NETWORK PROVISIONING USING MULTIPLE UAVS IN SEARCH AND RESCUE MISSIONS

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NETWORK PROVISIONING USING MULTIPLE UAVS IN SEARCH AND RESCUE MISSIONS

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I'd like to dedicate this work to my parents for their continuous support.

DECLARATION OF ORIGINALITY

I hereby declare that I am the sole author of this thesis and that this is the true copy of my thesis, including the final revisions, approved by my thesis committee. All data and information have been obtained, produced, and presented in accordance with the rules of research ethics and principles of academic honesty. As required by these rules, to the best of my knowledge I have acknowledged ideas, thoughts, and any copyrighted material in accordance with the standard referencing rules. I certify that any part of this thesis has not been submitted for a degree or diploma in another educational institution.

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ABSTRACT

Teams of Unmanned Aerial Vehicles (UAVs) are widely considered for civil applications, where UAVs collaborate as data collection or delivery nodes. For this reason, recent research has proposed UAV path planning algorithms that integrate connectivity as a constraint or optimization objective. However, most studies primarily focus on topological connectivity or average network performance, often using network simulators with randomized or sweeping mobility models to analyze higher-layer protocols. In this thesis, we first analyze the performance of multi-UAV path planners optimized for connectivity, investigating both collaboratively optimized networks and relay-assisted networks. Taking network-optimized multi-UAV paths as input, we show that topologically connected UAV paths do not inherently guarantee acceptable network performance in terms of Packet Delivery Ratio (PDR) and throughput. In addition, we develop a *trajectory-based scheduling approach* that exploits the future movements of UAVs to improve data delivery. By predicting imminent link availability, each node can forward its packets to neighbors that are expected to connect to the Base Station (BS) soon, thereby reducing overall transmission delays. Our results demonstrate that this scheduling and forwarding mechanism can outperform classical hop-based routing (e.g., Ad hoc On-Demand Distance Vector (AODV))——thereby underscoring the importance of incorporating trajectory information into both UAV path planning and data routing for mission-critical applications.

Keywords: Drone network, UAV, traffic scheduling, mobility-aware, ad hoc routing

ÖZET

İnsansız Hava Aracı (İHA) takımları, İHA'ların veri toplama veya dağıtım düğümleri olarak iş birliği yaptığı senaryolarda yaygın şekilde değerlendirilmektedir. Bu sebep ile, son dönemdeki araştırmalar, bağlantıyı bir kısıt veya optimizasyon amacı olarak entegre eden İHA rota planlama algoritmaları önermiştir. Ancak, mevcut çalışmaların büyük bir kısmı öncelikli olarak topolojik bağlantı veya ortalama ağ performansına odaklanmakta ve üst katman protokollerini analiz etmek için rastgele veya geniş kapsamlı hareketlilik modelleriyle çalışan ağ simülatörlerini kullanmaktadır. Bu tezde öncelikle, bağlantı için optimize edilmiş çoklu-İHA rota planlayıcılarının performansı incelenmiş ve bu kapsamda hem iş birliğiyle optimize edilen ağlar hem de röle destekli ağlar ele alınmıştır. Ağ için optimize edilmiş çoklu-İHA yolları girdi olarak kullanılarak, topolojik olarak bağlı İHA yollarının her zaman PDR ve veri aktarım hızı (throughput) açısından istenen seviyede ağ performansı sağlamadığı gösterilmiştir. Ayrıca, İHA'ların gelecekteki hareketlerinden yararlanarak veri iletimini iyileştirmeyi amaçlayan bir *yörünge tabanlı zamanlama yaklaşımı* önerilmiştir. Yakın gelecekteki bağlantı uygunluğunu öngörerek, her düğümün, paketlerini en yakında baz istasyonu ile doğrudan bağlantı kurması beklenen komşulara yönlendirmesi ve toplam aktarım gecikmesinin azaltılması hedeflenmektedir. Elde edilen sonuçlar, bu zamanlama mekanizmasının klasik yönlendirme (örneğin AODV) yöntemlerine kıyasla daha üstün performans sergilenebileceğini göstermekte ve görev-kritik uygulamalarda yörünge bilgisinin hem İHA rota planlamasına, hem de veri yönlendirme süreçlerine entegre edilmesinin önemini vurgulamaktadır.

Anahtar Kelimeler: Drone ağı, İHA, trafik zamanlama, hareketlilik farkındalığı, tasarsız yönlendirme

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LIST OF ACRONYMS AND ABBREVIATIONS

AODV Ad hoc On-Demand Distance Vector

AWGN Additive White Gaussian noise

BS Base Station

CDF Cumulative distribution function

CSMA Carrier Sense Multiple Access

DSDV Destination-Sequenced Distance Vector

DSR Dynamic Source Routing protocol

FANET Flying Ad hoc Network

FIFO First-in First-out

FP Flight Plan

GA Genetic Algorithm

GBS Ground Base Station

GM Gauss-Markov

GPSR Greedy Perimeter Stateless Routing

GRP General Routing Problem

İHA İnsansız Hava Aracı

IP Internet Protocol

IPv4 Internet Protocol version4

LEPR Link Stability Estimation-based Preemptive Routing

LoS Line of Sight

MAC Medium Access Control

MANET Mobile Ad hoc Network

mTSP multiple Traveling Salesman Problem

OF Objective Function

OLSR Optimized Link State Routing

PDR Packet Delivery Ratio

QoS Quality of Service

RPA relay positioning algorithm

RD Random Direction

RWP Random Waypoint

SAR Search and Rescue

SATCOM Satellite Communication

SDPC Self-Deployable Point Coverage

SINR Signal-to-Interference-plus-Noise Ratio

SNR Signal-to-Noise Ratio

SRCM Semi-Random Circular Movement

TCP Transmission Control Protocol

U2G UAV-to-Ground

U2U UAV-to-UAV

UAV Unmanned Aerial Vehicle

UDP User Datagram Protocol

VANET Vehicular Ad hoc Network

WLAN Wireless Local Area Network

WSN Wireless Sensor Network

ZRP Zone Routing Protocol

1. INTRODUCTION

1.1 Motivation

The use of UAVs has expanded significantly across various applications, including search and rescue, disaster management, surveillance, environmental monitoring, and data collection. In these scenarios, UAVs collaborate as data collection or delivery nodes, often operating within dynamic and challenging environments. Reliable connectivity and efficient data transfer are critical for mission success, yet maintaining these aspects in FANETs presents significant challenges due to obstacles, interference, and the inherent mobility of UAVs.

Recent research has proposed UAV path planning algorithms that integrate connectivity as a constraint or optimization objective. However, most studies primarily focus on topological connectivity or average network performance, often relying on simplified network simulators with randomized or sweeping mobility models to evaluate higher-layer protocols. These approaches can overlook practical limitations in real-world deployments, such as wireless channel constraints, congestion at hub nodes, and large-scale fading effects [2, 3].

While FANETs hold significant promise, their deployment faces several challenges and open issues. First, the high mobility of UAVs results in frequent and rapid changes in network topology. These dynamic changes lead to unstable communication links, interruptions in data flow, and increased routing complexity. Existing routing protocols often struggle to adapt to FANET-specific conditions, including rapidly changing structures and large-scale UAV teams. Ensuring reliable and scalable routing in such networks is therefore critical to preventing congestion and maintaining communication performance [4, 5].

Second, traffic congestion and uneven resource utilization further degrade network performance. Hub nodes that handle heavy traffic loads are prone to packet loss, delays, and eventual bottlenecks. Hence, efficient traffic management mechanisms are needed to ensure balanced resource utilization and optimized data flow. Additionally, FANETs operate under energy constraints since communication processes can consume significant power. Prolonging the operational duration of UAVs requires the development of energy-efficient communication protocols and resource management techniques [6].

Third, FANETs must satisfy stringent Quality of Service (QoS) requirements, including low latency, high throughput, and reliable communication. Achieving these QoS standards becomes particularly challenging in dynamic and resource-constrained environments. Real-world factors such as interference, fading, and bandwidth limitations further exacerbate these challenges, requiring robust and adaptive solutions [7].

Moreover, FANETs face critical security and robustness concerns. Their open communication environment exposes them to potential threats such as jamming, spoofing, and interception—particularly in military and critical infrastructure applications. Addressing these vulnerabilities demands secure, resilient communication protocols to safeguard sensitive data and ensure uninterrupted operations [8].

Another challenge lies in coordinating heterogeneous UAVs. Those with varying sensor capabilities, payloads, and flight endurance must collaborate seamlessly to optimize task execution. Developing advanced algorithms for coordination, mission planning, and data processing is thus vital. Additionally, environmental factors such as weather conditions, obstacles, and terrain variations can disrupt UAV communication and navigation, further complicating FANET deployment [9].

To address these challenges, this thesis identifies key issues in multi-UAV networks and proposes solutions to improve connectivity, resource management, and network performance, as discussed in the following section.

1.2 Problem Statement

Ensuring reliable connectivity and efficient data transmission in multi-UAV networks is a critical challenge, especially under real-world conditions where node mobility, heterogeneous service demands, and physical-layer constraints can degrade performance. Although numerous studies have proposed UAV path-planning algorithms that incorporate connectivity [10], most rely on simplified simulation scenarios (e.g., randomized or sweeping mobility) and focus primarily on topological connectivity or average network metrics. Consequently, factors such as wireless channel limitations, congestion at hub nodes, and large-scale fading effects are often overlooked, leading to suboptimal performance in practical deployments [11, 12].

To address these challenges, this research evaluates existing *network-optimized multi-UAV path planners* under more realistic wireless conditions. By introducing a dedicated simulation framework, we quantify the paths' ability to handle dynamic topology and link instability, highlighting their limitations. In addition, we propose a trajectory-based scheduling mechanism for multi-UAV networks, aiming to enhance data delivery and reduce end-to-end delay by leveraging future node connectivity. The approach not only considers connectivity at the current time but also how it will evolve in the future, thereby achieving more optimal scheduling decisions in each time slot.

