

**SEARCH AND RESCUE WITH MULTIPLE UAVS:
TARGET DETECTION AND CONNECTIVITY**



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SEARCH AND RESCUE WITH MULTIPLE UAVS: TARGET DETECTION AND CONNECTIVITY

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To my advisor and mentors, whose guidance, patience, and wisdom have been invaluable in shaping both this research and my personal growth.



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

In this thesis, we present a multiple Unmanned Aerial Vehicle (UAV) system for Search and Rescue (SAR) missions, focusing on efficient target detection, connectivity, and task assignment. The proposed framework addresses critical challenges in large-scale disaster scenarios, where UAVs must collaboratively detect, monitor, and maintain connectivity with multiple targets. To achieve these objectives, we employ two kinds of UAVs: search UAVs equipped with onboard sensors for rapid area scanning and relay UAVs that establish and sustain network connectivity among UAVs, targets, and Ground Control Station (GCS). Multiple target detection and connectivity strategies with varying levels of adaptability are proposed: (i) maintaining pre-planned paths while communicating detected targets to the GCS, (ii) deploying additional UAVs for monitoring detected targets without disrupting ongoing search operations, and (iii) dynamically re-planning UAV paths by assigning search UAVs to detected targets, providing the highest level of responsiveness to dynamic conditions. Our results demonstrate that less adaptive strategies achieve faster target detection but often compromise connectivity. Conversely, more adaptive methods significantly improve network performance at the expense of increased mission time. Integrating relay UAVs enhances connectivity by up to 60% compared to baseline planners, with the cost of increasing total mission time by up to 40% in specific configurations. An innovative connectivity-based target prioritization method is integrated into the proposed dynamic path planning algorithms for multi-UAV systems, customizing it for search and rescue missions. Our findings highlight the trade-offs between detection efficiency, network reliability, and overall mission time, providing valuable insights for deploying UAV systems in SAR missions.

Keywords: drone network, UAVs, relay positioning, path planning, target priority

ÖZET

Bu tezde, Arama ve Kurtarma (AvK) görevleri için etkili hedef tespiti, bağlantı sağlama ve görev ataması üzerinde yoğunlaşan entegre bir çoklu İnsansız Hava Aracı (İHA) sistemi sunulmaktadır. Önerilen yapı, İHA'ların geniş ölçekli felaket senaryolarında birden fazla hedefi iş birliği içinde tespit etme, izleme ve gerekli bağlantıları sürdürme gibi kritik zorluklara çözüm getirmeyi amaçlamaktadır. Bu hedeflere ulaşmak için iki tür İHA kullanılmaktadır: hızlı alan taraması yapmak üzere yerleşik sensörlerle donatılmış arama İHA'ları ve İHA'lar, hedefler ve yer kontrol istasyonu arasında ağ bağlantısını kurup sürdüren röle İHA'ları. Tezde, değişken uyarlanabilirlik seviyelerine sahip üç farklı hedef tespiti ve bağlantı stratejisi sunulmaktadır: (i) Önceden planlanmış rotalar takip edilirken, tespit edilen hedeflerin yer kontrol istasyonuna (GCS) bildirilmesi, (ii) Devam eden arama operasyonlarını kesintiye uğratmadan, tespit edilen hedefleri izlemek için ek İHA'ların konuşlandırılması, (iii) Tespit edilen hedeflere arama İHA'ları atanarak İHA yollarının dinamik şekilde yeniden planlanması. Elde edilen sonuçlar, daha az uyarlanabilir stratejilerin daha hızlı hedef tespiti sağladığını ancak bağlantının güvenilirliğini tehlikeye attığını göstermektedir. Buna karşılık, daha uyarlanabilir stratejiler ağ performansını önemli ölçüde iyileştirirken, görev süresinin uzaması gibi bir maliyete sahiptir. Özellikle, röle İHA'larının entegrasyonu, temel planlayıcılara kıyasla bağlantı performansını %60'a kadar artırırken, toplam görev süresini belirli yapılandırmalarda %40'a kadar uzatabilmektedir. Bu stratejilere ek olarak, arama ve kurtarma görevlerinde çoklu İHA sistemleri için dinamik konumlandırma ve yol planlamasına yönelik yeni bir bağlantı tabanlı hedef önceliklendirme yöntemi de önerilmiş ve farklı hedefler için sağlanabilen bağlantı kalitesi bakımından incelenmiştir.

Anahtar Kelimeler: drone ağı, insansız hava araçları, röle konumlandırma, rota planlama,

hedef önceliđi



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TABLE OF CONTENTS

DECLARATION OF ORIGINALITY	iv
ABSTRACT	v
ÖZET	vi
ACKNOWLEDGEMENTS	viii
LIST OF TABLES	xi
LIST OF FIGURES	xii
LIST OF ACRONYMS AND ABBREVIATIONS	xiv
1 INTRODUCTION	1
1.1 Search and Rescue Missions	1
1.2 Background: Drones in Search and Rescue Missions	2
1.3 Motivation	4
1.4 Problem Definition	7
1.5 Contribution	10
1.6 Thesis Outline	11
2 LITERATURE SURVEY	12
2.1 Ground Target Connectivity: Aerial Base Stations (Relay Drones)	13
2.2 Search and/or Relay Nodes: Search and Coverage Missions	18
2.3 UAV Path Planning as an Optimization Problem	24
2.4 Multi-Target multi-drone search and rescue under target prioritization in the SARs	27
3 SYSTEM MODEL AND ASSUMPTIONS	32
3.1 The UAVs and Mission Environment	32
3.2 UAV navigation	35
3.2.1 Performance metrics	35
3.3 Mathematical Formulation	36

3.3.1	Basic Search Path Planning	37
3.3.2	Basic Relay Positioning Algorithm (RPA)	38
4	DYNAMIC MULTI-UAV POSITIONING AND ASSIGNMENT ALGORITHM FOR MULTI-TARGET SEARCH AND CONNECTIVITY	41
4.1	Mission Overview	41
4.2	Drone Roles in Distinct Phases of the Mission	43
4.2.1	Phase 1: From Drone Take-off at GCS to the First Target Detection	44
4.2.2	Phase 2: Time interval between the detection of the first and last target	44
4.2.3	Phase 3: Time interval between the final target detection till the end of mission	48
4.3	Mission Phase Visualization	51
4.4	Results and Discussions	54
4.4.1	Benchmark planners	55
4.4.2	Required resources	59
4.4.3	Mission phase times	60
4.4.4	Connectivity	61
4.5	Summary	63
5	PRIORITY-BASED DYNAMIC MULTI-UAV PATH PLANNING ALGORITHM FOR MULTI-TARGET SEARCH AND CONNECTIVITY	65
5.1	Target Prioritization	65
5.2	Mission Overview	66
5.3	Priority-based Dynamic UAV Path Planning Algorithm	67
5.4	Target coverage visualization based on priority levels	69
5.5	Results and Discussions	69
5.6	Summary	73
6	CONCLUSIONS	74
	REFERENCES	76
	APPENDICES	84

LIST OF TABLES

Table 2.1: Relay Drone Optimization Criteria for Flight Trajectory Planning or Repositioning, Category 1.	14
Table 2.2: Relay Drone Optimization Criteria for Flight Trajectory Planning or Repositioning, Category 2.	19
Table 3.1: System Parameters.	33
Table 4.1: The algorithmic complexity of the path planners.	56



LIST OF FIGURES

Figure 1.1: Some scenes of disasters where urban infrastructure is destroyed [1, 2, 3, 4].	3
Figure 1.2: Frequency of the worldwide earthquakes between 2000 to 2023 [5]. ...	5
Figure 1.3: Frequency of the Turkey earthquakes between 1990 to 2024 [6].	6
Figure 1.4: Frequency of the Turkey wildfire between 2009 to 2024 [7].	7
Figure 3.1: Drone interfaces: (a) The interfaces of search and injected drone shown in white and green, respectively, (b) interface of relay drone.	33
Figure 3.2: Illustration of the multi-target SAR mission. Pre-planned search paths for two drones are depicted in blue and red solid lines. a) In EDPPP, search nodes adhere to pre-planned paths until the last target is detected. An injected node is shown in green and dispatched from the GCS to cover the newly detected target. b) In DAPP, the detecting search node hovers over the target, and path-replanning is performed for the remaining drones in the air, indicated by the dashed lines.	40
Figure 4.1: Multi-target search and connect workflow.	42
Figure 4.2: Final configuration of the multi-target search and connectivity mission. The graph of the network is shown in grey; <i>diamond</i> represents the four generated target random positions; The relay nodes labeled R1 and R2 and the search nodes labeled S1 to S4 represent the relay and search nodes, respectively.....	52
Figure 4.3: mTSP-computed Pre-detection search paths. The solid lines depict the flown paths of search nodes S1 to S4. The relay nodes (R1 to R3) flown paths are depicted in dashed lines. The flown paths by injected nodes IN1 and IN2 are depicted by dash-dotted lines. In subfigures c and d, lines get thinner to represent the re-planned paths.....	53
Figure 4.4: Comparison of detection times and connectivity versus number of search nodes (benchmark search algorithms).	57
Figure 4.5: Comparison of the connectivity and mission time metrics versus number of search nodes (benchmark search algorithms).	57
Figure 4.6: Resource utilization vs number of deployed search nodes.....	58
Figure 4.7: Analysis of path lengths versus the number of deployed search nodes. .	60

Figure 4.8: Comparison of mission phase times vs a number of deployed search nodes.	61
Figure 4.9: Analysis of connectivity metrics as a function of the number of search nodes.	62
Figure 4.10: Comparison of disconnected times vs the number of the deployed search nodes.	64
Figure 5.1: Example paths for 4 search nodes and 3 targets with different priority. The dotted and solid lines are the predefined and flown search paths respectively. The path of the injected node (shown in the dashed line) to cover the medium-priority target. Si, INi, and Ri correspond to labels for search, injected, and relay nodes, respectively.	70
Figure 5.2: Mission phase times vs a number of deployed search nodes in multiple-target search.	71
Figure 5.3: Comparison of target connectivity and injected resources vs a number of deployed search drones in multiple-target searches.	72

LIST OF ACRONYMS AND ABBREVIATIONS

SAR	Search and Rescue
AvK	Arama ve Kurtarma
İHA	İnsansız Hava Aracı
UAV	Unmanned Aerial Vehicle
WMO	the World Meteorological Organization
RCC	Rescue Coordination Center
GCS	Ground Control Station
INSARAG	International Search and Rescue Advisory Group
AI	Artificial Intelligence
AFAD	Turkey Disaster and Emergency Management Authority
IoT	Internet of Things
MST	Minimum Spanning Tree
UN	United Nation
US	United States
RPA	Relay Positioning Algorithm
DPPP	Detection Priority Path Planning
EDPPP	Extended Detection Priority Path Planning
DAPP	Detection Adaptive Path Planning
GPU	Graphics Processing Units
D2D	device-to-device

LEACH	Leveraging Low-Energy Adaptive Clustering
MEC	Mobile-Edge Computing
RISs	Reconfigurable Intelligent Surfaces
LoS	Line-of-Sight
UNDRR	United Nations Office for Disaster Risk Reduction
MPC	Model-Predictive Control
CSs	Charging Stations
QoS	Quality-of-Service
IGA	Improved Genetic Algorithm
GNs	Ground Nodes
MOEA	Multi-Objective Evolutionary Algorithm
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
E2E	End-to-End
MILP	Mixed Integer Linear Programming
ISSRM	Integrated Sensor Selection and Routing Model
PSO	Particle Swarm Optimization
MPOMDP	Multi-objective Partially Observable Markov Decision Processes
RFS	Random Finite Set
OCL	Opportunistic Cooperative Learning
FANETs	Flying Ad Hoc Networks
MTS	Mobile Target Search
KF	Kalman Filter

STS	Single-Time-Scale
NNs	Neural Networks
BLP	Binary Linear Programming
MTT	Multi Target Tracking
MTS	Multi-Time-Scale
ILP	Integer Linear Programming
VoIP	Voice Over Internet Protocol
ACO	Ant Colony Optimization
GA	Genetic Algorithms
MOEA	Multi-Objective Evolutionary Algorithms
DRL	Deep Reinforcement Learning
MARL	Multi-Agent Reinforcement Learning
CNNs	Convolutional Neural Networks
MTMC	Min-Time Max-Coverage
MOEA	Multi-Objective Evolutionary Algorithms
UCAVs	Unmanned Combat Aerial Vehicles
USVs	Unmanned Surface Vehicles
KMD	K-Means-Division
STTD	Shortest Travel Time Dispatch
LSAR	Layered-Based Search and Rescue
mPSO	modified Particle Swarm Optimization
IPOF	Island Policy-Based Optimization Framework

WTSC	Weighted Targets Sweep Coverage
NDN	Named Data Networking
DpML	Dynamic p-Median Loitering
BUC	Busy UAV Consideration
PPRP	Pre-Planned Relay Positioning
WSNs	Wireless Sensor Networks
DA	Dijkstra Algorithm
TSP	Traveling Salesman Problem
WS	Weighted Sum
EMST	Euclidean Minimum Spanning Tree
mTSP	Multiple Traveling Salesman Problem
UE	User Equipment
AoI	Area of Interest
ICBM-UAV	Intelligent Cluster-Based Multi-UAV
MATLAB	Matrix Laboratory

1. INTRODUCTION

Multi-UAV systems have emerged as a groundbreaking solution in SAR operations, offering exceptional efficiency and adaptability in responding to emergencies. These systems enhance the collaborative capabilities of multi-UAV systems to rapidly cover vast and complex terrains of disastrous regions, making them valuable assets in time-sensitive scenarios such as natural disasters, lost person searches, or hazardous environments. Incorporating Artificial Intelligence (AI)-based technologies like computer vision, autonomous navigation, and wireless technologies enables multi-UAV systems to detect, localize, and deliver essential assistance to individuals, i.e., rescue teams, in distress like earthquakes and flooding, while minimizing risks to human responders. These systems' scalability, adaptability, and ability to function in GPS-deprived or harsh terrains have the potential to revolutionize SAR missions. In this thesis study, we explore optimizing multi-UAV paths under some constraints, like connectivity and coverage for SAR applications, focusing on target detection, task allocation, and coordination strategies.

1.1 Search and Rescue Missions

The definition of search and rescue can vary significantly depending on the specific agency or country involved. Some of the universally accepted definitions for the search and rescue missions are as follows:

- **Canadian Armed Forces and Canadian Coast Guard:** Search and rescue encompasses identifying and providing aid to individuals, vessels, or other craft that are, or are believed to be, in danger or peril [8, 9].
- **United States Coast Guard:** The utilization of available resources to assist individuals or property facing potential or actual distress [10].

- **United States Department of Defense:** A search operation is typically coordinated by a Rescue Coordination Center (RCC), and involves utilizing available personnel and facilities to locate individuals caught in the disaster. On the other hand, a rescue operation focuses on retrieving individuals in distress, providing initial medical or other necessary aid, and transporting them to a safe location [11].

A United Nation (UN) organization, known as the International Search and Rescue Advisory Group (INSARAG), is organized to promote the exchange of information between national urban search and rescue organizations [12].

1.2 Background: Drones in Search and Rescue Missions

The initiation of drones in search and rescue missions occurred in the 2005 Hurricane Katrina disaster. Since 2005, drone deployments or assists in the United States (US), Italy, and Japan to federally declared disasters or their equivalent, including hurricanes, floods, building collapses, nuclear accidents, landslides, tornadoes, wild fires, earthquakes, and volcanic eruptions [13].

During disaster strikes, existing infrastructure is often unreliable or eradicated completely or partially (Figure 1.1). In such cases, relying on human resources and manned vehicles can be limited in terms of speed, coverage, and access to unavailable or harsh terrains. In contrast, a drone's ability to rapidly collect data from affected areas and deliver critical information to rescue personnel becomes invaluable. Drones, as highly versatile tools, can take on roles like monitoring sensors, aerial base stations, and relays to improve the performance of search and rescue missions. Disaster zones often encompass different kinds of targets, including damaged buildings, obstructed roads, and groups of victims dispersed over a wide area. The use of single or multiple UAVs, or multi-UAV systems, further enhances the effectiveness of SAR missions by allowing for greater area coverage, improved data collection, and more efficient task distribution.

Figure 1.1: *Some scenes of disasters where urban infrastructure is destroyed [1, 2, 3, 4].*



In the meantime, multi-UAVs have become game changers by offering much higher efficiency than single drones. They can work collaboratively to perform complex tasks such as simultaneous search patterns, target identification, and even coordination with rescue teams. This approach would reduce response times and increase the overall effectiveness of SAR operations, especially when time is critical for life-saving. The coordination between UAVs, including task assignment and communication, is an important aspect that impacts the mission's success. Recent advancements in AI technologies, both in terms of hardware and software, such as computer vision, machine learning and communication systems along with onboard Graphics Processing Units (GPU) , have also played a pivotal role in improving the capabilities of UAVs in SAR scenarios. Integrating these facilities with UAV systems automates the tasks of target (victims or signs of distress) detection, identification, connectivity, and tracking, minimizing the need for human intervention and enhancing the precision of the mission. Furthermore, advancements in path-planning algorithms have significantly resulted in dynamic optimization of search strategies. Despite the promising applications of UAVs and multi-UAV systems in SAR, several challenges remain, such as ensuring reliable communication in remote

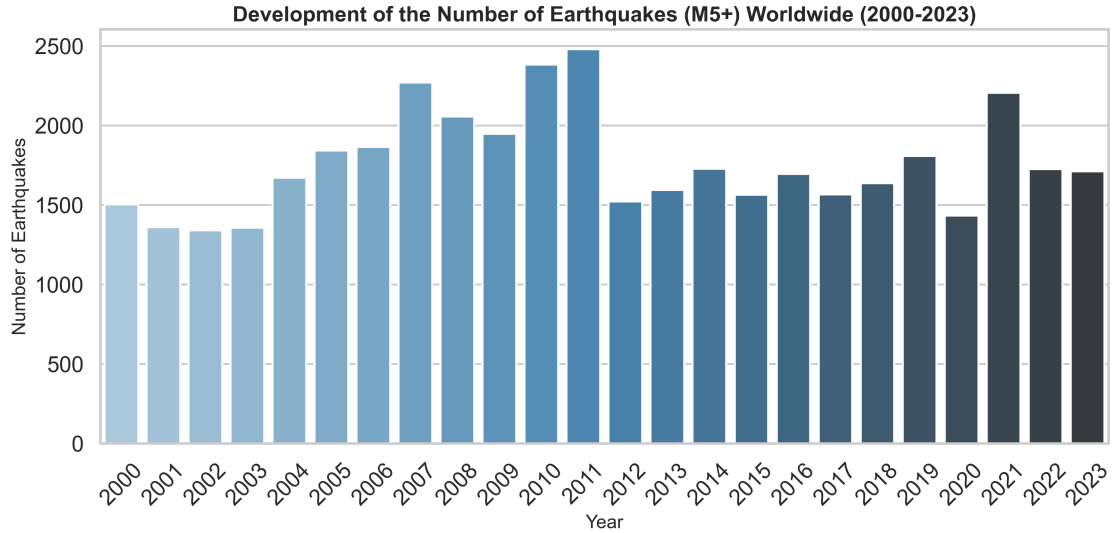
areas, managing large-scale UAV fleets, and enhancing the robustness of computer vision and machine vision algorithms in diverse and unpredictable environments. Continued research and development are necessary to address these challenges and improve the overall efficiency and safety of UAV-based SAR missions.

