the globe through IoT applications. It therefore studies the use of drones to assess the effect of malicious IoT implants. These IoT implants, "low-cost electronic implant to facilitate hardware-level attacks, are connected to the internet over an IoT infrastructure". These implants use the LoRa technology as the wireless communication interface. The drone has a gyroscope and accelerometer sensor and a microcontroller that takes readings from this sensor every 3 ms to stabilize the drone's rotor using I^2C communication. Simulating an attacker, eavesdropping and denial of service (DoS) were done through the implants over the data transmitted from the sensor to the microcontroller. These attacks caused the drone to lose its stability and hit the ground.

2.3.2.4 FSO

The study in [49], studied the design of short-length Raptor codes for a ground-to-UAV mobile UAV FSO channel. These codes are characterized by low complexity and independency of the channel state, which make them convenient for mobile FSO applications. The Raptor-coded mobile FSO channel provides 560 Mbps average rate and a low decoding cost of 4.14 operations per packet using 20 dBm transmit power.

The study in [50] explores the characteristics of a mechanical gimbal for the alignment and tracking of a ground-to UAV FSO link. The results show the effectiveness of the use of this FSO-based arrangement which could replace the RF-based technologies. The results also show that there is a very low probability of signal fading for the FSO link. In addition, the errors introduced by the alignment could be alleviated by the amount of beam divergence in the FSO link. Moreover, the geometric loss in the FSO link was not proven to influence the link performance.

2.3.3 Drones as Communication Relay/Helper

In this category, the drones connect communication points where the communications infrastructure does not reach the end users.

2.3.3.1 Cellular

As pointed out in [51] UAVs are used as static aerial relay in environments where it is hard or risky to deploy terrestrial base stations. The study presented only one drone which is meant to assist multi-hop device-to-device (D2D) communication between the base station and the terminal device thus presenting two hops in this experiment. Since the used QoS metric is the data rate of the communication links, the drone's optimal position is analyzed to maximize the data rate using efficient algorithms under both time division and frequency division resource allocation. The results show that the drone's only needed when the distance between the base station and the terminal device exceeds a certain threshold or its transmit power exceed another threshold [51].

The study in [52] main objective was to determine the path loss exponent and the shadowing models for the radio channel between the cellular network and UAVs. It was proven through system level simulations that the path loss exponent and shadowing parameters for the UAVs are functions of height dependent models. Empowering such models preserve an efficient spatial prediction where the UAVs' height in this case becomes less effective with respect to path loss.

2.3.3.2 WiFi

The study in [53] demonstrates experimentally the throughput performance of a UAV using IEEE 802.11ac technology. The aim of the study is creating a swarm of UAVs where the UAVs and the ground client can join in an ad-hoc mode. The demand to have a protocol to handle a multi sender system is so high, with a certain degree of fairness in addition. In a scenario of two UAVs transmitting downlink traffic in an ad-hoc mode to the ground station, the performance of 802.11ac outperforms 802.11n in the TCP and UDP throughputs by a factor of 33%. This is also the case when considering the UDP packet loss. The authors have demonstrated a higher throughput for 802.11n than in any other study in this area. They further discuss fairness in multi-sender aerial network where in their scenario the first UAV's throughput outperformed the second one. The mobility of the second UAV which negatively affects the chosen adaptive rate control in 802.11n, was the main reason behind [53].

The study in [54] enables the UAV as a WiFi node by deploying an Intel Galileo development board onboard the UAV. This WiFi node has two modes of operation that were both tested in this study; either an access point (AP) in the infrastructure mode or an intermediate hop in the ad-hoc mode. The study used two Linux Ubuntu laptops compatible with the IEEE 802.11 a/b/g/n standard which resemble the receiver and transmitter. The study focused on three metrics, namely, the system coverage area, transmission rate and energy efficiency. The system coverage was tested theoretically using Friis and WINNER D1 propagation loss models where the WINNER D1 model was the most restrictive. Then experimental scenarios were used to compare the modes of operations using the three metrics. The infrastructure mode exhibits better performance in all metrics except for the energy consumption, which was determined by the amount of current drained by the Galileo board where the ad-hoc mode demonstrated better performance.

2.3.3.3 LPWAN

Several studies e.g. [55] and [56] illustrate the use of LPWAN technologies by UAV assisted wireless sensor networks (WSN) systems. The main objective of the study in [56] is to achieve lower delay in data transmission and an acceptable level of packet loss in the Flying Ubiquitous Sensor Networks (FUSNs). In a FUSN that is based on the LoRa technology, the UAVs are used as mobile data collector from sensor nodes in the WSN network, where the UAVs act as a 6LoWPAN-LoRa gateway. The UAVs then, relay these data to a LoRa-IP base station. After running the simulation for the queuing system model of the FUSN network over AnyLogic simulator, the optimal bit-rate was found to be 240-480 bits/sec which corresponds to the minimal packets queuing time. The transmission delay is in range of 11-14 s with 3-10% packet loss [56].

Since the marine environment has special challenges as discussed in [55], such as high level of salinity and humidity. The SIMMA project, discussed in [55], is implemented through the deployment of UAV assisted WSN using the LPWAN's LoRa technology. The sensing buoys' network is the WSN network this time. The SIMMA project is concerned with data collection in connection to research and rescue operations. Through sets of simulations and network field test validation, the authors compared their findings to other studies to get the following results. With a transmission rate of 4 km and data–rate of 5.4 kbps, the study in [55] outperforms the one in [57] by the same author by almost 10 times. LoRa transceivers have very low transmission and receiving power consumption of 28.8 mA and 14.2 mA respectively.

In [57], the UAVs are used as data mules for retrieving data from underwater sensors using a custom buoy node where the buoy should be carrying the underwater sensors, giving access to their data and control interfaces. The authors study the data link performance in different cases for their field experimentally conducted scenario in a sub-arctic Norwegian fjord. The scenario is consisting of two buoys, 50m away, and a flying UAV using IEEE 802.15.4 network. The UAV takes off to gather the data collected by each buoy since it has underwater sensors for acoustic fish data and water quality parameters as salinity, density, dissolved oxygen, pH, water level and temperature. Short range surface to air and long-range surface to air cases are tested. In the short-range surface to air case, the DJI Phantom quadcopter having Tiny Mesh radio node hovers four meters from the first buoy and 59 away from the second one. The first buoy has an average PDR of 99.87% with 4793.29 bps average speed while in the second one the PDR was hard to attain because of some errors in the log file however the attained data rate was 3340.53bps. The long-range surface to air scenario was done by having the UAV 402 m away from the first buoy and 420 m away from the second one and hovering about 9 m high from the surface of the water. The first buoy transferred its datasets with a 99.63% average PDR and 3402.16 bps average speed and the second one with 99.64% average PDR and 4399.97 bps average speed.

2.3.3.4 FSO

In [58], the authors presented a data collection protocol for FSO based drones. An identification tree is built using optical codewords to serve the drone's hierarchical topology network architecture shown in Figure 2.2. Each drone is assigned a certain codeword where a child drone can forward a packet after identifying its parent drone's codeword as well. The results in [58] showed that using the identification tree reduces the data delivery latency which is the summation of the FSO transmission links delay, the optical switching delay in each transitional node plus the delay that results from the delivery of data from the root drone to the collection one. Another useful result of this paper is studying the quality of end-to-end FSO link, which concluded that the FSO link in the identification tree should not exceed 4km to reduce the BER. However, the paper did not specify how a drone is going to calculate its QoS to get attached to the collection tree.

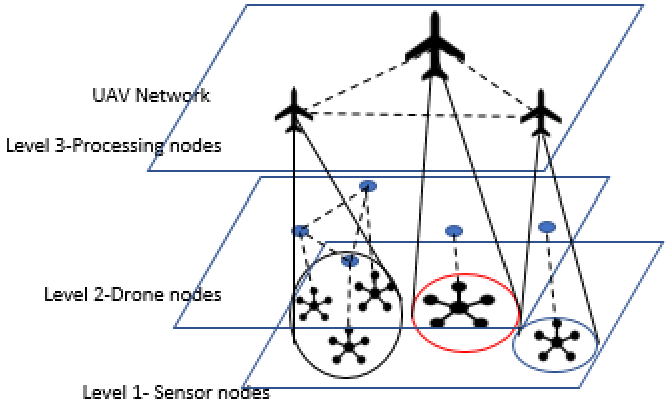

Figure 2.2 Drone Network Architecture [58]

The study in [59] studies the UAVs utilization in the formation of a relay assisted FSO system. A comparison is made between the conventional FSO system and the UAVs relay assisted FSO system in terms of the FSO outage probability where the FSO link is said to be available when its SNR is above a certain threshold. Incorporating UAVs in the FSO system has three main benefits as described in [59]. The UAVs' mobility decreases the cloud attenuation effect on the FSO links and roams between the source and the destination. Usage of UAVs also allows both source to relay and relay to destination links to be activated in the same time slot in contrast to conventional FSO system which has its transmission done in two-time slots. Two main cases are studied, shown in Figure 2.3, where the first case uses quasi-stationary buffer-aided UAVs while the second case uses moving buffer-aided UAVs. The outage probability was calculated for both cases versus the conventional relay- assisted FSO system. The first case of the conventional system is compared with four buffer free stationary relays while the second case was compared with three buffer free stationary relays. The outage probability was enhanced tremendously in both cases since the mobility of the UAVs increases the packet delivery performance to the destination. The study however left UAVs' energy consumption according to different weather or hovering circumstances for further research [59].

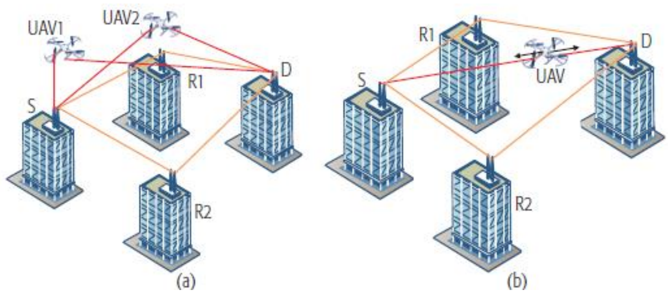

Figure 2.3 Two cases for relay-assisted FSO systems [59]

2.4 Marine Environment

Marine environment monitoring has lately attracted considerable research attention [60]. There is a significant challenge in retrieving data from the sensors distributed in remote coastal and oceanic sites. The presence of some restrictions as lack of mobile and terrestrial network coverage, satellite availability and the data transmission costs [57] were also among the reasons behind the motivation to address this issue. UAVs can be used as data mules where they collect and store the data from the sensor, then delivering these data whenever the user station is available [57].

The study in [9] discussed the unmanned maritime systems tasks which include sea-border patrolling, search and rescue (SAR) applications, marine oil spill clean-up and environmental monitoring. As presented in [60], Wireless sensor networks (WSN) are used for monitoring marine environments for numerous reasons including low cost, real-time monitoring and ease of deployment. The study also discusses many WSN-based marine environment monitoring applications examples as coral reef monitoring, ocean sensing, water quality monitoring and marine fish farm monitoring. The coral reef monitoring system is used to monitor the corals habitats and any bleaching that might occur. While, the water quality monitoring application can extend to include all water related conditions as pH, turbidity, dissolved oxygen (DO) and temperature. The marine fish farm monitoring system are used for detecting and measure any fecal waste in a fish farm.

2.4.1 Marine Environment Path Loss Profile

The study in [61] which examined the near-surface LOS radiowave propagation at 5 GHz, clarified that the propagation distance d_{break}threshold that decides on using 2 Ray path loss model or 3 Ray path loss one. In the study when d_{break} exceeds 2000 m, the 3- Ray path loss model behaves better.

$$d_{break} = \frac{4h_t h_r}{\lambda} \tag{2.2}$$

$$L_{3-ray} = -10\, log_{10}\left\{\left(\frac{\lambda}{4\pi d}\right)^2 [2(1+\Delta)]^2\right\} \tag{2.3}$$

where

$$\Delta = 2\, sin(\frac{2\pi h_t h_r}{\lambda d})\, sin(\frac{2\pi(h_e - h_t)(h_e - h_{r)}}{\lambda d}) \tag{2.4}$$

The study in [62] stated that the LTE in the sea environment differs than the LTE performance in normal urban landscape and not much has been done on as well. The formation of evaporation duct in the sea always influences the path loss propagation model to be a 3-Ray path loss instead of 2-Ray path loss in the urban environment. The 3-Ray model mainly consists of 2-Ray model of the LOS direct link and the reflections from the sea surface, in addition to the reflection from the evaporation duct.

The 3-Ray path loss model is incorporated in the SINR calculation which used by the throughput space matrix (defined as the throughput per RB between the user and eNodeB) in the MCS table to get the rates of the users.

2.4.2 UAV- Marine Communications

In [57], the UAVs are used as data mules for retrieving data from underwater sensors using a custom buoy node where the buoy should be carrying the underwater sensors, giving access to their data and control interfaces. The authors study the data link performance in different cases for their field experimentally conducted scenario in a sub-arctic Norwegian fjord. The scenario is consisting of two buoys, 50m away, and a flying UAV using IEEE 802.15.4 network. The UAV takes off to gather the data collected by each buoy since it has underwater sensors for acoustic fish data and water quality parameters as salinity, density, dissolved oxygen, pH, water level and temperature. Short range surface to air and long-range surface to air cases are tested. In the short-range surface to air case, the DJI Phantom quadcopter having Tiny Mesh radio node hovers four meters from the first buoy and 59 away from the second one. The first buoy has an average packet delivery ratio (PDR) of 99.87% with 4793.29 bps average speed while in the second one the PDR was hard to attain because of some errors in the log file however the attained data rate was 3340.53bps. The long-range surface to air scenario was done by having the UAV 402 m away from the first buoy and 420 m away from the second one and hovering about 9 m high from the surface of the water. The first buoy transferred its datasets with a 99.63% average PDR and 3402.16 bps average speed and the second one with 99.64% average PDR and 4399.97 bps average speed.

The study referred to wild Salmon migration tracking and monitoring campaign as future work to include the buoys in.

Since the environmental monitoring is one famous application in which sensor networks are used, the study in [63] shows how to further develop deploying and collecting information from clusters of LPWAN sensors nodes using Unmanned Aerial Systems (UAS). The UAS-SN system goes through a sequence of missions. The average Packet Reception Rate (PRR) measured in this experiment is 86% where the UAV collects data from 9236 different measurements done by each node. Clustering the sensor nodes has a positive impact on the battery lifetime which is measured to be considerably larger than one-by-one sensor node.

