MULTI-UAV COOPERATIVE SEARCH UNDER SENSING AND COMMUNICATION LIMITATIONS

KADİRCAN KARA

ÖZYEĞİN UNIVERSITY

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Kadircan Kara

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Advisor: Assoc. Prof. Evşen Yanmaz Adam

Graduate School of Science and Engineering
Özyeğin University
İstanbul

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Approved by:

Assoc. Prof. Evşen Yanmaz Adam, Advisor
Department of Electrical and Electronics Engineering
Özyeğin University

Assoc. Prof. Cenk Demiroğlu
Department of Electrical and Electronics Engineering
Özyeğin University

Asst. Prof. Gökhan Seçinti
Department of Computer Science
İstanbul Technical University

Approval Date: July 29, 2025

To my family, for their endless support, and to my advisor Assoc. Prof. Evşen Yanmaz Adam, for her invaluable guidance and patience

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.

Kadircan Kara

ABSTRACT

Multi-Unmanned Aerial Vehicle (UAV) systems have many uses in civil applications including search and rescue, surveillance, and environmental monitoring. In dynamic missions such as Search and Rescue (SaR), where multiple targets or areas of interest might need to be searched and monitored, the accuracy of target detection and information sharing among UAVs and with Ground Control Station (GCS) play a vital role in whether the mission will be successful or not. The state of the art sensors are still imperfect, hence, UAVs might need to take multiple measurement in each area of interest to increase the accuracy of sensor measurements. To that end, in this thesis we propose a joint area coverage, connectivity, and revisit time optimization framework within the context of multi-UAV multi-target cooperative search missions involving dynamic information exchange under imperfect sensing and communication constraints towards the goal of shortening time elapsed between consecutive visits to be able to take multiple sensor measurements as fast as possible (without suffering great losses in performance in terms of area coverage and connectivity), therefore increasing the accuracy of sensor measurements in the early stages of the mission in question. We utilize the Non-Dominated Sorting Genetic Algorithm (NSGA)-II evolutionary algorithm to solve the proposed optimization problem and compare our results on various scenarios. Our results show that by considering cell revisit times as well as connectivity in the path planning in the context of evolutionary algorithms, we observe up to 4-fold improvement in terms of observed times between visits and we see that the target detection times can be improved by 60% and we can achieve instant GCS inform post-detection in realistic, uncertain environments.

Keywords: search and rescue, area coverage, drone networks, unmanned aerial vehicles, maintaining connectivity

ÖZET

Çoklu-İnsansız Hava Aracı (İHA) sistemleri Arama ve Kurtarma (AvK), gözlemleme, çevresel izleme gibi birçok sivil uygulamada kullanılmaktadır. AvK gibi birçok hedefin veya ilgi alanının taranması ve izlenmesi gerektiği dinamik görevlerde, İHA'ların kendi arasındaki ve Yer Kontrol İstasyonu (YKİ)'na olan bağlılıkları, görevin başarısında hayati önem taşır. Son teknoloji sensörlerin hala mükemmelliğe erişememesi ile birlikte, ilgi alanlarındaki ölçüm güvenirliliğini artırmak için İHA'ların ilgi alanlarında birden fazla ölçüm yapması gerekebilir. Bu tezde, kusurlu algılama ve haberleşme kısıtları altında dinamik bilgi paylaşımının söz konusu olduğu çoklu İHA ve çok hedefli işbirlikçi arama görevleri kapsamında; alan kapsama, bağlılık ve yeniden ziyaret süresinin ortak optimizasyonunu gerçekleştiren bir sistem önerilmektedir. Böylece, art arda yapılan ziyaretler arasındaki süreyi mümkün olduğunca kısaltarak (alan kapsama ve bağlılık açısından büyük performans kayıpları yaşamadan) aynı bölgede daha hızlı şekilde birden fazla sensör ölçümü alınmasını ve böylece görevin erken aşamalarında sensör ölçümlerinin isabetliliğinin artırılması hedeflenmektedir. Önerilen optimizasyon problemini çözmek için NSGA-II evrimsel algoritması kullanılmış ve algoritma çeşitli senaryolar üzerinde test edilmiştir. Sonuçlar, evrimsel algoritmalar kapsamında yol planlamasında hem hücrelerin yeniden ziyaret sürelerinin hem de bağlılığın dikkate alınmasıyla, ziyaretler arasındaki gözlemlenen sürelerde 4 kata kadar iyileşme, hedef tespit sürelerinde %60 oranında iyileşme ve belirsiz, gerçekçi ortamlarda hedef tespiti sonrası YKİ'nin anlık bilgilendirilmesinin mümkün olduğunu göstermektedir.