1.3 Motivation

Natural disasters and emergencies, such as earthquakes, floods, wildfires, and accidents, threaten human life and property worldwide. Note that there has been a significant increase in the frequency and intensity of natural disasters over the past 50 years. Reports from the United Nations Office for Disaster Risk Reduction (UNDRR) and the World Meteorological Organization (WMO) show a nearly fivefold increase in weather- and climate-related disasters since the 1970s. From 1970 to 2019, the number of recorded disasters rose from 771 in the 1970s to over 3,000 in the 2010s [14, 15, 16]. Droughts, storms, floods, wildfires, and massive earthquakes are among the top 10 primary and hazardous disasters leading to the most significant human and property losses during this era of time. Massive earthquakes, wildfires, and flooding occur worldwide, and in Turkey as the most threatening events endangering human life, property, and natural resources like mountains and forests. A report by the GeoNet project claims between 50 and 80 earthquakes daily, or about 20,000 a year [17]. Figure 1.2 shows the frequency of earthquakes between 2000 and 2023 years, which alarms governments and individuals to take the necessary measurements and readiness for pre and post-operations to decrease life and property loss. A total of 1712 earthquakes of five or more magnitude were recorded worldwide as of December 2023 [5].

Since Türkiye's geographical area is almost entirely on fault lines, thousands of earthquakes of various magnitudes occur annually. Turkey Disaster and Emergency Management Authority (AFAD) documented nearly 26900 seismic events until November 5,

Figure 1.2: *Frequency of the worldwide earthquakes between 2000 to 2023 [5].*

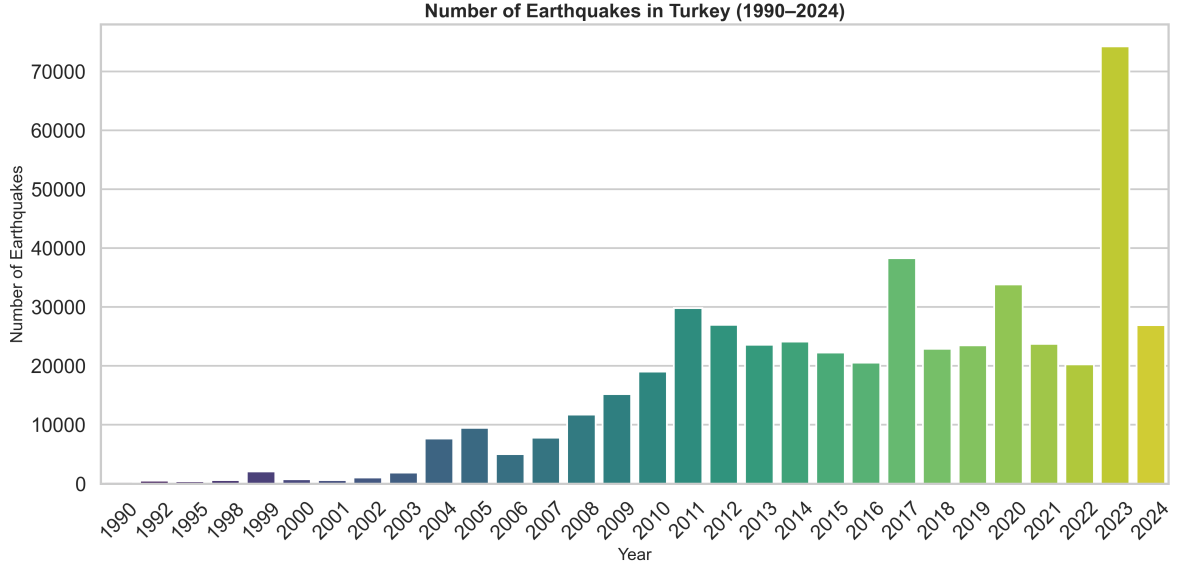


2024. The year with the highest number of earthquakes recorded was 2023, with over 74 thousand seismic events registered [6]. Figure 1.3 presents the number of earthquakes between 1990 to 2024 in Turkey.

Wildfires in Turkey and globally pose a significant threat and have consequently drawn the attention of search and rescue researchers. Turkey has lost nearly 120,000 hectares of its forest due to wildfires. As shown in Figure 1.4, Turkey experienced the largest wildfire-affected area in 2021, with fires burning more than 200,000 hectares across the country.

In such scenarios, the efficiency and speed of SAR operations play a pivotal role in life-saving, particularly during the "golden hours", i.e., the first 72 hours, immediately following a disaster. Traditional SAR methods often face limitations in terms of accessibility, speed, and safety, particularly in challenging environments such as dense forests, mountainous and harsh terrains, or structurally devastated urban areas. Some features of UAVs, like their agility, scalability, and power to reach dangerous and inaccessible places,

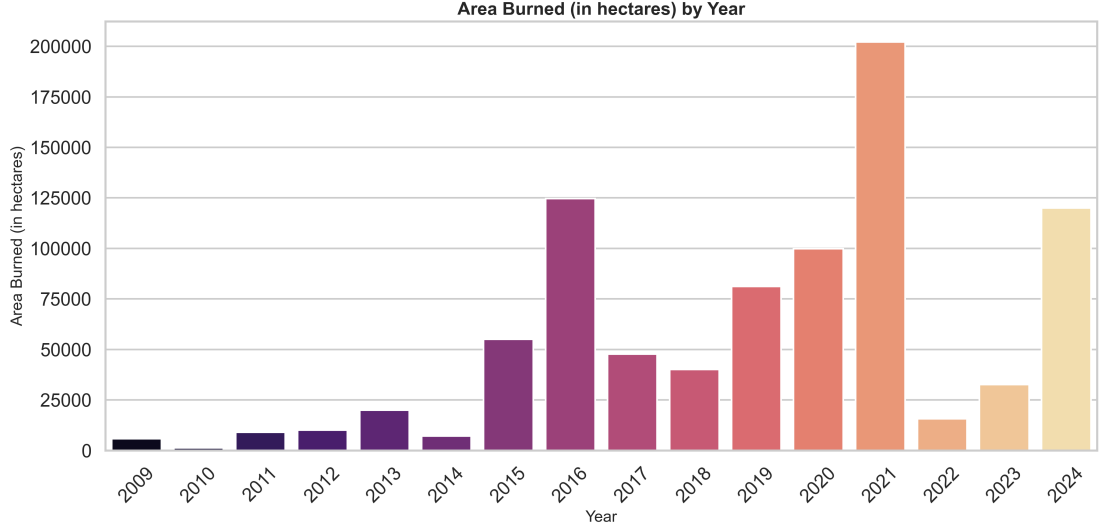
Figure 1.3: Frequency of the Turkey earthquakes between 1990 to 2024 [6].



have made them ideal tools for SAR missions. Additionally, equipping UAVs with advanced sensors, computer vision algorithms, and communication systems has the potential to significantly enhance the effectiveness of SAR operations by providing real-time situational awareness, automating target detection, and supporting the rapid deployment of resources.

The deployment of multiple UAVs in SAR introduces new dimensions of efficiency and coordination, particularly for covering a large area in a fraction of time. Such systems can perform complex tasks collaboratively, such as assigning UAVs to specific regions based on their capabilities, avoiding redundant searches, and the dynamic adaptation to evolving mission requirements. However, *deploying multi-UAVs systems in real-world SAR scenarios presents significant challenges*, particularly when it comes to *robust communication, reliable target detection, and effective task allocation*. This thesis is motivated by offering innovative solutions that address these challenges to fully leverage the potential of UAVs and multi-UAV systems in SAR missions. By integrating proposed

Figure 1.4: Frequency of the Turkey wildfire between 2009 to 2024 [7].



novel and innovative path planning and communication algorithms, *this research aims to contribute to the development of intelligent and efficient multi-UAV systems* capable of transforming SAR operations and ultimately saving more lives in distress.

1.4 Problem Definition

Efficient management of increasing natural disasters demand rapid and effective SAR operations to minimize human suffering and life loss. SAR operations often occur in complex and hazardous environments. In such cases, the deployment of traditional methods could be insufficient due to accessibility challenges and the dangerous nature of disaster scenarios. In this thesis, *we propose optimized path-planning algorithms for multi-UAV systems that can survey large areas, detect and monitor targets, and establish communication links among the operational nodes efficiently.* It is worth mentioning that deploying multiple UAVs in SAR missions requires significant coordination, connectivity, and optimization challenges. The proposed multi-UAV SAR mission involves several

critical tasks:

- *Searching the disaster area for multiple targets,*
- *Establishing continuous connectivity with a GCS and,*
- *Maintaining monitoring services for detected targets.*

To mitigate the mission's complexity, the deployed UAVs must be assigned diverse roles. Hence, we define two types of drones based on their roles throughout the mission, namely (i) Search (mission) and (ii) Relay drones, where the former are equipped with sensors for detection and monitoring of targets, and the latter are responsible for connecting the GCS to the targets. Search drones must coordinate with relay UAVs during the mission to establish a connected network between drones, targets, and the GCS. Managing this coordination requires sophisticated strategies to ensure mission success under time constraints and resource limitations. In this study, the SAR mission is structured into three distinct phases, marked with two events: first and last target detection. The paths of search and relay nodes are optimized in three phases and in a sequential order. In Phase 1, search drones traverse initial preplanned paths generated at the GCS at the start of the mission. These paths are optimized to minimize the total distance traveled. The dynamic Relay Positioning Algorithm (RPA) takes these generated search paths as input arguments to optimize the paths of relay nodes to guarantee continuous connectivity between search nodes and the GCS utilizing the minimum number of relay drones. Phase 2, occurs between the first and the last detection of targets. In this study, a target is labeled as detected when it lies in the sensing range of at least one search drone. As a response to each target detection, we propose 3 event-driven approaches:

- **Detection Priority Path Planning (DPPP):** In this approach, the operational nodes (relay and search UAVs) follow their initial paths until the final target is detected, and GCS notifies them about detecting all targets.

- **Extended Detection Priority Path Planning (EDPPP):** In this approach, the behavior of the search and relay nodes are similar to the approach DPPP, except GCS injects a new search node, called an injected node, toward the recently localized target to monitor it.
- **Detection Adaptive Path Planning (DAPP):** In this approach, upon the detection of each target, UAVs replan their paths to ensure continuous monitoring of the target and its connectivity to the GCS.

Phase 3 involves forming a drone-based network when the last target is detected, which guarantees the coverage of each target using a search drone, and then connecting it to the GCS using the fewest number of relays. Path planning is done centrally in phases 1 and 2 at the GCS. In the last phase, UAVs within the same network clique collaboratively determine their paths without central control, allocating the appropriate node to tasks that are open based on the minimum cost principle. From the perspective of target connectivity to GCS, mission phase times, and UAV network connectivity, each proposed method is responsive to events, i.e., target detection, and has its own benefits and drawbacks. Although DPPP and EDPPP end up with the lowest detection times, DAPP compensates for the lost detection time by instant reorganization to establish the network of relays in the final phase. Over the course of the mission, the worst target connectivity belonged to DPPP since the designated mission priority was to locate all targets. In contrast, DAPP allows continuous monitoring and enables the establishment of very high connectivity. Adding to these challenges is the fact that different targets might have different connectivity needs. To tackle this challenge, *we propose a novel approach to prioritize targets based on their connectivity requirements* within the context of a multi-target, multi-UAV search and connect mission without prior information. In disaster situations, some targets are critical and need constant, high-priority communication, while others can handle delays or lower-priority connections. For this purpose, we define three different levels of

connectivity priority: (i) high-priority targets which need continuous connectivity from the time of detection; (ii) medium priority targets that are tolerant to delays, and (iii) low-priority targets do not require immediate connectivity upon detection. With these in mind, we *propose a multi-UAV path planning algorithm* for an SAR mission, where the goal is to find all targets of interest and connect the targets to GCS to be monitored by the rescue team and/or serviced *based on their connectivity-priority level*.

1.5 Contribution

The primary contributions of this study are outlined below:

- We propose path-planning algorithms for the multi-UAV systems optimized for detecting, monitoring, and connecting multiple targets in a search and rescue mission, adopting diverse levels of adaptability while ensuring continuous connectivity between UAVs and the GCS [18].
- Our proposed algorithms adapt to search drones and relay drones to establish and maintain connectivity among UAVs, and UAVs and GCS, as well as detected targets and GCS. We present a workflow for optimizing search and relay drone paths sequentially in our dynamic path planner. This implementation enables the mission to have a flexible selection of initial search node paths, making the proposed path planners adaptable to various applications [18].
- We compare our solutions with multi-objective optimization-based path planners, i.e., using Weighted Sum (WS) and NSGA-II [19]. For a fair comparison of resource utilization, we also integrate these solutions into our dynamic path planner workflow [18].
- We extend our previously proposed methods for multi-target search and connectivity by incorporating target prioritization based on the level of connectivity required

upon detection, addressing a significant gap in the literature [20].

1.6 Thesis Outline

The thesis is structured into six chapters, each addressing a different aspect of the research on dynamic multi-UAV positioning and path planning for multi-target search and rescue under connectivity constraints. *Chapter 1* provides the foundation for the thesis by outlining the motivation behind the study and the challenges inherent in UAV-based SAR missions, along with defining the problem and marking the contributions to the field. *Chapter 2* reviews existing research relevant to UAV-based SAR missions with a focus on algorithms for multi-UAV path planning, target detection, and connectivity maintenance. The system model and assumptions of this study are addressed in *Chapter 3* which establishes the technical framework for the research by detailing the multi-UAV system architecture, distinguishing between the roles of search and relay UAVs. Moreover, it also encompasses the explanations and assumptions about the communication framework and the disaster area, UAV capabilities, and other constraints required by the proposed methods in the subsequent chapters. *Chapter 4* introduces a dynamic algorithm designed to optimize UAV positioning and assignments during SAR missions, aiming to minimize travel distances while maintaining consistent connectivity with the GCS. The priority-based dynamic multi-UAV path planning algorithm for multi-target search and connectivity is presented in *Chapter 5*. This chapter considers the varying connectivity requirements of different targets, ensuring that high-priority targets receive continuous monitoring and connectivity. *Chapter 6* wraps up the study by summarizing the research and outcomes of the proposed methodologies. It also illuminates the path forward by presenting recommendations for future research directions and identifying potential areas for further exploration and development.

2. LITERATURE SURVEY

Drones are becoming vital for rescuers, enabling them to conduct optimized search and rescue (SAR) missions during natural disasters such as earthquakes, floods, and tornadoes, where urban infrastructure, communication systems, roads, and bridges are often partially or completely destroyed. The advent of AI tools and algorithms, Computer Vision, and Deep Learning, along with high-tech devices like thermal cameras and their integration capability into drones, make their popularity two-fold in SAR missions, which has brought a growth trend in the search and rescue drone market. The search and rescue drone market has experienced significant growth since 2018, driven by technological advancements and the increasing adoption of drones for emergency response. This sector was valued at approximately 180 billion dollars in 2023. The economic experts forecasted a significant projection for this market that would enable it to reach nearly 450 billion dollars by 2032 [21].

Such significant growth is being fueled by several key factors, including (i) the ability of drones to quickly access hard-to-reach areas, (ii) their cost-effectiveness compared to manned aircraft, and (iii) their capacity for real-time data collection and surveillance, which enhances real-time perception and awareness during search and rescue operations.

Search drone functionalities have been improving with advancements in sensor technologies, AI-driven analytics and tools, and autonomous flight capabilities, which have greatly placed them at the center of the attention of rescuers. Nowadays, many drones include thermal imaging, LiDAR, and AI algorithms, which help rescue teams quickly identify and track targets, especially in rugged or hazardous environments. DJI

announced a new milestone in rescuing 1000 disoriented people in such regions [22]. Furthermore, the recent pandemic, COVID-19, underscored the utility of drones in emergencies, encouraging additional investment in this sector, the drone market, for applications like crowd monitoring and medical supply delivery [21].

Nowadays, deploying multi-UAV systems accompanied by optimized path planning methods and AI tools has made them a trend in SAR missions for efficiency. Depending on the mission types, UAVs can undertake various roles as a function of the tasks' requirements. *Our work has focused on tasks such as target search and connectivity between UAVs in a clique of the network and connectivity of the GCS to single/multi-UAVs systems.* The rest of this section has focused on reviewing the literature on deploying multi-UAV systems for missions where target search and connectivity maintenance among mission elements, i.e., UAV-UAV and UAV-GCS, are in primary preference.

2.1 Ground Target Connectivity: Aerial Base Stations (Relay Drones)

In this category, UAVs take on the role of the aerial base station or relay nodes serving to connect the ground-based nodes, i.e., mobile users, Internet of Things (IoT) sensors, and other interconnected devices, to the central station or each other. In this type, the positions of UAVs or flight paths are optimized to meet network-specific requirements. Table 2.1 summarizes the trajectory optimization or relay positioning criteria used in the works of this category.

Utilizing circle packing theory for the 3D optimization of the UAV placement as relay nodes can efficiently maximize coverage area and operational lifespan, considering factors like altitude, antenna gain, and beamwidth to minimize interference [23].