2.5 Machine-to-Machine (M2M) Communication

Machine-to-Machine (M2M) communication is the flow of data among different intelligent machines without any human intervention. M2M connects those machines by wired and wireless links [64]. M2M has very wide applications, which may include smart grids, vehicle to vehicle communications (V2V) systems, vehicle to infrastructure communication (V2I) systems, industrial automation and environmental monitoring [64]. The research in [65], the M2M communications is explained widely where the M2M infrastructure-based system is reviewed However, M2M suffers some challenges that are jeopardizing its implementation. The study in [66] highlighted the challenges facing the M2M communications as congestion and random channel access. Another problematic challenge is the use of LTE in M2M. LTE is mainly designed for human to human (H2H) communication where there's a cap for the number of users and humans can tolerate delays in voice connections. So, permitting M2M communication to work on the same H2H communications creates a network overhead problem since the "machines identifiers should be assigned to MTC devices" [67]. So, M2M accommodation requires a huge shift where applications are most likely delay intolerant, and machines/nodes need to run for a long period of time which puts a constraint on the power consumption and the lifetime of the battery. Enabling M2M on LTE network can also cause interference with the existing communication links.

The term Machine-to-Machine (M2M) communication arises to serve the future need of having billions of internet connected machines talking to each other without any human intervention [66]. M2M has very wide applications, which may include smart grids, vehicle to vehicle communications (V2V) systems, vehicle to infrastructure communication (V2I) systems, industrial automation and environmental monitoring [64].

The study in [64], clarified the system model of the M2M communication. In the M2M device domain, the network mainly consists of a huge number of devices/sensors and gateways which collect the data, send and receive them as well. Some of the intelligent nodes/devices take decisions as well based on these data. The second domain is the network domain. The network domain is responsible for relaying data from the device domain to the application domain. To guarantee a reliable coverage, wired or wireless network protocols can be used i.e. telephone network and cellular network [64]. The application domain, the final/last domain, is considered the integration point. The application domain contains mainly back-end server(s) that extracts, process and gather the data coming from the devices through the network domain. These servers also control and direct the M2M devices.

M2M communication has some serious challenges/characteristics that are quite different than that we are familiar dealing with human communications i.e. cellular networks. Challenges facing the M2M communication starts with the embedded system installed on its machines [66]. The embedded system installed in a machine like a sensor for example won't be only collecting data but also, it should be relaying this data to a sink node to further take an action about the sensor's reading. So, this installed embedded system should be suitable for the M2M application itself and should support exchanging data as well. The M2M communication also needs to be communicating with other technologies communications as well. However, moving between different types of communications technologies with different protocols and platforms, creates many difficulties as in the billing and automated security mechanisms. Lack of M2M communication standards, in addition, doesn't support interoperability between different machines/devices. These challenges hinder the scalability of the M2M communication technology. Another challenge encountering M2M communication is data handling. Since M2M communication is dealing with billions of devices, not all these devices will provide significant data to be processed. So, data handling is an essential parameter to take into consideration otherwise we will exceed our need storing/exchanging insignificant data [66]. Moreover, the M2M devices need to be extremely power efficient as they could be implanted in harsh environments where there's no way to recharge them back. However, there's a tradeoff between high data transmission and the node power consumption that we must deal with according to the application we are tackling.

Communication, however, is one of the crucial challenges facing M2M interactions. Each device has its own set of requirements i.e. bandwidth, reliability, mobility and power efficiency but there're some standard infrastructure technologies which can handle these M2M communication issues. LTE, for example, is mainly designed for human to human (H2H) communication where there's a cap for the number of users and humans can tolerate delays in voice connections. Humans depend more on downloading so they usually use high-bandwidth data where LTE downlink data rate is 50Mbps while 25Mbps for the uplink. Although cellular network was made to tolerate human to human communication, LTE-M is an enhanced version of LTE to reinforce M2M communication as well. This latest release of LTE serves M2M devices, using typical LTE infrastructure, by only upgrading the base stations' baseband software. The LTE based M2M system architecture consists of User Equipment (UE), Evolved UMTS Terrestrial Radio Access Network (E-UTRAN), Evolved Packet Core (EPC) where the E-UTRAN connects between M2M devices and the EPC.

Another standardized wide area network that could be used in M2M communication is Worldwide Interoperability for Microwave Access (WiMAX). However, deploying M2M on WiMAX technologies suffers from some problems. For instance, M2M needs large scale networks, however, WiMAX is still experiencing some coverage gaps. The need to have an optimized modulation schemes, to reduce the capacity of the applications installed on the M2M devices, is another crucial issue. So, WiMAX should be using optimized modulation techniques, to cut down the capacity and the communication cost.

Beside using standard wide area networks as LTE-M or WiMAX, short range networks can be used for M2M communication as well [66]. The capillary M2M mainly forms a tree architecture network of a given area, then gets connected to the cellular network via a gateway to guarantee a universal connection. So capillary M2M in this case acts as a Wireless Sensor Network (WSN). The advantage of using the capillary M2M is ease of shaping and aggregating the M2M traffic to send to the M2M back-end servers [68].

From studying different communication technologies to deploy the M2M networks, LTE cellular technology, however, is still be considered as the best candidate for M2M networks due to their native IP connectivity and scalability for massive number of devices. So, my research statement will be finding a way/ways to tailor the LTE to accommodate M2M networks by different resource allocation techniques/algorithms for massive M2M deployment.

2.6 Drone LTE-based Communications

Drones are increasingly involved in communications in LTE-based cellular systems. Many studies deal with different arrangements of such involvement.

In [69], a drone-mounted base station placement solution is implemented using a divide and conquer algorithm. Since the proposed algorithm has low complexity and minimal requirements on storage, it presents a good candidate for storage- and energy-constrained drones. Moreover, the authors propose a soft frequency reuse scheme where the transmit power and spectrum segment are not predefined. Instead, they are dynamically changed according to the position and interference of adjacent drones.

In [57], drones are used as data mules for retrieving data from underwater sensors using a custom buoy node where the buoy holds the underwater sensors, giving access to their data and control interfaces. The authors study the data link performance in different cases for their field experimentally conducted scenario in a sub-arctic Norwegian fjord. The layout consists of two buoys, 50 m apart, and a flying drone that uses a IEEE 802.15.4 network. The UAV takes off to gather the data collected by each buoy's sensors' acoustic fish data and water quality parameters such as salinity, density, dissolved oxygen, pH, water level and temperature. Short range surface to air and long-range surface to air cases are tested.

As discussed in [51], drones are used as static aerial relays in environments where it is hard or risky to deploy terrestrial base stations. The study focuses on the deployment of only one drone which is meant to assist in multi-hop device-to-device (D2D) communications between the base station and the terminal device thus presenting two hops in this experiment. Since the used QoS metric is the data rate of the communication links, the drone's optimal position is analyzed to maximize the data rate using efficient algorithms that belong to both time-division and frequency-division resource allocation techniques. The results show that the drone is only needed when the distance between the base station and the terminal device or its transmit power reach certain thresholds.

2.7 Drone Path Planning

The authors in [70] investigate the advantages of using drone-based architecture of wireless sensor network (WSN). Line-of-sight (LOS) communication channel and topology adjustment for the sensor nodes' location and linking the isolated WSN to other networks are among those advantages. They also report that the main important requirement of WSN application is to plan the path of the drone to ensure data collection from all nodes and to minimize the total path length at the same time. The paper also discussed why a sparse placement for the sensor nodes should be considered where, in some monitoring applications, the nodes could be sparsely distributed.

The study in [71] uses the drone as a sink node to collect data from WSNs. The authors propose the use of Particle Swarm Optimization (PSO) method for clustering and cluster heads selections such that the energy consumption, bit error rate (BER) and drone travel time are reduced. So, they assessed/compared the performance of the PSO method with the LEACH method to identify the optimal selection of the nodes to be visited by the drone [72]. PSO outperforms LEACH-C when simulated on wider WSNs, where the nodes are not close to each other.

In [73], the path and the number of drones required to cover and collect data for a WSN data gathering application are investigated. The problem can be formulated as a multiple traveling salesman problems (mTSPs) with additional constraints. Since it is an NP-Hard problem, the authors used the Set Covering Problem (SCP), which is an alternative integer linear programming formulation for the mTSP. The authors in this study concluded that some improvements should be done in terms of the heuristic methods for future developments.

Our ACO technique in this thesis is based on optimizing the path movements of a drone that acts as a flying base station. The optimization is based on ensuring the drone takes the path with minimum energy consumption in such a way that minimizes the data deadline missing of a set of MTCDs sparsely deployed at sea. This mimics the TSP with constraints that are based on the communication needs of deployed M2M formations.

2.8 The Traveling Salesman Problem (TSP)

The TSP is a very well-known problem where a salesman starts from his hometown and wants to take the shortest path passing by a given number of other cities and to visit each only once, then return home [74]. The TSP can be represented by a complete weighted graph $G = (N, A)$ with N being the number of cities and A is the set of arcs. Each arc $(i, j) \in A$ has a certain length d_{ij} which is the distance between city i and j with $(i, j) \in N$. d_{ij} is the Euclidean distance between city i and j [74], [75]. TSP goal is to find the shortest Hamiltonian circuit of the graph. This Hamiltonian circuit is mainly visiting all the cities N and passing only once by each and returning back to the initial one at the end of the tour.

The TSP could be generalized to serve n clusters of number of cities each as in [76]. The study demonstrates an exact algorithm for a generalized version of the TSP (GTSP) that consists of finding the minimum length Hamiltonian circuit through n clusters of nodes. Computational results are reported for problems including up to 100 nodes and 8 clusters.

Another study talked about TSP with profits (TSPwP) where the salesman passes only by the cities maximizing the profit such that the tour length does not exceed a given constraint C_{max} [77]. TSPwP is a version of TSP where it is not necessary to visit all vertices, instead salesman only passing by the cities having the highest profits associated to them. The problem is to find a cycle in a graph which maximizes collected profit but does not exceed a given cost constraint. Visiting a given vertex/city more than once is allowed in addition, but with an assumption that a profit is realized only during initial visit [77].

The contribution of study [78] is an extension for TSP available Held-Karp's lower bound to the Multiple Depot UAV Routing Problem (MDURP). Several UAVs are distributed among different depots. Each UAV should visit at least one unvisited depot such that the path length is the shortest among the UAVs. So, the authors presented 2-approximation algorithms for the UAVs' routing problem, where they only discussed the constraints' changes needed for their extension.

The paper in [79], presented three modified algorithms for the Nearest Neighbor (NN) algorithm to solve TSP problem. The main aim of the paper is to reduce data acquisition latency of UAV relay WSN. By-Passing of Nodes in the NN (PPN), Directional NN (DNN) and Directional NN algorithm Directed to the Next Nearest Node (DDNN) are the three modified algorithms of the NN. The main objective of PNN is to "by-pass a given node if the line that connects its neighboring nodes lies within the transmission range of the node". In DNN, the idea is to "enforce the drone tour direction to be changed on each of the first point where the normal path of the previous NN-TSP algorithm meets the boundary of the transmission range of each node to the next move until all the nodes are visited". While in DDNN, the idea is to "amend the previous TSP-NN algorithm to let the drone initially move directly to the first node until it reaches to the boundary of the transmission range of this node". The three modified algorithms show better performance in terms of the latency with DDNN achieving the shortest path tour.

2.9 The Research of This Thesis and its Dependence on Covered Concepts

The various, yet related, review we have presented earlier in this chapter, has built our knowledge in such a way to benefit from all of it in formulating our problem. Our problem formulation presented in the chapter 3, section 3.2 will mimic the TSP, explained in section 2.8. The constraints, however, are based LTE and M2M formations. We would need to deploy number of MTCDs having stringent transmission deadlines. These transmission deadlines are part of the LTE TDD uplink latency.

2.10 Chapter Summary

In this chapter, we introduced a novel classification of drone communications from a technological perspective. Then we, discussed the marine environment, UAV-Marine environment communications, Machine-to-Machine (M2M) communications, UAV-Trajectory management and the traveling salesman problem (TSP). Finally, we discussed the relationship of the discussed concepts with the technique that we introduce in the subsequent chapter. We indicated that our problem formulation mimics the TSP with constraints that are based on the communication needs of deployed M2M formations, mainly, stringent transmission deadlines.

CHAPTER 3. OPTIMAL TRAJECTORY PLANNING AND SCHEDULING – THE ACO TECHNIQUE

3.1 Introduction

As previously discussed, we see that the problem of deploying MTCDs for monitoring purposes off-shores requires a solution that augments the terrestrial networks and connects the deployed devices to the backhaul. In this chapter, we present our ACO algorithm which aims at providing LTE-based cellular services to such MTCDs. We first introduce the problem formulation with its constraints. We then discuss the methods for solving this problem. Then, we present the design and description of the technique that we propose to solve this problem.

3.2 Problem Formulation

Our ACO technique is based on optimizing the path movements of a drone that acts as an LTE-based flying base station. The optimization is based on ensuring the drone takes the minimum path (minimum distance covered), and hence consumes the least energy, in such a way that minimizes the data deadline missing of a set of MTCDs sparsely deployed at sea. This mimics the TSP with constraints that are based on the communication needs of deployed M2M formations, mainly, stringent transmission deadlines.

The problem can be formulated as

$$min \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} P.C_{ij}.X_{ij} \tag{3.1}$$

subject to

$$\sum_{i=1, i \neq j}^{N} X_{ij} = 1\,; \quad \sum_{j=1, j \neq i}^{N} X_{ij} = 1 \tag{3.2}$$

$$i = 1, \ldots\ldots, N; \;\; j = 1, \ldots., N;$$

$$\sum_{i,j \,\epsilon\, S} X_{ij} \leq |S| - 1 \tag{3.3}$$

$$S \subset V; \;\; 2 \leq |S| \leq N - 2; \tag{3.4}$$

$$X_{ij} \,\epsilon\, \{0,1\} \tag{3.5}$$

$$D_i < \; D_{imax} \;\;, \;\; i{=}1{,}2{,}3{\ldots}.N \tag{3.6}$$

The cost function in 3.1 minimizes the tour length (optimal tour) passing through all MTCDs, where N is the total number of MTCDs. Therefore, this cost function minimizes the drone's battery power consumption, P, given that C_{ij} is the distance covered from node i to node j and X_{ij} is a binary indicator that takes the value 1 if the path from node *i* to node *j* is in the tour and 0 otherwise. It should be noted that the summation in 3.1 is done such that $i \neq j$. The constraints in 3.2 ensures that for a certain node, *i*, only one path/edge is chosen to a given node, *j*.