Specifically, we analyze how topologically connected UAV paths do not inherently guarantee high packet delivery or throughput. Using predefined network-optimized multi-UAV paths (including relay-assisted and collaboratively optimized solutions), our scheduling approach coordinates data transfers on a slot-by-slot basis, ensuring significant performance gains. For instance, dynamic relay scenarios can reduce reliance on static relays while maintaining comparably strong delivery rates. Collaborative optimization schemes show particular promise in scenarios with higher node densities or extended transmission ranges, minimizing hub-node congestion [13].

Ultimately, this study aims to *bridge the gap* between purely connectivity-focused path planning and the real-world need for reliable throughput. Our findings demonstrate that an advanced scheduling layer, which carefully orchestrates link activations and data flows, can substantially enhance network performance in multi-UAV missions. The insights gained will guide the design of robust and efficient FANET solutions, enabling UAVs to operate effectively in complex and demanding operational contexts.

1.3 Thesis Organization

This thesis consists of five chapters. Chapter 1 (the present chapter) introduces the motivation and problem statement. Chapter 2 provides the theoretical background, including a review of FANETs, UAV mobility models, routing protocols, and existing path-planning approaches. It also highlights the gaps in the current literature to establish the need for the proposed work.

Chapter 3 evaluates the performance of connectivity-optimized multi-UAV path planners. It describes the simulation environment, methodology, and metrics used to assess the performance of collaboratively optimized and relay-assisted networks, and it also explores the limitations of these approaches under various conditions.

Chapter 4 proposes a trajectory-based scheduling mechanism for multi-UAV networks, aiming to enhance data delivery and reduce end-to-end delay by leveraging future node connectivity. Rather than relying on conventional hop-count routing alone, this approach factors in each node's anticipated "time-to-BS" based on future connections to deliver packets more efficiently.

Chapter 5 summarizes the findings, discussing the broader implications for Search and Rescue (SAR) and similar mission-critical UAV applications, and outlines directions for future research.

2. LITERATURE REVIEW

2.1 Introduction

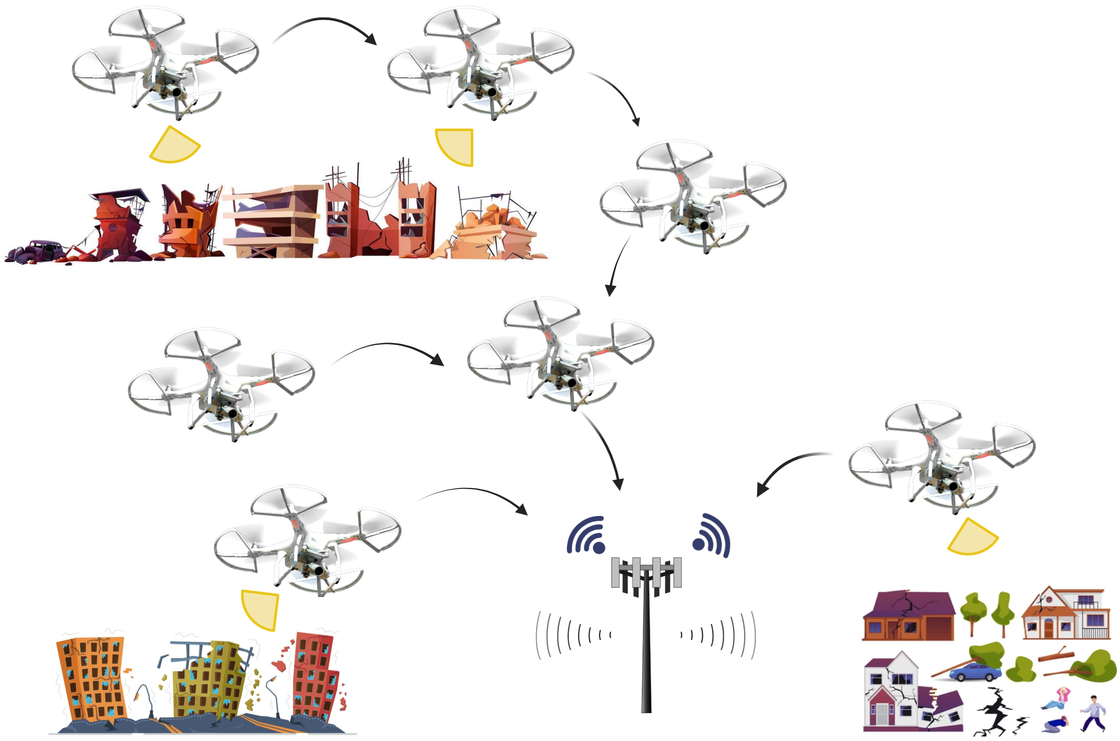
This chapter surveys the state of the art in FANETs, with a particular emphasis on multi-UAV networking challenges and scheduling strategies. While a significant body of work has explored how MANETs protocols (e.g., AODV, Optimized Link State Routing (OLSR)) can be adapted to UAV environments, fewer studies investigate the explicit integration of route planning, collision-free scheduling, and mobility modeling—especially under Signal-to-Interference-plus-Noise Ratio (SINR)-based constraints or time-slot assignments. Since SAR missions depend on fast, reliable coordination among UAV teams, this integration is central to addressing high mobility, partial connectivity, and heavy traffic scenarios in the field.

The chapter begins by characterizing the fundamentals of FANETs and their application domains (Section 2.2), then examines the MANET-derived routing protocols frequently employed in UAV networks and their limitations (Section 2.3). Next, various UAV mobility models are reviewed (Section 2.4), highlighting how realistic flight patterns influence connectivity and route stability. To connect these ideas with practical experimentation, Section 2.5 discusses a range of FANET studies, focusing on adaptive routing, scheduling, and system-level design for UAV swarms. We then survey widely adopted simulation tools (Section 2.6), which are essential for validating novel protocols or mission plans. Finally, in Section 2.7, we identify the research gaps that this thesis aims to address, specifically the need for holistic scheduling and path planning that transcends local collision-avoidance mechanisms.

2.2 Flying Ad-Hoc Networks

FANETs are formed by autonomous UAVs that establish multi-hop wireless communication in highly dynamic, often three-dimensional environments. Their deployment has proven valuable across applications such as disaster relief, real-time surveillance, precision agriculture, and border security. Compared to terrestrial MANETs, FANETs must confront elevated mobility, unpredictable flight trajectories, and limited on-board resources.

Figure 2.1: *Schematic of a FANET.*



2.2.1 FANETs and Their Applications

FANETs enable the rapid formation and reconfiguration of aerial communication infrastructures, often in settings where ground connectivity is unavailable or unreliable. Common use cases include:

- *SAR:* Coordinated UAVs sweep disaster zones, locate victims, and relay data to ground stations [14, 15].

- *Disaster Management:* Temporarily deployed UAV relay networks compensate for damaged terrestrial infrastructure [16].

- *Environmental Monitoring:* UAV fleets sample sensor data across large areas, ensuring coverage through cooperative flight paths [17].
- *Surveillance and Security:* Multiple UAVs share real-time video and sensor information, enhancing situational awareness [18].

These applications highlight the flexibility and agility of FANETs but also expose critical networking challenges, such as ensuring robust connectivity under frequent link disruptions [19].

2.2.2 Characteristics and Challenges of FANETs

FANET deployments exhibit several complicating factors:

- *Three-Dimensional Mobility:* Frequent altitude or directional changes demand rapid route reconfiguration and robust link estimation [20].
- *Limited Energy:* UAVs typically have restricted battery power, which affects both flight and transmission range.
- *Dynamic Topology:* Rapid movements cause frequent link formation and breakage [5].
- *Latency Sensitivity:* Real-time tasks, such as streaming or live telemetry, require low-delay communication.
- *Risk of Fragmentation:* Sparse UAV distributions or large coverage areas easily lead to network partitions.

Environmental disruptions, weather, or unexpected obstacles further amplify the difficulty of maintaining reliable data exchange at all times.

2.2.3 *Communication Modalities in FANETs*

A FANET can incorporate various link types:

- *UAV-to-UAV (U2U)*: It connects UAVs to UAVs. Multi-hop paths among aerial nodes extend coverage beyond any single UAV's range.
- *UAV-to-Ground (U2G)*: Communication with a Ground Base Station (GBS) facilitates command and control.
- *Satellite Communication (SATCOM)*: Near-global coverage for isolated or remote theaters, at the expense of higher latency and cost [19].

Regardless of the modality, effective scheduling and interference control become critical as UAV density rises or traffic demands increase.

2.3 Routing in MANETs

Most FANET routing protocols build on earlier MANET designs, adapted to the faster and more volatile dynamics of aerial nodes. These protocols can be broadly classified as topology-based or position-based, with various hybrid approaches in between [19].

2.3.1 *Topology-Based Protocols*

Proactive Protocols Proactive (table-driven) schemes, such as OLSR and Destination-Sequenced Distance Vector (DSDV), maintain current topology information at every node. While immediate route availability is useful, the periodic control overhead can be high, especially when UAV mobility invalidates routes rapidly [21].

Reactive Protocols Reactive (on-demand) protocols like AODV and Dynamic Source Routing protocol (DSR) discover routes when a node needs to send data [22]. Although this reduces overhead under light traffic, repeated route repairs become costly when UAV links break often. Nevertheless, AODV remains a popular choice because of its simplicity and adaptability, as demonstrated in several studies [23].