The problem of deploying UAVs as aerial base stations trying to reduce the energy usage of ground users and deployed UAVs on their optimizations has been addressed in

Table 2.1: *Relay Drone Optimization Criteria for Flight Trajectory Planning or Repositioning, Category 1.*

	Optimization Criteria
[23]	maximizing network coverage area and lifetime
[24], [25]	minimizing the number of drones and energy consumption of ground users
[26], [27]	maximizing energy efficiency
[28]	data transmission and coverage fairness
[29], [30]	minimizing the number of UAVs
[26], [31]	maximizing network throughput
[32]	maximizing minimum data collection speed
[33]	minimizing the number of UAVs and data rate dissatisfaction
[34]	optimizing target coverage ratio and charging operation scheduling
[35]	optimizing data service and flight time
[36]	maximizing minimum rate
[37]	maximizing connectivity

[24, 25]. [24] has utilized heuristic methods like K-means clustering and Genetic Algorithms (GA) to generate solutions ending up with optimized locations for the minimum number of UAVs. Considering of the constraints, including maximum altitude of UAV and minimum Voice Over Internet Protocol (VoIP) quality, assisted in managing energy use at user devices. [25] has achieved this goal by formulating their problem as a complex optimization problem to RL-Generated paths and dynamic role-switching algorithm.

Some works in the literature have aimed to maximize energy efficiency by deploying UAVs to serve as aerial base stations. [26] has proposed a multi-UAV and SAR device-to-device (D2D) communication model by utilizing a clustering approach for enhancing energy efficiency, maximizing network throughput, and connectivity in disaster scenarios. The clustering of SAR devices has enabled UAVs to act as aerial base stations, improving energy efficiency by minimizing redundant energy use and extending network lifetime. The reduction in UAV energy consumption has been carried out through optimal positioning, Leveraging Low-Energy Adaptive Clustering (LEACH) techniques

to balance energy loads. [27] has developed a joint path planning and communication scheduling problem for a swarm of UAVs performing Mobile-Edge Computing (MEC) in a network of IoT devices with Reconfigurable Intelligent Surfaces (RISs) to improve energy efficiency and task completion. By leveraging RISs, the system has addressed Line-of-Sight (LoS) obstructions due to uneven terrain, enhancing communication via direct and reflected paths. The proposed algorithm has optimized UAV trajectories to maximize task execution while minimizing energy consumption, incorporating a Model-Predictive Control (MPC) framework for real-time adaptability.

UAVs have been deployed to serve as aerial base stations for continuous data transmission without energy outage in [28] through an energy-efficient trajectory optimization scheme for UAV-assisted IoT networks, focusing on sustainability through solar energy and Charging Stations (CSs), particularly for dynamic conditions such as terminal availability and energy harvesting based on-policy and off-policy RL approaches.

Minimizing the number of relay nodes required for efficient resource management is a strategy explored in several studies. A heuristic method, utilizing PSO, to determine the optimal 3D locations and a minimum number of drone base stations has proposed in [29]. The algorithm iteratively has positioned drones to meet network Quality-of-Service (QoS) requirements, removing any redundant stations without impacting coverage. An innovative approach has been developed by [30] for the deployment of UAVs as aerial base stations in wireless networks, focusing on minimizing the number of necessary UAVs while guaranteeing adequate coverage and connectivity for ground users. The problem has tackled in both static and dynamic user scenarios. For static users, a heuristic algorithm has been proposed based on an Improved Genetic Algorithm (IGA) to determine the optimal 3D deployment of UAVs, and for dynamic user scenarios, i.e., users move or increase in number, a UAV redeployment scheme has been presented that adjusts the UAVs' locations to maximize coverage without increasing the number of UAVs.

Studies [26, 31] have focused on maximizing the network throughput where UAVs deployed as aerial base stations or relay drones. [31] has maximized throughput of UAV-Enabled Mobile Relaying Systems using UAV-mounted mobile relays to enhance wireless communication by optimizing the network using UAV mobility flexibility for dynamic channel optimization. They have based their study on an algorithm that jointly optimized the UAV's trajectory and power allocation, balancing source-relay and relay-destination links while adhering to practical constraints like UAV speed and data causality.

A multi-UAV-enabled IoT network has been designed to enhance data collection by utilizing UAVs that power IoT devices using wireless switches [32]. They aimed to maximize the minimum data collection rate for a network of IoT devices by optimizing UAVs' 3D trajectories and time allocation for energy and data transfer within a limited time-frame that has been formulated as a complex and nonconvex problem which has been solved using an optimization problem utilizing a successive convex approximation algorithm to solve it iteratively.

A study to optimize the UAV placement in mesh networks has been conducted in [33], particularly for ensuring optimal communication among Ground Nodes (GNs) and UAVs aiming to minimize the data rate dissatisfaction and number of UAVs. In this study, a centralized UAV placement strategy using UAVs as flying access points (aerial base stations) has been presented that allowed the formation of a mesh network to provide connectivity for ground nodes in a target area. To achieve this, a Multi-Objective Evolutionary Algorithms (MOEA) has been employed, specifically the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), to optimize UAV positioning aiming to minimize the number of UAVs while maximizing the data rate requirements (dissatisfaction) of the ground nodes. The main objective of this study was to achieve network coverage by utilizing the fewest UAVs while maintaining connectivity and maximizing data rate satisfaction.

The challenges and solutions for deploying UAVs in a network to maintain persistent coverage over a target area while managing battery recharging needs has been examined in [34]. The main objective of this study was to optimize coverage of a target area using a limited number of UAVs while maintaining the connectivity among UAVs to form a mesh network and managing charging due to the limited battery life. A centralized approach based on distributed game-theory-based scheduling presented to solve this joint problem of UAV positioning for coverage and scheduling UAVs for recharging, which balanced coverage, connectivity, and battery constraints.

An algorithm has been proposed for optimizing the use of UAVs as flying base stations [35], where each UAV had a specific hovering duration due to battery limits and has been assigned to serve a pre-defined region, to provided wireless services to ground users utilizing the optimal transport theory to optimize the hover time and data transmission of UAVs, which were flight-time constrained due to battery limitations. The main objectives of this study were to maximize the average number of bits transmitted to users, i.e., optimizing data service while optimizing hover time, ending up with developing strategies for optimal UAV placement and bandwidth allocation to minimize hover time while still meeting the data demands of users.

The study in [36] has focused on optimizing UAV-enabled communication systems by addressing the challenge of maximizing the minimum rate across multiple users, which has been achieved through joint optimization of UAV trajectory, user association, and power allocation. The primary objective of this was to ensure fairness by maximizing the rate of the user with the weakest communication link. They have been formulated the problem as a non-convex optimization task and proposed an iterative algorithm based on block coordinate descent and successive convex approximation to solve it efficiently. The proposed method significantly improved the minimum rate compared to traditional static UAV placement or suboptimal trajectory designs, highlighting the critical role of dynamic

UAV mobility and resource allocation in maintaining robust and equitable communication for all users.

Relay drones have been utilized in [37] to enhance connectivity, addressing the limitations of mmWave networks such as poor connectivity and high packet loss, along with the optimization of the throughput and reducing delay of End-to-End (E2E) devices. To achieve this, they formulated a constrained optimization problem to determine the optimal number, placement, and transmission power of UAVs, focusing on enhancing the algebraic connectivity of the network graph while ensuring minimal E2E delay.

2.2 Search and/or Relay Nodes: Search and Coverage Missions

In this category, UAVs are incorporated into missions such as environmental monitoring, surveillance, and search and rescue. Depending on the objective, UAVs must fulfill a variety of tasks. Connectivity has been integrated into the planning missions either as a constraint, an objective, or with the assumption of constant availability. In these studies, UAV paths were optimized collectively. UAVs can undertake relay/search roles, and missions include search, coverage, target detection, and tracking etc. Table 2.2 provided a summary of studies in this category.

Minimizing energy consumption for UAV coverage and search missions has been tackled using innovative approaches. Utilizing Mixed Integer Linear Programming (MILP) [38] proposed an Integrated Sensor Selection and Routing Model (ISSRM) approach to optimize sensor assignments and routes, addressing the impact of sensor weight on flight time for both small and large missions. Similarly, a MILP-based model with relay nodes has been proposed in [39] to cut the energy costs of long-range communication for iterative path adjustments to maintain realistic communication limits, reduce unnecessary travel, and enhance operational efficiency. For the same issue, [40] has presented a distributed 3D path-planning framework integrating PSO and the Bresenham Algorithm for

Table 2.2: *Relay Drone Optimization Criteria for Flight Trajectory Planning or Repositioning, Category 2.*

	Optimization Criteria
[38], [39], [40]	Minimizing energy
[41], [42], [43], [44]	Minimizing flight time or path length
[45], [46]	Minimizing search time
[45], [47], [48]	Maximizing target detection
[46], [49], [50]	Maximizing information gain or minimizing uncertainty
[51], [52], [53]	Maximizing area coverage
[51], [52], [54], [55], [56], [57], [58], [59], [60], [61], [62]	Optimization of coverage and search objectives under connectivity considerations
[25], [52]	Specified UAV types (relay, search, articulate, jammer, collector) based on distance between GCS and other UAVs
[52], [55], [61], [62], [63]	Connectivity to GCS (GCS)
[59], [64], [65], [66]	Target monitoring with UAV cooperation in tracking mobile ground nodes

collision-free, and energy-efficient trajectory planning. These studies emphasized balancing energy consumption, flight safety, and surveillance requirements in diverse applications.

The reviewed studies have focused on UAV path planning with an emphasis on minimizing travel time and path length. [41] developed a multi-objective path planning (MOPP) framework for navigating complex, dynamic urban areas, addressing challenges like limited UAV computational resources and unpredictable obstacles. A modified A* algorithm has been introduced in [42] to optimize path planning for coordinated UAV patrolling, prioritizing revisit time, 3D terrain navigation, and coverage while balancing altitude, obstacle avoidance, and computational complexity. With the same constraints, i.e. minimum flight time and path, [43] proposed a multi-objective optimization model for UAV routing, balancing travel distance, satisfaction, and fleet size using a rolling horizon

strategy for real-time adaptability. In the same category, [44] has presented NSGA-III-TEHOD, an enhanced GA addressing hierarchical task priorities, obstacle avoidance, and wind interference, achieving superior performance in complex, dynamic environments. These studies underscored advancements in UAV path planning to improve efficiency and adaptability in diverse scenarios.

In some search missions, search time can be a crucial factor for successful search and rescue operations. The studies [45, 46] have emphasized on minimizing search time and maximizing target detection probability in multi-UAV path planning for SAR. [45] proposed an asynchronous distributed cooperative search algorithm for UAVs in non-convex environments with obstacles, focusing on efficient target detection and reduced search times. Their approach used dynamic probability and uncertainty maps for adaptive path planning, along with a transformation method to handle complex environments by converting non-convex regions into convex equivalents. Similarly, [46] has developed a centralized MILP framework for iceberg monitoring, optimizing UAV waypoint sequences to minimize travel distance and reduce target position uncertainty using a KF for real-time updates.

The main concern of some missions was the maximization of target detection in the SAR missions. For this purpose, [47] has developed an autonomous UAV path-planning framework using a multi-objective optimization function that optimized two conflicting objectives of path-planning algorithms: (i) Maximizing the detection and localization of targets and (ii) Ensuring the UAV to avoid hostile threats and survives the mission. To tackle this concern, an efficient UAV path planning based on a Bio-Objective optimization framework as a Binary Linear Programming (BLP) model that has been focused on designing efficient UAV paths trying to maximize target detection probability and minimize the path length is proposed by [48].

The works [49, 50] have addressed the maximizing information gain and minimizing uncertainty in multi-agent path planning. [49] has proposed a centralized multi-objective framework using Multi-objective Partially Observable Markov Decision Processes (MPOMDP) and Random Finite Set (RFS) modeling to balance discovering new objects and tracking them. Their approach leveraged mutual information value functions and a greedy algorithm for efficient, adaptive planning, outperforming single-objective methods in scenarios like wildlife monitoring and surveillance. Similarly, [50] has utilized RL and Neural Networks (NNs) to propose a cooperative search framework to optimize search efficiency. The developed hybrid Opportunistic Cooperative Learning (OCL) paradigm enhanced information sharing among agents, achieving superior performance with non-redundant search paths. These approaches highlighted advancements of their study, minimized uncertainty, and maximized information in dynamic, constrained environments.

Maximizing coverage in multi-UAV missions is a trend in multi-UAV path planning. A distributed optimization approach for coordinating UAVs to search unknown environments was proposed in [51], using real-time updated digital maps to track target probabilities and uncertainties. By enabling UAVs to revisit high-interest areas and employing an MST algorithm, the method has enhanced search efficiency, target detection, and environmental coverage while minimizing energy consumption. Similarly, [52] has introduced a cooperative surveillance framework with dynamic relay UAV selection and decentralized motion planning where UAVs adjusted roles dynamically to ensure connectivity and optimal task allocation, improving surveillance coverage and connectivity reliability. [53] has developed a MOEA to optimize UAV flight trajectories, focusing on maximizing unexplored area coverage and monitoring points of interest. The tailored NSGA-II model demonstrated significant performance improvements in exploration and

surveillance. These advancements by these works highlighted the importance of maximizing area coverage in diverse applications such as disaster response, surveillance, and environmental monitoring.

Some works have been focused on optimizing UAV operations for coverage, connectivity, and efficiency in diverse mission scenarios. [54] has introduced a distributed mobility model balancing area coverage, connectivity, and energy efficiency through decentralized decision-making and weighted velocity adjustments, outperforming traditional models in coverage and stability. [55] has proposed strategies integrating coverage and communication goals for SAR missions, enabling adaptive path planning and balancing mission priorities via a tunable parameter. [67] has explored MAV coordination for stationary target searches, employing bayesian updates and dynamic path adjustments to reduce search time and maintain connectivity, with distributed approaches proving more efficient than centralized ones.

To address connectivity, [57] has developed an Ant Colony Optimization (ACO) based minimum-time search algorithm for UAVs, ensuring communication and collision avoidance while minimizing target detection time along with connectivity maintenance. [58] has proposed the ICBM-UAV protocol for disaster scenarios, enhancing search and rescue through cluster-based connectivity, energy-efficient strategies, and dynamic coordination, achieving superior network performance and reduced SAR times. [59] has developed a hierarchical modular framework for scalable multi-UAV systems, optimizing coverage and tracking tasks with distributed decision-making and anti-flocking algorithms guaranteeing connectivity. [60] has focused on emergency response, combining UAV communication and real-time traffic monitoring to optimize routes for emergency vehicles, reducing delays and energy use. [61] has explored decentralized algorithms for connectivity area coverage, leveraging pheromone-based mechanisms to balance connectivity and exhaustive area scanning. To optimize mission performance and network

connectivity [62] has introduced a dynamic FANET operation algorithm, though it lacked energy management considerations.

The connectivity between the UAVs and the GCS has been considered in [52, 54, 61, 62, 63]. The [63] investigated algorithms for constructing and adjusting topologies in Flying Ad Hoc Networks (FANETs) to support relay-based connectivity between mission UAVs and a GCS where relay UAVs establish multi-hop communication links between mission UAVs and a GCS.

Target monitoring after detection has been addressed in some works of this category in [59, 64, 65, 66]. The [64] has introduced a framework, CF-UAVs-MTST, designed for Multi-Time-Scale (MTS) and tracking Multi Target Tracking (MTT) using UAVs. Target detection has been detected using a cascade classifier (Haar-like features), ensuring quick and accurate identification, and motion prediction and tracking have been accomplished using the Kalman Filter (KF). Cooperative MTT leveraged connectivity between UAVs and a GCS to share data and improve tracking. The accounted constraints have been limited energy, flight time, and computational costs. A decentralized control framework designed for multi-UAV systems to maintain symmetric formations around a mobile target while ensuring robust network connectivity and target connectivity has been proposed in [65]. This algorithm also supported tracking a desired connectivity profile over time, addressing the challenges posed by dynamic network topologies and varying UAV positions. A novel distributed estimation protocol for UAV swarms to efficiently track and monitor a mobile target while maintaining a rigid network formation, emphasizing reduced communication and computational costs compared to centralized and traditional decentralized methods has been introduced in [66] by leveraging a Single-Time-Scale (STS) estimation approach, where the framework eliminated the need for high-frequency consensus iterations required by MTS methods, making it more suitable for real-time applications with constrained resources.

2.3 UAV Path Planning as an Optimization Problem

Typically, UAV path planning has been formulated as an optimization problem, where the goal was to find the most efficient path or set of paths for UAVs to accomplish specific tasks such as coverage, search, surveillance, or connectivity while adhering to constraints such as battery life, obstacle avoidance, and connectivity maintenance. The path planning task can be formulated as a single or multi-objective optimization task, where multiple conflicting objectives or constraints, such as minimizing travel time, maximizing coverage, or maintaining connectivity, must be balanced.

A variety of classic solvers have been used to address this problem, including methods such as Integer Linear Programming (ILP), WS optimization, and evolutionary or bio-inspired algorithms. ILP-based models [45, 35] have been applied to multi-UAV scenarios to optimally assign tasks and plan paths while considering various operational constraints. WS optimization techniques [23, 24, 38, 39, 41, 46, 47, 49, 50] has provided a flexible framework for combining different objectives into a single cost function, allowing for the simultaneous optimization of multiple mission parameters like coverage, time, and energy consumption.

Recently, evolutionary algorithms such as Particle Swarm Optimization (PSO) [68], ACO, and GA [40, 42, 51, 52, 54, 55, 57] have gained popularity due to their ability to solve non-linear and complex optimization problems. These algorithms outperformed in exploring large, multi-dimensional solution spaces and were well-suited for dynamic environments where UAVs must adapt to changes in real-time, such as shifting target locations or unexpected obstacles. NSGA-II and NSGA-III, which are MOEAS [44, 53, 33] are particularly effective for problems where multiple objectives need to be optimized simultaneously, such as balancing coverage with connectivity or minimizing energy along with maximizing the detection rate.

Approaches leveraging machine learning and deep learning techniques have also

been increasingly employed in the domain of UAV path planning. RL and Deep Reinforcement Learning (DRL) have been used to teach UAVs how to adapt their paths based on rewards and penalties associated with mission success, such as maintaining connectivity and reducing search times. In multi-UAV applications, Multi-Agent Reinforcement Learning (MARL) has been applied to maintain connectivity and optimize search and tracking missions. [69] have shown that RL-based approaches allow UAVs to dynamically adjust their behaviors and interactions, learning to cooperate in complex, unpredictable environments where traditional methods might fail.