So, the first constraint in 3.2 makes sure that each node is visited once and only one path from certain node *i* to node *j* is taken. So, if we have 3 nodes, then the first equation in 3.2 will give the following equations 3.7, 3.8 and 3.9. This summation in 3.7 must be equal to 1 which means only one path should be taken either X_{12} or X_{13} (the other one should equal to zero). Same will apply for $j \neq 2$ and $j \neq 3$.

$$\sum_{i=1,\;\; i \neq j}^{N} X_{ij} = \sum_{i=1,\;\; i=j}^{3} X_{ij} = X_{12} + X_{13}\,, \qquad for\; j \neq 1 \tag{3.7}$$

$$\sum_{i=1,\;\; i \neq j}^{N} X_{ij} = \sum_{i=1,\;\; i=j}^{3} X_{ij} = X_{21} + X_{23}\,, \qquad for\; j \neq 2 \tag{3.8}$$

$$\sum_{i=1,\ i\neq j}^{N} X_{ij} = \sum_{i=1,\ i=j}^{3} X_{ij} = X_{31} + X_{32}\,, \qquad for\ j \neq 3 \tag{3.9}$$

The same goes for the second constraint in 3.2, where X_{12} is equivalent to X_{21}, which assures that the path X_{21} is as taking the path X_{12}. This further confirms that this path should be set as 1 in both cases, so if $X_{12} = 1$ then X_{21} must be equal to 1 as well.

Equations 3.3 and 3.4 prevent the creation of sub-tours. Sub-tours usually result from tours which have less than V vertices (N MTCDs). So, for example if we have 4 nodes, the tour 1231 is considered a subtour. To eliminate that, we have $S = 3$, where S is the number of nodes in the subtour formed, but $\sum_{i,j\,\epsilon\,S} X_{ij}$ can not be ≤ 2. So, this constraint would be violated if a subtour is formed.

However, the constraint in 3.5 ensures that X_{ij} can only take binary values either 0 or 1. This indicates if this edge is passed by or not. In equation 3.6, the transmission deadline missing constraint is introduced. The deadline missing is defined as the time by which data must be transmitted to avoid unwanted consequences e.g. in the case of emergency alerts. In [80], an equation for the LTE TDD uplink latency $T_{Uplink}$was formulated as follows

$$T_{Uplink} = T_1 + T_2 + T_{3,} \tag{3.10}$$

where T_1 is the time spent by a packet in the transmit buffer of the device before a scheduling request (SR) is sent, T_2 is the duration between sending the SR and receiving the associated grant and T_3 is the time for which the device has to wait until it can send the actual data within the assigned physical resource block(s) (PRB). To ensure the system meets the deadlines for delay sensitive M2M applications, the maximum of T_{Uplink} should not exceed T_{Budget}. In delay sensitive M2M networks, the traffic is prioritized based on the packet delay budget T_{Budget} [81]. This results in the following equation

$$max\{T_2\} \leq T_{Budget} - T_{SR-PERIOD} - T_{3,}, \tag{3.11}$$

where

$$\max\{\mathrm{T}_3\} = 7 \text{ subframes} = 7 \text{ ms} \tag{3.12}$$

$$max\{T_1\} = T_{SR-PERIOD} \tag{3.13}$$

The absolute deadline, D_i, in 3.6 , is for the scheduler to provide an uplink grant in response to the request. Its maximum value is given by

$$\mathrm{D}_{\mathrm{imax}} = \mathrm{t} + \mathrm{T}_{\mathrm{iBUDGET}} - \mathrm{T}_{\mathrm{SR-Period}} - 7, \tag{3.14}$$

where t is the current time.

A combinatorial optimization, also, refers to the problem of finding elements of X that minimize or maximize f, where f is a real-valued objective function defined on a large set of states X [82].

The complexity characterization of the optimization problems has been established by connections between "combinatorial properties and complexity decision and optimization technique". In addition, the NP-completeness concept has been proven in the "theory of approximation of optimization problems" [83].

Many combinatorial search algorithms employ some perturbation operator, mathematical methods/algorithms to find approximate solution to the given problem. These algorithms are "state of the art for many classes of NP-hard combinatorial optimization problems such as maximum k-satisfiability, scheduling, and problems of graph theory" [82].

Many of them are NP-hard problems that cannot be solved within a polynomial computation time [84]. TSP is a famous example of a combinatorial optimization problems. To be able to solve them and get near optimal solutions in short time, we need to use approximate methods. These algorithms are named heuristics. In addition, a set of heuristic methods is called a metaheuristic algorithm which is suited for a set of different problems. Metaheuristics with other optimization techniques, like branch-and-bound, are also ubiquitous nowadays [85].

3.3 Path Planning Algorithms

Path planning is one of the most important areas of research when it comes to drone deployment. To better understand path planning algorithms, we need to differentiate between its four categories, namely, Grid-based Algorithms, Evolutionary Algorithms, Geometry Algorithms and Linear Algorithms [84]. Both Geometry and Linear Algorithms are combined under what is termed as the Curve Algorithm.

3.3.1 Grid-based Algorithms

Path planning in Grid-based Algorithms is divided into three main processes, feasible path grid generation, path cost calculation and feasible path selection. However, to generate the grid in the first place, the environment and the mission objectives should be studied. The data generated by the environment being static or dynamic could be online or offline data.

The Grid-based algorithm is an effective path planning algorithm whenever the minimal cost between two nodes is needed. Grid-based algorithm computes iteratively all the waypoints between the two nodes to identify the optimal path. Although it can be easily implemented for static path planning, its disadvantage is the large number of iterations and the computational time [84].

3.3.2 Curve Algorithm

Curve algorithm has one main process which is defined as a polynomial equation. The equation builds the path planning from the initial point till the final one. Curve algorithm is affected by the environment. It is difficult to apply the curve algorithm to a dynamic environment and this difficulty lies in constructing the static path planning from initial point to the end.

3.3.3 Evolutionary Algorithms

Path planning in Evolutionary Algorithms depends on generating all the possible candidates. Then, by using several parameters, the fitness values will be calculated by all these candidates. Lastly, the best path is obtained once convergence occurs. Once the best path is calculated the drone can follow it.

The most famous evolutionary algorithms are Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Artificial Immune Algorithm (AIA) and Ant Colony Optimization (ACO). All of these algorithms were applied in UAV path planning such as in [84] and [86].

One of the big advantages of the evolutionary path planning is its ability to be used in both static and dynamic path planning. The ability to create static and dynamic path planning is one of evolutionary algorithm advantages.

We now elaborate more on GA and ACO due to their extensive use in path planning techniques. We also use evolutionary techniques as basis for our proposed path planning and scheduling technique.

3.3.3.1 Genetic Algorithm (GA)

GA was first introduced by Holland in his book *Adaptation in Natural and Artificial Systems* in 1975. GA has six main steps , as explained in [87]:

1- It undergoes generating an initial population called chromosomes, each chromosome represents a unique candidate solution of the problem, that uniformly covers the search space.
2- It then uses a fitness function to evaluate the population. This fitness function is mainly the optimization problem at hand.
3- Parent selection is done when the algorithm decides which chromosomes are best fit to undergo the reproductive phase of the GA. This is based on the fitness function evaluation.
4- Two main genetic operators are then applied. The first is “crossover”. Crossover is achieved by randomly pairing every two chromosomes (parents) in the population together to produce an offspring (child) that contains portions of both of their codes.
5- The second genetic operator is “mutation”. Mutation creates a new child by altering a randomly chosen part of a selected parent.
6- Final selection is done for parents and offspring to form a new population.

Figure 3.1 illustrates the GA process.

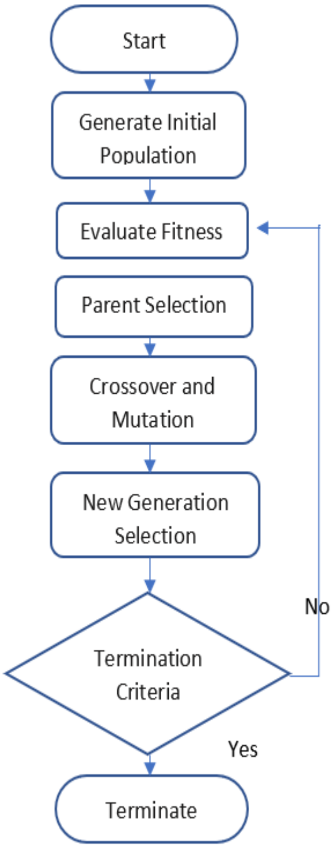

Figure 3.1 GA Steps

GA has been used in path planning. In [17], the authors developed a technique to optimize the Unmanned Aerial Base Stations (UABSs) locations through a genetic algorithm (GA). This technique is basically done to maximize the fifth percentile throughput of the network. The GA can run simultaneous candidate solutions, chromosomes, at the same time since, it has a parallel search capability. The results show that the throughput coverage and the fifth percentile throughput are enhanced significantly when the UAVs' locations are optimized through the GA. Deploying more UAVs also increases the gains when using range expansion bias.

In [24], the authors compare between 3GPP Release 11 further-enhanced inter-cell interference coordination (FeICIC) and the PSC application in

Release 10 using 2-tier LTE-Advanced HetNet with Mobile Base Stations (MBSs) and UABSs. The UABSs deployment is studied in two cases. First, when the deployment is done on a hexagonal grid in deterministic locations. Second, when the deployment is optimally done using a genetic algorithm (GA) which has shown to be more effective in case of high inter-cell inference. The UABSs' locations and inter-cell interference coordination (ICIC) parameters for the GA and the hexagonal grid are identified respectively, such that they result in the maximum 5th percentile spectrum efficiency (5pSE) [24].

3.3.3.2 Ant Colony Optimization (ACO)

According to [84], ACO is one of the famous evolutionary algorithms that has been used in many studies for path planning such as [88], [89] and [90]. ACO is an example of a metaheuristic technique for solving hard combinatorial optimization problems [85]. In [85], Metaheuristics are defined as "solution methods that orchestrate an interaction between local improvement procedures and higher level strategies to create a process capable of escaping from local optima and performing a robust search of a solution space".

The ACO algorithm was inspired by real ants searching for food. It is widely applicable for any combinatorial optimization problem. ACO is a stochastic search method based on indirect communications between a colony of ants, as defined by [74] and [91], through updating the pheromone trails of a set of ants. The ants use these pheromone trails to construct solution to the problem. In addition, the ants reflect their search experience where they keep modifying the pheromone trails during execution.

The ACO is particularly applied for [74]:

1- NP- hard problems, that needs to be efficiently solved.
2- Dynamic shortest path problems.
3- Problems having spatially distributed computational architecture.

ACO has a unique approach based on population which utilizes a memory for the previous performance. These exceptional characteristics are what distinguish the ACO over any other metaheuristic technique.

In the following, we explain in some detail the merits of using the ACO in solving problems like ours. This will serve as the basis for our rationale of using it as the core of our proposed solution. We also provide the main elements of ACO's functionality.

ACO Algorithm mainly goes through the following steps:

1- An initialization for the ACO parameters is done.
2- Ants are located randomly across the grid to construct the initial solutions
3- The quality of the constructed solutions is measured by the objective function of the optimization problem, which is sometimes referred by as the fitness function. In section 3.3.3.2.3, we will present the ACO tour construction in details.
4- The pheromone levels are then updated. The pheromone levels of the edges included in the solutions with higher fitness than those of less fit solutions give these edges a higher chance of being included in tours in the next iterations.
5- The algorithm terminates either after a given number of iterations or when a solution with the desired fitness or higher is obtained.

3.3.3.2.1 ACO versus GA

In [92], a comparison was made between ACO algorithm and other heuristic techniques for machine scheduling problem. Comparison with branch and bound, local search method, has also been made. Results showed that ACO has advantages over these techniques.

According to [84], [93] and [94], ACO performs faster in terms of speed of convergence and computational time. GA shows slow speed to converge. The reason behind this lies in the way GA initializes the population. It is based on random approaches. Using this random process, the algorithm requires to go through the process of selection to determine the optimal path [94]. This is mainly why the number of iterations needed for convergence is quite high as the number of nodes increases. Also as stated in [95] and [96], ACO is the best approach for TSP like problems.

So, we decided to compare between an ant colony optimization (ACO) based technique that optimizes the drone movement among the sparsely-deployed MTCDs and Genetic Algorithm (GA) based solution from the literature. However, we expect that the ACO will outperforms the GA in terms of convergence speed, based on the literature. So, we decided to perform the ACO algorithm and compare it to GA-based solution that serves the same purpose.

3.3.3.2.2 Using ACO for the TSP

As we now know, TSP is an intriguing problem that has been extensively studied in the literature.

The ACO has two main phases; ants' solution construction, when each ant decides on the next point to visit, and pheromone update. The pheromone trails in the ACO is referred to by τ_{ij} which indicates the desirability to visit point j after point i. The heuristic desirability from point i to point j is inversely proportional to distance between them where $\eta_{ij} = 1/d_{ij}$:

Each ant tour is created by applying the following steps:

1- A start point is chosen by each ant to start from.
2- The ant uses pheromones and heuristic values to construct the tour, passing by all the points but only once for each.
3- The ant returns to the start point at the end.

After the above steps, we would now have all the ants' tours. The pheromone levels are updated for all the tours [74].

3.3.3.2.3 ACO Tour Construction

The ants are positioned on randomly chosen points. At each step ant k applies the below probability rule to decide on the next point to visit. This probability value, P_{ij}^{k}, indicates the probability for ant k to go from point i to point j.

$$P_{ij}^k = \frac{[\tau_{ij}^{\alpha}][\eta_{ij}^{\beta}]}{\sum_{l \in N_i^k} [\tau_{il}^{\alpha}][\eta_{il}^{\beta}]}, \quad if\ j \in N_i^k, \tag{3.15}$$

where α and β are the parameters set to determine the relative influence of the pheromone trail and the heuristic information, and N_i^k is the set of points not visited by ant k measured at point i.

As for the optimal values for these parameters as stated in [74], α should be equal to 1, β's optimal range is $2 \leq \beta \leq 5$, and ρ, the pheromone evaporation that we will talk about in the next section, is 0.5.

3.3.3.2.4 ACO Pheromone Trail Update

After each ant constructs its tour, the pheromone trails are to be updated. This is done by adding pheromones on the arcs the ants have passed by, where the pheromone evaporation is carried out as follows

$$\tau_{ij} \leftarrow (1 - \rho)\tau_{ij}, \forall (i, j) \in L, \tag{3.16}$$

where $0 < \rho \leq 1$ is the rate of pheromone evaporation. This parameter is used to prevent the pheromone trails accumulation and hence forgetting previously taken bad decisions. After the evaporation step above, all the ants deposit pheromones on the arcs they passed by in their tours:

$$\tau_{ij} \leftarrow \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^k \ , \forall (i, j) \in L, \tag{3.17}$$

where $\Delta\tau_{ij}^k$ is the amount of pheromone ant *k* deposited on the arcs it has visited.

$$\Delta\tau_{ij}^k = \begin{cases} 1/C^k, & if\ arc(i,j)\ belongs\ to\ T^k \\ 0 \quad , & otherwise \end{cases} \tag{3.18}$$

where C^k is the length of tour, T^k, made by ant *k*, and is calculated as the summation of the all the arcs lengths for tour T^k.