Hybrid Protocols Hybrid approaches (e.g., Zone Routing Protocol (ZRP)) exploit localized proactive updates for neighbors within a certain zone but use reactive discovery for more distant nodes [24]. Although promising for moderate levels of mobility, hybrid methods can still degrade if node movement is too frequent or unpredictable.

2.3.2 Position-Based Protocols

Position-based routing protocols (e.g., Greedy Perimeter Stateless Routing (GPSR)) forward packets to neighbors that are geographically closer to the destination [25]. While well-suited to large-scale or highly dynamic networks, GPSR requires accurate position data and suffers in the presence of voids or uncharted no-fly zones. High-altitude changes may also compound GPS accuracy issues, making purely geographic solutions less robust under real-world conditions.

2.3.3 Challenges and Future Trends

Recent research seeks to fuse routing logic with physical-layer conditions (e.g., SINR thresholds) and mobility predictions. However, most existing work still relies on local MAC-layer backoff strategies for collision avoidance [26, 27]. In heavy-traffic or interference-prone scenarios, purely reactive protocols can incur significant packet losses or route flaps. These challenges motivate more centralized scheduling approaches, which can systematically allocate transmission slots or manage interference across the whole network. Chapter 4 of this thesis demonstrates that such strategies can dramatically improve packet delivery rates compared to traditional MANET-based routing alone.

2.4 Mobility Models in MANET and FANET

Mobility profoundly affects link stability, throughput, and network lifetime in a FANET. While ground MANETs often assume random movements, UAVs may follow more structured paths for tasks like target tracking, area scanning, or formation flights.

2.4.1 Random-Based Mobility Models

- *Random Waypoint (RWP)*: Simple but can lead to unnatural node clustering and does not model deliberate flight patterns [28].

- *Random Direction (RD)*: Forces more uniform spatial distribution than RWP, yet remains insufficient for most mission-oriented UAV deployments.

2.4.2 Time-Based and Path-Based Models

- *Gauss-Markov (GM)*: Smooth speed and heading updates, capturing moderate real-world UAV dynamics [11].

- *Semi-Random Circular Movement (SRCM)*: UAVs orbit a designated region or point of interest, common in SAR scanning.

- *Flight Plan (FP)*: Predetermined waypoint sequences, useful in structured missions (e.g., delivery, environmental sampling).

2.4.3 Group- and Topology-Based Models

Leader-follower and swarm formations represent a collaborative approach, ensuring UAV spacing and coordinated trajectories [16]. Models like Self-Deployable Point Coverage (SDPC) adapt flight paths to maintain connectivity [11], yet still rarely incorporate advanced scheduling. As UAV counts rise and tasks become more complex, synergy between mobility planning and collision-free communication is increasingly necessary.

2.4.4 *Open Issues in Mobility Modeling*

Most mobility models remain disconnected from network scheduling considerations, typically relying on default Carrier Sense Multiple Access (CSMA) backoff. Under high load or dense UAV clusters, such local contention often breaks down, leading to collisions and route instability. Lack of integrated scheduling with mobility is a central focus of this thesis, wherein Chapter 3 addresses connectivity-oriented flight planning and Chapter 4 introduces a scheduling framework that capitalizes on global SINR-awareness.

2.5 Adaptations of MANET Protocols to FANET

Numerous papers have examined routing, mobility, and protocol optimizations in FANETs. Bujari *et al.*[11] survey UAV mobility models suitable for SAR, including scan and circle patterns for covering rectangular or circular target areas. They emphasize that multiple UAVs can speed up rescue tasks but may suffer from connectivity deficits unless carefully managed. Wen *et al.*[14] address local, delay-constrained routing, acknowledging that high UAV mobility hinders global topology knowledge. Tan *et al.*[22] compare topology-based and location-based routing under varying traffic loads, concluding that node density and UAV speed significantly increase packet drops. Among AODV, DSR, OLSR, and General Routing Problem (GRP), AODV fares well but still degrades as mobility intensifies. Leonov *et al.*[23] observe that AODV adapts quickly to moderate network changes with limited overhead. Meanwhile, expansions to AODV, such as Link Stability Estimation-based Preemptive Routing (LEPR) [29], leverage GPS data to track link stability more robustly, and BR-AODV [16] integrates a swarm-based mechanism to maintain routes. These improvements underscore AODV's popularity in FANET research, although they remain largely local or reactive in their handling of collisions.

In broader contexts, Liu *et al.*[30] propose a nanosatellite-UAV integration that reduces end-to-end delays in beyond-Line of Sight (LoS) scenarios. For large-scale testing, simulation remains vital. Liu *et al.*[30] use OPNET Modeler to validate multi-UAV architectures, showing how real-world trials often prove too costly for iterative refinements. Others compare UAV routing in ns-2 or ns-3, highlighting how parameter changes like transmission range or node density influence connectivity [31, 23]. A thorough overview of simulator features is provided by Dahiya *et al.*, who recommend ns-3 for its open-source flexibility and advanced tracing.

Notably, most existing work focuses on refining MANET-style routing or adjusting mobility for better coverage, with comparatively little attention to centralized, time-slot scheduling. As validated by the results in Chapter 4, such scheduling can dramatically mitigate collisions in dense or high-traffic FANETs, enhancing the reliability of multi-hop flows in ways that traditional backoff protocols cannot.

2.6 Simulation Tools for FANET Analysis

Simulation is indispensable for exploring complex UAV network scenarios at scale. Tools like ns-3, ns-2, OPNET, OMNeT++, QualNet, and NetSim each offer different balances of realism, ease of use, and extensibility. Table 2.1 contrasts their core features, showing that ns-3's open-source nature and packet-level detail make it especially attractive for academic research. However, implementing advanced scheduling (e.g., SINR-aware collision avoidance) often requires custom modules, as standard 802.11 MAC implementations focus on contention-based approaches.

2.7 Discussion and Chapter Summary

This literature review underscores how FANET research has matured in both routing and mobility modeling. Protocols such as AODV remain widespread, reflecting their reactive, on-demand simplicity; however, under heavy traffic loads, contention-based Medium Access Control (MAC) approaches can lead to collisions and suboptimal

Table 2.1: *Simulator Comparisons[1]*

Simulator	Language	OS	License	GUI	Ease of Use	UAV Usage	Network Support
ns-2	C++, OTcl	Win, Linux, Mac	Free, Open-Source	Limited	Hard	37%	Wired, Wireless, Ad Hoc
ns-3	C++, Python	Win, Linux, Mac	Free, GNU GPL	Yes	Hard	12%	Wired, Wireless, Ad Hoc, WSN
OPNET	C/C++	Solaris, Windows	Commercial	Yes	Easy	10%	Wireless, Ad Hoc, WSN
OMNeT++	C++	Win, Unix, Mac	Free, Commercial	Yes	Easy	5%	Wireless, Ad Hoc, WSN
QualNet	C++	Win, Unix, Mac	Commercial	Yes	Moderate	3.3%	Wired, Wireless, Ad Hoc, Mixed
NetSim	C, Java	Windows, Mac	Commercial	Yes	Easy	N/A	Wired, Wireless, Sensor

throughput. Meanwhile, advanced mobility schemes attempt to maintain connectivity or coverage, yet they often treat scheduling as an afterthought, relying on standard backoff or retransmissions.

A major gap, therefore, lies in the *integration of routing and scheduling*; particularly, where collisions are prevented by design rather than reacted to via retransmissions. Such integration is even more pressing in SAR operations, where timely data delivery can be mission-critical. The findings in this thesis aim to bridge this divide by proposing a collision-free scheduling framework and coupling it with path-planning methods that anticipate and accommodate real UAV trajectories.

The next chapters detail these contributions. Chapter 3 develops UAV trajectory optimizations to preserve network connectivity, thus mitigating the fragmentation risk identified throughout the literature. Chapter 4 then builds upon these ideas by introducing a trajectory-based scheduling framework that integrates routing logic with the capability to leverage link availability. We suggest implementing a scheduling mechanism for multi-UAV networks that relies on trajectory data to improve data delivery and reduce end-to-end delays by capitalizing on future trajectory information. Specifically, by analyzing both current and forthcoming trajectory data, our method determines the optimal node-to-neighbor data transmission path. This dual-time perspective—evaluating both present connectivity and its future evolution—enables more efficient scheduling decisions for each time slot. SAR operations.

3. NETWORK PERFORMANCE EVALUATION OF CONNECTIVITY-OPTIMIZED MULTI-UAV PATH PLANNERS

3.1 Introduction

Use of unmanned aerial vehicles (UAVs) or drones is considered for many civil applications including search and rescue, disaster management, surveillance, environmental monitoring, network coverage [12]. Many of these applications have data collection and/or delivery components, where UAVs can be utilized as sensing nodes, aerial base stations, or as relays. As such, teams of UAVs are treated as wireless sensor networks and/or FANETs.

For FANETs, the initial research focused on identifying the differences of aerial network characteristics from other ad hoc networks such as mobile ad hoc networks (MANETs) or Vehicular Ad hoc Networks (VANETs). To this end, many works analyze the performance of typical network architectures, such as Wireless Local Area Networks (WLANs), and routing protocols such as AODV, OLSR, Better Approach to Mobile Ad-hoc Networking B.A.T.M.A.N., etc. [10, 32, 19, 22]. The goal of these works is to determine the performance deficit, if any, of existing ad hoc routing protocols and propose solutions to address the deficit. Therefore, mobility of the UAVs is generally modelled using randomness-based mobility models (such as RWP, GM) or using sweeping or circling-based mobility [11, 33, 34]. On the other hand, works on the design of multi-UAV systems focus on designing UAV paths to achieve certain tasks and optimize certain parameters related to the application the UAVs are deployed for. Typical parameters to be optimized are coverage time, search time, travelled distance, detection probability, consumed energy, etc. For applications that require some form of connectivity, parameters such as network throughput [35], network lifetime [36], percentage connectivity [37], communication graph connectivity [38], data collection rate [39, 40], etc. can also be optimized. However, in these works communication models usually adopt a disc model, where the range is determined from measurements based on different wireless propagation models such as free-space, log-distance propagation models, or extension of these models to aerial links [41]. Therefore, the works on FANETs mainly focus on networking performance improvement of aerial networks and not necessarily UAV mission-based mobility paths, whereas multi-UAV path planners focus on mobility paths and not necessarily real-world network performance.