Anahtar Kelimeler: Arama ve kurtarma, alan kapsama, dron ağları, inansız hava araçları, bağlantı sürdürme

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LIST OF ACRONYMS AND ABBREVIATIONS

A2C	Advantage Actor–Critic
ACO	Ant Colony Optimization
ACER	Actor-Critic Experience Delay
AI	Artificial Intelligence
AvK	Arama ve Kurtarma
BINN	Biologically Inspired Neural Network
BS	Base Station
CNN	Convolutional Neural Network
CPP	Coverage Path Planning
DDQN	Double Deep Q-Network
DRL	Deep Reinforcement Learning
DQN	Deep-Q-Network
EMI	Electromagnetic Interference
GA	Genetic Algorithm
GCS	Ground Control Station
İHA	İnsansız Hava Aracı
ISSA	Improved Sparrow Search Algorithm
LSTM	Long Short Term Memory
MARL	Multi-Agent Reinforcement Learning
MDP	Markov Decision Process

ML	Machine Learning
MOO	Multi-Objective Optimization
MST	Minimum Spanning Tree
mTSP	Multiple Travelling Salesmen Problem
NSGA	Non-Dominated Sorting Genetic Algorithm
PPO	Proximal Policy Optimization
PSO	Particle Swarm Optimization
QoS	Quality of Service
RL	Reinforcement Learning
RNN	Recurrent Neural Network
SaR	Search and Rescue
SOO	Single Objective Optimization
TC	Area Coverage Time and Percentage Connectivity Joint Optimization Model
TCD	Area Coverage Time, Percentage Connectivity, Max and Mean Disconnected Time Joint Optimization Model
TCDT	Area Coverage Time, Percentage Connectivity, Max and Mean Disconnected Time and Max Mean TBV Joint Optimization Model
TSP	Traveling Salesmen Problem
UAV	Unmanned Aerial Vehicle
USV	Unmanned Surface Vehicle
WiSAR	Wilderness Search and Rescue

YKİ	Yer Kontrol İstasyonu

1. INTRODUCTION

Occurrences of natural disasters, especially earthquakes, have been increasing in Turkey over the years [1]. Although experts give precautionary warnings and engineers work on ways to construct buildings resistant to disasters, efforts may come short in terms of preventing damages and fatalities. Therefore, efficient search of affected areas after disasters is of utmost importance. In recent years, use of multiple UAVs has become essential in search and rescue missions to reduce search time, increase connectivity, and improve detection reliability through redundancy and collaboration.

In this thesis, we aim to improve the efficiency of multi-UAV SaR missions in the aftermath of disasters. In the following, we provide our motivation, problem statement and main contributions to the field of multi-UAV cooperative search and we conclude this chapter by giving an outline for this thesis.

1.1 Motivation

Coordinating multiple UAVs introduces several challenges, including maintaining connectivity among the UAVs and with GCS, avoiding redundant exploration, and dealing with sensor imperfections that introduce uncertainty into target detection. These challenges become critical in dynamic environments, where timely and informed decision-making is highly dependent on reliable communication and shared situational awareness. Therefore, target detection in an unknown dynamic environment heavily relies on effective positioning of the UAV swarm due to the need for balancing conflicting requirements. For instance, target detection time should be minimized to respond to the emergencies, which requires the UAVs to spread in the search area as fast as possible focusing on uncovered areas. On the other hand, cooperation between UAVs relies on information exchange within the team and with the GCS requiring the UAVs to stay connected (i.e., within multi-hop connectivity range). Furthermore, sensing imperfections and likely target miss probabilities require that certain regions be revisited. These challenges have been handled in various ways in the literature. The main objectives may include minimizing search time [2, 3], maximizing target detection [2, 4], maximizing information gain (or minimizing uncertainty) [5, 6]. In [7], joint optimization of area coverage and connectivity for multi-target detection is proposed in a perfect sensing setting, where no cell (i.e. point of interest) revisits are considered. In [8], coverage optimization with a controllable revisit mechanism is proposed. Revisit mechanism helps guide the UAVs to revisit areas with high uncertainty or high target occupancy probability instead of fixed number of visits on each cell, however, the mission studied in this paper does not include an inform stage. In [9], only coverage path-planning algorithm is proposed with no cell revisits (no target detection). In [10], search and surveillance mission is conducted with multiple Base Station (BS) (GCS) locations under flight time constraints, which simplifies maintaining full connectivity. In [11], a cooperative area search algorithm is proposed that also considers repeated searches, collision avoidance between UAVs and maintaining connectivity utilizing a distributed genetic algorithm. In [12], an extensive study is done on grid-based coverage path planning that focuses on search and rescue scenarios. In [13], a cooperative mapping and target-search algorithm is proposed, where a single moving target is considered and cell revisits are done in high likelihood regions based on mutual information shared among the UAVs.

In this thesis, we aim to build on the many studies done in the field of joint optimization of area coverage and connectivity by adding cell revisit time as an objective to optimize the sensing aspect of multi-UAV search missions and show the output multi-UAV paths' performance on cooperative SaR missions. Our work provides a novel MOO framework and time metrics that can serve as benchmarks in future studies done in the fields of multi-UAV path planning and cooperative search missions.