There are several studies that used ACO for path planning. The study in [97], presents a swarm intelligence based method for UAVs' path optimization. The problem mimics TSP where the aim is to find the route having the shortest path passing by a given number of waypoints while visiting each point only once. The ACO algorithm is implemented and compared to Nearest Neighbor search. The Nearest Neighbor search is to build the tour such that to select the closest unvisited city before returning back to the initial one [85]. Results showed that the proposed algorithm is more effective especially as the number of waypoints increases.

The study in [95], investigates the feasibility of a 2-layered approach for path planning mission using probabilistic roadmaps and ACO for task planning. The path planner explores paths in a finite, obstacle-constrained 3D space. However, task planning, which is an instance of the TSP problem, discovers a near optimal task order for a set of tasks and heterogeneous UAV agents. The study found that at lower speeds, the UAV can follow a linear path with a certain error distance. If the speed gets higher, flight dynamics should be taken into consideration.

The study in [96], proposes a new obstacle avoidance UAV path planning by using a mutli-colony ACO algorithm. The authors conducted a comparison between their proposed approach and the typical single colony ACO approach. The proposed approach showed better results in terms of the cost function in comparison with the typical one colony ACO. However, the performance degrades with increasing the number of control points.

The study in [98], discusses multi-UAVs coordination trajectory planning using Max-Min adaptive ACO method in dynamic environments. This coordination is done through two phases; air-space collision avoidance and simultaneous arrivals. The collision avoidance between UAVs is obtained by setting the minimum and maximum pheromone trails in ACO to improve the searching capabilities. While, for the simultaneous arrival, an Estimated Time of Arrival (ETA) is determined. Then each UAV trajectory and velocity are decided. The results shown in the paper are in favor of the proposed approach feasibility.

3.3.4 Algorithms' Comparison

TABLE 3.1 shows the comparison among different path planning approaches that we discussed in the previous sub-sections. We listed different algorithms under each family. A* and triangulation are based on grid-based algorithms. While, GA, PSO, AIA and ACO are evolutionary algorithms. Finally, dubins algorithm belongs to curve algorithm. We can also see that computational complexity of both the grid-based and the evolutionary is O(n^2) as they need to iteratively run to reach their target. In [84], the author stated that the grid-based algorithm can only be applied within a camera range when it deals with tracking a moving target. This is also the case for curve algorithm where it is very challenging for it to be used for dynamic path planning. However, evolutionary algorithm can be used for dynamic path planning but not for a moving target interception.

TABLE 3.1 Comparison of path planning approaches [84]

Approach	Example Algorithms	Concept	Minimum Computational Complexity	Path Planning constrains
Grid	A*, Triangulation	Iterations, Minimum cost between two nodes	O(n^2)	Static and dynamic
Evolutionary	GA, PSO, AIA, ACO	Iteration	O(n^2)	Static and dynamic
Curve	Dubins	Polynomial	Depend on the polynomial equation	Static and dynamic

3.4 System Model

We assume a set of N MTCDs that are sparsely deployed according to a certain distribution in a given 2D marine environment area. The drone flies above all the MTCDs to provide cellular communications for gathering their delay-sensitive data.

The objective is to plan the path of the drone in such a way that ensures that the deadlines of the MTCD data transmissions do not exceed certain thresholds. This is done by minimizing the total drone's path distance as it visits the sparsely deployed MTCDs. The problem formulations has been introduced in Section 3.2

3.5 Algorithm Design

Since TSP falls under NP-hard combinatorial optimization problems, it is hard to find an exact solution for it. Therefore, the model formulated above could be solved using a heuristic approach and we would need to use a path planning algorithm such as evolutionary algorithms [84]. Genetic Algorithm (GA) and Ant Colony Optimization (ACO) Algorithm are most commonly used in drone path planning. So, we will compare both techniques. However ACO was shown to converge faster than GA, with the increase of the number of nodes [94]. ACO, also, is most commonly used in path planning problems [99]. So, we decided to go with the literature and examine the ACO technique first. Then, we will compare the ACO results to the GA-based ones to see which technique performs better in terms of our chosen metrics.

Our ACO-based algorithm is mainly used to plan the path of the base station-mounted drone for allocating communication resources to delay-sensitive M2M communications data. Therefore, the algorithm uses data transmission deadlines as a constraint while it minimizes the total cost, as expressed in covered distance, of the tour. In terms of ACO procedures, the ants' tours which should result in the minimum distance covered by the drone such that data deadlines missing would be minimized as well. To further study the effect of the resulting tour pattern on data transmission, we also calculate the packet delivery ratio (PDR).

The technique is divided into the following phases:

Phase 1: The MTCDs locations is generated using uniform distribution along with the distances between them. The MTCDs' traffic is generated afterwards. The traffic profile used is present in chapter 4, section 4.2.

Phase 2: The ACO technique starts. UAV flies over the best path chosen to collect the data of the MTCDs, calculate Deadline Missing Ratio (DMR) and Packet Delivery Ratio (PDR). The UAV might apply ACO again if a sudden request came to it while the best path is executed. This repeated ACO will be done on the rest of unvisited MTCDs after serving the sudden request.

Figure 3.2 and Algorithm 1 summarize the proposed ACO-based algorithm.

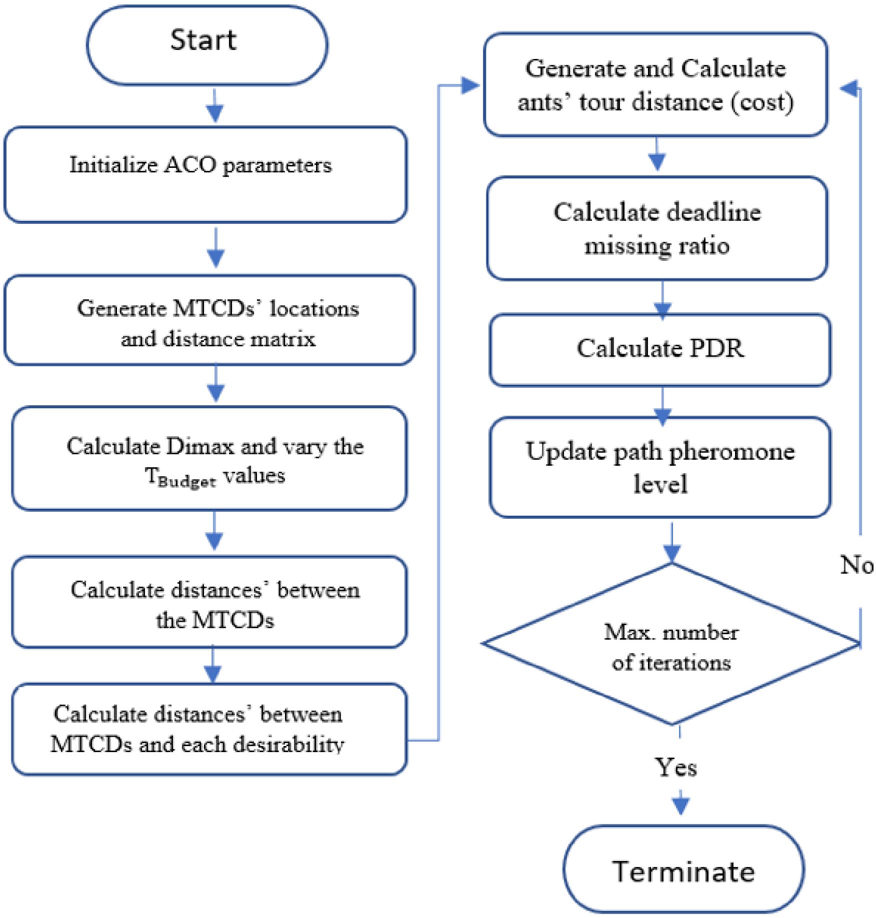

Figure 3.2 ACO path planning algorithm flowchart

Algorithm 1: Pseudo-Code of the Proposed Algorithm

1: Input: Population Size, Number of MTCDs, MTCDs 2D Coordinates, Max number of iterations, T_{BUDGET} for each node, $T_{SR-PERIOD}$

2: Initialize: Number of ants, pheromones evaporation coefficient, pheromones deposited for transitions, effect of ant's sight, trace's effect and elimination cost

3: Output: Optimum Path, Minimum distance (cost of the best route), deadline missing ratio and PDR

4: Generate the MTCDs coordinates using uniform distribution

5: Calculate the distances between the located MTCDs

6: Calculate the edge desirability (heuristic visibility) for each MTCD

7: Generate MTCDs traffic, and hence calculate the Dimax for each MTCD.

8: For iterations < Maximum number of iterations then

9: Start ACO

10: Generate the initial places for the ants

11: Forward the ants and formulate the ants' tours

12: Calculate the cost of each tour (formulated solution)

13: Calculate the tour distance

14: Update the pheromones level of the paths.

15: Determine the best solution

16: ACO end

17: Start executing the best tour

18: Create a loop that iterates through the MTCDs of the best path

19: Calculate the interim cost

20: Calculate the interim Deadline Missing Ratio (DMR)

21: Calculate the interim Packet Delivery Ratio (PDR)

22: If a sudden request emerged

23: Break, taking the new request and rest of the path and feed into step 9

24: Done with the whole path

25: Calculate the final/whole tour cost, DMR and PDR

3.6 Chapter Summary

In this chapter, we introduced the problem formulation for our path planning and scheduling technique. Then, to investigate problem solution methods, we discussed the different path planning techniques and algorithms, and then focused our attention on two of the most popular heuristic algorithms that are suitable for solving our problem, namely, the GA and ACO. We also discussed why we chose to solve our problem using ACO. Then, we presented our system model. Finally, we concluded the chapter with the ACO-based algorithm design.

CHAPTER 4: EXPERIMENTAL EVALUATION RESULTS

4.1 Introduction

The technique that we introduced in Chapter 3 is designed in such a way that optimizes the distance traveled, and hence the energy consumption, by a drone that provides communication services to sparsely deployed MTCDs.

In this chapter, conduct several simulation experiments to validate the performance of the ACO-based technique. We first evaluate the use of the ACO-related parameters and their effect on algorithm performance. Then, we use the best performing set of parameters to conduct the experiments that evaluate the performance of the scheduling function associated with the proposed drone trajectory optimization technique. We use several metrics for assessing the performance of the technique as follows

1. **Deadline missing ratio (DMR):** The number of the missed data deadlines divided by the total number of required transmissions.
2. **Packet Delivery Ratio (PDR)**: This is calculated by dividing the number of data packets received by the drone over the total number of packets generated by the MTCDs.
3. **Algorithm speed of convergence**: The convergence of the algorithm is expressed as the number of ACO algorithm iterations required to reach a certain accuracy.
4. **Total cost**: This is the used cost function and has been measured in terms of the drone distance to cover a certain round of scheduling for a certain experimental run.

To evaluate the scheduling performance, we perform the following experiments

- Varying the number of MTCDs for a given area
- Varying the deployment area size

Finally, we compare the performance of the ACO-based technique to a GA-based technique from the literature along the same comparison experiments and metrics.

4.2 Experimental Set up and Parameters

In all experiments, the MTCDs are uniformly distributed within the deployment area. The results are the averages of 100 experimental runs. The 95% confidence interval is also calculated and plotted for every experimental scenario which was calculated over 1000 runs. The used traffic profile values and parameters are given in TABLE 4.1.

T_{BUDGET} is uniformly distributed random variable generated at the beginning of the simulation. T_{BUDGET} varies for the different nodes. $T_{SR-PERIOD}$ is determined before the start of the experiments. Time, t, is the clock/current time of the simulation. The velocity of the drone is set to 13 m/sec to mimic the DJI Spark drone available in the market [100]. Finally, the generated alarm MTCDs' data are uniformly generated in 1 second interval.

TABLE 4.1 Default Traffic Profile and Parameters

Category	Value
Number of MTCDs (N)	5-10-15-20
T_{BUDGET} (min)	10-15
$T_{SR-PERIOD}$ (m sec)	10 m sec
T_3	7 m sec
Packet Size (bits)	168
Arrival Rate (pkts/s)	1
Data Size/node (bits)	168
Drone's Velocity (m/sec)	13

4.3 ACO Algorithm Performance Evaluation

In this section, we first evaluate the ACO algorithm performance under two different sets of ACO-specific parameters. We refer to these experiments as case 1 and case 2, respectively, where each case uses a given set of ACO parameters.

The parameters used in the experiments for this case are as given in Table 4.2. They are defined as follows. The parameter α is used for controlling the relative importance of pheromone. The parameter β is used for controlling the relative importance of the local heuristic factor η [101].

TABLE 4.2 ACO Algorithm Simulation Parameters

Parameter	Value
Max. number of iterations	500
Number of Ants	10
Pheromones evaporation Coefficient	0.5
Trace effect (β)	4
Effect of Ants' sight (α)	1
Elimination Cost	0.6
Simulation Time (sec)	1

We change some of the parameters in TABLE 4.2 to take values as specified in in TABLE 4.3 and measure the performance changes. Comparing cases 1 and 2 we get the results shown in Figures 4.1, 4.2, 4.3 and 4.4 with 20 deployed MTCDs. We notice that the modified parameters (case 1) result in better performance for all the metrics. According to [102] and [103] , β best range is from 3 to 5. In the second case we have increased β to 4 instead of 2 and we notice such a great improvement for all metrics. While the pheromone evaporation is mainly to prevent the unlimited increase of pheromone values and to provide the ant colony the ability to forget poor choices done previously [104]. So, we have chosen the evaporation coefficient to be equal to 0.5, as in [94] ,with equal probability to forget and remember the choices. The optimal value for the pheromones evaporation coefficient , as stated by [102], is around 0.6.

Figures 4.1, 4.2, 4.3 and 4.4 show the DMR, PDR, cost and convergence speed between case 1 and 2. As we can see from these results that TABLE

4.2 parameters performed better than Table 4.3 ones. We will therefore proceed with these parameters in our further scenarios and experiments in the next sections.