In this work, our goal is to bridge this gap and to analyze the network performance during a multi-UAV area coverage mission, where the UAV paths are designed taking into account the multi-hop connectivity based on a disc communication model. During the mission, the multi-UAV team senses an unknown area and continuously sends the data to a ground control base station (GBS). Many other UAV applications might require real-time transfer of data, such as video streaming data, telemetry data, or mission commands. *Our premise is that while the UAVs might be topologically connected for the connectivity-optimized paths, network performance in terms of PDR or throughput might not be at an acceptable level during the mission due to not only wireless channel characteristics but also due to the large number of hops, occurrence of congested hub nodes, or large number of nodes accessing the channel in the generated paths.* Therefore, experienced connectivity during the mission might not be as the mission planner aims. In this work, we analyze the network performance of a diverse set of path planners that model multi-UAV path planning as an optimization problem. We consider two different architectures. In the first architecture, all UAVs are both sensing and communication nodes, and their paths are jointly designed optimizing total mission time and percentage connectivity individually or simultaneously. In the second architecture, we consider an overlaying relay network consisting of communication UAVs positioned such that the sensing UAVs can deliver their data to the GBS [42]. With these different planning approaches, we aim to illustrate a diverse set of mission situations. To analyze the network performance, we use the network simulator ns-3, because it is open-source with good documentation; it contains the classical protocols in the protocol stack; it has the ability to analyze different types of wireless networks; and there are recent efforts to interface it with physics-based simulators. In fact, ns-2 and ns-3 simulators were used in almost 50% of the studies on FANETs [19].

In this chapter, we first generate mission path plans for a multi-UAV system optimized according to different criteria. We then format the generated paths to be used in ns-3. Within ns-3, we test the network performance during the multi-UAV mission in terms of packet delivery rate and average throughput. Our results show that when the transmission range is high enough, the aimed connectivity by the connectivity-optimized mission planners matches the experienced connectivity in the network simulator. However, when the range is low, the number of nodes is high, or fading is considered, the packet delivery rate can significantly drop for even the relay-assisted schemes. Therefore, when the paths are planned for missions that require some sort of connectivity, not only topological connectivity parameters but also network parameters or quality of service requirements need to be considered.

3.2 System Model

3.2.1 Mission Planner Environment and the UAVs

The mission parameters are defined in Table 3.1. The goal of the mission is to search a given area with a multi-UAV team and deliver the sensed data to the BS over possibly multi-hop links. The area of interest A is divided into equally-sized, disjoint cells such that each cell corresponds with the ground sensing coverage range r_s of the

Table 3.1: *Mission Parameters*

System Parameters	Definition
N_s, N_r	Number of search drones and relay drones
A	Total mission area
r_c, r_s	Transmission and sensing range
V_s, V_r	Maximum search and relay drone speed
t_s	Time step duration
F	Maximum flight time

UAVs. We consider multi-rotor UAVs which know their own positions and are capable of waypoint flying and hovering. We assume that UAVs fly at a given height from the ground. We consider two-types of UAVs: (i) mission UAVs are tasked with sensing and connecting and are equipped with onboard sensors and wireless interfaces; (ii) relay UAVs are tasked with only connecting mission UAVs and do not collect/generate own data.

3.2.2 UAV network simulation environment

In this work, we use ns-3 to simulate the UAV network. The ns-3 simulation script environment features a layered architecture that allows the evaluation of various protocols under predefined network conditions. Each layer corresponds to a specific aspect of the network, such as the physical layer, the link layer, or the network layer. In this work, our goal is to evaluate a typical configuration for a multi-UAV area coverage application. The performance metrics of interest are summarized below:

- *Percentage connectivity (p_c)* is the percentage of time UAVs are connected to the BS averaged over number of UAVs and the mission time.
- *Mission Time (T)* is the time taken to sense the area of interest.
- *Average throughput* is the average rate of data received at the sink node (BS) during the mission.
- *PDR* is the ratio of successfully delivered packets to the sink node.

In the following, we briefly explain each step for the UAV network simulator.

Node mobility modelling from planned mission paths In ns-3, the installed mobility model provides the next position for each node and nodes move to these positions in their successive iterations. There are several mobility models in ns-3, many of which work based on randomness. In this work, we define mission-oriented mobility, where the UAV paths are generated using different path planning algorithms. To simulate mission-oriented mobility, we use *Ns2MobilityHelper* class, which can read ns-2 movement files and configure nodes' mobility.

Data link layer, radio propagation, network and transport layer ns-3 provides various protocol stack modules to be used in simulations. In this work, 802.11a is chosen as the PHY and MAC layer protocol to be able to utilize findings and assumptions from our earlier field tests [43] and to avoid infrastructure-dependency. Due to the simulator structure, the selection can be changed to other protocols such as 802.11b/g/n/ac/ax. We use *WifiNetDevice* class from ns-3 to model a wireless network interface. *WifiNetDevice* works in conjunction with *WifiPhy* class, which manages the physical layer of wireless network, including modulation and demodulation of wireless signals, interference management and error handling. There are several models in ns-3 for channel and physical layer for a wireless network in ns-3. As a benchmark, first, the *FriisPropagationLossModel* is chosen for the channel model and the *YansWifiPhy* model is chosen for the physical layer. We also analyze the network performance under Rayleigh fading by configuring the *NakagamiPropagationLossModel*. The transmission power, data rate, and other properties of the *YansWifiPhy* are set in accordance with field measurements and mission plan assumptions.

For the transport layer, User Datagram Protocol (UDP) is chosen, as it is faster and less resource-intensive compared to the Transmission Control Protocol (TCP), though less reliable in terms of data delivery. Internet Protocol version4 (IPv4) protocol is implemented as the network layer protocol, which allows assignment of Internet Protocol (IP) addresses to the nodes in the network, and enables them to communicate with each other using this addressing scheme. Furthermore, AODV protocol, which forms the basis of many ad hoc routing protocols and current IEEE 802.11 mesh networks, is chosen.

Application layer Application layer refers to the highest layer of the protocol stack and is responsible for providing the interface between the network and the end-user applications. The sensing data traffic in the simulation is generated using the *OnOffApplication* class, which is a built-in class in ns-3 that implements a traffic pattern characterized by an on and off period. Specifically, the on time is set to 1 second and the off time is set to 2 seconds. The *OnOffApplication* class is chosen due to its ability to emulate the traffic patterns of real-world UAV networks.

Data collection Data collection is done using *FlowMonitor*, which is an important component in network simulation and monitoring tools. Its purpose is to observe and accurately report the statistics and characteristics of individual data flows in a simulated network. This monitoring tool collects a wide range of data, including details on the number of packets sent and received, end-to-end delay, end-to-end jitter, throughput, packet loss, and more for each individual session or communication flow on the network.

3.3 Multi-UAV Path Planners

In multi-UAV missions, the UAVs act as both a Wireless Sensor Network (WSN) and MANET, where they are responsible for sensing an area and delivering data to a GBS. Key applications include area coverage, search and rescue, surveillance, and remote monitoring. For these applications, UAVs are usually tasked with coverage of a given area, whereas some form of connectivity needs to be maintained between the UAVs and potentially a ground control station. Path planners for such missions are designed as single or multi-objective optimization problems, targeting parameters such as mission time and connectivity.

In this work, we consider various multi-UAV path planners, where the UAVs work as a team to sense an unknown area and deliver the sensed data to a ground base station over possibly multi-hop links. Therefore, the UAVs team is operating simultaneously as a wireless sensor network and a mobile ad hoc network. Area coverage, surveillance, search and rescue, remote monitoring are a few applications that have both such sense and connect tasks. For such missions, many multi-UAV path planners have been proposed, where the path planners are modeled as single or multi-objective optimization problems. The objective functions of interest in this paper are total mission time and percentage connectivity, defined below. For the joint optimization based schemes, we consider a single type of UAV, namely mission UAVs. For the sequentially optimized, relay based schemes, we consider both relay and mission UAVs .

We assume the UAVs are equipped with an omni-directional antenna setup such as in [43] and hence, assume a disc model for communication ranges.

In the following, we select representative path planners that individually or jointly optimize the aforementioned parameters for different UAV types.

3.3.1 Single and multi-objective optimization for mission UAVs

In this section, we assume that all UAVs in the system are mission UAVs and their paths are jointly optimized under the following constraints: (i) UAVs start and end their mission at the GBS ; (ii) each cell is visited only once; (iii) the sensing range, the node velocity, the maximum mission time, the number of nodes are limited to r_s, V_s, F, N_s, respectively. All optimization problems are solved using Genetic Algorithm (GA). The Objective Functions (OFs) and the path

- *OF1: Minimize total mission time*. This is a benchmark scheme, where the path planning problem is treated as a multiple travelling salesmen problem and the total mission time is minimized subject to above constraints.

- *OF2: Maximize percentage connectivity, p_c* . The UAV paths are optimized such that p_c is maximized, where p_c is defined as the mission duration the UAVs are connected to BS over possibly multi-hop links averaged over all UAVs and total mission time.

- *OF3: Minimize total mission time and maximize p_c*. This path planner models the multi-objective optimization problem as a weighted sum of T_n (Time normalized with respect to maximum allowed flight time) and p_c. We assume equal weights; i.e., $OF3 = \frac{1}{2}(T_n - p_c)$ [44].