1.2 Problem Statement

In time-sensitive missions where a team of UAVs need to convey location information to a central location (GCS in our case), such as search and rescue, one needs high performance in area coverage time, connectivity and sensor measurement accuracy. Since the state-of-the-art sensors are still imperfect, in order to improve sensor reliability, UAVs have to take multiple measurements on each cell. Due to additional visits on each cell, the area coverage time will have to increase if the mission needs require fast improvements on measurement accuracy; i.e. to increase sensor measurement accuracy, UAVs would have to decrease the time elapsed between visits on cells and in doing so, they will have to limit the amount of distance they cover between consecutive waypoints. As a result, the time it takes to cover the whole search area will increase. In addition to area coverage time and revisit time, area coverage and connectivity are also inversely proportional since for the UAVs to be connected to the GCS, they have to be in close proximity even if multi-hop links are possible, as in our case, with at least one of the UAVs being connected directly to the GCS which limits the search capability of a number of available drones as they have to be close to the GCS. As the transmission range increases, this effect fades, but realistically, the state of the art in ad-hoc network transmission range is still limited, also it makes sense to be prepared for situations where wireless interfaces with high transmission range are not readily available.

Due to these conflicting performance metrics; i.e. area coverage time, connectivity and cell revisit time, we provide a diverse set of multi-UAV path plans that offers trade-offs between the aforementioned performance metrics for cooperative search and test their performance in terms of target detection and information relaying to GCS over multiple target distributions. To this end, we propose a novel MOO based multi-UAV path planning framework in [14]. To test the effectiveness of the resulting multi-UAV paths' for target search missions, we simulate a number of multi-UAV cooperative search and inform missions with random target distributions for various scenarios, using sensor models proposed in [3] and adopting the information sharing paradigm presented in [15]. We report the detection time and GCS inform time performance of the objective-optimal multi-UAV paths in [16].

1.3 Main Contributions

Main contributions of this thesis are summarized below:

- We propose two new multi-objective optimization problems, one *jointly optimizing coverage time, topological connectivity to GCS and UAV disconnectivity*, and the other adding *cell revisit time* to the optimization objectives [14].
- We propose custom genetic operators to solve the proposed MOO problem, which can be used in any genetic algorithm.
- We offer Pareto fronts comprised of a diverse set of solutions for multiple scenarios that offer trade-offs between each objective function so that the user can pick the solution that best fits the current mission's needs.
- We compare the performance of the objective-optimal multi-UAV paths for cooperative search time metrics and discuss which objective function optimality is more beneficial for either the search phase or the inform phase of the mission [16].

1.4 Thesis Outline

In Chapter 2, we give a review of the literature in four categories of research topics regarding multi-UAV systems which are also relevant to the work proposed in this thesis, including Coverage Path Planning (CPP), connectivity-aware path planning, revisit time optimization and cooperative search. We identify research gaps in the solutions brought to each problem and set the course for the main contributions offered in this thesis.

In Chapter 3, we propose a multi-UAV path planner that jointly optimize area coverage time, percentage connectivity to GCS and cell revisit time for cooperative search missions in which it is required that each cell has to be visited a predefined number of times. We propose a novel connectivity formulation which includes topological connectivity to GCS, maximum amount of timesteps where UAVs are disconnected from GCS and the average timesteps where UAVs are disconnected from GCS and a novel cell revisit time metric which incentivizes the path planner to minimize the mean of the average time elapsed between consecutive visits for each cell. We propose novel genetic operators tailored towards our problem definition. We provide objective function performance analysis between the proposed models and the benchmark models mTSP as a Single Objective Optimization (SOO) problem which minimizes area coverage time and TC as a MOO problem which minimizes area coverage time and maximizes percentage connectivity.

In Chapter 4, we report on the performance of our multi-UAV path planners on target detection and GCS information relay. We provide detection time and GCS inform time metric comparisons between the benchmark mTSP model and the proposed multi-UAV path planners. Also, we show the benefit of UAV-UAV information sharing and multi-visit path planning (as opposed to multi-tour where the same tour is repeated a number of times) by providing the time metric performance of each combination. Finally, we provide analysis regarding which multi-UAV paths are best for which phase of the mission; i.e. target detection phase, GCS inform phase or total mission.

Finally in Chapter 5, the thesis is concluded with a summary of our main contributions and potential future works.

2. LITERATURE REVIEW

2.1 Introduction

There have been significant improvements in the field of UAV systems throughout the years. In order to illustrate the value we intended to bring to the world of UAVs, we will go through the research done relative to the work presented in this thesis. We start by reviewing the most generalized path planning problem CPP and gradually move on to the studies done which resemble the problem/mission scenarios, algorithms and performance metrics studied in this thesis by limiting our scope to connectivity-aware path planning, cell revisit time optimization and cooperative search in the later sections.