TABLE 4.3 ACO Algorithm Tuned Parameters

Parameter	Value
Pheromones evaporation Coefficient	0.15
Trace effect	2
Effects of Ants' sight	0.9
Elimination cost	0.97

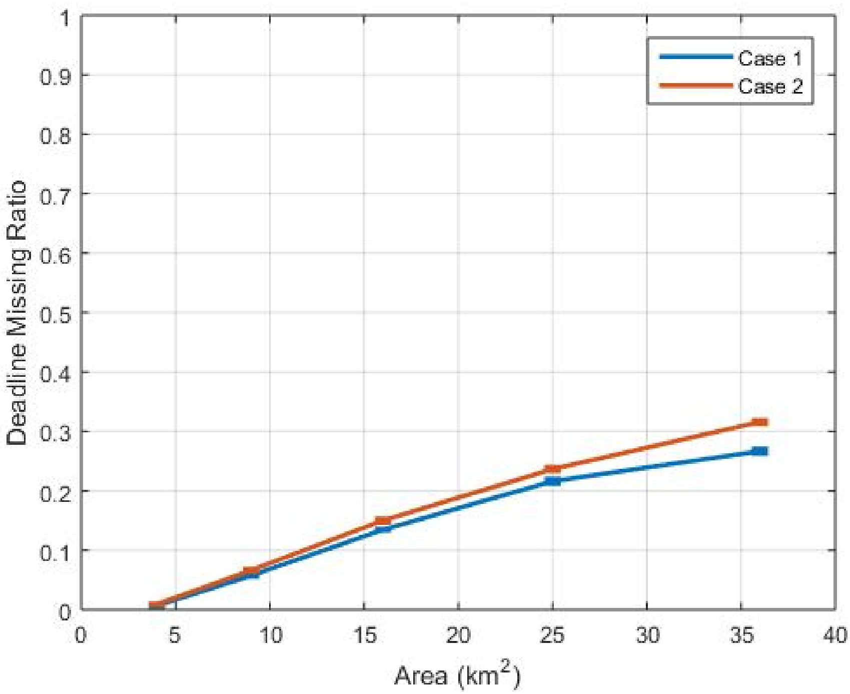

Figure 4.1 ACO Algorithm DMR Case 1 and 2 Comparison

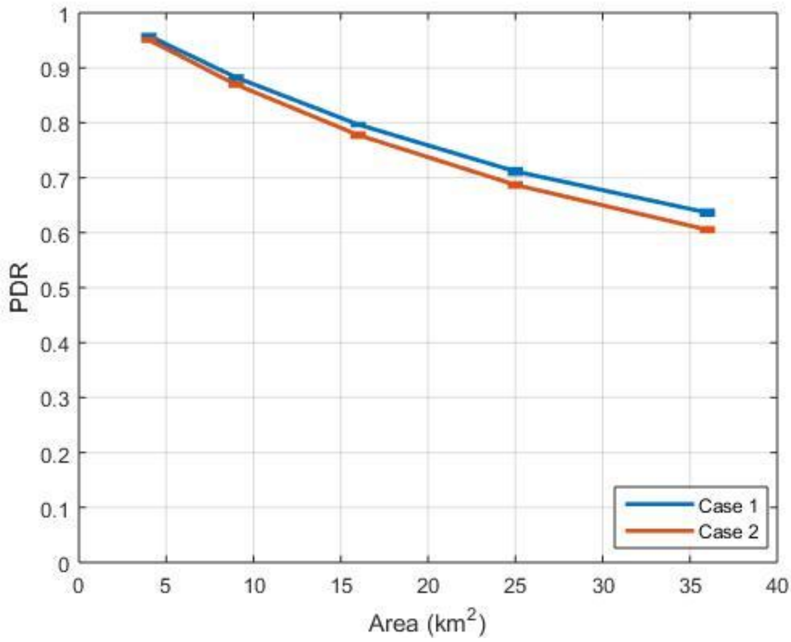

Figure 4.2 ACO Algorithm PDR Case 1 and 2 Comparison

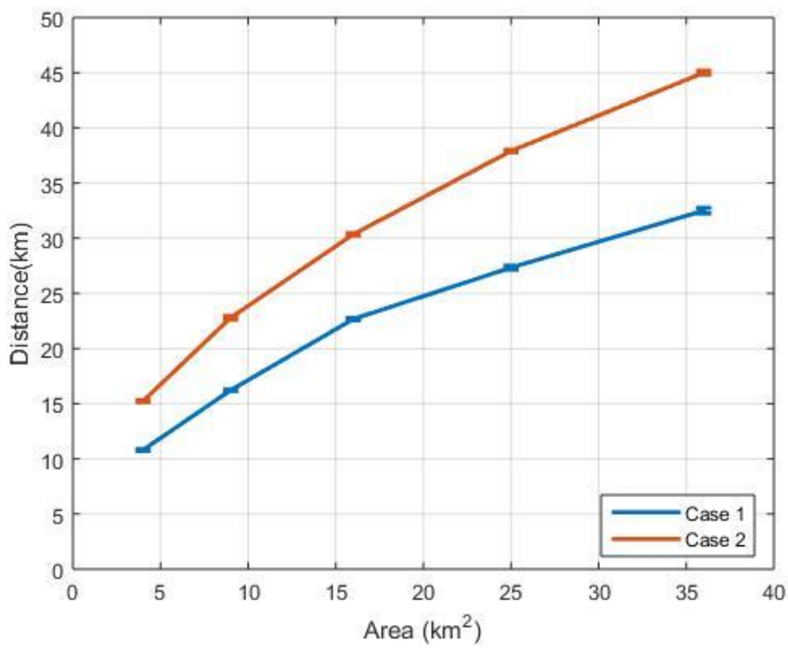

Figure 4.3 ACO Algorithm Cost Case 1 and 2 Comparison

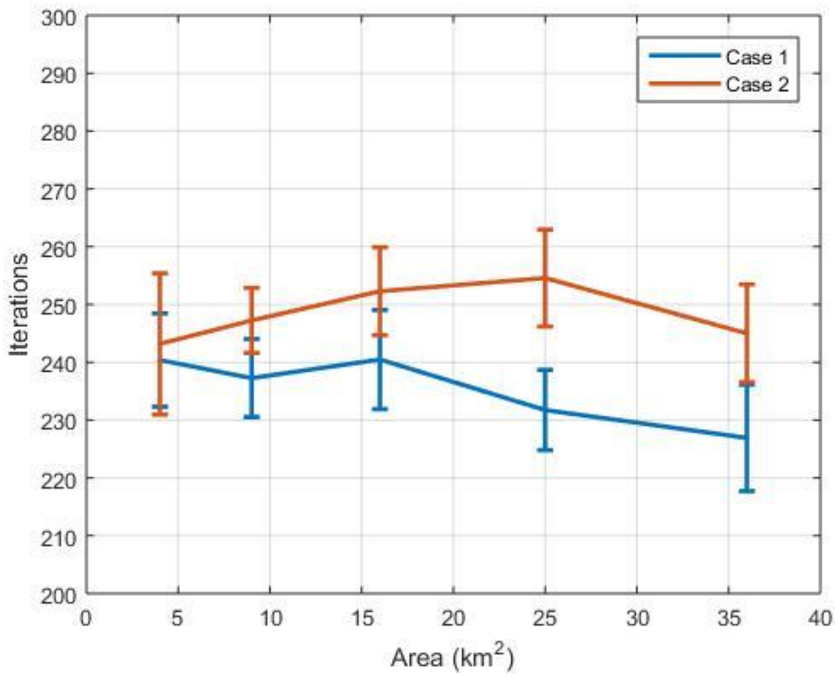

Figure 4.4 ACO Algorithm Convergence Case 1 and 2 Comparison

4.4 Scheduling Performance Evaluation

In this section, we evaluate the performance of the scheduling aspect of the proposed technique under different operating conditions. For this purpose, we experiment with three different scenarios:

1. Scenario 1: One data point per MTCD
2. Scenario 2: Multiple generated data points
3. Scenario 3: Receiving sudden requests while already in tour

4.4.1 Scenario 1: One Data Point per MTCD

In this scenario, we are trying to solve our optimization problem explained in chapter 3 section 3.2. Our metrics' results collected for this scenario are shown in Figures 4.5, 4.6, 4.7 and 4.8.

In Figure 4.5 The DMR is shown, as we can see the following,

1- The trend with respect to the area is as follows: As the area, where the MTCDs are uniformly distributed in, increases, the DMR performances degrades.
2- As the number of nodes per certain area increases, the performance of DMR gets improved.

These observations can be explained as follows,

1- As the area increases, the chances of missing deadlines for a certain number of uniformly distributed MTCDs increases because of increasing the distances covered/flight time by the UAV.
2- As the density of the MTCDs increases for a certain area, the MTCDs become closer to each other in such a way that missing their deadlines decreases. That is why we notice a considerably better performance when increasing the number of the MTCDs.

In Figure 4.6 The PDR is shown, as we can see the following,

1- As the area increases, the PDR performance deteriorates.
2- The performance gets improved by increasing the number of MTCDs.

These observations can be explained as follows,

1- It is expected that the PDR performance would also decrease as per increasing the area, because of decreasing the DMR. We might think of them as inverse pair i.e. as increasing the DMR would affect the PDR to be degraded.

In Figure 4.7 The total cost is shown, as we can see the following

1- As the area increases, the total distant cost covered by the UAV increases.

These observations can be explained as follows,

1- As the nodes are being distributed in a larger area, an increase in the covered distance is expected.

2- As the number of nodes increases, the distance covered by the UAV is expected to increase.
3- Increasing the total cost per area also verifies both DMR and PDR performance as the area increases.

In Figure 4.8 The convergence of our proposed algorithm is shown, as we can see the following

1- The number of iterations needed for our proposed algorithm to converge is slightly affected by the area.
2- Increasing the number of MTCDs slightly increases the number of iterations needed.

These observations can be explained as follows,

1- As stated by [94], ACO has an efficient state transition rules which enables it to find the optimal path. This efficient approach helps reducing the number of iterations needed by the ACO to converge, in contrast to the GA as we will see in section 4.5.

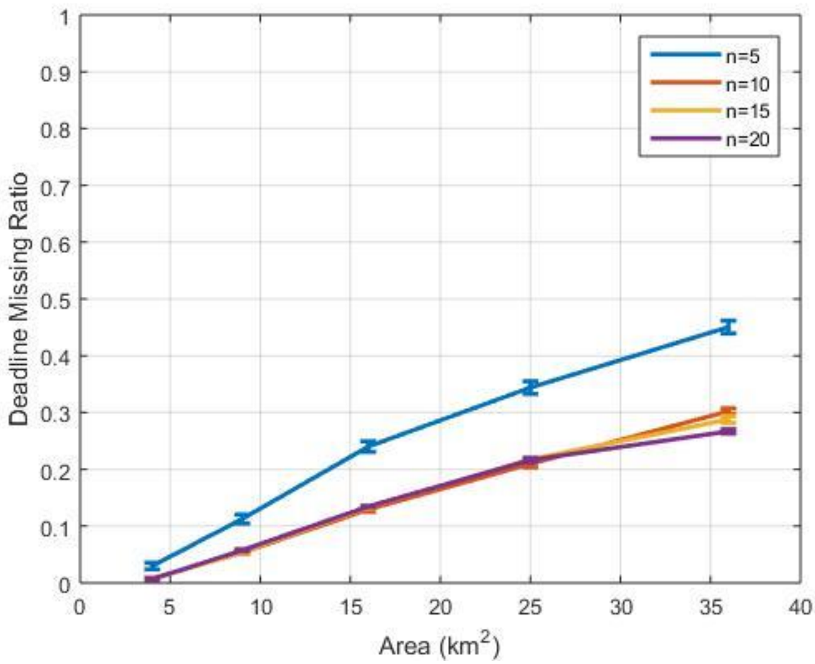

Figure 4.5 ACO Algorithm Scenario 1 DMR

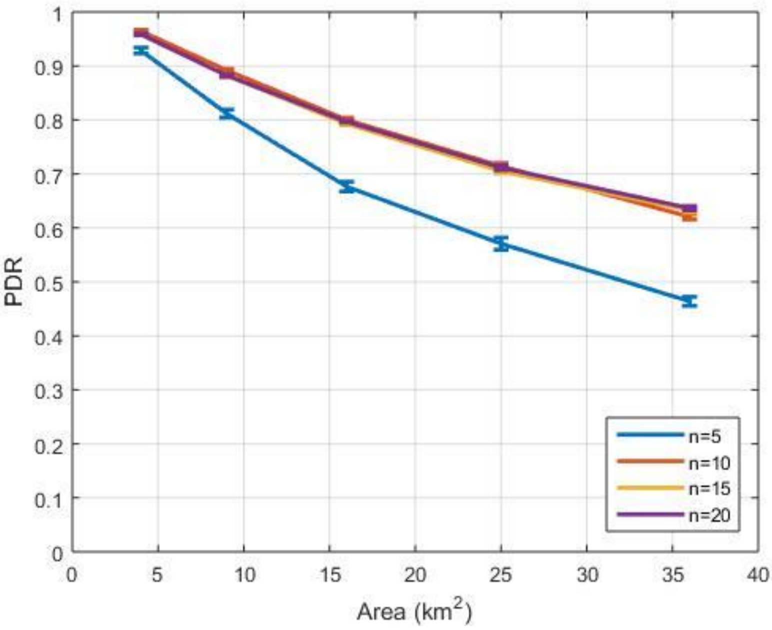

Figure 4.6 ACO Algorithm Scenario 1 PDR

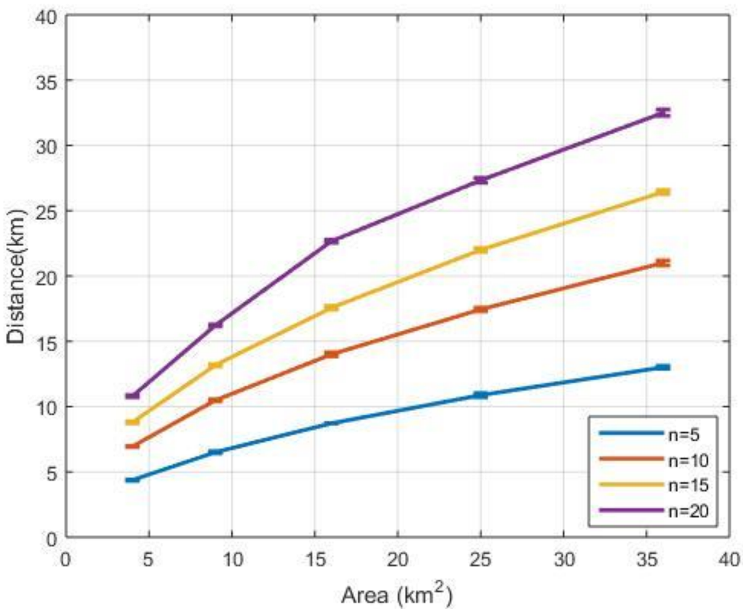

Figure 4.7 ACO Algorithm Scenario 1 Cost

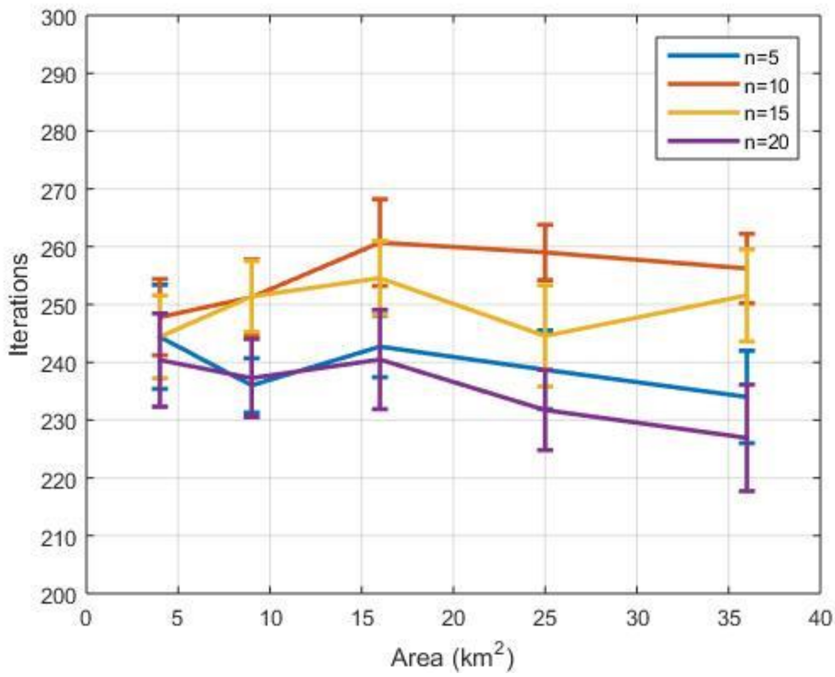

Figure 4.8 ACO Algorithm Scenario 1 Convergence

4.4.2 Scenario 2: Multiple Generated Data

The nodes' transmission schedules have been already reported via the Buffer Status Report (BSRs) of the different nodes. BSRs include the amount of data queued in the buffers of devices [105]. In this case, the drone will collect all generated data by the node all at once, assuming the involved total transmission time is negligible compared to the travel/flying time. Best solution in this case is to flush the whole queue of the current node. Each MTCD generates different numbers of packets at different times, between the interval [0 1000] msec. The maximum of these number of arrivals times will be added to the total delay allowed for this MTCD.