3.3.2 Sequential optimization for mission and relay UAVs

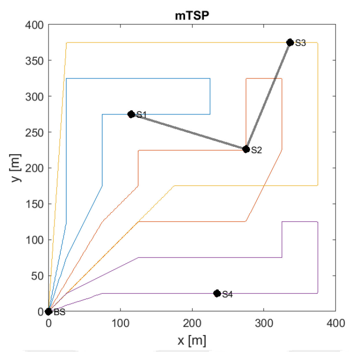
Here, we assume both mission and relay UAVs. The mission UAV paths are planned such that the total mission time is minimized as in $OF1$, without considering connectivity. Relay UAVs are then positioned such that the mission UAVs are connected to BS throughout the mission.

We consider the following relay network architectures:

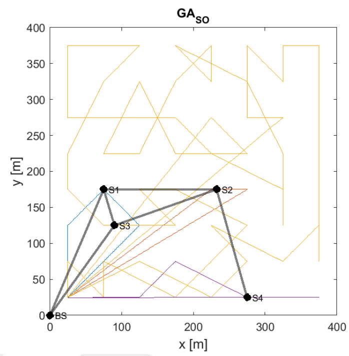
- *Static relays*: In this architecture, the mission area is divided into uniform cells, given the transmission range r_c and the total area A such that a minimum number of hovering relay UAVs can provide connectivity for the whole mission area. The relay UAVs form a grid-like mesh network.

- *Mobile relays*: In this architecture, a set of relay UAVs are positioned, given the mission UAV paths using a recently proposed dynamic relay positioning algorithm (RPA) [42]. RPA takes mission UAV paths as input and generates relay UAV paths such that the number of relay UAVs is minimized. The algorithm combines Steiner Tree Problem and minimum cost UAV assignment. For details, the reader is referred to [42].

Figure 3.1: *Generated multi-UAV path plans and network connectivity in the middle of the mission*



(a)



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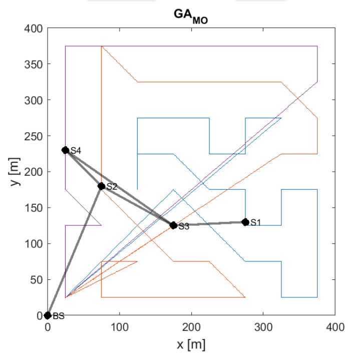

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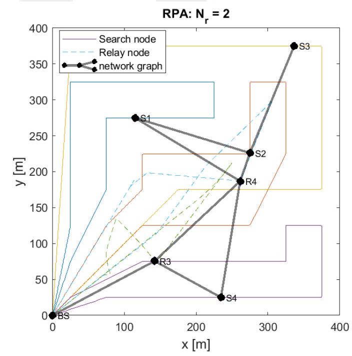


(d)

Figure 3.1 shows the generated multi-UAV path plans using the above four algorithms which, we denoted as multiple Traveling Salesman Problem (mTSP) (from $OF1$), GA_{SO} (from $OF2$), GA_{MO} (from $OF3$), and RPA. Number of search nodes is 4; area is $400mx400m$; r_c is 200m, r_s is 50m. The network graph snapshot in the middle of the mission is shown, where Si and Ri correspond to mission and relay UAVs, respectively. For the RPA scheme, number of relay UAVs is 2, and the mission UAV paths are the mTSP paths shown in Fig. 3.1(a). Observe that mission UAVs following mTSP paths are not connected to the BS as shown in Fig. 3.1(a) although the transmission range is high. When 2 relay nodes are added (shown in (d)) the connectivity is established, at the expense of 2 additional nodes. Fig. 3.1 (b) and (c) show that connected paths can be generated without relay UAVs, when connectivity is also optimized. However, this may come at a cost of longer mission times and longer paths for individual UAVs. For instance, GA_{SO} paths that maximize p_c lead to positioning of 3 UAVs such that a relay chain is formed, whereas 1 UAV senses the area. GA_{MO} paths, on the other hand, are more uniform in terms of distances travelled and are also providing connectivity.

3.4 Results and Analysis

In this section, we investigate the network performance of the provided multi-UAV path planners. The chosen simulation setting is given in Table 3.2. We run simulations for different parameter combinations, where we change the traffic rate, the transmission range and number of nodes. The chosen wireless network parameters are representative of a typical WiFi network. The mission plan is generated in MATLAB and the computed UAV coordinates are then formatted for use in *Ns2helper*. The population size and number of iterations for the genetic algorithm are 100 and 4000, respectively. These values are chosen by observing the progress of the GA solution. We have also tested the performance for OLSR and log-distance propagation model and observed that performance trends do not significantly change. Therefore, due to space limitations, these results are omitted.

3.4.1 Mission performance

Figure 3.2 shows the area coverage time for mTSP, RPA, GA_{SO} and GA_{MO} schemes. The mission UAV paths for mTSP and RPA are the same and do not depend on r_c, whereas GA_{SO} and GA_{MO} paths depend on the transmission range. Observe that the coverage time of mTSP and RPA for small N_s is significantly lower than the connectivity-optimized algorithms. As r_c is increased, the mission UAVs for GA_{SO} and GA_{MO} can

Table 3.2: *Simulation Parameters*

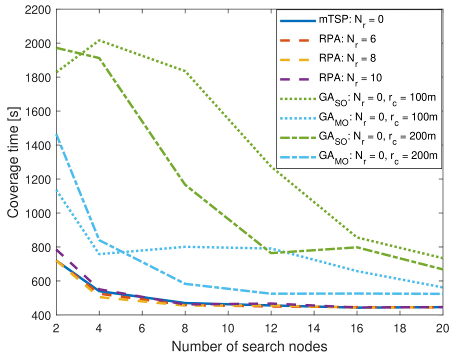
Simulation parameters	value
N_s	2, 4, 8, 12, 16, 20
Number of receiving nodes (sinks)	1
Packet size	1480 Bytes
MAC layer	802.11.a
r_c	100m ,200m
Transmit power	7dBm, 11dBm
Routing protocol	AODV
Mobility model	Ns2helper
Application traffic rate	100kbps, 500kbps
Propagation Model	Free space, Rayleigh fading
Simulation area	400mx400m
Simulation time	400-2000s
Maximum V_s, V_r	2.5m/s, 10m/s

spread faster and the coverage time is respectively reduced. When only connectivity is optimized, the mission time can be very high, whereas when p_c and T_n are jointly optimized, as N_s increases the performance approaches that of mTSP. When we analyze the p_c values, we observe that the trends are changed. RPA scheme utilizes additional relays and can guarantee close to 100% connectivity even for small N_s. When r_c is small, mTSP leads to p_c values less than 60% even for high N_s, whereas GA_{SO} and GA_{MO} can leverage coverage time for p_c and reach very high connectivity also for small N_s. When r_c is increased, all schemes reach full connectivity beyond a certain node density. For GA_{SO} and GA_{MO}, as low as 4 mission UAVs can cover the area at a reasonable time with above 80% connectivity. RPA also can guarantee connectivity with even 2 relay nodes.

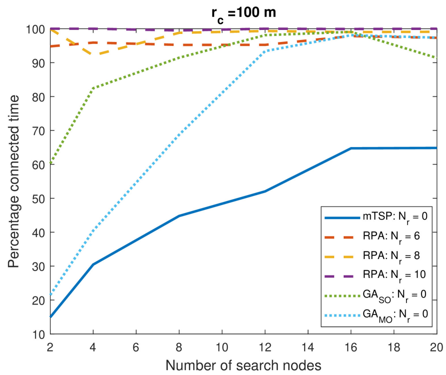
3.4.2 Network Performance

Figures 3.3 and 3.4 show the network performance in terms of average throughput and PDR for different transmission ranges and propagation losses. The traffic generated on mission UAVs is at 2 different levels (100kbps, 500kbps). The top row of the figures present results for $r_c = 100$m and bottom row corresponds to $r_c = 200$m. Figure 3.3

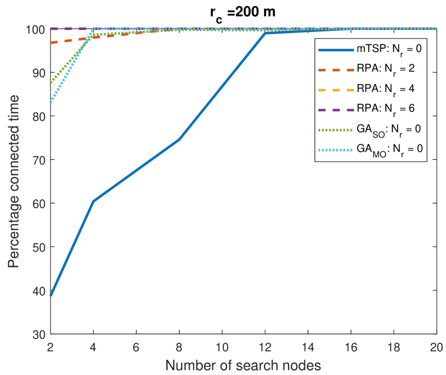
Figure 3.2: *Comparison of mission performance metrics*



(a) Coverage time vs N_s



(b) Percentage connectivity vs N_s for r_c = 100 m



(c) Percentage connectivity vs N_s for r_c = 200 m

shows the results for free-space propagation only, whereas Fig. 3.4 shows the performance for free space propagation with Rayleigh fading. In addition to RPA with mobile relays, we also provide results for static relay architecture as a benchmark. For this architecture, to cover the given simulation area, 16 and 4 hovering relay UAVs are placed in a square grid layout, when $r_c = 100$m and 200m, respectively.

As observed in Figure 3.2 (b) and (c), connectivity can be very low due to communication range constraints, especially in paths such as mTSP, where instantaneous connection between UAVs is not taken into account in the path plan. We can observe this trend also in the PDR results. Observe from Fig. 3.3(a) and (e) that thePDR of mTSP is similar to the computed percentage connectivity. However, for the path planners that take into account the connectivity in the design show some differences. In particular, both static and mobile relay-based schemes have lower PDRs, when $r_c = 100$m. When r_c is increased to 200m, PDR also implies full-time connectivity and data delivery, when traffic rate is low. When the rate is increased, PDR also decreases even for high transmission range. The results show that even if topology-wise all UAVs can reach the BS at all times, 100% PDR is not guaranteed depending on the transmission range and traffic rate. When r_c is smaller, the number of hops between the BS and the UAVs increase. Furthermore, although increasing N_s leads to higher network density, since more nodes need to access the wireless channel, probability of collisions also increases. Similar trend happens when the application traffic rate is increased.