2.2 Coverage Path Planning

CPP is one of the foundations of the many problems researched in the field of UAV path planning and it can be defined as determining a path or collection of paths (multiple UAVs) such that the path(s) pass over all points of interest while avoiding obstacles. The research problem covered in this thesis can be defined as CPP without obstacle avoidance since the UAVs are capable of aerial traversal. The solutions brought to CPP has a wide range of applications such as cleaner robots[17, 18], lawn mowers[19, 20], painter robots[21], automated harvesters[22, 23] and so on. CPP is a variant of the Traveling Salesmen Problem (TSP) problem. The main difference between them is that in TSP, the agent (i.e. robot) has to visit the neighborhood of each city[24] while in CPP, the agent must must pass all points in the target area. There are many variants of CPP researched in literature such as the lawn mover problem[25] in which a path is determined such that all the grass is cut in the obstacle-free and grass covered target region, piano movers problem[26, 27] in which a collision-free path is found between a start-point and an end-point, art gallery problem[28] in which the minimum number of guards needed is found such that each point in the gallery is visible to at least one guard and the watchman route problem[29] in which the shortest route from one point to the same point is found such that each point in the target area is visible in at least one point along the route. All these problems researched are proven to be NP-hard, thus the computational time required to find solution(s) increase exponentially as the size of the target area and/or the number of cities (i.e. points to visit) increases. Since the target area will most likely be large, bio-inspired methods such as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) have been utilized extensively in the literature to find solutions to CPP-based problems. In [30], ACO is utilized to plan a complete-coverage path with obstacle avoidance for underwater gliders. In [31], a novel PSO-based algorithm Tent-PSO is proposed to ensure that the particles are more evenly distributed in the search space, improving coverage and throughput in the context of multi-UAV coverage for dynamic users. In [32], CPP of a rectangular target area is solved utilizing GA with the objective function being the weighted sum of total time and total distance covered by robots each with specific weights. Out of all these studies, only [31] considers (UAV-UAV) connectivity and the rest considers only the optimization of time and/or total distance covered. In [33], CPP is solved utilizing Boustrophedon decomposition[34], ensuring complete coverage by multiple robots. Additionally, robots are capable of information sharing but only if they are within line of sight of each other which leads them to move together in groups while repeat coverage is minimized. Since minimizing repeat coverage can be interpreted as minimizing cell revisit time and the fact that information sharing and at least inter-robot connectivity considerations exist, we can say that this study is the most similar study to ours in the context of CPP. Though bio-inspired algorithms are great for generating near-optimal solutions to CPP problems with large target areas, they lack adaptability to dynamic events. Machine Learning (ML)/Artificial Intelligence (AI) algorithms such as Reinforcement Learning (RL) offer adaptability but they require a huge amount of data to be trained properly which can be time consuming. In

[35], a neural network and Q-learning hybrid algorithm is proposed to solve CPP that minimizes path repetitions, achieving 100% coverage ratio. In [36], a Double Deep Q-Network (DDQN) model is trained to balance energy consumption and coverage goal using a single UAV. In [37], a Recurrent Neural Network (RNN) model is trained with Long Short Term Memory (LSTM)[38] layers using RL to solve CPP for large large complex environments based on TSP. In [39], a Convolutional Neural Network (CNN) with LSTM layers is trained using the Actor-Critic Experience Delay (ACER) RL algorithm to generate tiling shapes and trajectory with minimum overall cost for a modified hTriHex[40] robot which is a honeycomb-shaped tiling robot. In [41], Deep Reinforcement Learning (DRL) is used to solve CPP for an Unmanned Surface Vehicle (USV), proposing a preporcessing method for raster maps and an improved Deep-Q-Network (DQN) method to enhance the convergance by reducing the risk of dangerous action selection. In [35], Q-learning is used to improve a Biologically Inspired Neural Network (BINN) algorithm in the context of CPP, solving the local optima issue and minimizing path repetition ratio, especially around obstacles. In [42], DRL algorithms Advantage Actor–Critic (A2C) and Proximal Policy Optimization (PPO) are used to solve CPP for an area divided into cells with obstacles modeled as prohibited cells, minimizing coverage time steps. It is proven in the paper that PPO is a more efficient, adaptable and stable algorithm, especially for environments with obstacles.

2.3 Connectivity-Aware Path Planning

Connectivity-aware path planning is a research area that has been gaining popularity in the recent years for the benefit of improving the performance of missions requiring efficient communication between nodes (UAV-UAV or UAV-GCS). Our work is based on the joint optimization of coverage and connectivity in the context of multi-target cooperative search so we will start our literature review by going over the research done on the topic of connectivity-aware path planning. There have been many studies in literature that took on the topic of connectivity-aware path planning utilizing various algorithms. In [43], a modified A* algorihtm was proposed for generating an offline multi-UAV paths as short as possible under connectivity constraints. In [44], an iterative algorithm utilizing Dijkstra's algorithm has been proposed for finding the shortest path possible under connectivity and obstacle avoidance constraints. In [45], a DRL based algorithm was proposed that solves the joint optimization of mission (completion) time and expected communication outage duration, however, in this study, a single UAV is considered and its cellular-connectivity to base stations is optimized as well as the time elapsed from the initial (take-off) point until the final (landing) point. In [46], a connectivity-aware path planning solution to path planning in a mountainous area is proposed where AI methods are used to predict areas where relay intervention may be required, then a viewshed analysis is done to identify visibilities between points of interest and feeding those to the A* algorithm, an energy-aware path plan is generated that optimizes signal coverage. In [47], a DRL based algorithm is proposed to generate UAV paths with trade-offs between flight distance and signal quality (better data transmission quality and lower signal loss risk). In [48], NSGA-II[49] and NSGA-III[50, 51] based MOO frameworks are proposed as well as an RL based approach towards jointly optimizing area coverage time, connectivity to GCS and maximum duration where UAVs are disconnected from GCS under certain constraints including flight time and number of UAVs . In [52], two algorithms are proposed that both consider cellular coverage map, the drone budget of energy, and the possible presence of wind with one algorithm optimizing the worst-case throughput and the other optimizing the average throughput of a single UAV. In [53], a new multi-UAV path planning algorithm is proposed under Quality of Service (QoS) constraints. All these studies aim to jointly optimize area coverage (flight time or flight distance), energy consumption (either indirectly as a result of optimizing flight time or as a direct optimization focus) and connectivity (either cellular connectivity of a single drone or drone-drone or drone-GCS connectivity) by considering connectivity related metrics and energy consumption values as constraints or objectives besides area coverage.