Learning-based approaches have also demonstrated particular promise in multi-UAV systems for dynamic tasks, such as target search and connectivity maintenance. These methods enabled UAVs to adaptively modify their paths based on real-time observations, with some studies even integrating connectivity strategies into the learning framework to ensure that UAVs maintain a reliable network for data transmission, which was critical in search and rescue operations. [19], where UAVs were trained using Convolutional Neural Networks (CNNs) to process trajectory histories and maintain a relay chain to ensure continuous communication with the GCS while detecting disturbed targets in an unknown environment.

Additionally, UAV path planning can integrate various constraints into a single optimization framework, including minimizing energy consumption, optimizing target detection, or maximizing network coverage. Energy-efficient models have been developed in [35, 38] focusing on minimizing UAV energy usage while maintaining operational requirements such as communication range and data throughput. In these models, UAVs can dynamically adjust their position or altitude to optimize energy usage while ensuring effective coverage and connectivity. Studies like [51], which used dynamic mapping and real-time decision-making, further illustrated how UAVs can use optimization algorithms to reduce energy consumption by planning efficient paths that balance mission goals with

power limitations.

MTT and area coverage are common goals in UAV path planning. Researchers have developed models that combine traditional optimization techniques with AI methods to ensure optimal coverage while reducing search time, such as in the Min-Time Max-Coverage (MTMC) problem [38]. In these models, UAVs have been tasked to cover critical targets while minimizing the time required for coverage, ensuring that higher-priority targets are covered first.

Combining communication optimization with coverage maximization is a key aspect of UAV path planning. UAVs are often required to relay information between GCSs and other UAVs, which can affect path planning. Solutions like those presented in [41] and [46] have been proposed algorithms that allow UAVs to not only plan their paths based on coverage objectives but also dynamically adjust to maintain communication with each other and with the GCS. These studies show that UAVs can adapt their paths in real-time to balance connectivity and coverage requirements.

Hybrid approaches, combining pre-planned optimization with online decision-making, have also been proposed to improve path planning for real-time missions. By combining traditional optimization methods with learning-based approaches, UAVs can optimize their paths ahead of time but can also dynamically adjust based on unfolding mission events, as discussed in the study [19]. In scenarios with unpredictable elements, the hybrid models have been expected to be highly reliable, such as in disaster response or search-and-rescue missions, where immediate decisions must be made based on changing conditions. In conclusion, UAV path planning as an optimization task encompasses a wide range of methods and algorithms, from traditional optimization techniques like ILP and WS optimization to more advanced machine learning and evolutionary approaches. Each method has its strengths, and as UAV applications evolve, hybrid approaches that

integrate the best features of each are expected to offer the most promising solutions, especially for real-time, multi-UAV operations in dynamic and challenging environments.

2.4 Multi-Target multi-drone search and rescue under target prioritization in the SARs

Fast target identification, rapid data gathering, and timely information delivery to rescue teams are crucial for successful SAR operations, especially within the initial 72 hours of a disaster [70]. The initial hours after a disaster are crucial for saving lives, as this is when survivors are most likely to be found. Rapid situation assessment and immediate relief efforts can significantly enhance the success of rescue operations. Given the vastness of disaster-stricken areas, relying solely on human rescuers and ground vehicles may not be adequate to reach all affected regions. This is especially relevant when the disaster area is large or inaccessible due to infrastructure damage or environmental obstacles. In these scenarios, multi-drone systems offer significant advantages by enabling real-time area surveillance, victim detection, and network provisioning, which are essential for ensuring efficient operations and maximizing the chances of successful rescue missions [71]. Target prioritization is a key aspect of SAR operations that involves determining which areas or victims should be addressed first based on factors like environmental conditions, risk levels, target criticality, available resources, and urgency. For instance, in the aftermath of an earthquake, buildings that are at risk of collapse or individuals in need of immediate medical attention are prioritized for the search efforts. The prioritization of targets ensures that the limited resources, i.e., UAVs or rescue team members, are allocated to the most critical areas first, reducing response times and improving rescue efficiency. Many studies have explored ways to define and implement these priorities. In literature, targets have been prioritized according to mission-specific factors, such as military operations, marine rescues, or civilian victim detection. Target

prioritization is an essential step in mission planning for Unmanned Combat Aerial Vehicles (UCAVs), enabling effective allocation of resources and optimization of operational outcomes across various domains. Priority-based routing for UCAVs has emphasized the strategic allocation of resources to high-priority targets in military applications. [72] has utilized a MILP approach to assign UCAVs to targets based on priority weights and service constraints, ensuring minimal collateral damage and efficient resource utilization. They have deployed a heuristic solution using Tabu Search coordinates sub-problems such as target assignment and routing, achieving near-optimal solutions for large-scale scenarios while addressing constraints like fuel and payload limits. Similarly, in maritime rescue missions [44], cooperative path planning frameworks for Unmanned Surface Vehicles (USVs) have integrated advanced algorithms like K-Means-Division (KMD) for navigable zone identification and reward-mechanism genetic optimization for priority target assignment. These systems have been enhanced computational efficiency while ensuring collision avoidance and path optimization for critical targets, such as rescuing personnel or delivering vital supplies. In aerial surveillance, multi-UAV systems have been leveraged PSO to prioritize high-importance zones dynamically, adapting to operational changes such as emerging threats or new mission parameters. By incorporating dynamic priority updates and energy-efficient trajectory planning, these frameworks ensured comprehensive coverage and adaptability to evolving scenarios [73]. Across these applications, prioritization mechanisms have played a pivotal role in enhancing mission efficiency, safety, and responsiveness to critical needs.

The [74] has been explored the effective management of UAV systems in dynamic scenarios with multiple-priority targets. It examined decision-making strategies for task allocation and vehicle positioning to maximize response efficiency. Through simulation, the study assessed the combinations of dispatching rules and loitering strategies under various conditions, including region size, arrival rate, and service rate. Key dispatching

approaches were categorized into two classes: (i) target-initiated, e.g., closest available UAV, or UAV-initiated, e.g., shortest travel time, each optimized for different operational scenarios. Loitering strategies, such as p-Median and its dynamic recalculations, positioned idle UAVs to minimize response times. The combination of Shortest Travel Time Dispatch (STTD) and Dynamic p-Median Loitering (DpML) with Busy UAV Consideration (BUC) consistently showed superior performance, highlighting the value of think-ahead policies. The findings underlined the importance of aligning dispatch and loitering strategies with mission-specific factors, such as priority distribution and environmental constraints.

In literature, continuous priority ranges have been defined, from high to low, based on proximity to the center of the disaster area [75, 76]. Targets closer to the center of the disastrous area or in more critical conditions received higher priority, while those located in less affected areas are assigned lower priorities. [75] investigated a framework for using UAVs with advanced computing to improve disaster response and search and rescue operations with a key contribution of a UAV-assisted SAR framework that integrated UAV computing, SAR missions, and disaster centers with a high priority to optimize disaster response. [76] has proposed a Layered-Based Search and Rescue (LSAR) algorithm for efficiently conducting SAR missions using multiple UAVs to minimize rescue time and maximize the number of survivors rescued. The layered structure of the algorithm gave high priority to the disaster center, where survivors were most likely concentrated and progressively expanding outward. This approach prioritized areas with a high probability of interest, leading to efficient resource usage and quicker response times.

A variety of advanced UAV path planning frameworks have been developed to address prioritization in dynamic and complex environments. A distributed approach prioritized edge areas deemed more vulnerable by balancing energy consumption, flight risk,

and surveillance priorities using a modified Particle Swarm Optimization (mPSO) algorithm [40]. Incorporating an Island Policy-Based Optimization Framework (IPOF) further enhanced UAV swarm efficiency by dynamically splitting and rejoining sub-swarms to track multiple targets, optimizing obstacle avoidance and navigation based on novel reward functions [77]. Similarly, [78] has proposed a task allocation algorithm for heterogeneous targets prioritized coverage by target type, minimizing task execution time and energy usage through an opposition-based GA. Addressing the MTMC problem, the Weighted Targets Sweep Coverage (WTSC) algorithm assigned higher weights, i.e., priority, to critical targets, ensuring efficient resource allocation and achieving significant improvements in coverage quality [79]. Moreover, a persistent surveillance framework has been incorporated dynamic prioritization to revisit critical sub-regions, deploying a modified Dijkstra Algorithm (DA) to adjust weights based on urgency and proximity, while a Minimum Spanning Tree (MST) algorithm optimized continuous resource distribution [80]. These methodologies collectively highlighted the importance of prioritization for efficient UAV operations in applications such as disaster monitoring, border security, and infrastructure inspection.

However, in an SAR mission, information exchange between a team of UAVs and the GCS, i.e. connectivity, also needs to be taken into account along with area coverage or target detection times. Furthermore, in addition to search and sensing tasks, due to a lack of or intermittently available communication infrastructure, network provisioning might also be required. The incorporation of connectivity requirements into multi-UAV path plans has been typically performed via constrained or multi-objective optimization formulations. While area-based prioritization was common in multi-UAV missions that consider priority or heterogeneous targets, connectivity-based prioritization has not been typically defined explicitly. Instead, the optimization formulations aimed to produce flight

paths that assign more UAVs to the regions with heterogeneous targets or more concentration of ground users to provide connectivity; hence, prioritizing some regions implicitly based on expected connectivity requirements.

In literature, several innovative approaches have been proposed to enhance UAV operations by prioritizing critical targets in dynamic scenarios. [81] has been presented a UAV-enabled IoT platform by prioritizing wildfire regions, leveraging Named Data Networking (NDN) to improve disaster response by enabling robust communication in fragmented networks. An energy-efficient data-gathering framework for UAV-assisted Wireless Sensor Networks (WSNs) used target prioritization strategy and clustering techniques to minimize travel distances and energy consumption [82]. For airborne networks, algorithms have prioritized coverage by optimizing UAV deployment and motion, adapting to known or unknown User Equipment (UE) locations concluding with a solid connectivity among UAVs [82]. The Intelligent Cluster-Based Multi-UAV (ICBM-UAV) protocol was proposed to dynamically manage clusters based on battery levels and connectivity needs, prioritizing victim detection and minimizing rescue times in search and rescue (SAR) missions [58]. In this category, a FANET management framework integrated mission-critical target prioritization with dynamic topology management, balancing mission success and connectivity reliability in real-time operations [62]. In these works, the proposed methods have underscored the critical role of target prioritization in improving UAV efficiency for disaster management, SAR, and emergency response.

3. SYSTEM MODEL AND ASSUMPTIONS

The success of a dynamic multi-UAV application in complex and hazardous environments, like earthquakes, flooding, etc., strongly depends on a robust system model that integrates environmental factors, UAV capabilities, and mission-specific requirements. This chapter establishes the groundwork for the proposed methodology in this thesis by establishing a comprehensive system model and detailing key assumptions underlying the research.

First, we define the mission environment, including characterizing its dynamic nature and the specifications of the deployed UAVs in this study. In the following sections, we will explore UAV movement strategies during the mission, focusing on how these vehicles adapt to changing mission phases and environmental challenges. A set of performance metrics is also introduced to evaluate the efficiency and effectiveness of the proposed path algorithms. Then, we present the mathematical preliminaries that form the heart of our system model by clearly formulating the problem and the critical variables involved. This structured framework ensures consistency and precision throughout the subsequent analysis and algorithm development. By establishing these foundational elements, this chapter serves as a crucial step toward understanding the intricacies of multi-UAV systems for dynamic search and connectivity for SAR missions.

3.1 The UAVs and Mission Environment

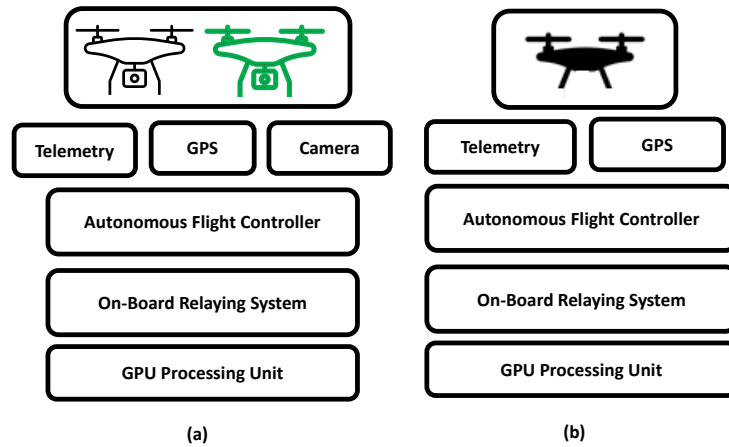
An overview of the system parameters is summarized in Table 3.1. The Area of Interest (AoI) referred to as A , is assumed to have a square shape and is modeled as a grid of disjointed cells, each in the shape of a square with dimensions $r_s \times r_s$, where r_s represents the UAVs' ground sensing range.

Table 3.1: *System Parameters.*

System Parameters	Definition
N_s, N_i, N_r	Total number of search, maximum injected and relay drones
N_{tar}	Number of targets
A, A_{uncov}	Total and uncovered mission area
r_c, r_s	Transmission and sensing ranges
V_s, V_r	Maximum search and relay drone speed
t_s	Time step duration
$\mathbf{F}$	Maximum flight time
$\mathbf{P}_{GCS}$	GCS position

The UAVs deployed for this mission are assumed to be multi-rotor drones called quad-copters, capable of precise waypoint navigation and hovering. Each search (mission) UAV is equipped with essential sensors, such as GPS for position tracking and cameras for environmental observation and monitoring. Moreover, all UAVs are equipped with wireless communication interfaces that enable them to interchange data with the GCS and other UAVs. Figure 3.1 illustrates the communication and operational interfaces of the UAVs, highlighting that search and injected UAVs (depicted in green) share similar interface configurations.

Figure 3.1: *Drone interfaces: (a) The interfaces of search and injected drone shown in white and green, respectively, (b) interface of relay drone.*



The maximum flight duration of UAVs is constrained by F . A constant number of search UAVs (N_s) commence the mission, with the possibility of injecting at most of N_r relay nodes and additional search nodes N_i at various mission phases. To simulate the mission, we have assumed the presence of N_{tar} targets, which are randomly distributed across the AoI. These targets represent various points of interest, such as victim groups, damaged infrastructure, or rescue personnel, as shown in Figure 3.2.

The primary objective of this study is to establish connectivity among these targets and GCS by forming an efficient shortest-path route using the minimum number of UAVs. During the mission, search UAVs actively monitor their coverage areas, exchanging data with other UAVs within their communication range. This exchanged information, which occurs either directly or over multiple hops, includes information about detected targets, GCS updates, positional data, and mission status. The sensing mechanism is assumed to be perfect, meaning that when a cell is scanned, it is sensed with certainty, and any target present within that cell is detected with 100% probability. While prior research has explored path planning under sensor uncertainty (e.g., [67]), this work assumes certainty in sensing for simplicity and scope.

Relay UAVs, unlike search UAVs, lack sensing capabilities and are solely responsible for facilitating data exchange among UAVs. It is assumed that the UAVs employ the antenna setup described in [83], ensuring free-space path loss omnidirectionally, without considering orientation or altitude differences, as long as there are no obstacles. Consequently, a disk model is adopted for the communication links, simplifying the connectivity assumptions.

3.2 UAV navigation

The proposed approach for multi-target search and connectivity algorithm for SARs is divided into three distinct phases: (i) the *pre-detection phase*, (ii) the *post-detection phase* (continuing the process until the final target is detected), and (iii) the *final configuration phase* (occurring after all targets have been detected). During the mission, search UAVs can fly with a maximum allowable speed of V_s . UAVs are restricted from re-visiting previously scanned cells to ensure efficient area coverage during the pre-detection phase. Upon detection of a target, certain search UAVs may start hovering above these targets to monitor them based on the selected path-planning method. From a different perspective, relay UAVs are capable of traveling at speeds up to V_r . Unlike search UAVs, they are allowed to hover or revisit previously scanned locations as needed to maintain or establish connectivity throughout the mission. This flexibility allows relay UAVs to dynamically adapt their positions to support the overall mission objective, which is establishing connectivity. The movement strategies for search UAVs are either pre-planned or dynamically re-planned based on the current mission phase, as detailed in Section 3.3.2. In contrast, at each time step t_s , relay UAVs calculate their positions by considering the search UAVs and the targets' positions. To ensure predictable and safe movements, relay UAVs are assumed to fly along straight-line paths to their next positions or way points, maintaining a fixed altitude that can be adjusted to accommodate safety requirements.

3.2.1 Performance metrics

The following performance metrics relevant to connectivity and mission phase times are defined to evaluate the performance of the proposed methods during the mission:

- *Percentage connected time*: The fraction of time that search drones are tethered to the GCS during the SAR operation.

- *Detection time*: A specific time-step during the mission at which all points of interest (targets) have been localized (detection and informing GCS).
- *Mission time*: The elapsed time counted from the UAVs' take-off until the final configuration's formation.
- *Target connected time ratio*: The time ratio from the moment a target is detected and connected to the GCS until it achieves the final configuration.
- *Number of relay nodes*: The mean and maximum of the on-air relay drones during the mission.
- *Number of injected nodes*: The number of search drones injected into the mission as extra resources to manage the SAR mission.
- *Distance traveled*: The total or maximum distance traversed by all drones.
- *Disconnected time*: The successive time period during which a search node is unable to communicate with the GCS.
- *Relay network formation time*: It is defined as the time duration between the detection of all targets and the completion of the final network configuration.

3.3 Mathematical Formulation

In this section, an overview of the fundamental path-planning algorithms for both search and relay UAVs is explained, which are essential for a successful SAR mission. These algorithms are based on the foundation of the mission strategy, ensuring efficient area coverage, target detection, and connectivity throughout the operation.