Our metrics' results collected for this scenario are shown in Figures 4.9, 4.10, 4.11 and 4.12.

In Figure 4.9. The DMR is shown. Comparing this scenario's DMR with scenario 1, we notice slight increase. Since the only difference between this scenario and scenario 1 is the data size transmitted per node. Here each node can generate more than 1 packet and the UAV collect them all at once.

In Figure 4.10. The PDR is shown. Comparing it to the PDR plot in scenario 1, we would conclude that, both plots are very similar. A slight decrease, however, is noticeable.

In Figure 4.11. The total cost plot is shown. It exhibits almost same cost appeared for varying the number of MTCDs and area size in scenario 1 also.

In Figure 4.12. The speed of convergence is illustrated. Comparing it with the pervious scenario, one would notice that convergence speed in this scenario almost remains the same.

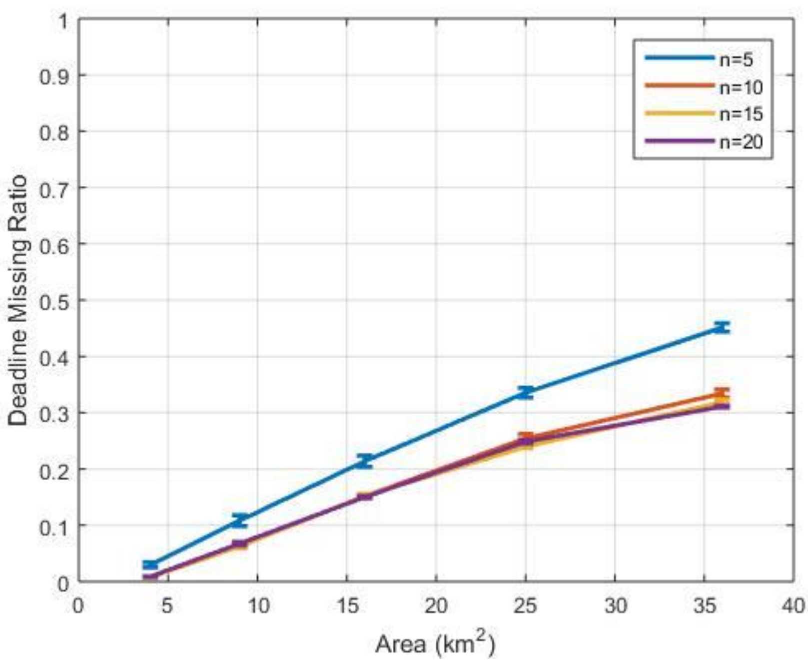

Figure 4.9 ACO Algorithm Scenario 2 DMR

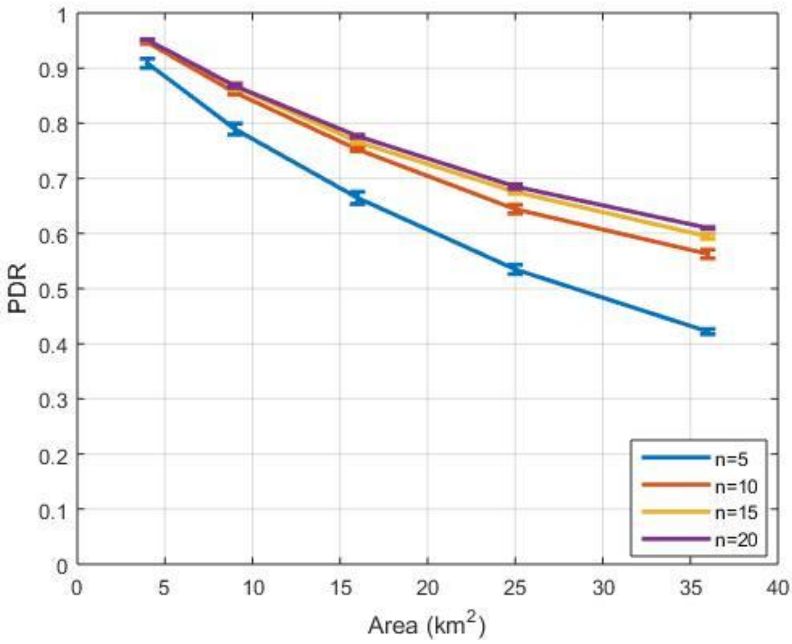

Figure 4.10 ACO Algorithm Scenario 2 PDR

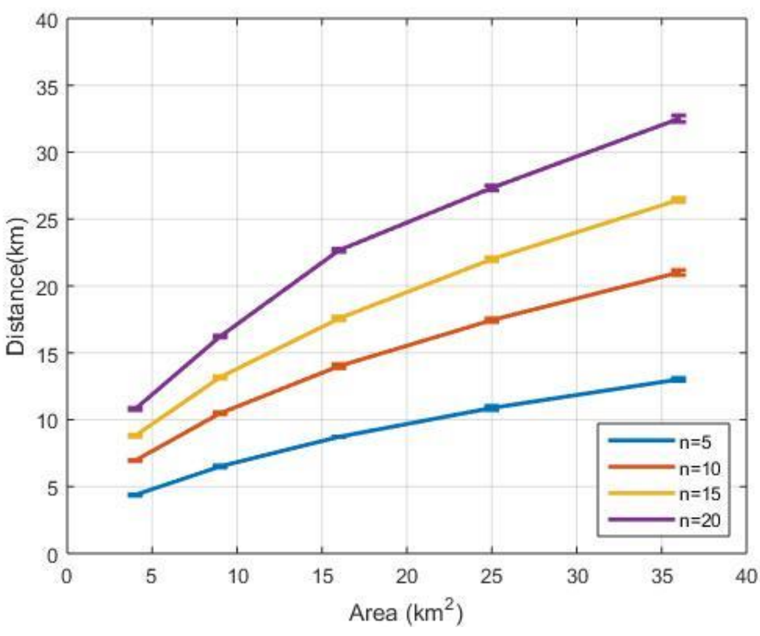

Figure 4.11 ACO Algorithm Scenario 2 Cost

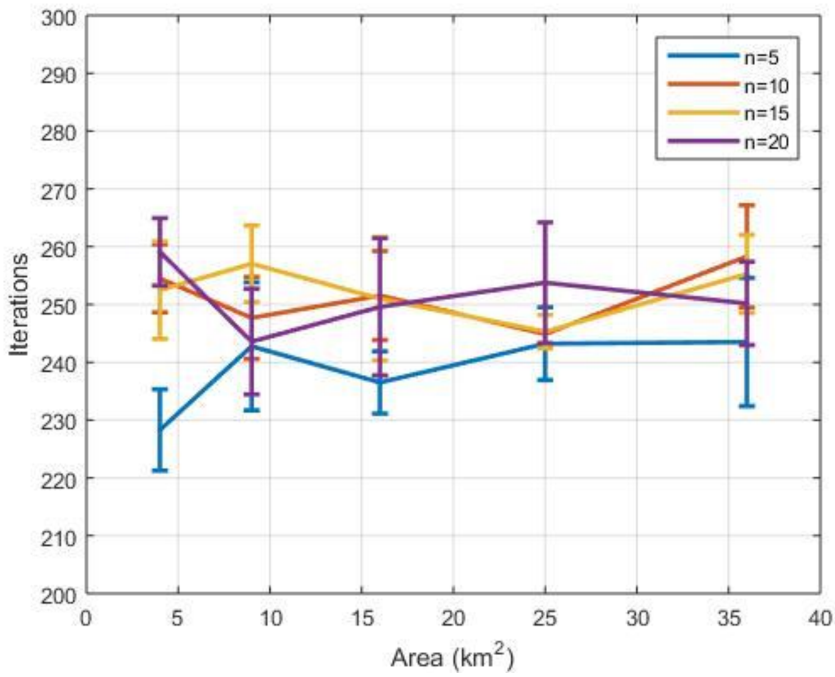

Figure 4.12 ACO Algorithm Scenario 2 Convergence

4.4.3 Scenario 3: Receiving Sudden Requests While Already in Tour

In this scenario, we address the case of nodes receiving sudden requests after the original tour path has been decided and already started by the drone. In this case, while the drone is carrying out the originally calculated tour, it gets information of the change of the sequence of MTCD communication requests that should be served. This information is supplied to the drone from a satellite link or a feedback channel. Therefore, it should abort the current tour, recalculate the new optimal tour of the new set of requests and then restart the new tour. It is expected that the costs will be a bit higher than if the whole set of requests was readily available from the beginning.

Our metrics' results collected for this scenario are shown in Figures 4.13, 4.14, 4.15 and 4.16. The effect of serving sudden requests while executing the best tour chosen by our purposed algorithm, is obvious in the results of all the metrics compared to scenario 1 and 2 results.

In Figure 4.13 The DMR is shown. Comparing this scenario's DMR with both scenarios 1 and 2, we notice the following:

1- Having the number of MTCDs to be equal to 5, exhibits the worst/highest DMR.
2- As the number of nodes increases beyond 10 MTCDs, the DMR performance improves.
3- Increasing the area size degrades the DMR performance

These observations can be explained as follows,

1- Since the performance of the DMR was affected by the number of deployed MTCDs from scenario 1, it was expected that DMR would be negatively affected when random requests to be served.
2- As the density of the MTCDs increases for a certain area, the MTCDs become closer to each other in such a way that missing their deadlines decreases. That is why we notice a better performance when increasing the number of the MTCDs.

In Figure 4.14 The PDR is shown. As we have agreed that the DMR and PDR are inverse pair i.e. as increasing the DMR would affect the PDR to be degraded, it is quite expected that the PDR plot would look like that for the same reasons stated in scenario 1.

In Figure 4.15 The total cost plot is shown. The total cost in this scenario was calculated to be higher than the previous scenarios as accounted for traveling to the suddenly requested MTCD node. Also, as the number of MTCDs increases, the total cost calculated would be much higher as the size of the area also increase.

In Figure 4.16 The speed of convergence is illustrated. The speed of convergence in this scenario turned to be a bit higher than the previous ones, yet stable for the different number of MTCDs and the different area sizes.