2.4 Cell Revisit Time Optimization

In Section 2.3, we went over the studies done on connectivity-aware path planning in recent years. Notice that cell revisit time is not considered in any of these studies. To the best of our knowledge, there is only one research [8] done in 2018 that jointly optimizes area coverage, connectivity and cell revisit time. Furthermore, there is a small number of studies that jointly optimize area coverage time and cell (area of interest) revisit time. In [54], a multi-UAV patrolling mission in a mountainous area is considered where critical cells are revisited throughout the mission. Area coverage and cell revisit time objectives are optimized alongside some other metrics including altitude, turn cost, minimum flight distance and collision avoidance. To the best of our knowledge, these two studies [8, 54] are the ones that are most relevant to our work presented in this thesis. There are numerous studies on the solution of multi-visit TSP problems in the context of routing problems [55, 56, 57, 58], however, no consideration is given to sensing imperfections, connectivity or revisit times in these studies.

2.5 Cooperative Search

In this section, we go over the research done on improving the effectiveness of cooperative search missions. In this thesis, our main focus is multi-UAV cooperative search missions being motivated by the recent increase in natural disasters, especially earthquakes, in Turkey. Naturally, the studies mentioned in both Section 2.3 and Section 2.4 lay the foundation for optimizing the success rate and efficacy of cooperative search missions like SaR since there are three main components that decide the efficiency of cooperative search missions; area coverage time, connectivity and sensing. Alongside these components, in this thesis, we also implement drone-drone and drone-GCS *information merging (sharing)* which has been researched in depth in [15] and report on its benefits on the target detection performance in cooperative search missions.

In the recent years, there have been a growing interest in cooperative search research. To the best of our knowledge, area coverage, connectivity and revisit time optimization under imperfect sensing limitations has been researched in only [8]. In this comprehensive study, a distributed update and fusion scheme for the cognitive map which is comprised of the target probability map, the uncertain map and the digital pheromone map is proposed and it is proven that the cognitive map of each UAV converges to the same cognitive map that reflects the true target existence status of each cell in the search region. A controllable (i.e. dynamic) revisit mechanism based on the individual digital pheromone maps of the UAVs is proposed that controls the UAVs to visit sub-areas in the search region with high uncertainty or large target occupancy probability. Minimum Spanning Tree (MST) topology optimization is used to achieve trade-offs between area search efficiency and UAV-UAV connectivity. The difference between our research and this study is that in this study, there is no inform phase in the cooperative search mission, there is no GCS (i.e. only UAV-UAV connectivity is being achieved) and cell (i.e. sub-area) revisits are done dynamically based on digital pheromone maps while in our research, we focus on the GCS inform phase of the mission as well as the detection phase, cell occupancy updates are done using bayesian updates and cell revisits are done statically until GCS knows all target locations. Most of the focus has been on area coverage optimization and joint optimization of area coverage and connectivity in either stationary target search or moving target search and/or tracking in literature proposing novel algorithms, bio-inspired optimization algorithms (e.g. ACO, PSO, GA) and ML/AI based algorithms (e.g. RL).