3.3.1 Basic Search Path Planning

Under the assumption of perfect sensing, the problem of determining search paths can be formulated as a coverage optimization problem [84]. In the pre-detection phase, search UAVs must traverse the area of interest efficiently, minimizing the total travel distance while adhering to mission constraints. We have formulated our proposed mission algorithms as optimization problems:

$$\text{Minimize} \quad \sum_{m=1}^{N_s} \sum_{i=1}^P \sum_{j=1}^P \sum_{k=1}^K X_{i,j,k}^m D_{i,j} \quad (3.1)$$

$$\text{s.t.} \quad \sum_{j=1}^P X_{i,j,k}^m \in (0, 1), \forall i \in P, \forall m \in N_s, \forall k \in K, \quad (3.2)$$

$$\sum_{m=1}^{N_s} \sum_{i=1}^P \sum_{j=1}^P \sum_{k=1}^K X_{i,j,k}^m = \|P\|, \quad (3.3)$$

$$X_{i,0,k}^m = 1, \forall m \in N_s, \exists i \in P, \quad (3.4)$$

$$X_{0,i,k}^m = 1, \forall m \in N_s, \exists i \in P,$$

$$\text{Minimum tour length} = d_m, \quad (3.5)$$

$$\text{Search drone speed} \leq V_s, \quad (3.6)$$

$$\frac{1}{V_s} \max_{\forall m \in N_s} \sum_{k=1}^K X_{i,j,k}^m D_{i,j} \leq \mathbf{F}, \quad (3.7)$$

$$\text{Number of drones} = N_s, \quad (3.8)$$

$$\text{Transmission range} \leq r_c, \quad (3.9)$$

$$\text{Sensing range} \leq r_s, \quad (3.10)$$

$$\text{Area of interest} = A. \quad (3.11)$$

In this formulation, $X_{i,j,k}^m$ is a binary variable that equals 1 if at time step k , UAV m flies from cell i to j ; otherwise, it is 0. $D_{i,j}$ represents the Euclidean distance between cells i and j . P and K denote the sequence of cells visited and the number of time

steps, respectively. Constraints (3.2)-(3.4) ensure that each cell is covered precisely once and guarantee the start and end of the paths at the GCS and the efficient utilization of drones. Additional constraints (3.5)-(3.11) address speed, range, and mission-specific requirements detailed in Sections. 3.1 and 3.2.

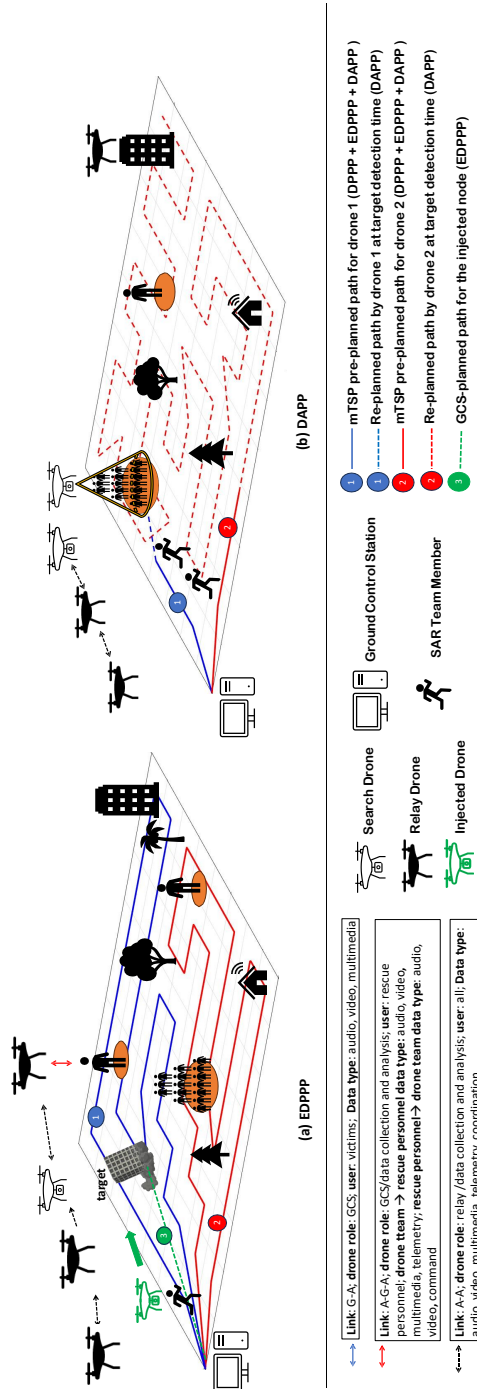
The problem is modeled as a Multiple Traveling Salesman Problem (mTSP), a well-known extension of the classical Traveling Salesman Problem (TSP) [85]. The mTSP involves multiple agents (salesmen) departing from a central point to visit a set of locations, minimizing the total travel distance. We solved this problem using a genetic algorithm-based approach. For example, Figure 3.2 illustrates two initial search UAV paths (depicted in red and blue lines) covering the mission area. This pre-defined path can be replaced with alternate optimization criteria as required, providing flexibility for dynamic mission requirements.

3.3.2 Basic Relay Positioning Algorithm (RPA)

The relay positioning and assignment algorithm [86] focuses on maintaining uninterrupted connectivity between a GCS and a group of UAVs performing search tasks. The algorithm operates in two main phases: (i) initialization and (ii) optimization. These phases ensure that relay UAVs are positioned efficiently to connect the search UAVs to the GCS at every time step while minimizing redundancy and resource management. In the initialization phase, relay positions are determined to guarantee connectivity at the next time step. The process begins with a connectivity check to determine if the current relay setup will maintain connectivity. If any search UAV risks losing connectivity, new relay positions are computed. This involves using a MST to determine the minimum number of relay points required for connection. Steiner points are added to split longer edges into shorter segments, ensuring all connections are within the communication range of the relays. However, the initialization phase balances two factors: minimizing the number of

relays and utilizing the existing UAVs in the air efficiently. For example, nodes already deployed may move toward steiner positions, even if they cannot reach them immediately, to reduce the need for additional relay deployments. Relay assignment during initialization uses a cost-based method, factoring in distances and idle times of relay nodes. The algorithm assigns nodes to positions based on calculated costs, allowing for flexibility when relays cannot reach their assigned locations immediately. This step may leave some positions unoccupied temporarily, which is resolved in subsequent connectivity checks and adjustments to ensure the search UAVs remain connected. The optimization phase refines the relay positions determined during initialization to remove redundancies and improve resource utilization. Redundant relays—those not required for maintaining the shortest communication paths—are eliminated. The assignment process in this phase is stricter than during initialization, as relays must reach their assigned positions within their idle durations. This prevents unfeasible assignments and ensures all nodes fulfill their roles within operational constraints. Busy nodes continue their relay functions, while idle nodes either move to assigned positions, hover, or return to the home base if they are far from active operations. The algorithm, throughout its execution, incorporates a range of practical constraints, including UAV speed limits and pre-planned search trajectories. This approach incorporates a forward-looking perspective on future connectivity needs, thereby ensuring efficient planning while simultaneously mitigating the risk of unnecessary deployments. This structured approach not only maintains critical connectivity and reduces operational expenditures but also optimizes the utilization of relay and search UAVs by effectively balancing connectivity requirements with resource management constraints.

Figure 3.2: Illustration of the multi-target SAR mission. Pre-planned search paths for two drones are depicted in blue and red solid lines. a) In EDPPP, search nodes adhere to pre-planned paths until the last target is detected. An injected node is shown in green and dispatched from the GCS to cover the newly detected target. b) In DAPP, the detecting search node hovers over the target, and path-replanning is performed for the remaining drones in the air, indicated by the dashed lines.



4. DYNAMIC MULTI-UAV POSITIONING AND ASSIGNMENT ALGORITHM FOR MULTI-TARGET SEARCH AND CONNECTIVITY

In this chapter, a team of UAVs is launched to investigate randomly distributed targets in the mission area, aiming to establish a link between the detected targets and the GCS for real-time monitoring while ensuring uninterrupted UAV-GCS communication.

4.1 Mission Overview

The proposed mission is structured into three distinct phases. In the first phase, search and relay nodes follow their pre-planned paths until the detection of the initial target. The initial paths are mainly designed at GCS at the beginning of the mission to maximize coverage and efficiency before any dynamic adjustments are required.

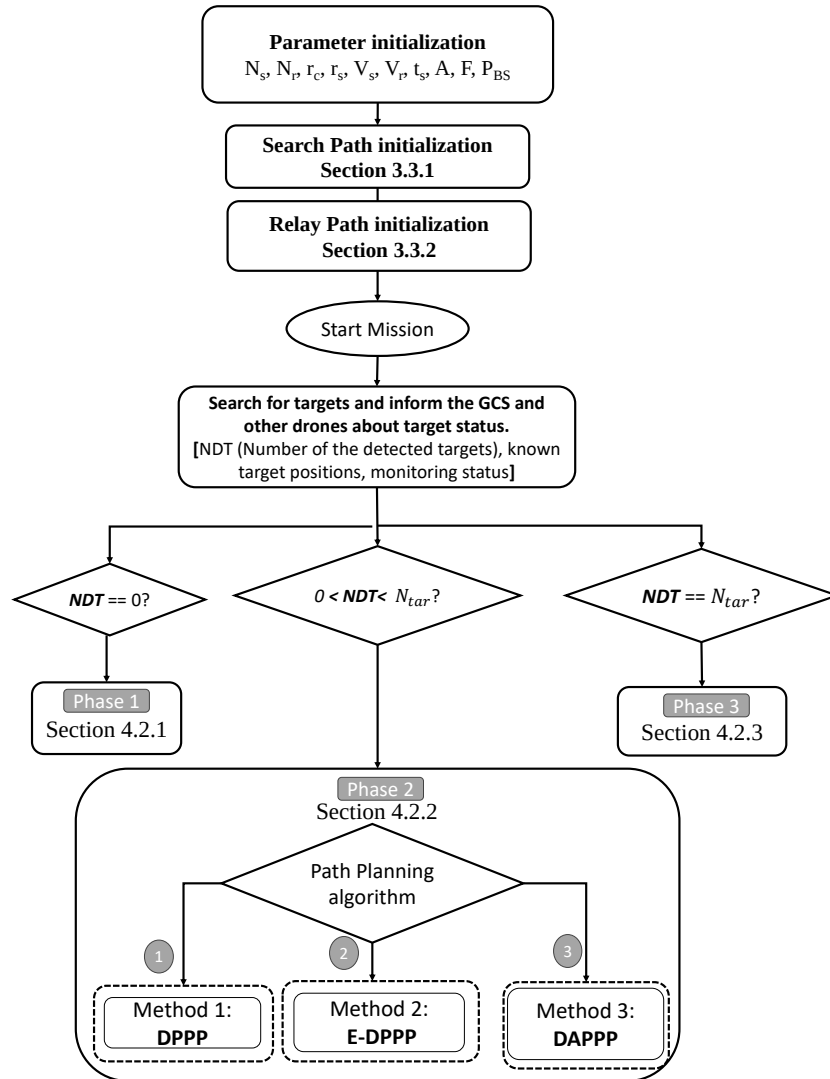
Detecting the first target triggers the commencement of the second phase, wherein all UAVs adhere to their pre-planned paths up to the final target detection. During this phase, the system dynamically responds to detection events. The drones' movement trajectories can switch between pre-planned trajectories and event-driven trajectory computations based on the evolving mission requirements. Adaptability in switching between pre-planned and event-driven trajectories grants the mission to respond efficiently to changing conditions and new information. In the final phase, the drones establish a stable network configuration, called the final configuration, to enable continuous monitoring of all identified targets. This setup ensures that each target remains under surveillance while maintaining connectivity within the network.

Throughout all phases, drones share vital data with other nodes in their clique and local network at every step. This shared data encompasses drones' current positions,

the status of target detection and monitoring (e.g., which targets have been found and are actively being observed), and the status of communication with the GCS, e.g., whether the GCS has been updated on target statuses. This constant exchange supports coordinated decision-making and effective mission execution.

Figure 4.1 presents the workflow of the proposed multi-target search and connectivity mission planner.

Figure 4.1: *Multi-target search and connect workflow.*



At each time-step, t , while the mission is ongoing, the search and relay drones can adapt to one of the following states, which specify the actions that the drone can undertake during the mission:

- Search drones:
 - Searching: The drone has neither detected nor been informed of any targets, and some targets remain undetected.
 - Detecting: At least one target has been detected by the drone.
 - Monitoring: The drone hovers over a detected target while collecting or relaying information to other nodes or the GCS.
 - Relaying: The drone hovers at a relay position to establish a communication link to connect targets to the GCS.
 - Unassigned: There is no pending task, and the drone is flying to GCS.
- Relay nodes:
 - Networking: The drone serves as a connecting node, creating links for search and/or targets prior to the detection of all targets.
 - Hovering: The drone hovers at relay positions, facilitating connectivity between targets and the GCS.
 - Unassigned: There is no pending task, and the drone is flying to GCS.

4.2 Drone Roles in Distinct Phases of the Mission

The UAV positions are computed according to their states at each time step of the mission. The subsequent sections outline the actions applicable to the various states of the drones and the status of the detected target after each time step t .

4.2.1 Phase 1: From Drone Take-off at GCS to the First Target Detection

The mission launches are based on the initial search and relay drone paths detailed in Section. 3.3, referred to as search and relay path initialization, Figure 4.1, with the search and relay nodes active in the searching and networking modes, respectively. From the start of the mission until the detection of the first target, the drones' path actions are outlined in Algorithm 1

Algorithm 1 Pre-detection search and relay path procedure.

- 1: **procedure** PreSearchConnect($A, N_s, N_r, r_c, r_s, V_s, V_r, t_s, \mathbf{P}_{\text{GCS}}$)
 - 2: Compute paths of search nodes using mTSP (Section 3.3.1)
 - 3: Compute paths of relay nodes using RPA (Section 3.3.2)
 - 4: At each time step, at each search and relay node repeat:
 - 4.1: Broadcast current position.
 - 4.2: Form a local network graph based on known drone positions and compute the node clique.
 - 4.3: Exchange GCS and target detection/monitoring status information with all nodes in the clique and update status information if necessary.
 - 5: At each time step, at each search node repeat:
 - 5.1: Sense the area within sensing coverage and check if a target is present.
 - 5.2: If a target is present, update the target detection status and move the detecting node and the nodes in its clique to post-detection phase (Section 4.2.2) or final configuration phase (Section 4.2.3); if not keep flying the current path.
 - 6: **end procedure**
-

4.2.2 Phase 2: Time interval between the detection of the first and last target

The second mission phase operates in an event-driven manner, in which the event means the act of detecting targets. As mentioned above, until a target is detected, the search and networking nodes are in search and relay modes, respectively, and they are flying over their pre- or re-planned paths, meanwhile swapping information with any other drones they meet during the mission (Algorithm 1, lines 3-4). The search drones transition to the target-detecting state and remain in this state till the time step that at least one target

is detected. As search drones are in the search state, drones can switch between searching and monitoring states based on their path-planning algorithm. This study unveils a suite of path-planning algorithms with unique priorities and strategies responsive to events (target detection). Every approach tackles various requirements of the mission, illustrating their flexibility in diverse UAV missions in terms of target detection.

- Detection Priority Path Planning (DPPP): We propose this methodology as a baseline or reference benchmark, giving precedence to the search operations. In this method, until the last target is detected, relay and search drones will adhere to their pre-defined paths, which are shown as solid red and blue lines in Figure 3.2(a). This method sticks to the plan (Algorithm 1) until every target is spotted. One major strength of the DPPP path planning approach lies in its ability to maintain the mission plan without needing any updates until all targets are detected. This means that even if the search drones temporarily lose connection with the GCS, they can still proceed with their pre-determined tasks. The prioritizing of detection in this method effectively reduces search times. However, targets may remain unoccupied for extended long periods. As a result, *This approach is well-suited for missions regarding environmental monitoring where timing is not a critical factor; however, it could be less effective for missions with continuous monitoring requirements or consistent connectivity with targets.*
- Extended Detection Priority Path Planning (EDPPP): Using this approach, search and relay drones follow their pre-planned trajectories while additional injected nodes are dispatched from the GCS to monitor detected targets to obtain target information faster. For the injected nodes, the GCS computes the path of the injected drones as a straight line starting from the GCS till the position of the detected target. In Figure 3.2(a), as drones 1 and 2 follow their preplanned paths, i.e., solid lines in red and blue, the injected drone (green) is introduced to the mission to fly toward the

detected target when drone 1 detects it. If, at the time step, the injected node flies toward the newly detected target and, on its way to the target, is informed of another target detection, then depending on the total cost of the traveled distance, there may be reassignment to a different target position. Upon the arrival of the injected node to the designated target, its state switches from search to monitoring, and then it starts hovering on top of the target to sense it continuously. The original search and relay nodes would stick to their flight trajectories (lines 3 and 4) in Algorithm 1, till the detection of the last target. Algorithm 2 shows the required actions that should be taken at drones and GCS from the time step that each target is detected. Compared to DPPP, this method substantially minimized the time duration when targets remain unmonitored. The main downside of this method is the deployment of more drones in the air, which means more resource utilization.

Algorithm 2 Extended Detection Priority Path Planning-EDPPP.

Input: known target location(s), N_i , V_s

Output: paths from time of new target detection

- 1: From the time of detection till GCS is informed at each time step, at each search and relay node repeat lines 3 and 4 of Algorithm 1, respectively.
 - 2: At the time of detection, the detecting search node and its clique update the target detection status, GCS knowledge status and keep flying pre-defined paths.
 - 3: At the time GCS knows that at least one target is detected:
 - 3.1: GCS computes the shortest flight path from GCS to detected target location
 - 3.2: GCS injects a new search node in the air and assigns it to the newly detected target location
 - 3.3: Injected node flies the assigned path to the target. On the way to the target, at each time step repeats step 5 of Algorithm 1. If it detects another target during its flight, it updates its target detection status and informs the nodes in its clique, starting the next event.
-

- Detection Adaptive Path Planning (DAPP): In this method, the paths of relay and search drones are replanned at each time step of the mission when a new target is

detected, which we call dynamic re-planning. The dynamic re-planning enables the method to establish a continuous connectivity link between the detected targets and the GCS upon their detection, as shown in Figure 3.2(b). Algorithm 3 shows the procedure that each node should be taken at the time of a target detection. Whenever a target is detected, the search node's state that detects the target switches from the search state to the monitoring state. Subsequently, it starts hovering at the target location and commences sensing the information of that target (the solid blue path (drone 1) in Figure 3.2 (b)). Meanwhile, the other search nodes remain in the search state, and the proposed path planning should update their paths for the uncovered areas. Whenever a target-detection event occurs, the GCS executes an open mTSP (Algorithm 3-line 3.1) for the remainder of the search area (uncovered cells). Hence, the search nodes that have not yet detected any target and are not covering any targets restart their mission for the remainder of the search from where they are currently located. The newly created paths must be optimized to minimize the total distance covered, and there is no need to return to the initial positions. In other words, upon detection of a target by drone 1 and hovering over it, the drone's 2 path is replanned (Figure 3.2(b) - the red dashed line). Given that, at this time step, a reduced number of search nodes will continue the search process, the GCS also executes a new open mTSP algorithm using an extra injected node waiting at GCS to have a fair comparison in using the EDPPP method (line 3.2). This step specifies the necessity for a drone replacement. In the following, we shall discuss how this step becomes critical, especially for mission scenarios when there are fewer original search nodes. The paths of the relay node are calculated after generating new search node paths (refer to line 3.4). One significant advantage of this approach is the immediate coverage of targets, ensuring they are occupied by a node while making more efficient use of available resources. Nevertheless, a limitation of this

method is the reduced availability of relay and search nodes to fulfill the requirements of the mission at each target detection event. This method is tailored for SAR missions using multi-UAVs that would serve ground targets such as mobile users with connectivity requirements.