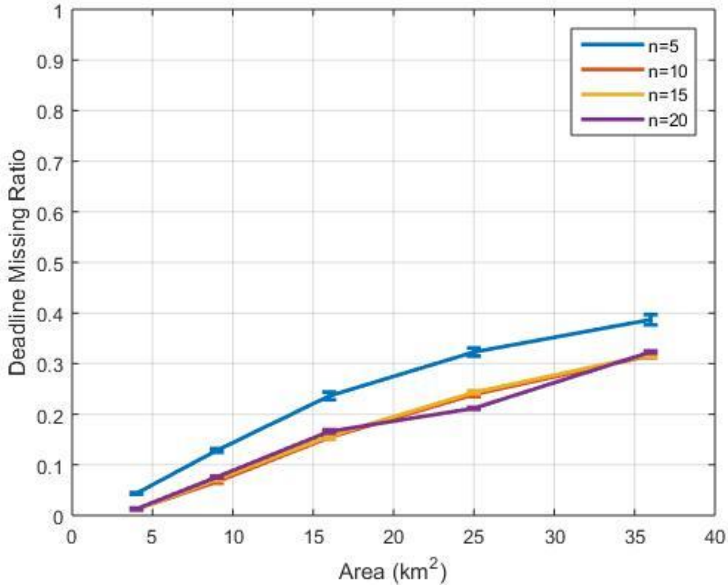

Figure 4.13 ACO Algorithm Scenario 3 DMR

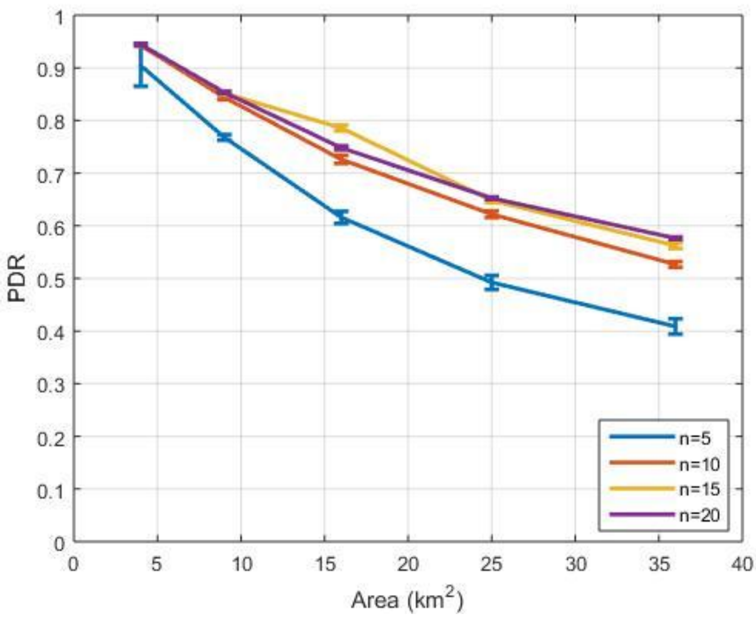

Figure 4.14 ACO Algorithm PDR Scenario 3

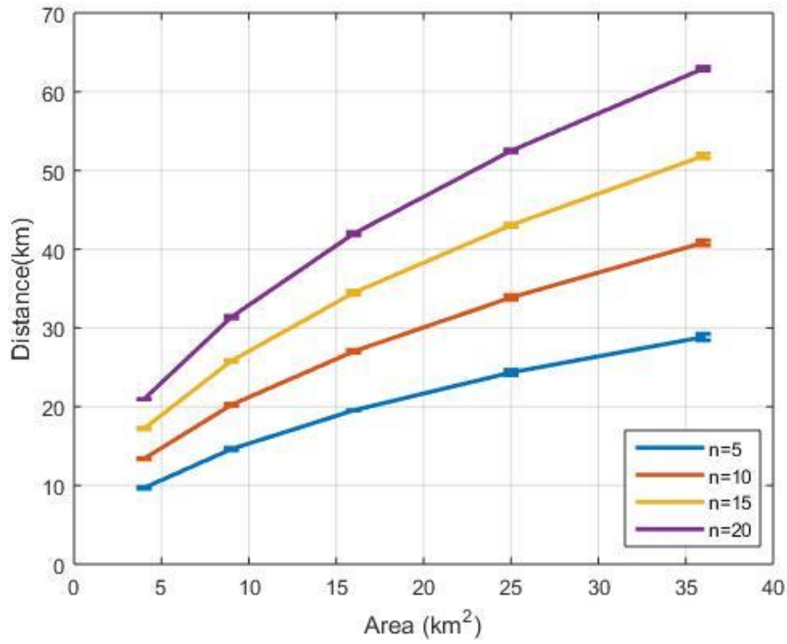

Figure 4.15 ACO Algorithm Cost Scenario 3

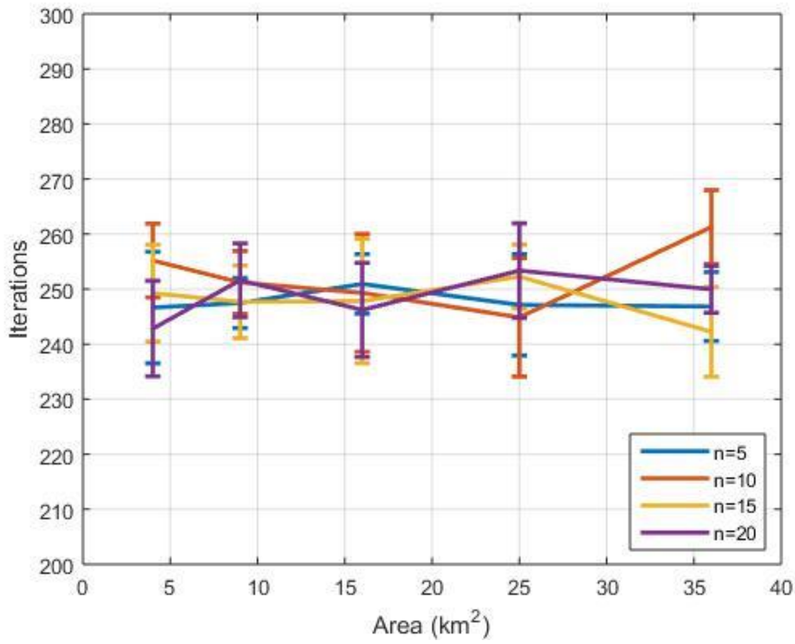

Figure 4.16 ACO Algorithm Convergence Scenario 3

4.5 Comparing the ACO Technique with a GA-Based Technique

In this section, we compare the ACO based technique performance to that of a GA-based technique from the literature [106] using the same evaluation experiments and metrics. The GA algorithm's specifications are given in TABLE 4.4. We have also applied the same exact scenarios done in the ACO algorithm to have a fair comparison. For the scenarios description, please refer to Section 4.4.

TABLE 4.4 GA parameters

Parameter	Value
Selection operator	Tournament Selection
Crossover operator	Partially mapped crossover
Mutation operator	Reciprocal exchange mutation
Probability of crossover	0.6
Probability of mutation	0.05
Population size	100
Maximum number of generations	5000

According to [84], [93] and [94], ACO performs faster in terms of speed of convergence and computational time. The reason behind this lies in the way GA initializes the population. It is based on random approaches. Using this random process, the algorithm requires to go through the process of selection to determine the optimal path [94]. This is mainly why the number of iterations needed for convergence is quite high as the number of nodes increases.

Therefore, we would expect that our results using the GA would reflect the same conclusion reached by these studies.

In our experiments, we compare the two techniques using 20 deployed MTCDs.

4.5.1 GA Scenario 1: One Data Point per MTCD

As we have discussed in the previous section 4.4, DMR and PDR can be through of as inverse pair. In this section, we will relate all four plots together and we will clarify the relation between them. So, first we will discuss the trend of each plot, then provide an analysis to all of them together.

In Figure 4.17 The DMR is shown, as we can see the following,

1- The trend with respect to the area is as follows: As the area, where the MTCDs are uniformly distributed in, increases, the DMR performances degrades, for both ACO and GA cases.
2- The difference between the GA and ACO DMR performance increases with increasing the deployment area.
3- The GA exhibits a better performance than the ACO especially with decreasing the area.

In Figure 4.18 The PDR is shown, as we can see the following,

1- As the deployment area increases, the PDR performance deteriorates.
2- The difference between the GA and ACO DMR performance increases with increasing the deployment area.

In Figure 4.19 The cost is shown, as we can see the following,

1- As the area increases, the total distant cost covered by the UAV increases.
2- ACO and GA exhibit almost the same distance covered, however as the deployment area increases ACO has slightly less covered distance.

In Figure 4.17 The convergence speed is shown, as we can see the following,

1- The number of iterations needed for our ACO algorithm to converge is slightly affected by the area.
2- The huge difference in the speed of convergence is obvious. GA needs thousands of iterations to converge.
3- It is worth mentioning that the computational time for the ACO is almost 25 mins, however for the GA it is almost 50 hours.

These observations can be explained as follows,

1- As we have previously explained, when the area increases, the chances of missing deadlines for a certain number of uniformly distributed MTCDs increases because of increasing the distances covered/flight time by the UAV. And therefore, the PDR deteriorates.

2- As the nodes are being distributed in a larger area, an increase in the covered distance is expected.
3- Increasing the total cost per area also verifies both DMR and PDR performance as the area increases.
4- The distance covered by the GA shows that it does not follow the best solution as it has slightly higher cost than the ACO as the area increases. This might be the reason why the GA exhibits a better DMR and PDR performance.
5- As presented by [94], [84] and [93], GA is slower in terms of convergence relative to the ACO. We also expect the number of iterations to be increased as the number of MTCDs increases. This gives the ACO algorithm a large advantage in terms of speed which is much needed in the real-time application at hand.
6- There is an obvious tradeoff between the ACO and GA. The number of iterations and computational time needed for GA to reach good solution is quite large and exceeds that is needed for the ACO by 20 times. In addition, the DMR and PDR performances for both techniques are close if compared to the huge difference in the convergence speed.

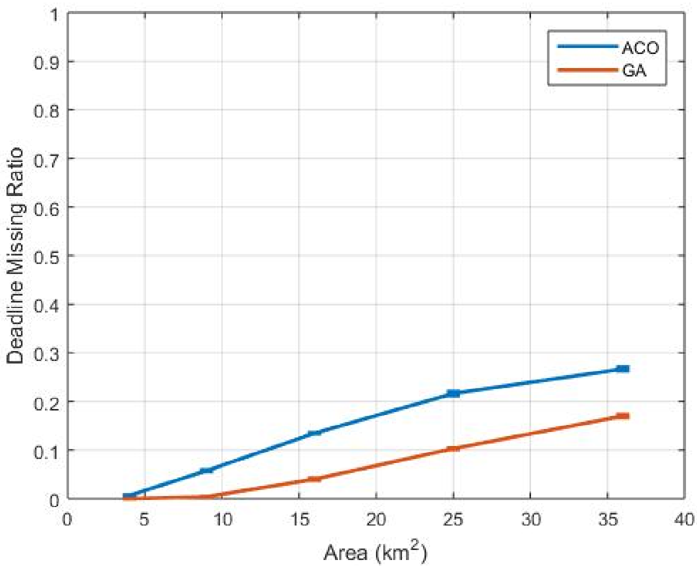

Figure 4.17 Comparison between GA and ACO algorithm in terms of DMR for Scenario 1

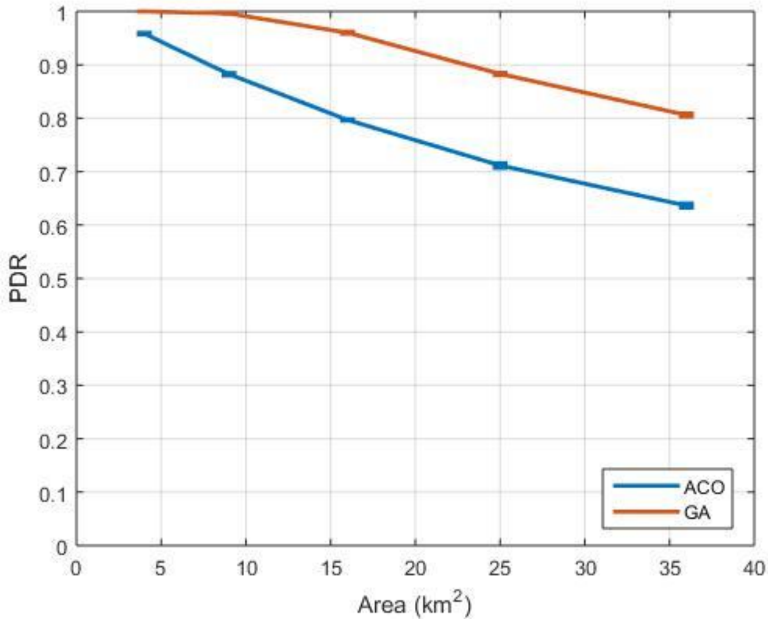

Figure 4.18 Comparison between GA and ACO algorithm in terms of PDR for Scenario 1

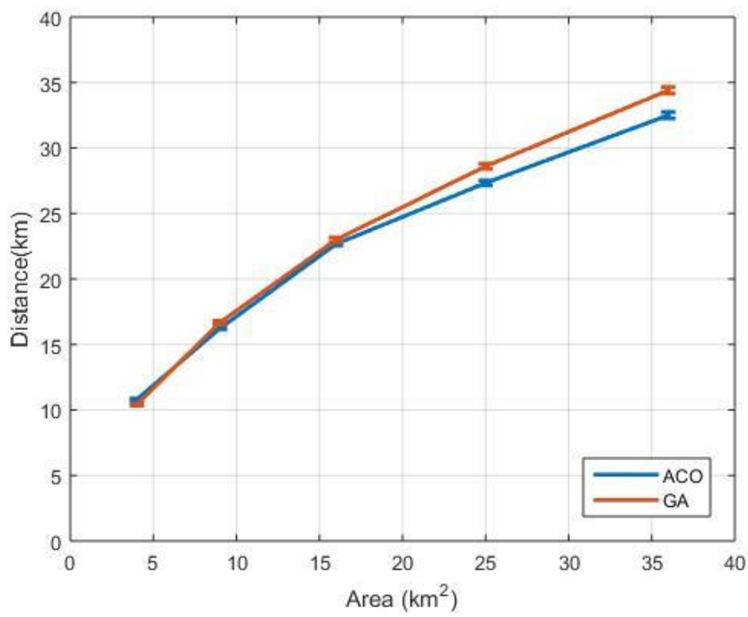

Figure 4.19 Comparison between GA and ACO algorithm in terms of Cost for Scenario 1

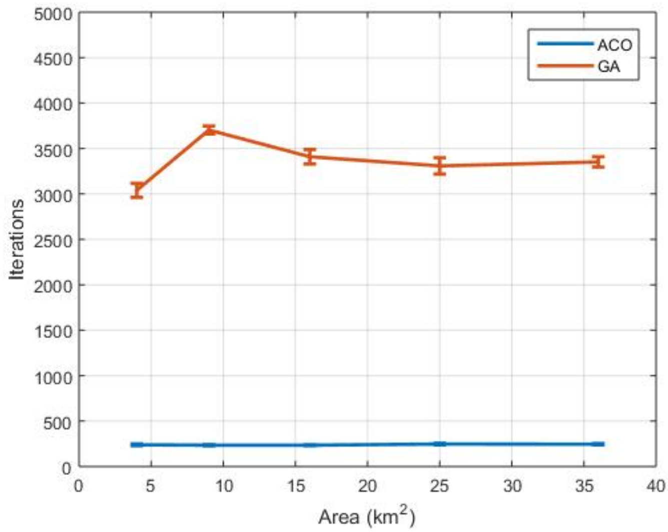

Figure 4.20 Comparison between GA and ACO algorithm in terms of Speed of Convergence for Scenario 1

4.5.2 GA Scenario 2: Multiple Generated Data

Comparing this scenario's results to scenario 1, we notice that it exhibits almost the same behaviors for all metrics. Having quite similar results for both scenarios 1 and 2 is also the case in our ACO algorithm.

Our metrics' results collected for this scenario are shown in Figures 4.21, 4.22, 4.23 and 4.24.

In Figure 4.21. The DMR is shown. Comparing this scenario's DMR with scenario 1, we notice slight differences. Since the only difference between this scenario and scenario 1 is the data size transmitted per node. Here each node can generate more than 1 packet and the UAV collect them all at once. The DMR performance slightly deteriorates than the previous scenario for both techniques.

In Figure 4.22. The PDR is shown. Comparing it to the PDR plot in scenario 1, we would conclude that, both plots are very similar with a slight decrease in the performance.

In Figure 4.23. The total cost plot is shown. It exhibits the same cost appeared for both the GA and ACO in scenario 1 also.

In Figure 4.24. The speed of convergence is illustrated. Comparing it with the pervious scenario, one would notice that convergence speed in this scenario almost remains the same for both techniques.