In [59], a cooperative waypoint path planner which was proposed by the same authors of this study in their previous works is used to generate multiUAV paths that maximize opportunity region visits and minimizes hazardous region visits while the UAVs stay connected throughout the mission with collision avoidance algorithm implementation. In [60], Wilderness Search and Rescue (WiSAR) mission is researched. A multi-UAV cooperative search system based on the object detection framework YOLOv5 is proposed with three components; independent control of each UAV, real-time target detection and monocular positioning to shorten search time and improve success rate of SaR missions. In [2], a distributed cooperative search algorithm with obstacle avoidance and information sharing is proposed aiming to minimize the expected search time of multiple stationary targets in nonconvex environments under sensing and communication limitations. In [61], a novel UAV swarm cooperative search algorithm is proposed with obstacle avoidance and information sharing under sensing limitations and dynamic communication distance conditions, aiming to counter the effect of Electromagnetic Interference (EMI) in the mission area while searching for multiple moving targets. In [62], a novel distributed multi-UAV cooperative search control method for a moving target is proposed. Individual target probability maps are updated with the Bayesian theory. To calculate prediction probability of moving target existence, a Gaussian distribution of target transition probability density function is proposed and target probability map is further updated in real-time with this function. In [63], cooperative hunters problem (i.e. cooperative search for multiple evading targets) is taken on. Perfect sensing is assumed in this study; i.e. if there is a target within the sensing range of the sensors equipped by a UAV, that target will be detected. The objective is to maximize the probability of targets' detection and minimize the expected search time while minimizing the number of UAVs required. If one or more UAVs malfunction, operational UAVs reconfigure their flight patterns and continue their search. [64] mainly focuses on minimizing work time, aiming to counter the constraint of limited battery capacity of UAVs . Two path planning algorithms are proposed, one based on greedy algorithm and the other based on binary search algorithm. These two algorithms are applied to five different flight paths comprised of a snake curve path, a square wave signal curve path, a Peano curve path, a Hilbert curve path, and a Moore curve path. In [65], an uncertainty minimization-based cooperative target search strategy, in which the mobility model of UAV, search task computing and offloading models are presented is proposed as a work-around to the short battery life and moderate computational capability of the state-of-the-art UAVs and to obtain a high-efficiency and high confidence search result at the unpredictable uncertainty in search area. In [66], a decentralized control model for cooperative search is proposed, in which threats are incorporated and a model that simulates battlefield situations is introduced. In [67], a receding-horizon cooperative search algorithm is proposed, in which UAV routes and sensor orientations are jointly optimized for single moving target cooperative search in a bounded finite region. Graphs are updated dynamically based on each sample of the search area at locations with high target probability at each time step. In [68], a decentralized cooperative approach to the solution of a search and destroy problem is proposed. UAVs are able to perform an attack task or an assessment task and the task are determined dynamically by the actions and results of UAVs . In [69], an optimization-based cooperative search algorithm is proposed under dynamic network condition changes (e.g. EMI) and unknown moving target trajectory. The communication network cost and formation benefit are included in the optimization function to optimize the multiUAV formation and to minimize the search time, digital pheromone strategy is utilized to make UAVs focus on undeveloped regions and avoid search path repetitions. Improved Sparrow Search Algorithm (ISSA) [70] is proposed to solve the optimization model. In [71], a Multi-Agent Reinforcement Learning (MARL)-based algorithm for multi-UAV cooperative search is proposed where a large map is divided into multiple small maps and an MARL-based search method is designed based on sequential Markov Decision Processs (MDPs) [72]. In [73], an ACO-based path planning framework is proposed involving three algorithms; pheromone matrix consensus update, UAV position consensus update and a collision avoidance algorithm based on the UAV position updates. In [74], an improved ACO algorithm for multi-UAV cooperative search is proposed where UAVs search the mission area and share their individual pheromone maps which include environment information, if they are within communication range of each other. In [75], a distributed PSO algorithm is proposed, where each particle represents a single UAV and artificial potential functions are used for collision avoidance and attraction to targets. Multiple simulations are carried out in different environments with varying number of targets and varying number of obstacles with different sizes using a combination of Python and V-Rep [76]. In [77], the problem of moving target search is tackled, proposing a novel PSO-based algorithm. The motion model of the moving target is modeled as a Markov Process, considering the uncertainty of target motion and Bayesian theory is used to maximize the cumulative probability of detection of target in finite time. A number of the aforementioned studies incorporate communication constraints (e.g. EMI, exploration as one connected component) but they do not jointly optimize mission time and connectivity. Instead, they optimize the target detection time and sensing aspects of the mission and some include certain connectivity requirements as constraints. Also, they do not include a central location (e.g. BS, GCS) inform phase and only focus on target detection and information sharing between (e.g. map fusion) UAVs under imperfect sensing conditions.

In [78], a GA-based MOO algorithm that allocates tasks between UAVs and assigns paths to UAVs among a multi-UAV system for a single target search and relay chain formation mission is proposed. The algorithm can be tuned to prioritize mission completion time or connectivity, emulating a weighted sum approach. Three different connectivity strategies are proposed and their effect on search time and complete mission time (search, inform, relay) are analyzed as well as the effects of UAV density and communication range. In [79], work done in [78] is extended to allow multiple targets with equal weights given to mission time and connectivity. Also, search and inform tasks are strictly divided among search UAVs and relay UAVs . A hybrid planner is proposed that optimizes mission time and connectivity, utilizing joint optimization for the search drones and decoupled optimization for the relay drones. The hybrid planner's performance in mission time and connectivity are then analyzed and compared to decoupled optimization and joint optimization and it is proven that the joint optimization outperforms the other schemes in terms of mission time while hybrid and decoupled schemes offer better performance when it comes to maintaining connectivity. In [80], a MARL based path planner is proposed that allows UAVs to continuously search for targets and dynamically form relay chains, connecting the targets to the BS. The proposed planner shows improvement over pre-planned optimized path planner in terms of detection and total mission times. In [7], a comprehensive study is done, proposing three different path planning algorithms for multi-UAV cooperative search and inform missions with one algorithm allowing relay UAV injection to the mission area. The goal is to optimize total area coverage time and percentage connectivity with minimum number of relay nodes. The mission contains three different phases, with separate UAV actions for the period until the detection of one target, the period from the first target detection until the time when all targets are detected and the period from the detection of each target until the relay chain connecting target locations and GCS is formed. The aforementioned studies jointly optimize area coverage time and percentage connectivity to GCS but no consideration is given to sensing imperfections. This thesis incorporates sensing uncertainties to the multi-UAV cooperative search missions by adding cell revisit time optimization to the joint optimization of area coverage and percentage connectivity.