Throughput results are more uniform between the different schemes. mTSP throughput is much lower as expected (2-4 times less than the other schemes for some cases). Both static and mobile relay based schemes perform similarly and better than the others. Clearly, use of additional nodes to support connectivity leads to significant improvements. But, results show that RPA can achieve as good a throughput as the static relay architecture at a fraction of a relay nodes (e.g., for $r_c = 100$m, RPA needs 6 relay nodes, whereas static architecture has 16 nodes). Therefore, as expected mobility improves capacity and utilization of the additional resources. The jointly optimized schemes on the other hand lead to throughput as well as the relay-based schemes, by simply better positioning the mission UAVs. However, these schemes tend to form relay-chains to provide connectivity (as shown in previous sections), which means that there will likely be some hub nodes that need to be shared by many others and some nodes flying longer than the others. This effect can be seen in Fig. 3.3 (d) and (h), where the throughput of GA_{SO} and GA_{MO} saturate earlier than the relay-based schemes.

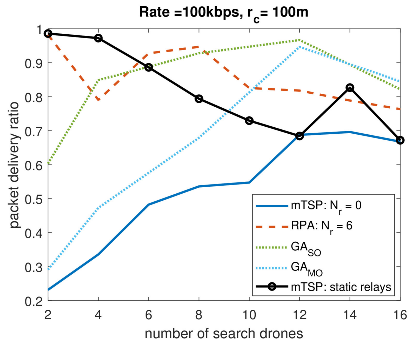
Figure 3.4 shows similar trends for the performance metrics, when Rayleigh fading is also considered. Recall that the investigated path planners that optimize connectivity consider a binary disc model; i.e., only nodes within r_c of each other can communicate with each other. Since the planners also aim to optimize time, it is likely that the UAVs are positioned at the very edge of the transmission range. However, in real-world fluctuations due to fading will occur and can be detrimental. Figure 3.4 illustrates this impact. Observe that in particular GA_{SO} and GA_{MO} suffer significantly due to fading. All schemes have much lower PDRs and throughput compared to free-space propagation case. The trends for relay-based schemes and mTSP remain similar, whereas GA_{SO} and GA_{MO} perform worse as the application traffic rate increases.

While these results show that certain performance improvements can be achieved in routes planned considering connectivity, they also indicate that further study is required on traffic scheduling and designing network protocols according to wireless channel and node positions.

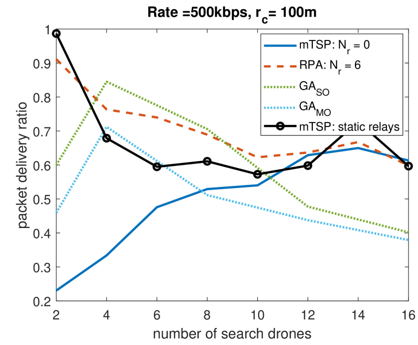
3.5 Summary

In this chapter, we analyzed the network performance of connectivity-optimized multi-UAV path planners. We showed that topologically connected multi-UAV paths not necessarily lead to acceptable network performance in terms of packet delivery rates and throughput. Connectivity optimized path planners that did not utilize additional relay nodes were more affected by channel imperfections such as fading. Relay assisted schemes that aim to utilize minimum number of relay nodes on the other hand also led to worse performance than estimated by the path planners, due to occurrence of hub nodes that need to carry a high amount of traffic. Therefore, for missions that require a form of connectivity, paths need to be planned taking into account network parameters for an acceptable real-world performance.

Figure 3.3: *PDR and average throughput comparison with large scale fading*



(a)



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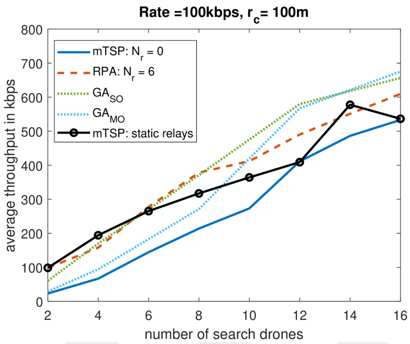

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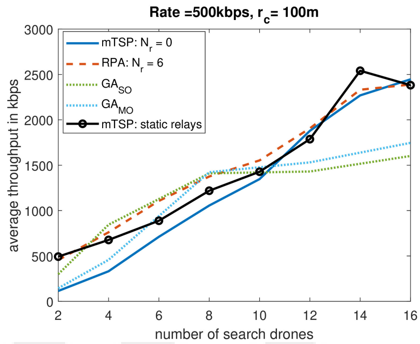

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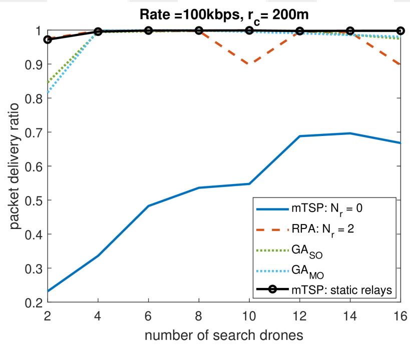
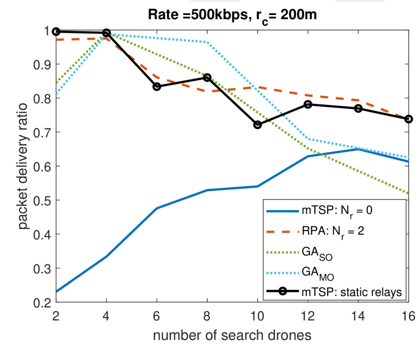
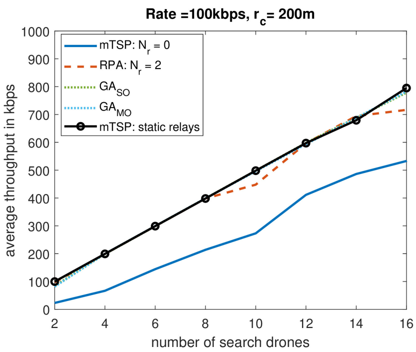


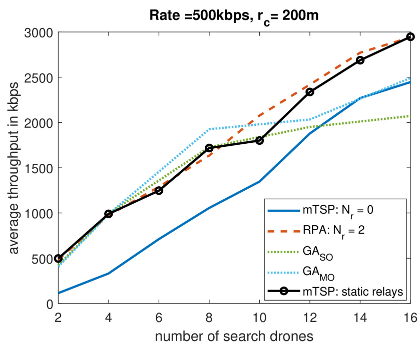
(e)



(f)

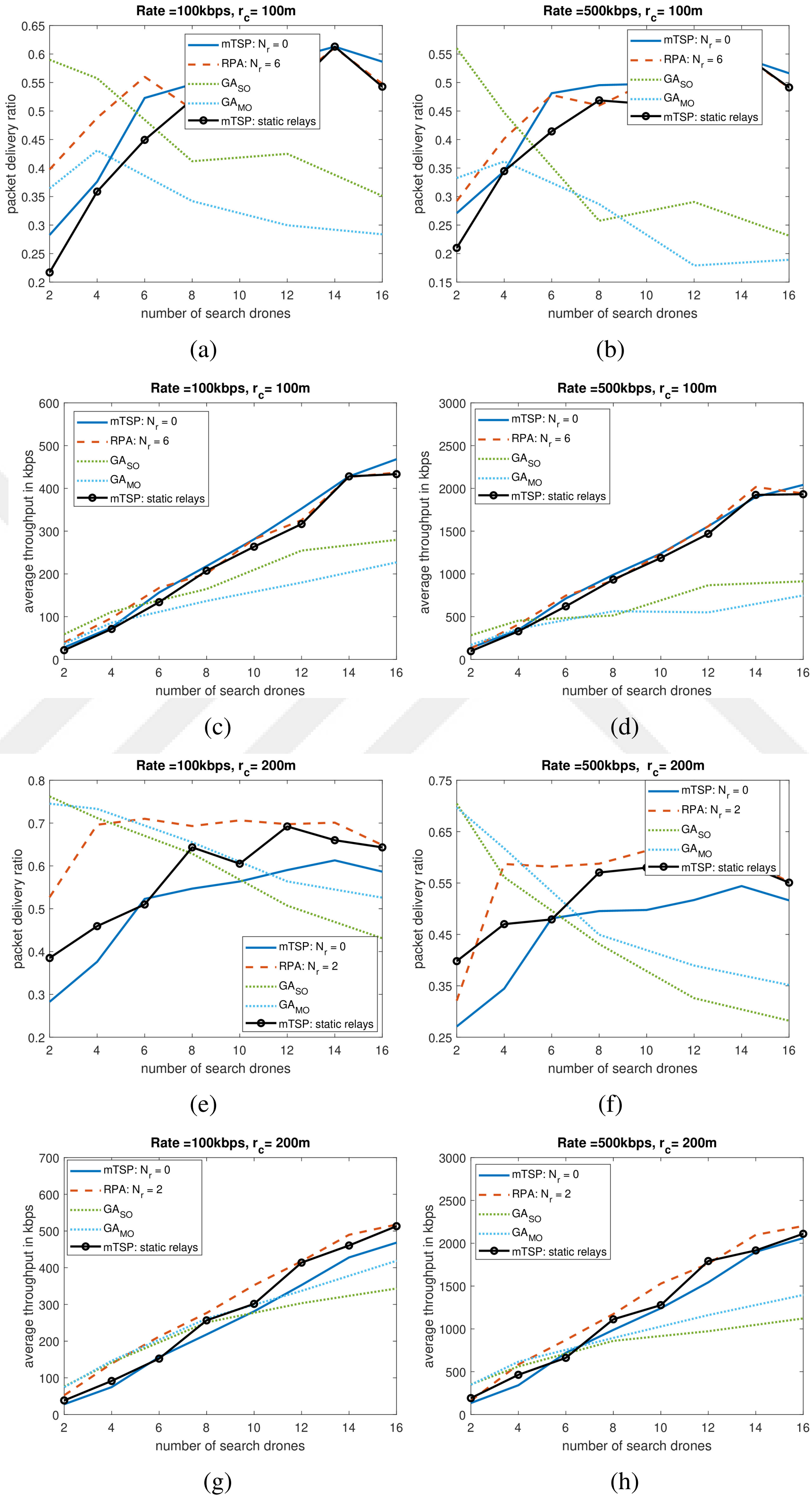


(g)