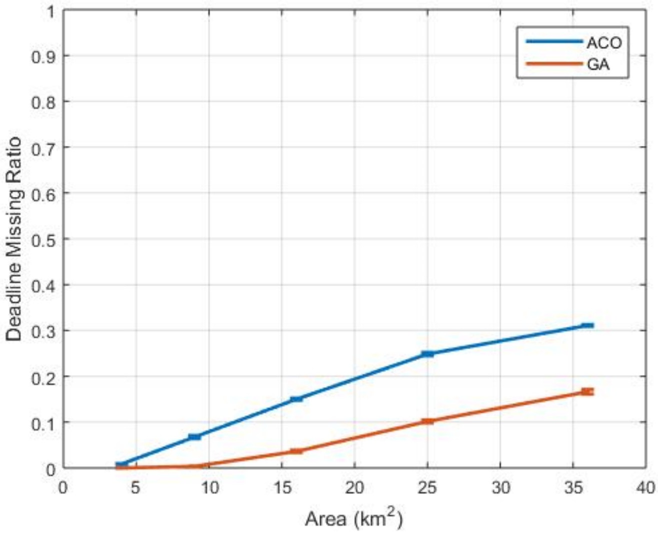

Figure 4.21 Comparison between GA and ACO algorithm in terms of DMR for Scenario 2

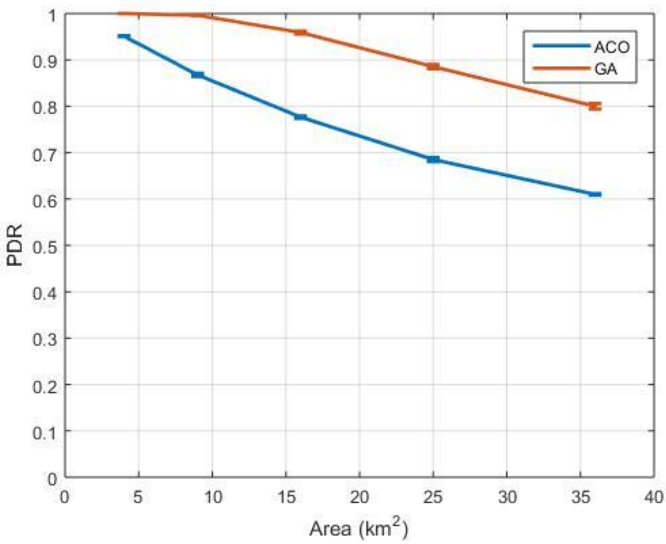

Figure 4.22 Comparison between GA and ACO algorithm in terms of PDR for Scenario 2

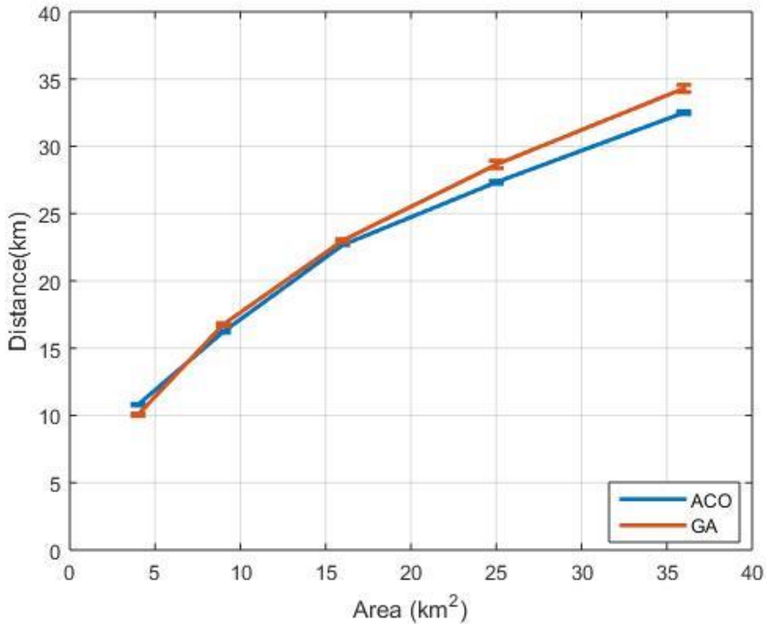

Figure 4.23 Comparison between GA and ACO algorithm in terms of Cost for Scenario 2

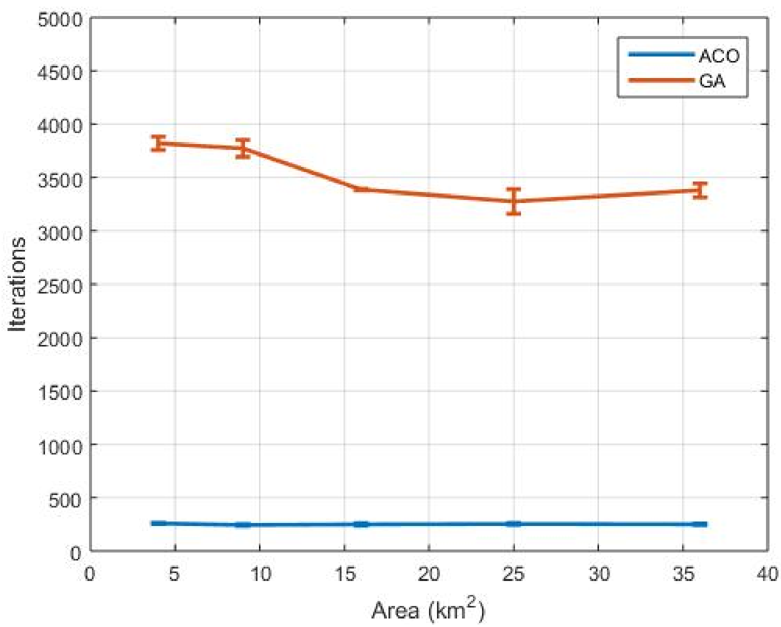

Figure 4.24 Comparison between GA and ACO algorithm in terms of Speed of Convergence for Scenario 2

4.5.3 GA Scenario 3: Receiving Sudden Requests

Our metrics' results collected for this scenario are shown in Figures 4.25, 4.26, 4.27 and 4.28. The effect of serving sudden requests while executing the best tour chosen by our purposed algorithm, is obvious in the results of all the metrics compared to scenario 1 and 2 results.

In Figure 4.25. The DMR is shown. Comparing this scenario's DMR with scenario 1 and/or 2, we notice slight differences in both techniques. Since the only difference is that we are now serving sudden request/s, we expected a degradation in the DMR performance.

In Figure 4.26. The PDR is shown. Because of getting a degradation in the DMR performance, we notice a deterioration in the PDR performance as well.

In Figure 4.27. The total cost plot is shown. The ACO calculated cost is expected to be higher than the previous scenarios as accounted for traveling to the suddenly requested MTCD node. The GA also has got a higher cost, however not higher than the ACO, which assures that the GA didn't follow the best path. However, we can't really judge the increase in the distance covered in this scenario as the random requests received might be unequal, so we can only judge if there's an increase or not.

In Figure 4.28. The speed of convergence is illustrated. Comparing it with the pervious scenario, one would notice that convergence speed in this scenario is a bit higher for both techniques.

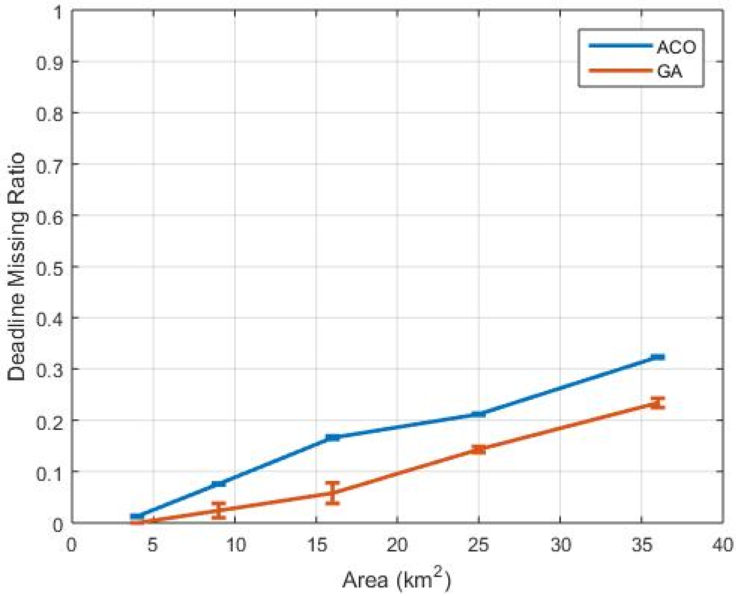

Figure 4.25 Comparison between GA and ACO algorithm in terms of DMR for Scenario 3

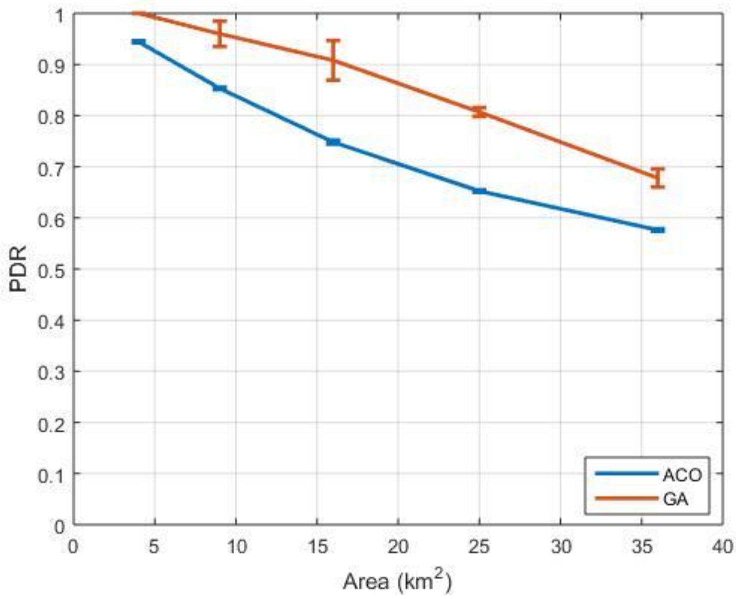

Figure 4.26 Comparison between GA and ACO algorithm in terms of PDR for Scenario 3

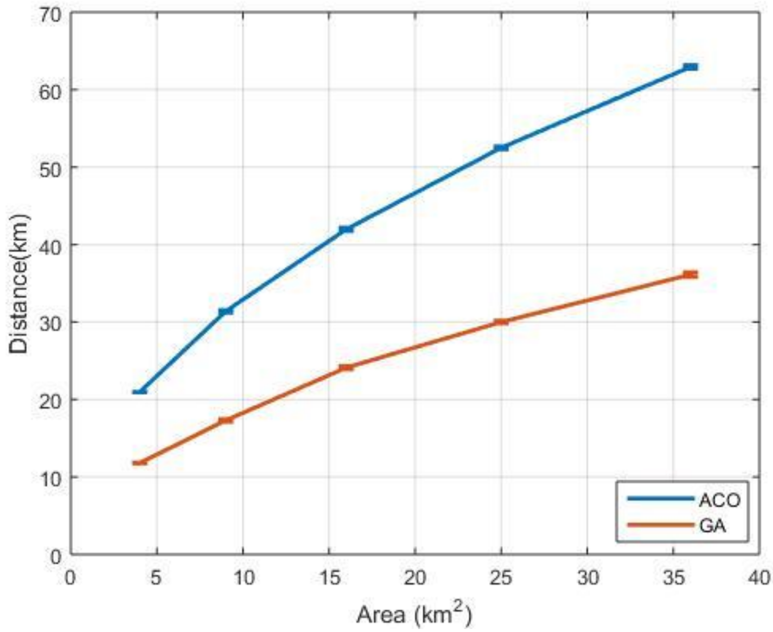

Figure 4.27 Comparison between GA and ACO algorithm in terms of Cost for Scenario 3

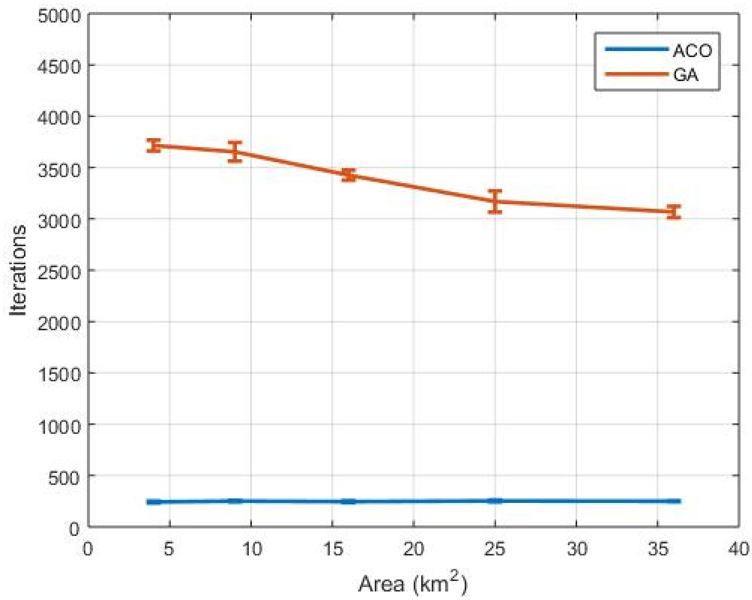

Figure 4.28 Comparison between GA and ACO algorithm in terms of Convergence for Scenario 3

4.6 Chapter Summary

In this chapter, we presented the evaluation results of simulating our ACO algorithm under different operating scenarios. We have also compared the ACO algorithm with a Genetic Algorithm (GA) from the literature.

The ACO algorithm generally converges fast and offers good deadline missing and packet delivery performance that improve as the sparsity of the network decreases.

We have also compared the ACO algorithm with a Genetic Algorithm (GA) from the literature. For the used dataset, GA performs better, however its convergence is slower than ACO.

We also found the ACO algorithm to perform significantly better than the GA-base algorithm in terms of cost and convergence speed.

The key differentiators of the ACO technique, based on these experiments, are the small number of iterations needed for convergence along with the total cost attained. This gives the ACO algorithm a large advantage in terms of speed which is much needed in the real-time application at hand. It is worth mentioning that the large speed advantage of the ACO algorithm does not come at the expense of the quality of the obtained solution (distance cost).

CHAPTER 5. CONCLUSION

5.1Thesis Summary

Drones are increasingly used to provide communication services in areas out of reach of the terrestrial communication coverage. In this thesis, we gave an overview about drones along with their applications and challenges.

We have investigated the use of drones with their different roles in communication services. For this reason, we have presented a novel classification of drone communications from a technological perspective. We have also presented a review about the marine environment, UAV-marine environment communications, Machine-to-Machine (M2M) communications, UAV-Trajectory management and the traveling salesman problem (TSP) on which we base the drone trajectory planning and scheduling technique that we proposed in this research.

We then studied the most suitable optimization scheme to use for optimal path planning for the purpose delivery of communication services by a flying drone-mounted base station. Then, we introduced a new technique to provide communication coverage by a flying base station-mounted drone to sparsely deployed MTCDs at sea. The technique is based on minimizing the distance covered by the drone, and hence its energy consumption, as it passes by the deployed MTCDs. This is done such that the MTCDs data deadline missing ratio is minimized. Since this is an NP-hard problem, we used the Ant Colony Optimization (ACO) methodology as a basis for our solution.

We validated the performance of the ACO technique along specific metrics and compared it to that of an existing GA-based solution.

5.2 Future Work

The work presented in this thesis can be further extended in the following directions:

- The problem formulation can be extended to include N number of clusters, which have many MTCDs in each. Interference among the different clusters will be a limiting factor that needs to be incorporated into the optimization problem in this case.
- Multiple of drones can be deployed to serve massive MTCD deployments. The coordination and collision avoidance among the drones could also be another direction of extension.
- Since drone height was not involved in our study, we may also include drone height optimization with the purpose of optimizing the energy consumed in communicating with deployed MTCDs

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