3. JOINT OPTIMIZATION OF CONNECTIVITY, COVERAGE, AND REVISIT TIME IN MULTI-UAV PATH PLANNING

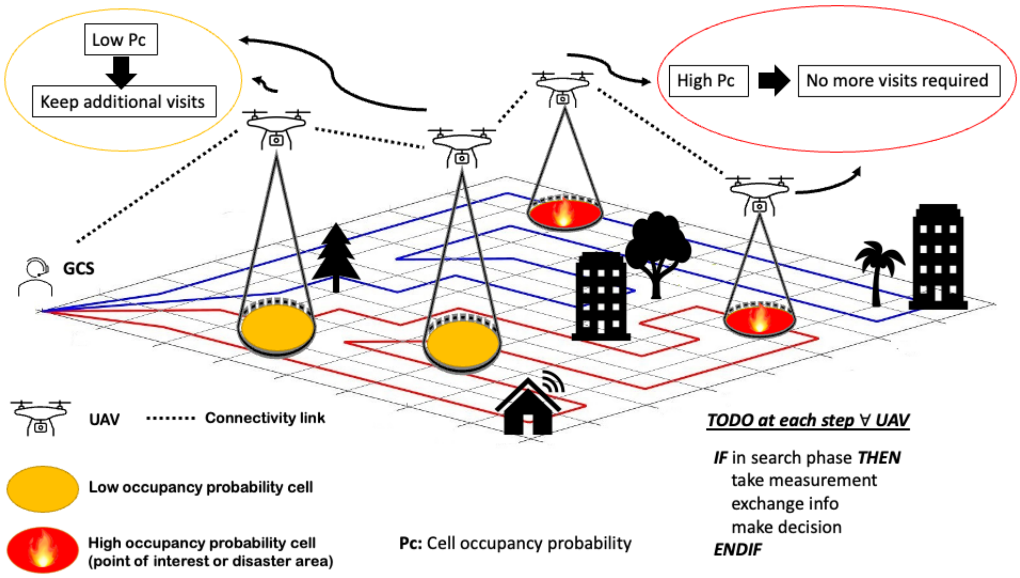
3.1 Introduction

In this chapter, we propose a novel multi-UAV path planning algorithm that incorporates cell (i.e. sub-area or area of interest) revisit times into path decisions, without compromising area coverage and connectivity requirements. The desire for high area coverage and connectivity performance in the context of multi-UAV cooperative SaR missions is trivial since ideally the mission area would have to be covered as fast as possible while the UAVs and GCS maintain connectivity as much as possible in order for the UAVs to be able to relay the locations of the targets to GCS as soon as possible. However, the need for optimized revisit times mainly comes from sensor imperfections and dynamic update requirements; e.g., during disasters. In Figure 3.1, an example for a disaster scenario is given to illustrate the importance of taking multiple sensor observations. The circular red areas define the disaster areas while the circular yellow areas define parts of the mission area where there is no disaster. In a single visit cooperative search mission, each point of interest (i.e. cell) is in the *low occupancy probability* state but with additional visits on each cell, high priority cells start to indicate *high occupancy probability* like the red circular areas, therefore the rescue team knows which cells to give priority to. To solve this problem, we propose an NSGA-II based multi-objective evolutionary framework and implement it using the open source PyMOO library [81] in Python. Our results show up to 4-fold improvement on the proposed maximum time between visits metric with trade-offs on mission time and percentage connectivity with respect to a benchmark.

The key contributions of this chapter are:

- We propose a *novel* MOO framework that *jointly optimizes area coverage time, topological connectivity to GCS and cell revisit time*

Figure 3.1: *Multi-UAV mission scenario with multiple visits*



- We provide *novel* genetic operators that can be used in *any* genetic algorithm

- We implement the proposed MOO frameworks, *TCD* and *TCDT*, on the PyMOO library [81] and provide a set of pareto optimal solutions using NSGA-II[49]. Then we compare our results to the benchmark models *TC* and *mTSP*. Since we provide a solution set rather than a single solution, the user can pick the solution most fitting to the mission needs.

The rest of this chapter is organized as follows. In the rest of this section, the system model is given, explaining the mission definition and assumptions. In Section 3.2, we explain our system model, namely the multi-UAV mission including input and model parameters is given and the mission area and UAV movements are explained .Section 3.3, the objective functions and constraints used in the proposed and benchmark models are explained with their formulations. In Section 3.4, the proposed and bechmark MOO models are given in standard form. In Section 3.5, our novel GA operators useful for any genetic algorithm are explained, In Section 3.6, we present our results and analyze the performance of the proposed MOO models and compare them to benchmark models. Finally in Section 3.7, we conclude this chapter by summarizing the work done and the results.