Algorithm 3 Detection Adaptive Path Planning-DAPP.

Input: known target location(s), current search and relay node positions, A_{uncov} , number of unassigned search nodes, $N_r, N_i, r_c, r_s, V_s, V_r$

Output: paths from the time of new target detection

- 1: From the time of detection till GCS is informed at each time step, at each search and relay node repeat lines 3 and 4 of Algorithm 1, respectively.
 - 2: At the time of detection, at detecting node and its clique update the target detection status and GCS knowledge status and start hovering until re-planning is complete.
 - 3: At the time GCS knows that at least one target is detected:
 - 3.1: GCS computes paths of search nodes still in searching state ($path_{searchonly}$) using mTSP given in Section 3.3.1 without the return to start point constraints, where number of drones is number of unassigned search drones, and area of interest is A_{uncov} . GCS computes the mission duration for the computed paths ($time_{searchonly}$).
 - 3.2: GCS computes paths of search nodes still in searching state and an additional injected node (which is at GCS location, $path_{withinjected}$) using mTSP as above. GCS computes the mission duration for the computed paths ($time_{withinjected}$).
 - 3.3: GCS compares $time_{searchonly}$ and $time_{withinjected}$. If $time_{searchonly}$ is smaller, the re-planned search paths are $path_{searchonly}$; otherwise, GCS injects a new node in the air and returns the $path_{withinjected}$.
 - 3.4: GCS computes paths of relay nodes using RPA (Section 3.3.2) with re-planned search paths and the hovering search node locations as the set of nodes to be connected and the current relay positions as input and returns $path_{relays}$.
 - 3.5: GCS informs the search, relay and injected (if any) nodes of their new plans.
 - 3.6: The drones resume their mission.
-

4.2.3 Phase 3: Time interval between the final target detection till the end of mission

After the detection of all targets, the mission's action changes to connect all of them to the GCS using the minimum number of nodes (relay and search). In this time step,

drones automatically update their paths distributedly. The notified drones, drones that are informed about the detecting of targets, estimate the final topology of the network (final configuration), Algorithm 4. This algorithm formulates the connectivity problem between the GCS and drones as an STP by adopting the approximation method proposed by Lin in [87]. The Euclidean Minimum Spanning Tree (EMST) uses the targets' positions and the GCS to achieve this goal (lines 2–3). Within the EMST, long links are partitioned by r_c to estimate the position of relays according to line 4 of Algorithm 4.

Algorithm 4 Final configuration computation.

```

1: function finalConfig(target locations,  $P_{\text{GCS}}$ ,  $r_c$ )
2:   Form the Euclidean graph  $G$  with target and GCS locations as vertices and Euclidean distance  $d_{jk}$  between each vertex as the edge weights. Node 1 is assumed to be the GCS.
3:   Compute Euclidean MST  $T$  for  $G$ , starting at node 1.
4:   Find edges  $e$  in  $T$  with weights  $w(e)$  larger than  $r_c$  and insert  $\lceil w(e)/r_c \rceil - 1$  Steiner points into  $T$ .
5:   Return the computed Steiner points.
6: end function

```

The rest of phase 3 is explained in Algorithm 5. At each iteration of time, each drone collaborates with others in its clique to decide its next action. As long as available resources reside, all open positions are in the final configuration, and the algorithm assigns the best-suited node to available positions (Refers to lines 12-15 in Algorithm 5). The non-assigned nodes in the final configuration start flying back to GCS (line 10). Conversely, in case a node is assigned to an open position meanwhile meets other nodes who could complete the task more efficiently and in less time, it may be re-allocated or left unallocated, redirecting its flight to the GCS.

MinCostTask: The open positions and the nodes' current positions inside a clique are taken as the input parameters by this function to compute the cost matrix using the Euclidean distances between position pairs; refer to lines 4-5 in the Algorithm 6.

Algorithm 5 Final Configuration Phase: From last target detection to mission end.

Input: Target, drone, and GCS positions, r_c, r_s, V_s, V_r, A

Output: Drone paths from last target detection until all nodes in final position

```
1: while All positions in final configuration not yet occupied, repeat on each Drone do
2:   Information exchange
   • Broadcast current position.
   • Form a local network graph based on known drone positions and compute the
     Drone clique.
   • Exchange target detection/monitoring status and GCS status with all nodes in
     the clique and update status if necessary.
3:   if Drone knows all targets then
4:     if Drone knows GCS is informed of all targets then
5:       if Drone is in final configuration then
6:         Drone stays where it is.
7:       else
8:         if Drone knows all target positions are covered then
9:           if Drone knows all relay positions are covered then
10:            Drone is unassigned and it flies back to GCS.
11:          else
12:            Assign the nodes in the connected component of Drone to
              open relay positions using the function MinCostTask().
              Generate the direct paths corresponding to the assignment.
13:          end if
14:          if Node is a search or injected node then
15:            Assign the search or injected nodes in the connected com-
              ponent of Drone to open target positions using the function
              MinCostTask(). Generate the direct paths corresponding
              to the assignment.
16:          end if
17:        end if
18:      end if
19:    else
20:      Drone flies toward GCS to inform it about all targets.
21:    end if
22:    Drone flies its current path.
23:  end if
24: end while
```

Then, nodes are allocated to open positions to minimize the total cost using a linear assignment approach shown in line 8 of the Algorithm. If the open position is a target

position, the current positions of search nodes within the clique are the only ones considered. Conversely, suppose the open position is designated for a relay node. In this case, all nodes within the clique that remain unassigned to the final configuration are included in the calculation of the final configuration assignment.

Algorithm 6 Minimum cost assignment to open positions.

```

1: function MinCostTask(open positions, current positions)
2:   for each current relay position  $j$  do
3:     for each open position  $k$  do
4:       Compute Euclidean distance  $d_{jk}$  between position  $j$  and position  $k$ 
5:       Set cost  $Cost(j, k) = d_{jk}$ 
6:     end for
7:   end for
8:   Match a current position to an open position such that total cost is minimized
   solving the linear assignment problem.
9: end function
10: Return matched location pairs.

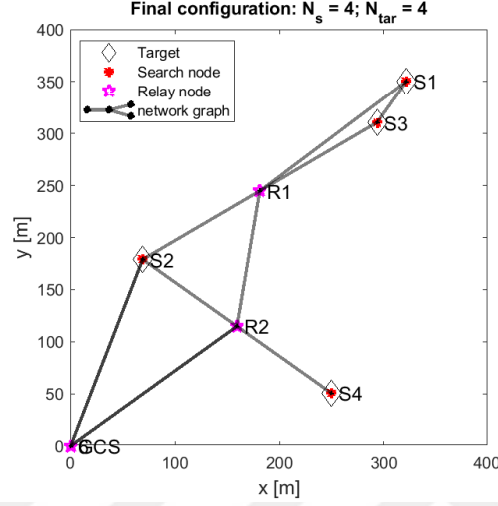
```

4.3 Mission Phase Visualization

In this section, we will outline the positions of nodes at various steps involved in the mission. To better visualize, it is assumed that four targets are randomly distributed across the mission area, and four search nodes are deployed for this purpose. Under the assumption of 200 m for the transmission range, three relays would guarantee connectivity among the search nodes while the mission is ongoing. Figure 4.2 shows the final network configuration. The target represented by $\diamond$ is occupied (cover and monitor) by a search node (Si) and two relay nodes (Ri). The nodes are positioned such that the GCS is connected to the target with minimal relay drones, i.e., resources.

In Figures 4.3(a) and (b), the pre-planned paths for the DPPP and EDPPP methods are illustrated. The mission starts with the search and relay nodes following their pre-planned paths, which are calculated using mTSP and RPA for all methods, and ends with the final configuration. All four search nodes adhere to their pre-planned paths until the

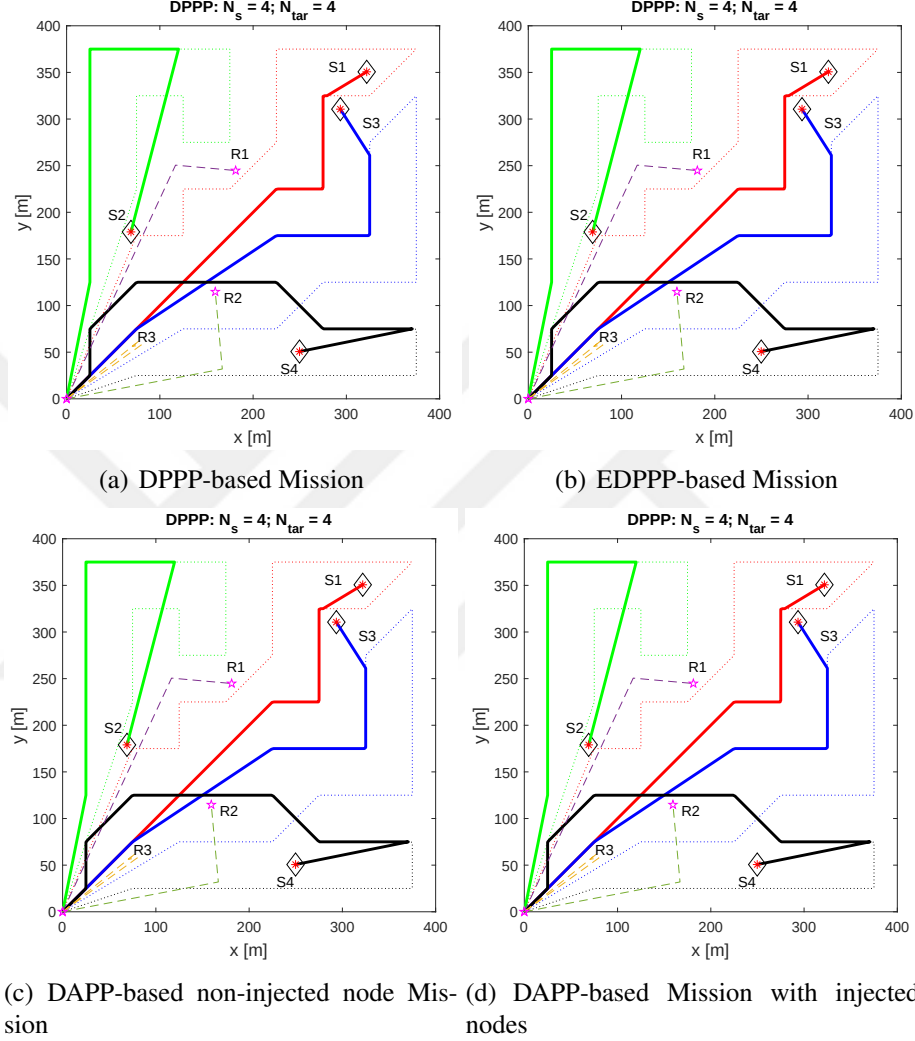
Figure 4.2: Final configuration of the multi-target search and connectivity mission. The graph of the network is shown in grey; diamond represents the four generated target random positions; The relay nodes labeled R1 and R2 and the search nodes labeled S1 to S4 represent the relay and search nodes, respectively.



last target is detected, maintaining connectivity with one another and the GCS through relays R1, R2, and R3 at both approaches. Two additional injected nodes are deployed in EDPPP, compared to DPPP which is shown by dash-dotted lines. When the first target is detected by S2, it notifies the GCS, prompting it to send injected node IN1 to the position of the target as S2 continues its flight over its initial path. Similarly, when detecting the second target proclaimed by S4, the GCS injects IN2. As IN2 travels toward its target, the rest of the targets are detected, and the final configuration phase of the mission starts. Using the `MinCostTask` algorithm, search drones S1, S2, S3, and S4 are allocated to target positions, and similarly, relays R1 and R2 are dedicated to relay positions. The relay node R3 and injected node IN2, which are not assigned, return to the GCS.

Figures 4.3 (c) and (d) depict the search paths flown using DAPP, with and without the inclusion of extra search node injections, INs. Varying line widths represent the re-planned paths, with decreasing widths illustrating that the drone's path has been re-planned because it has detected a target. In both scenarios, the first target is detected by S2 and

Figure 4.3: *mTSP-computed Pre-detection search paths. The solid lines depict the flown paths of search nodes S1 to S4. The relay nodes (R1 to R3) flown paths are depicted in dashed lines. The flown paths by injected nodes IN1 and IN2 are depicted by dash-dotted lines. In subfigures c and d, lines get thinner to represent the re-planned paths.*



proceeds to the target's position. Without the use of injected nodes, the paths of the search drones S2 to S4 and the relay nodes (connecting nodes) are updated by running the open mTSP algorithm, Figure 4.3 (c). By incorporating the injected nodes into the mission, re-planning also accounts for the injected node IN1. Without injected nodes, S4 undertakes the longest path, covering the remaining areas assigned to hovering search nodes. When

no injected nodes are included, S4 undertakes the path with the longest distance, covering the rest of the areas assigned to the search nodes in the hovering state. By contrast, in the case of the deployment of IN1 and IN2, the path lengths are more evenly distributed. The key benefit of injected nodes, INs, becomes much apparent, as expected, when only a few search nodes remain to cover a vast area. However, as the mission progresses, the necessity for injecting additional nodes decreases.

4.4 Results and Discussions

This section presents an evaluation of the performance of the proposed search and relay positioning algorithm for SAR missions. The mission area is a square with a side length of $400m$. The maximum speed of the relay and search nodes is 10 m/s and 2.5 m/s , respectively. The sensing range of search drones is 50 m , and the relay transmission range for search and relay nodes is 100 m . These parameters are extracted from prior experimental studies [83, 88]. For speed and transmission range, standard drone specifications are utilized. In contrast, the sensing range r_s was determined based on the ground coverage of the drone's camera, ensuring satisfactory qualities for the acquired images. Based on photogrammetry principles [89], and assuming a standard drone camera with a $28mm$ focal length and a $1/2.3$ inch image sensor, the flight height was calculated as 200 meters, which allows for high-quality image capture and effective coverage of $50m \times 50m$ cells of the mission area. In EDPP, the number of relay nodes and targets (N_i) is set to 20 and $N_{tar} - 1$, respectively. In DAPP, N_i is set to 1 as the default, but it is possible to change it. Matrix Laboratory (MATLAB) was employed to run the simulations, with more than 1,000 runs, to generate 1000 randomly distributed targeted configurations over the mission area. In the next sections, the performance of multi-objective optimization-based path planners is evaluated to establish a benchmark testbed, and subsequently, an analysis will be carried out to assess the proposed path planners' performance.

4.4.1 Benchmark planners

The outlined algorithms are designed to determine the deployed nodes' pre-planned or flight trajectories. The initial three approaches create search drones' paths in the absence of relay nodes:

- *mTSP*: The problem of path planning for multi-UAV systems is formulated in the context of a single objective optimization problem to minimize the total distance traveled as the pursued optimization goal (refer to Section 3.3.1 for the formulation). A GA approach is used to solve the proposed algorithm.
- *WS*: The problem of the multi-UAV path planning is formulated as a bi-objective optimization problem, seeking to maximize the percentage of connected time and, at the same time, minimize total coverage time. All objectives are weighted equally, and its associated optimization problem is solved by employing GA.
- *NSGA-II*: By employing this approach, the problem of multi-UAV path planning is formulated in the context of a multi-objective optimization problem, sharing identical objective functions as the WS approach. NSGA-II is used to optimize both objectives simultaneously. The results of our analysis ensured that we could select the best connectivity paths among the set of generated paths from the Pareto-optimal solutions.
- *The combination of mTSP and RPA, NSGA-II with RPA, and WS and RPA*: Mixed scenarios are explored by integrating NSGA-II, mTSP, and WS for the search paths into our proposed workflow (Figure 4.1) and evaluating them alongside their basic forms without relay, using method 1. To specify further, search paths are initialized using mTSP, WS, or NSGA-II in the first step. Then, in the next step, we used these initial paths as the input arguments of the RPA algorithm to compute the paths of

relay nodes. It is noteworthy that using the sequential order of mTSP+RPA and method 1 is identical to DPPP.

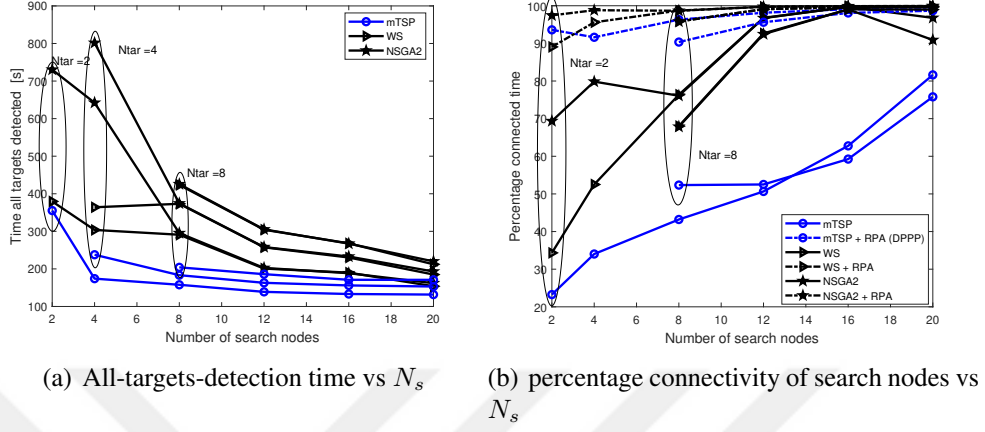
Table 4.1: *The algorithmic complexity of the path planners.*

Algorithm	Computed Time Complexity
DPPP	$O(G \times P \times (N_s \times m + N_s^2))$
EDPPP	$O(N_{tar} \times G \times P \times (N_s \times m + N_s^2))$
DAPP	$O(N_{tar} \times G \times P \times (N_s \times m + N_s^2))$
NSGA-II	$O(P \times \log(P) \times G \times (N_s \times m + N_s^2))$

Table 4.1 presents the worst-case algorithmic complexities of the proposed methods. The DPPP's complexity is a function of the number of search drones, the number of cells, population size (P), and the number of generations (G). The position of each drone relative to other drones is checked with the aim of calculating the connectivity level between drones. In evaluating the worst-case scenarios, it is assumed that during the analysis, all drones remain in the connectivity state. Additionally, every drone's traversed distance within the mission is calculated by verifying whether they traversed the specified cells (cities) along their respective flight trajectories. In the EDPPP method, the number of targets (N_{tar}) determines the re-calibration of paths. In the worst-case scenario, DAPP (like EDPPP) performs path recalibration for all dispersed targets. A non-dominated sorted approach with a complexity of $P \times \log(P)$ [90] is deployed by NSGA-II.