(h)

Figure 3.4: *PDR and average throughput comparison with large scale and Rayleigh fading*



4. OPTIMIZED TRAFFIC SCHEDULING AND FORWARDING FOR MULTI-UAV TEAM CONNECTIVITY DURING SEARCH AND RESCUE MISSIONS

4.1 Introduction

Multi-hop wireless networks often rely on intermediate nodes to relay data to a central BS. The AODV protocol is a well-known baseline solution that discovers routes based on hop count through reactive route requests and replies. In stable or low-mobility networks, AODV can perform well, achieving high packet delivery ratios with minimal complexity. However, it does not explicitly leverage future connectivity or node trajectory data to optimize packet scheduling.

This chapter introduces a **trajectory-based scheduling approach** designed to utilize network topology and node movements for more efficient packet delivery. By predicting future link availability, nodes can forward packets through neighbors that will soon have a direct connection to the BS, thereby reducing end-to-end delay. Although the tested scenarios involve relatively low node mobility and idealized assumptions (such as unlimited buffers and no MAC-layer losses), our experiments reveal that this scheduling mechanism has the potential to outperform classical hop-based routing—especially in more dynamic network environments. The remainder of the chapter details the environment design, scheduling algorithm, simulation setup, and performance evaluation that underpin this comparison.

4.2 Methodology

In this chapter, we re-evaluate network performance in a multi-UAV network, where drones cooperate to deliver data to a central BS. We propose a trajectory-based scheduling approach that leverages node mobility to optimize throughput while minimizing delay. Additionally, we employ a refined version of the classical AODV protocol, designed to maintain fresh routes and ensure that each data packet is transmitted through a distinct route at any given time. Both methods share the same fundamental queue management and link capacity models, ensuring that any performance differences arise solely from the scheduling logic. This allows us to quantify the impact of trajectory information on network performance, demonstrating its potential to enhance both delay reduction and throughput improvement.

4.2.1 Network Model and Assumptions

Each node in the network maintains a First-in First-out (FIFO) queue for packet storage. All nodes except BS operate in half-duplex transmission mode. To isolate and evaluate the impact of utilizing trajectory information on network performance, we relax the queue size constraint to infinity. Additionally, to assess the worst-case performance comparison with AODV, we assume that AODV is also refined and operates under the following conditions:

- **Out-of-Band Control Packets**: The control overhead for constructing and maintaining routes does not consume data channel capacity.
- **Freshness**: All nodes update their routes in every time slot to always use the most recent routes.
- **Unlimited Buffers**: No packet drops occur due to queue overflow, ensuring that every generated packet remains in the queue until transmission.

In the trajectory-based scheduler, the utilization of an unlimited buffer size significantly contributes to a high PDR. Similarly, the AODV protocol also achieves a high

PDR by employing a combination of an unlimited buffer, out-of-band control packets, and frequent route updates.

4.2.2 Scheduling Algorithm

The trajectory-based scheduling approach dynamically determines which node should transmit packets in each time slot and the intended recipient. This decision process leverages both current connectivity and future connectivity, characterized as "time-to-BS." The fundamental mechanism is implemented as follows:

1. Each node continuously evaluates its available links based on the current network topology. When a node has a direct link to the BS, it greedily transmits as many packets as the link's capacity permits. In the absence of a direct link, the node calculates its own "time-to-BS", i.e., the estimated number of time slots until a direct connection with the BS becomes available based on its trajectory.

2. To this end, the node examines its neighboring nodes. Neighbors with a direct link to the BS are excluded from this consideration, as they are assumed to transmit directly. For each remaining neighbor, the node evaluates the neighbor's estimated time-to-BS. Let the candidate set be defined as

   $$\mathcal{S} = \{i \mid i \in \{\text{self}\} \cup \{\text{neighbors without a direct BS link}\}\}.$$

   The node then selects the candidate j^* such that

   $$j^* = \arg\min_{i \in \mathcal{S}} \text{time-to-BS}(i).$$

   This choice ensures that the packet is forwarded to the node with the minimal estimated time-to-BS, thereby optimizing the overall transmission process.

3. Once the optimal forwarding option is determined, the status of the involved nodes are updated from idle to busy. During transmission, the node sends as many packets as permitted by the capacity of the chosen connection, following a FIFO queue

discipline. If the packet is forwarded to a relay node rather than directly to the BS, the packet is appended to the relay's queue for subsequent forwarding. Finally, each packet that successfully reaches the BS is considered delivered, and its delay—defined as the difference between the current time and its generation time—is recorded.

4. Each node independently undergoes this process, evaluating its situation with the remaining pool of idle neighbors. If a neighboring node exhibits superior link quality and a shorter estimated time-to-BS, the node forwards its packets accordingly. Conversely, if the node itself is deemed the best candidate among its neighbors, it retains the packets for subsequent transmission.

5. This sequential decision-making process of 1–4 is repeated at every time step.

   Note: This greedy transmission to the BS and sequential selection of the best neighboring candidate may lead to sub-optimal performance; however, it substantially reduces the computational complexity compared to assessing all nodes in parallel.

4.2.3 Performance Evaluation Metrics

As the assumptions presented earlier in Section 4.2.1 for the scheduler and AODV yield the PDR to be 1 for the scheduler and nearly 1 for AODV, we focus our analysis on the delay of data delivery to the BS by examining both the Cumulative distribution function (CDF) and the average delay:

- **Average End-to-End Delay**: Measured as the total time elapsed from when a packet is generated until it is delivered to the BS.
- **CDF of Packet Delivery Times**: This metric provides a detailed view of the delivery delay profile. The CDF shows the fraction of packets delivered by a given time,

allowing us to assess not only the average delay but also the spread of delays. A higher CDF indicates faster and more consistent packet delivery.

4.3 Network Topology and Capacity Calculations

The received power and link capacity calculation in an Additive White Gaussian noise (AWGN) channel primarily relies on the path loss, which is a function of the distance between nodes. For two nodes located at (x_i, y_i) and (x_j, y_j), the distance between them is given by:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}.$$

This distance also determines whether the nodes are considered connected. Specifically, if d_{ij} is less than a predefined threshold distance r_c, a link is assumed to exist between the nodes.

Once the distance is known, the link capacity is computed based on the AWGN channel model. The channel capacity in bits per second is given by Shannon's theorem:

$$C_{ij} = BW \cdot \log_2 \left(1 + SNR_{ij}\right),$$

where BW is the channel bandwidth and SNR_{ij} is the signal-to-noise ratio between nodes i and j. The Signal-to-Noise Ratio (SNR) is estimated using a free-space path loss model:

$$\text{SNR}_{ij} = \frac{P_{\text{tx}} \cdot \left(\frac{\lambda}{4\pi d_{ij}}\right)^2}{\text{Noise Power}},$$

with P_{tx} as the transmission power, λ as the wavelength (computed by $\lambda = \frac{c}{f}$, where c is the speed of light and f is the frequency), and the Noise Power is given by $BW \cdot N_0$, where N_0 is the noise power spectral density (often computed as $N_0 = k \cdot T$, with k as Boltzmann's constant and T as the noise temperature). The capacity is then converted into a number of packets per slot by dividing by the packet size (in bits):

$$\text{Capacity in Packets} = \left\lfloor \frac{C_{ij}}{\text{Packet Size (bits)}} \right\rfloor.$$

Table 4.1: *Simulator Parameters*

Simulation parameters	**Value**
Path type	mTSP, GA_{SO}, GA_{MO}
N_s	4-12
Distance Threshold	100.0
Traffic Period (T)	2015 time slots
Flush Window	0
Total Simulation Time	400-2000s
Packet Size	1480 Bytes
Traffic rate	100kbps
r_c	100m
Transmission Power	0.005 W
Bandwidth	20 MHz
Frequency	5.25 GHz

4.4 Results and Discussion

In this section, we compare the performance of the AODV routing protocol with the proposed trajectory-based scheduling approach that leverages node trajectories to minimize the delay in data transmission to the BS. The simulations were conducted using three different mobility path sets—with objectives $OF1$, $OF2$, and $OF3$, as defined in Chapter 3(3.3.1)—across networks containing 4 and 12 search nodes. These paths correspond to mTSP, GA_{SO}, and GA_{MO} algorithms, respectively.

As shown in Table 4.1, we evaluate three distinct multi-UAV networks in these three path-planning strategies. The simulations are performed for networks with $N_s \in \{4, 12\}$, with a distance threshold of 100.0 to determine whether two nodes can establish a link. Total simulation time is between 400 and 2000 seconds. Packet sizes are fixed at 1480 Bytes, and the traffic load is 100 kbps. We set the communication range r_c to 100 m and the transmission power to 0.005 W. The channel operates at 5.25 GHz with a 20 MHz bandwidth. By adjusting these parameters, we can systematically assess the performance of different path-planning and routing protocols under a range of realistic conditions for multi-UAV networks.