The percentage connected times and the target detection times of WS, NSGA-II, and mTSP approaches using different numbers of N_{tar} and N_s are shown in Figure 4.4. The detection times are independent of RPA, i.e., with or without RPA. Hence, the detection results for NSGA-II + RPA and WS + RPA are eliminated from Figure 4.4 (a) for clarity. The mTSP method focuses on minimizing coverage time along with total traversed distance; therefore it has the shortest target detection time. In contrast, connectivity is incorporated in the mission plans using WS and NSGA-II methods. Therefore,

Figure 4.4: Comparison of detection times and connectivity versus number of search nodes (benchmark search algorithms).



the percentage of connected time calculated by these methods is considerably superior to that of the mTSP method. As a result, despite all efforts to maintain the connectivity of the drones to the GCS, the detection times of the NSGA-II and WS show an increasing trend. Though this makes the NSGA-II approaches more complex, it also causes these algorithms to have an improved level of connectivity compared to WS, with a cost of longer detection times.

Figure 4.5: Comparison of the connectivity and mission time metrics versus number of search nodes (benchmark search algorithms).

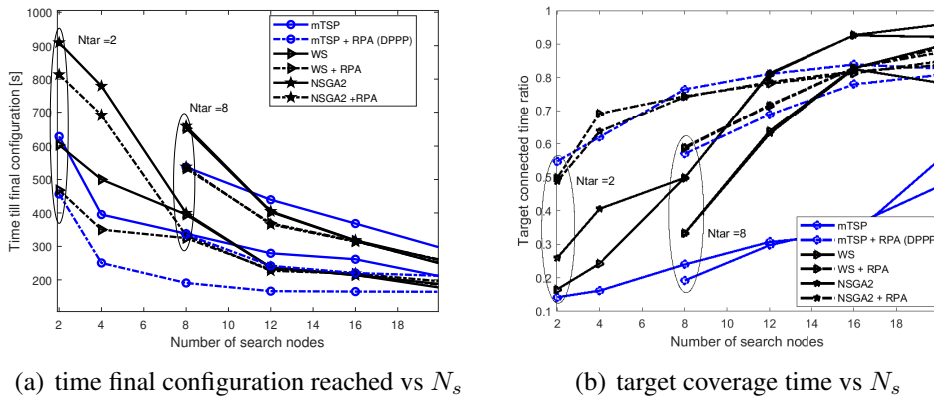
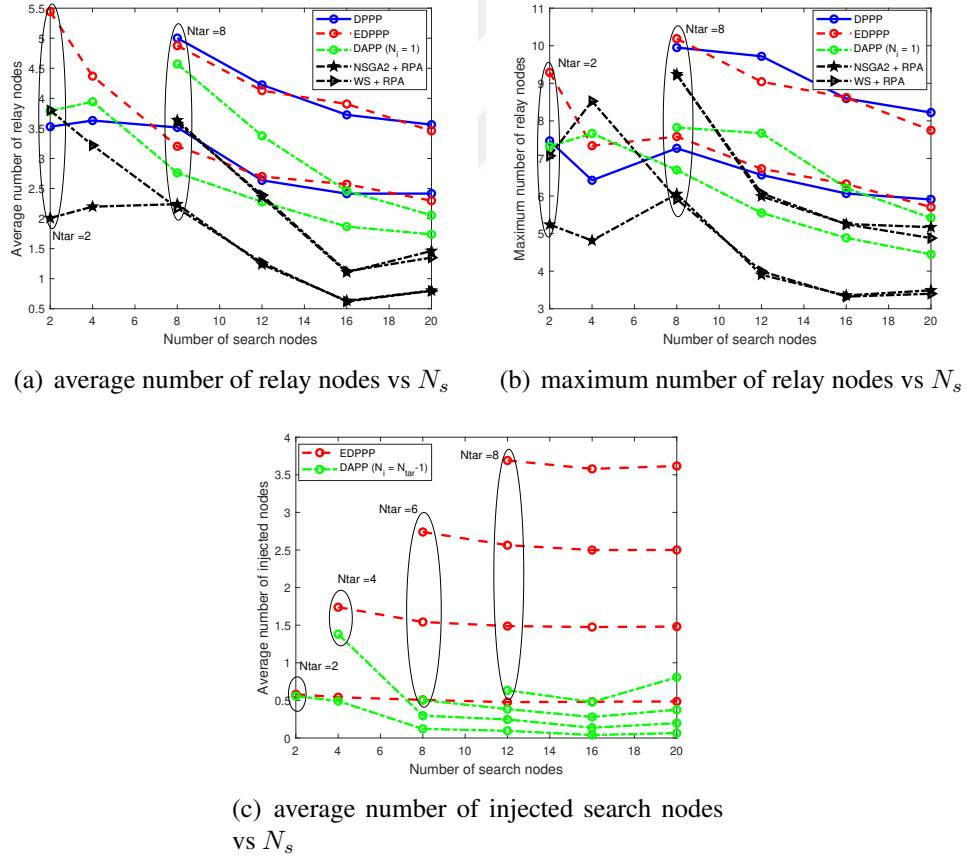


Figure 4.5 illustrates the duration of the mission and the performance of the target connectivity using WS, mTSP, and NSGA-II approaches in both their original forms and in the RPA-integrated method. The Deployment of relay drones helps to improve the performance of all schemes by ensuring that target detection information is promptly available to the GCS and other drones, thereby reducing the final configuration time. DPPP (mTSP + RPAs) complete missions faster than WS and NSGA-II. The reason behind this is that the time saved by using relays to share information with the GCS outweighs the extra time needed for the relays to operate. NSGA-II and WS are evaluated in our study with RPA-amended versions as a fair comparison.

Figure 4.6: Resource utilization vs number of deployed search nodes.

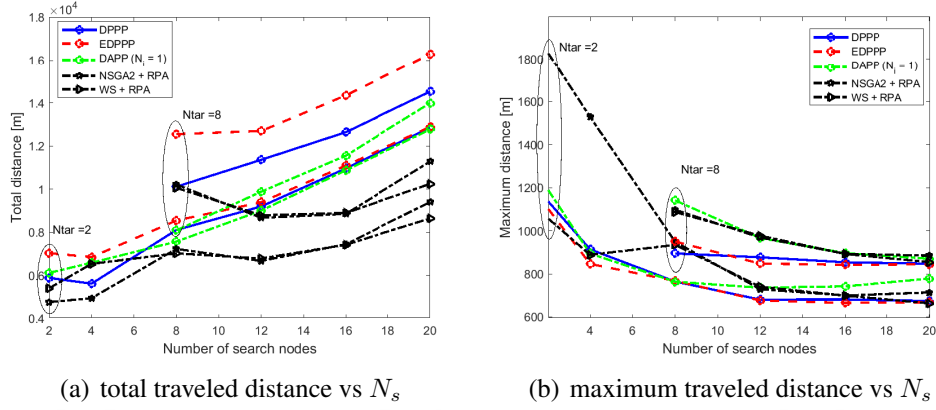


4.4.2 Required resources

First, we determined how many injected nodes and additional relay drones were needed during the SAR mission regarding the search and connectivity. The mean and maximum number of relay nodes and the mean number of injected nodes utilized in this simulation are represented in Figure 4.6. Even though many relay drones were available, a maximum of 11 were deployed. Between 3 and 5 relay drones, on average, were used when there were few search drones, Figure 4.6 (a) and (b). The connectivity of the network of search nodes increases with the increase in search nodes, along with the need for fewer relay nodes to maintain their connectivity to the GCS. EDPPP and DPPP perform similarly because they use the same paths for search and relay drones till the detection of the last target. Nevertheless, DAPP used fewer relay drones. The average number of relay nodes required for the combination of WS and NSGA-II integrated with RPA diminished. The reason behind this is that the connectivity of search nodes has already been considered in the initial path-planning step. For the DAPP and EDPPP methods, the average number of injected nodes (INs) when $N_i = N_{tar} - 1$ is shown in Figure 4.6 (c). In the EDPPP, it is worth noticing that about 50% of the injected nodes are deployed, whereas one injected node is dispatched in the DAPP method to help the mission on average. Hence, node injection is only necessary if the targets are found early enough to leave a significant uncovered area. In the following, for the DAPP case, the value of N_i will be constrained to 1.

The total and maximum traveled distance by all drones employed in the mission is shown in Figure 4.7. In general, the total distances traveled exhibit comparable values, with WS and NSGA-II demonstrating lower distances. In contrast, in NSGA-II, the maximum distance using a low number of N_s exceeds that of the other schemes. A subset of search nodes is tasked to cover greater areas, as the remaining nodes aim to sustain the

Figure 4.7: Analysis of path lengths versus the number of deployed search nodes.



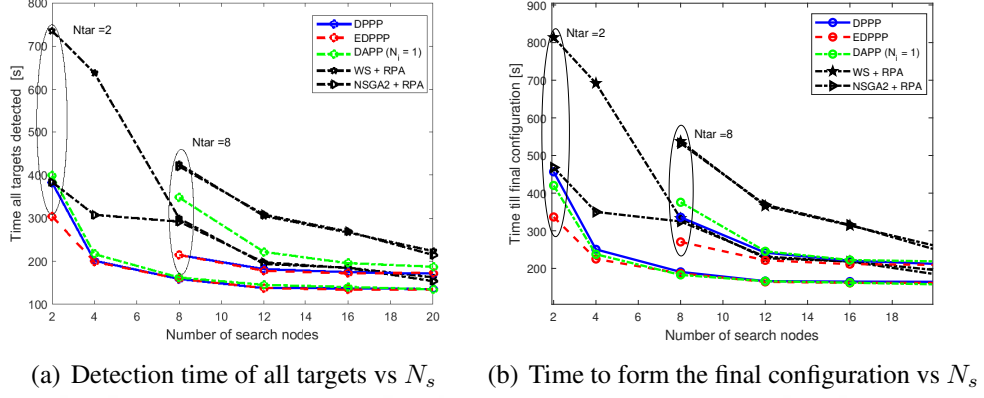
network connectivity. As the number of targets increases, DAPP shows a greater maximum distance since the uncovered routes of detecting nodes need to be reassigned to other nodes.

4.4.3 Mission phase times

We now present the time durations corresponding to different mission phases. A comparison of the time to detect all targets and the time to attain the final configuration for varying numbers of targets and search drones is shown in Figure 4.8. As anticipated, EDPPP and DPPP have identical detection times, given the pre-defined nature of the search node paths. In scenarios where the number of search drones is equivalent to the number of targets, DAPP exhibits longer detection times, as a reduced number of drones are available for continued search missions following each target detection. For a given N_{tar} , increasing the number of drones leads to performance convergence in the detection times of all approaches. NSGA-II and WS approaches result in longer mission times because the drones do not distribute across the coverage area as effectively as mTSP, prioritizing connectivity to the GCS.

A comparison of the total time from take-off to the final configuration, where

Figure 4.8: Comparison of mission phase times vs a number of deployed search nodes.

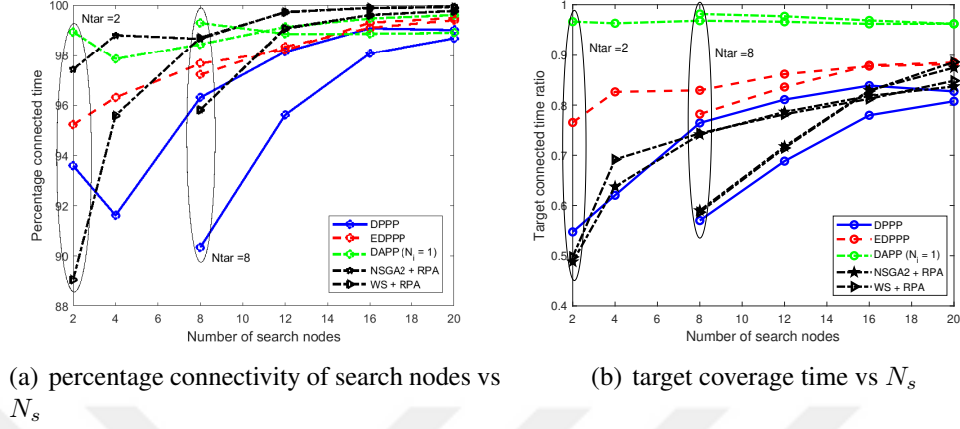


all targets are monitored by a search drone and connected to the GCS using a minimal number of nodes, reveals that the rapid formation of the relay network nearly offsets the additional time spent on searching in DAPP. For example, for DPPP, when $N_{tar} = 2$ and $N_s = 2$ the target detection time is about 350s, and the relay network construction requires approximately 100 seconds, resulting in a total duration of 450 seconds, which surpasses that of DAPP. Consequently, although DPPP expedites target detection, the initiation of information transmission (monitoring phase) is delayed. The advantage of the EDPPP is that the injected nodes are already sent to the position of the targets, although, possibly, they are not connected to the GCS during this time, which affects the relay formation time by reducing it and yielding a shorter total time. The variations in detection time, as predicted, have an impact on the overall mission time for NSGA-II and WS.

4.4.4 Connectivity

As outlined below, the performance of the proposed path planning algorithms is compared in terms of target connectivity and drones. The connectivity between the GCS and search nodes is illustrated in Figure 4.9 (a). This representation shows the connectivity from the start of the mission to the final configuration formation. In this case, all the

Figure 4.9: Analysis of connectivity metrics as a function of the number of search nodes.



proposed schemes achieve a connected time percentage exceeding 85%. The reason is that there is a sufficient number of relay nodes, and high levels of connectivity are anticipated during the mission. During the mission's final phase, disconnectedness is possible, particularly during the time interval of reconfiguration of the final configuration. The DAPP method exhibits the highest percentage of connected time since the final detecting search nodes are deployed to establish a connection link to the GCS via the fewest relay nodes, while there is a lower number of unoccupied node positions. In the DPPP approach, there will be a very small number of search nodes in the vicinity of a target position at the time step of detecting the final target, which happens in cases N_s is limited to a minimum number. Connectivity is not guaranteed during the reconfiguration phase, so the percentage of connectivity is lower. With an increase in N_s , connectivity sees a notable improvement indebted to a denser connectivity network. EDPPP falls between DAPP and DPPP due to the fact that injected nodes facilitate connectivity.

The connectivity of detected targets to the GCS from the point of detection to the attainment of the final configuration is depicted in Figure 4.9 (b). As anticipated, DAPP achieves nearly 100% in connectivity. As previously discussed, the target connectivity,

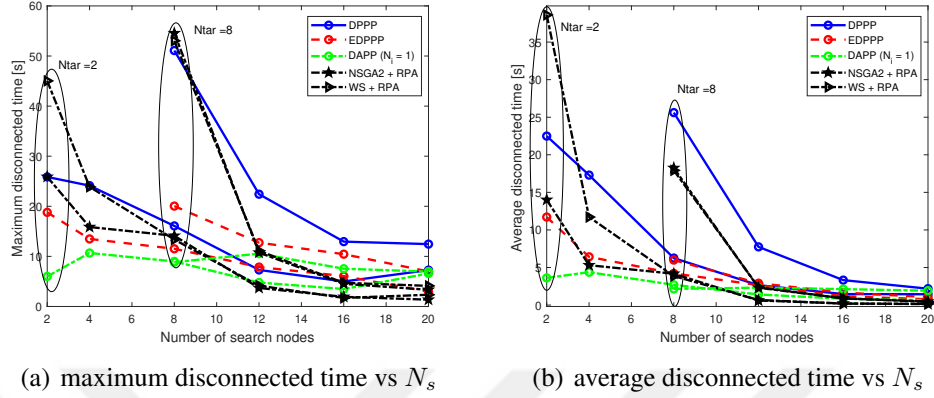
with potential disconnections arising from forming the final configuration phase. Depending on the values of N_{tar} and N_s , DPPP and EDPPP may experience severe target connection disruptions, potentially causing the ratios to drop below 50%. As injected nodes facilitate target monitoring and data transmission to the GCS, EDPPP surpasses DPPP in performance, even under intermittent connectivity conditions. The selection of the optimal path-planning approach is contingent upon the tolerance of the applications to delays in updating targets. As shown previously, NSGA-II and WS act similarly to DPPP.

To gain deeper insight into connectivity levels, we can examine the continuous time intervals where the search drones are disconnected from the GCS. Figure 4.10 shows the search nodes' average and maximum disconnected times across various scenarios. On average, DPPP experiences longer disconnection durations around $\sim 25 - 40$ s when utilizing a small number of N_s . When more search nodes are added (N_s), all schemes will witness a convergence in the disconnected time as a consequence of the increase in spatial density and network-wide connectivity. When N_s is small, the WS algorithm may experience longer disconnection periods; in contrast, NSGA-II exhibits performance analogous to DPPP. Nevertheless, when N_s increases, disconnected times decrease for all methods.

4.5 Summary

In this chapter, we have proposed and analyzed multi-UAV path planners for multi-target search and connectivity with different levels of adaptability to target detection. We have compared our proposed planners with joint optimization-based planners, where all UAVs are both search and relay UAVs and the paths are optimized in terms of total coverage time and percentage connectivity. Our results showed that the less adaptive schemes, DPPP and EDPPP, detect all the targets faster; however, the connectivity of the UAVs and the targets to GCS is significantly better for more adaptive DAPP. The WS and

Figure 4.10: Comparison of disconnected times vs the number of the deployed search nodes.



NSGA-II methods, on the other hand, in their basic forms, trade-off detection times to improve connectivity. When WS and NSGA-II are used in conjunction with relays, the performance is improved; however, overall mission times and connectivity are still not as good as the proposed schemes. Therefore, while initial pre-planned paths are important, depending on the tasks to be achieved, the available resources might be utilized more efficiently if some tasks are handled by dedicated UAVs during different phases of the mission.

5. PRIORITY-BASED DYNAMIC MULTI-UAV PATH PLANNING ALGORITHM FOR MULTI-TARGET SEARCH AND CONNECTIVITY

Environmental conditions, risks, available resources, and urgency are factors that should be considered when prioritizing and allocating resources to achieve mission goals. Simply put, visiting and serving of targets by UAV agents can be prioritized based on specific factors [74], e.g., rescuing individuals trapped in catastrophic events such as collapsed structures can be classified as a high-priority target, and animal or property rescue can be classified as a low-priority target or task. Therefore, depending on the purpose of an SAR mission, targets can have a priority spectrum spanning from low to high levels with intermediate levels in between.

5.1 Target Prioritization

In this part of our study, we assume that N_{tar} targets with different connectivity priorities are randomly distributed in the square area of interest A . The GCS is situated at corner A , serving as both the departure and arrival point for UAVs during the mission. In disaster-stricken areas, the targets can consist of objects of interest, including victim groups, critical infrastructures, rescue personnel, damaged buildings, evacuation routes, etc. Each target has its own unique connectivity demands. For instance, if the communication infrastructure is destroyed or non-functional, the victim groups need to be provided with a temporary communication network where reliable communication can be established between the victims and the disaster management centers. On the contrary, critical buildings that have not suffered any damage might not require continuous connectivity after the ground personnel is informed of their condition. Areas that should be

monitored but do not have their own data to send, such as damaged areas or roads with congested traffic, might tolerate a certain level of disconnections as long as the situation is monitored and data is collected. For this purpose, *3 levels of priority based on the connectivity needs* of the detected targets is defined in this study:

- *High priority (HP)*: targets that generate their own data and require immediate connectivity upon detection;
- *Medium priority (MP)*: targets that require monitoring but can tolerate delays in connectivity;
- *Low priority (LP)*: targets whose conditions should be assessed but are not required to be continuously monitored (i.e., best-effort).

5.2 Mission Overview

As mentioned in Chapter 4, the multi-target search and connectivity mission comprises two primary tasks: search and connection. All mission nodes remain in sensing and information-sharing mode until all targets are detected. Concurrently, relay nodes adjust their positions to ensure the connectivity of search nodes and high-priority targets to the GCS throughout the mission. The mission commences with pre-defined trajectories for search and relay nodes, with the assumption of uniform importance across the entire search area. Upon detecting a target, search and relay paths may be re-planned depending on the connectivity priority of the detected target. When all targets are detected and GCS is informed about it, a final configuration is computed so that a search node is placed at each target to monitor it. Relay nodes are strategically positioned to ensure target connectivity to the GCS through a minimal number of relays.

5.3 Priority-based Dynamic UAV Path Planning Algorithm

At each time step, the UAV positions are computed depending on the mission status. Algorithm 7 presents the path decision procedure at different mission phases. While the GCS computes the initial path plan, the paths after each target detection can be calculated by the GCS or on the UAVs. In the final configuration phase, and when the relay network is formed, the decisions regarding position assignments are made dynamically as a function of the UAV's local information. UAVs exchange information with their clique at each step.

In this study, we consider multi-hop connectivity; consequently, any UAV can relay its information to all nodes it can reach, which can be the search and relay UAVs or the GCS. The exchanged information encapsulates information about target detection, target monitoring status, position, and the status of the GCS. When re-planning is necessary, the paths of the search node are computed in the first step. The second step calculates the relay paths given the search node paths and high-priority target positions. The number of targets is constrained to the total number of initial search drones starting the mission and the reserve nodes on the ground that can be injected when necessary. At any point throughout the mission, if all search UAVs are monitoring a high-priority target but the whole search area still needs to be searched, GCS may inject a reserve node into the air, assuming drones are still available at the GCS.

The initial search paths are computed using mTSP (line2), a widely employed technique in the relevant literature. Depending on the mission objectives, arbitrarily choosing initial search drone paths is an acceptable approach [86]. Once the initial search drone paths are computed, these paths, along with transmission ranges, are given as input to the Pre-Planned Relay Positioning (PPRP) [86] (line 3). The PPRP algorithm deploys a minimal number of relay drones to ensure connectivity between all search drones and the GCS throughout their trajectories, employing STP and minimum cost assignment

Algorithm 7 Priority-based Dynamic Multi-UAV Path Planning Algorithm.

```
1: Initialize the system parameters (given in Chapter 3)
2: Compute paths of search nodes using mTSP (Section 3.3.1)
3: Compute paths of relay nodes using PPRP algorithm (Section 3.3.2)
4: At each time step:
5: if GCS is informed of a target(s) except the last target then
6:     Determine target priority level
7:     if target priority is High then
8:         Paths for all SNs and RNs are re-planned as follows:
            8.1: Assign the detecting SN to the newly found target
            8.2: Replan the paths of remaining SNs using mTSP for the unvisited areas.
            8.3: Replan the RN paths using PPRP with updated SN paths and high-priority
                target locations as input.
9:     else if target priority is Medium then
10:         No re-planning necessary for SNs and RNs. GCS sends an IN to the detected
            target location for monitoring the target.
11:     else
12:         Target is of low priority.
13:         No re-planning necessary.
14:     end if
15: else
16:     GCS knows about all targets.
17:     Final configuration forms.
18: end if
```

▷ SN: Search node, RN: Relay node, IN: Injected search node

techniques. For more details, the reader can refer to [86]. Search UAVs continuously monitor their designated areas and transmit target detection information to the GCS at each time step until the final target detection. At the time of detection, the priority of the target is examined, and the path re-planning algorithm is executed if necessary (lines 6-14). Suppose a high-priority target, such as victims, is found. In that case, a search drone hovers over the target, and the remaining search and relay nodes' paths are re-planned so that the remaining area is covered at a minimum time, and the high-priority targets and the search nodes are continuously connected to GCS. If the detected target is identified as medium-priority, the GCS will dispatch an injected search node to initiate monitoring

of the newly identified target. In both medium and low-priority target detection cases, the search and relay nodes that have not been assigned to an open task would keep flying their current path without re-planning. When all targets are detected, the flying drones are positioned such that a network of relay nodes establishes a connection network of all targets to the GCS that can be formed using a minimal set of drones [86]. The final relay position computation is presented in Algorithm 4 which formulates the connectivity of the network in terms of the STP and relies on the approximation in [87] as the solution.

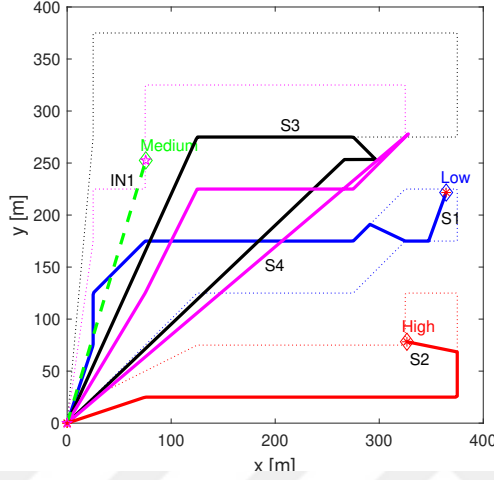
5.4 Target coverage visualization based on priority levels

To better visualize, the paths for a multi-priority target search and connect mission are presented in this section. Figure 5.1 illustrates the pre-defined and flown paths for the original and injected search nodes. There are 3 targets, each with different priorities, and four search nodes are initially in the air. The pre-defined paths for S1-S4 are shown as dotted lines. S2 detects a high-priority target, then flies directly to the target location and hovers there till the end of the mission. Then, S3 detects a medium-priority target, and IN1 is injected into the target location, whereas S3 continues its search. Finally, drone S1 detects the low-priority target, and since it is the last target to be found, it flies to the target location. When all targets are detected, relay nodes reposition themselves such that a relay network with a minimum number of relays is formed, where a search node covers each target. The unassigned search nodes, i.e., S3-S4, injected, and relay nodes fly back to the GCS.

5.5 Results and Discussions

In this section, we evaluate the performance of the proposed priority-based multi-target search and connectivity method. The search area is assumed to be $400m \times 400m$.

Figure 5.1: Example paths for 4 search nodes and 3 targets with different priority. The dotted and solid lines are the predefined and flown search paths respectively. The path of the injected node (shown in the dashed line) to cover the medium-priority target. S_i , IN_i , and R_i correspond to labels for search, injected, and relay nodes, respectively.



The maximum speed of the relay and search nodes are up to 10 m/s and 2.5 m/s, respectively. The transmission and sensing ranges are 100 m and 50 m, respectively. The number of available relay nodes is constrained to 10; conversely, the number of injected nodes is limited to $N_{tar} - 1$.

In the following, the performance of the proposed path planner in terms of mission phase times, the number of additional search and relay nodes injected into the system during the mission, and target connectivity are evaluated. We analyze performance across different configurations of target and search nodes. In MATLAB, mission scenarios are simulated using over 1000 randomly distributed target configurations. For benchmark comparison, results are shown for a scenario where all targets are considered low-priority (All LP). We designate this method as "All LP" in the figure legends. Moreover, a mixed-priority scenario, which was a combination of Low-priority, Medium-Priority, and High-Priority targets, is analyzed, with an assumption of an equal distribution of targets across

priority levels. Simulations were also conducted with randomly assigned priorities but did not exhibit significant performance variations and were therefore omitted.

Figure 5.2 illustrates the detection of all targets and the subsequent interval of time required to establish the final relay network configuration. Results are shown for $N_{tar} = \{3, 6, 9\}$. As expected, with an increase in the number of targets, the detection time also increases. Since "All LP" case allows the search UAVs to continue their pre-planned paths until the final target is discovered, the detection time for this case is lower in comparison to the mixed priority case. With an increasing number of UAVs, the time required to detect all targets converges to a certain value, indicating diminishing returns in terms of detection time. In contrast, the relay network formation results show a reversed trend. For the mixed priority cases, the relay network is gradually formed by assigning search nodes to the newly detected targets and connecting the high-priority targets as soon as they are detected. As the number of targets increases, the re-positioning of the search and relay UAVs takes up to 60% longer than the mixed scenario. The trade-off between detection time and connectivity depends on available resources.

Figure 5.2: Mission phase times vs a number of deployed search nodes in multiple-target search.

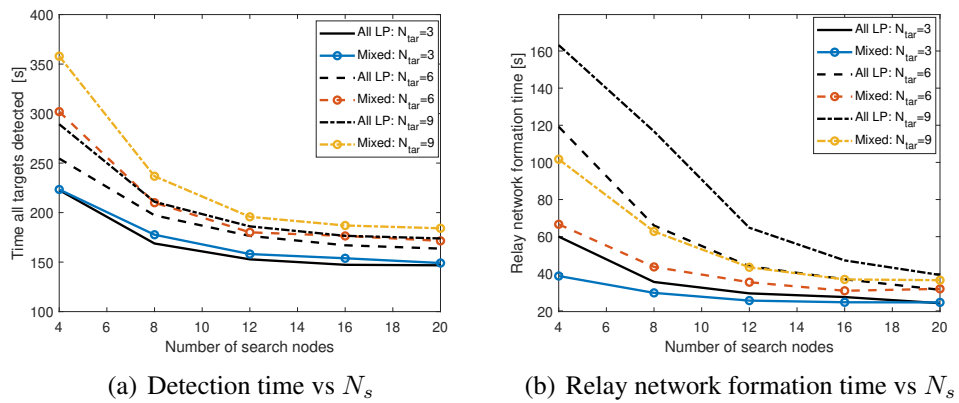


Figure 5.3: Comparison of target connectivity and injected resources vs a number of deployed search drones in multiple-target searches.

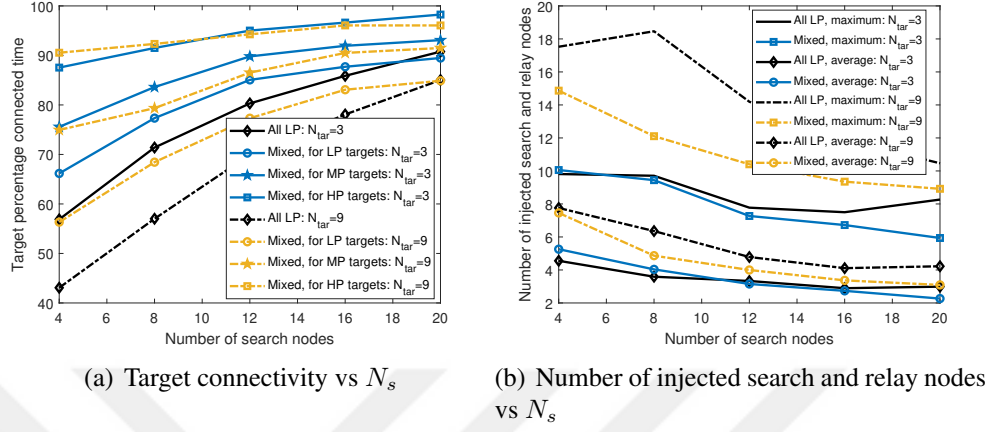


Figure 5.3(a) illustrates the percentage of time during which detected targets remain connected to the GCS from the moment of detection until the relay network is fully established. The black curves depict the results obtained when all targets are assigned low priority (All LP). In the mixed-priority scenario, target connectivity is presented individually for each priority level. For the "All LP" case, the target connectivity is lower than the mixed priority case, and as the number of targets increases the performance difference also increases. The connectivity for high-priority targets (HP) remains above 90% throughout the majority of the time. In this case, the connectivity loss may occur during the repositioning of the nodes at the end of the mission. The results demonstrated that the number of targets does not have a significant effect on the target connectivity since each target is immediately and continuously covered by the detecting search node. As the priority level decreases, the connected times for the targets also decrease. The connectivity for medium-priority targets exceeds 75%, while the connectivity for low-priority targets remains above 55%. As HP targets are found, the partial construction of the relay network improves the connectivity of MP and LP targets as well.

Figure 5.3 (b) illustrates the average and maximum number of relay and search

nodes injected into the system during the mission. It is important to note that when the number of targets exceeds the number of search nodes ($N_{tar} > N_s$), a minimum of $N_{tar} - N_s$ additional search nodes must be injected to ensure adequate monitoring. The decision to inject additional relay nodes is made dynamically, depending on the real-time search nodes' positions and the overall network connectivity. If a search node is at risk of losing connectivity to the GCS, a relay node is deployed to establish a reliable communication link. Therefore, while on average the number of additional nodes for both "All LP" and "mixed priority" cases is similar to each other, the maximum total number of injected search and relay nodes for the "All LP" case is higher than the "mixed case" when the number of targets is increased. Therefore, although HP and MP target detection may cause injected search nodes since these nodes also help with connectivity, the resources can be more efficiently used if the connectivity priority of the targets differs.

5.6 Summary

In this chapter, we have addressed the task of integrating connectivity requirements into multi-UAV dynamic positioning and path planning for SAR missions, where targets have been prioritized based on their connectivity needs in scenarios without prior information about targets. We have defined three levels of connectivity priority, corresponding to continuous, delay-tolerant, and best-effort connectivity. We have then proposed an adaptive and event-driven multi-UAV path planner for multi-target search and connectivity taking into account target connectivity priorities. We have analyzed the performance of the proposed path planner in terms of detection and network formation times as well as target connectivity and compared it with a benchmark path planner without priorities. While prioritization has improved network-related performance significantly, the target detection times of priority-based planners for the small number of search nodes have increased illustrating the trade-off between search and connect tasks.

6. CONCLUSIONS

This study proposes, develops, and analyzes adaptive multi-UAV path planning algorithms for multi-target search and connectivity tasks in SAR missions. The contributions were designed to address challenges in disaster scenarios where UAV systems must simultaneously perform search, detection, connectivity, and monitoring tasks with limited resources and dynamic mission constraints. This research integrates innovative approaches to optimize UAV behavior, balancing the competing objectives of rapid target detection, robust connectivity, and efficient mission execution. Several key insights have been gained from the study outcomes:

- DPPP and EDPPP, while effective in rapidly detecting targets, may experience temporary loss of communication links, especially in challenging environments or when the number of targets and UAVs is large.
- DAPP, on the contrary, dynamically adjusts the mission plan based on real-time information, such as target detections and network conditions, leading to improved connectivity and monitoring capabilities.
- Weighted-sum and NSGA-II optimization methods, while effective in improving network connectivity, may prioritize connectivity over detection speed, leading to longer mission times, especially in complex scenarios with numerous targets and obstacles.

Moreover, we introduced a priority-based dynamic positioning strategy that integrates target connectivity priorities into UAV path planning. By categorizing targets into high, medium, and low connectivity needs, the system dynamically adjusts UAV deployment, significantly enhancing network formation and connectivity metrics without excessively compromising detection performance.

Key Contributions:

- Developed a novel multi-UAV path planning framework that can be adapted to various mission objectives and constraints, including target detection, surveillance, and communication relay.
- Introduced a novel connectivity prioritization mechanism to ensure reliable communication between UAVs and the GCS, especially in challenging environments with obstacles and interference.
- Conducted extensive simulations to evaluate the performance of the proposed framework under various scenarios, demonstrating up to a 60% improvement in network formation time and target connectivity compared to state-of-the-art methods.

Future Directions: In future work, we will focus on extending the proposed algorithms for time-sensitive missions, including real-time target detection and tracking. To improve the system's autonomous capabilities, we will incorporate advanced AI techniques like reinforcement learning to enable UAVs to learn optimal behaviors and respond to variations in environmental factors and mission objectives. Computer vision algorithms will be used to enhance target detection and tracking capabilities, as well as obstacle avoidance. We will also conduct extensive field tests in various environments, such as urban, suburban, and rural areas, to validate the robustness and effectiveness of our proposed approach. This research has shown that by employing adaptive path planning and priority-based resource allocation, UAV systems can significantly improve their ability to detect and respond to critical events, such as natural disasters and accidents. These findings provide a solid foundation for the development of more sophisticated and efficient UAV-based solutions for search-and-rescue and disaster management operations.

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