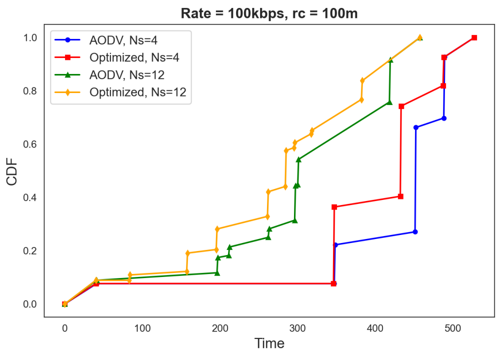
Figures 4.1-4.3 present the CDF plots and average delays for the mTSP, GA_{SO} and GA_{MO} paths for the fraction of packets delivered at 100 kbps, comparing the performance of AODV with the trajectory-based scheduling approach for 4 and 12 search nodes. In these scenarios, the trajectory-based scheduler generally outperforms AODV. As the number of nodes increases (from 4 to 12), the probability of constructing more routes with the BS increases. Consequently, AODV might experience a slight improvement in data transmission delay, and the performance gap between the scheduler and AODV becomes less pronounced. For the mTSP paths (Fig. 4.1), since connectivity is not optimized, when $N_s = 4$, most drones are not connected to the BS during the mission. Therefore, most packets are delivered as the drones fly back toward the BS. But, even in this case, the scheduler leads to better allocation of resources as it aims to deliver the packets to the drones that will connect to the BS faster. When GA_{SO} is used (Fig. 4.2), the more connected nature of the drone network leads to more uniform packet delivery over time, trading-off mission time. GA_{MO} paths on the other hand, lead to a delivery performance in between mTSP and GA_{SO}, by jointly optimizing connectivity and mission times.

The average delay performance for all path algorithms lead to an improved performance over AODV with the proposed scheduler. The results show that specially for sparse networks significant improvements can be achieved with an optimized forwarding strategy.

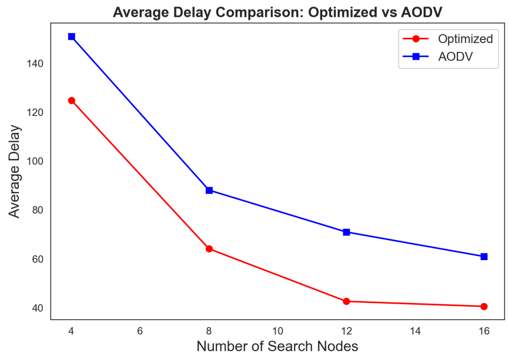
4.5 Summary

In this Chapter, we leveraged trajectory information to route data packets from search nodes to the BS. The simulation results indicate that when trajectory information is available in advance, in most cases, packets can be routed to the BS in a shorter time, thereby making the network more suitable for mission-critical applications. Further investigation is required for heavier traffic loads and denser networks.

Figure 4.1: *CDF and average delay for the mTSP path set at 100 kbps for* $N_s = 4$ *and* $N_s = 12$.

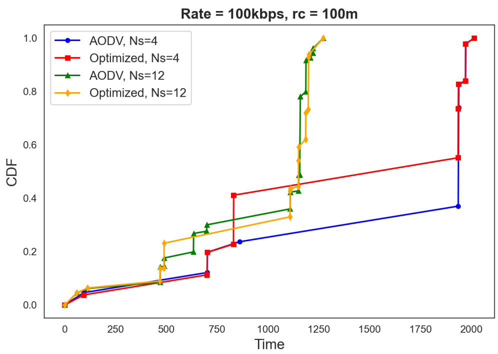


(a) Packet delivery time CDF

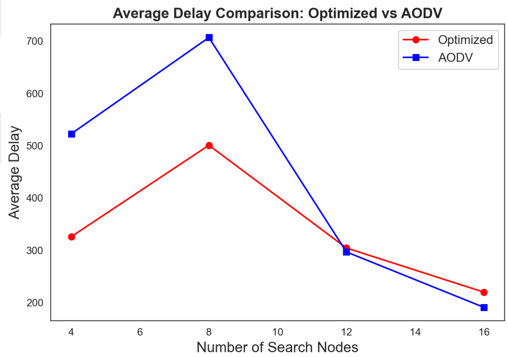


(b) Average delay in s

Figure 4.2: *CDF and average delay for the* GA_{SO} *path set at 100 kbps for* $N_s = 4$ *and* $N_s = 12$.

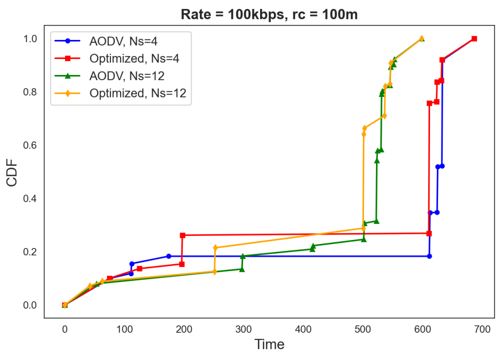


(a) Packet delivery time CDF

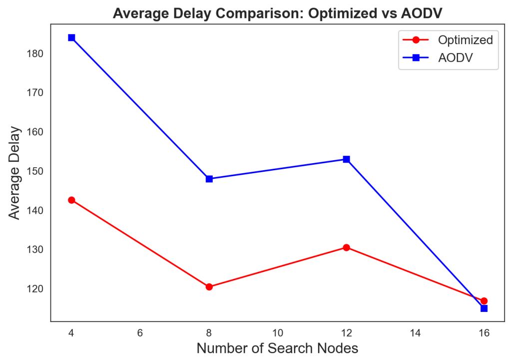


(b) Average delay in s

Figure 4.3: *CDF and average delay for the* GA_{MO} *path set at 100 kbps for* $N_s = 4$ *and* $N_s = 12$.



(a) Packet delivery time CDF



(b) Average delay in s

5. CONCLUSION

In this thesis, we have investigated the problem of reliable network provisioning in multi-UAV systems used for SAR missions. The primary objective has been to bridge the gap between mission-oriented path planning and realistic wireless network performance. While existing literature often focuses either on network protocols under idealized mobility models or on mission planning without rigorous communication analysis, this work demonstrates the value of jointly considering detailed wireless connectivity, channel conditions, and dynamic UAV mobility.

Chapter 3 of the thesis addressed multi-objective path planners intended to optimize both the total mission time and connectivity. Representative approaches included mTSP, GA_{SO}, and GA_{MO}, which respectively minimized overall mission times, maximized connectivity to the BS, or struck a balance between these two parameters. Additionally, a relay-based strategy introduced extra UAVs to form a dedicated aerial backbone. The simulation results, obtained via the ns-3 network simulator, showed that—even for connectivity-optimized algorithms—the presence of fading, congestion, or hub overloading can degrade the anticipated PDR and throughput. This indicates that purely geometry-based or disc-model connectivity assumptions can overlook the complexity of real-world wireless channels.

Building on these observations, Chapter 4 focused on a trajectory-based scheduling algorithm designed to exploit knowledge of each UAV's future movement. Instead of merely relying on reactive hop-count protocols, each node predicts its own time-to-BS and compares it with that of its neighbors. Nodes then forward their packets to whichever neighbor will connect to the BS soonest, thereby reducing latency. Under optimistic network conditions—where buffer overflow issues are eliminated and frequent route updates are permitted in AODV, and control packet overhead of these route updates is assumed to be out-of-band—the AODV protocol exploits these ideal assumptions more effectively than the scheduler. Consequently, AODV appears to operate more efficiently than would be expected in real-world environments, leading to an overestimation of its performance. Nevertheless, even under these worst-case conditions, the proposed scheduling mechanism effectively outperforms AODV and reduces end-to-end delivery delays across all file path types mTSP, GA_{SO}, and GA_{MO}. However, For GA_{SO} and GA_{MO}, which strive to maintain connectivity throughout the mission, increasing the number of nodes raises the likelihood of forming multiple routes to the BS. Consequently, the performance of both AODV and the trajectory-based scheduler becomes similar.

Although the scheduling approach yielded promising results, several open challenges remain. First, buffer limitations and realistic medium access control must be incorporated to account for queue buildups, collisions, and retransmissions. Furthermore, energy consumption and battery constraints will be critical factors in real multi-UAV operations, especially when mission durations are extended or when continuous hovering drains the power supply. The reliability of channel-state information under non-LoS or heavily obstructed conditions poses another significant challenge that can drastically influence connectivity. It will also be crucial to analyze how real-time mission updates or unexpected events affect predictive scheduling decisions.

For future work, we plan to extend the trajectory-based scheduling mechanism introduced in Chapter 4 by integrating it more deeply into the network protocol stack in ns-3. In Chapter 3, we utilized AODV-based routing to evaluate various mission path planners. We now aim to replace or complement that reactive approach with our proposed scheduler and compare both methods under a full communication stack. This setup will allow us to account for buffer management, collisions, and retransmissions, thus providing a more comprehensive and realistic evaluation. In doing so, we aim to gain deeper insights into how predictive scheduling, combined with multi-objective mission planning, can deliver improved performance in actual deployments of multi-UAV networks. Such an integrated framework—assessed under more stringent ns-3 conditions—will facilitate a reliable comparison and guide the development of protocols better aligned with real-world flight scenarios and mission constraints.

In conclusion, this thesis has demonstrated that UAV missions requiring both coverage and efficient data forwarding can benefit substantially from trajectory-aware routing strategies. By combining mission objectives and realistic wireless models, the proposed framework moves beyond purely geometric considerations of connectivity and provides a more robust and delay-optimized solution for mission-critical multi-UAV networks. These insights form the foundation for designing next-generation aerial communication systems capable of operating reliably under the inherent uncertainty and constraints of real SAR scenarios.

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