3.2 System Model

In this section, we explain the multi-UAV mission we considered and assumptions about UAVs' movements and capabilities. In Table 3.1, parameters defining the mission setup scenario is given in the *input parameters* section of the table.

3.2.1 Multi-UAV Mission

We consider a team of UAVs exploring an unknown area, while maintaining connectivity to the GCS to continuously provide mission status and sensed data. We assume that revisits of certain regions might be necessary. In general, this necessity can come due to practical reasons or due the application for which the UAVs are deployed. For instance, the UAVs might be equipped with imperfect sensors leading to uncertainty in terms of data acquired from the search or coverage region (See Figure 3.1 showing areas with low and high confidence in target detection). In such a case, it might be desirable to revisit certain areas to improve reliability. There might also be missions where updates about the mission area are required; e.g., in a disaster situation where the changes need to be tracked. Therefore, our goal is to optimize the path plan for the team of UAVs considering coverage time (τ), connectivity (ψ), and revisit frequency (n_{visits}).

3.2.2 Mission Area and UAV Movements

The unknown environment we operate in is modeled as a square area consisting of G disjoint square shaped cells in which the circular sensing area of the sensors equipped by the drones can fit (i.e. if the sensing range is 50 meters than cell side lengths are also 50 meters). M UAVs take-off from GCS and fly at a fixed altitude; there are no obstacles or restricted flight zones. They are capable of waypoint-flight. The maximum speed and flight times of the UAVs are fixed. The movements of the UAVs are synchronized (i.e., they reach their next step simultaneously). UAVs are equipped with (i) GPS, such that they know their own position; (ii) a camera to observe the environment; (iii) wireless communication interface to exchange information with other UAVs and the GCS. Each UAV senses the cell it is currently in and exchanges information with all drones in its communication range (r_c). Each drone has the role of searching and relaying, so multi-hop connection to the GCS is maintained. We assume imperfect sensing in this thesis, so each cell has to be visited a specified number of times (n_{visits}) to improve reliability. The required number of visits depends on the desired coverage quality and sensor uncertainty and can be obtained using a Bayesian update rule [3].

3.3 MOO Problem Formulation

In this section, we introduce the proposed objective functions and constraints used in our MOO framework. The mission we consider in this thesis has conflicting requirements; e.g., lower coverage time requires fast spreading of the nodes, whereas connectivity requires nodes to stay within range, and revisit requires minimal redundancy to improve reliability. Therefore, we treat the multi-UAV path planning problem as a MOO problem such that we can illustrate the trade-offs between these parameters. The objective functions to be minimized are mission time, maximum and mean disconnected times, and maximum time between visits, whereas percentage connectivity to the GCS is to be maximized.

3.3.1 Objective Functions

We formulate the optimization problem such that the objective functions defined below are jointly optimized.

Table 3.1: *Multi-UAV multi-visit path planning: scenario and model parameters*

Input Parameters	**Definition**
$\boldsymbol{M}$	Number of drones
$\boldsymbol{r}_c$	Maximum transmission range in cells
$\boldsymbol{n}_{visits}$	Number of visits on each cell
$\boldsymbol{v}_{max}$	Maximum drone speed in meters/second
$\boldsymbol{G}$	Set of cells to be visited
$\boldsymbol{A}$	Cell side length in meters
Model Parameters	**Definition**
$\boldsymbol{\tau}$	Mission time in seconds (objective)
$\boldsymbol{\tau}_{th}$	Maximum mission time in seconds (constraint)
$\boldsymbol{T}$	Total timesteps
$\boldsymbol{S}$	Total number of speed violations
$\boldsymbol{S}_{th}$	Maximum number of speed violations allowed (constraint)
$\boldsymbol{D}$	Distance matrix that represents distances between cells in meters
$\boldsymbol{\Psi}$	Percentage connected time to GCS (objective)
$\boldsymbol{\Psi}_{th}$	Minimum percentage connected time to GCS (constraint)
$\boldsymbol{\Phi}_{max}$	Maximum number of timesteps any drone is disconnected (i.e. isolated) (objective)
$\boldsymbol{\Phi}_{mean}$	Mean of the number of timesteps each drone has been isolated throughout the mission (objective)
$\boldsymbol{\Lambda}$	Maximum mean time between visits in seconds (objective)

- *Mission time (τ)* is the time elapsed from take-off till landing at GCS. It is given by [48]

$$\tau = \frac{1}{v_{max}} \sum_{i=1}^{\mathbf{G}} \sum_{j=1}^{\mathbf{G}} \max_{m=1}^{M} (X_{i,j,t}^{m} D_{i,j}) \tag{3.1}$$

  where $X_{i,j,t}^{m}$ is a binary value of 1 if cell j is visited after cell i at timestep t by drone m (otherwise 0), $D_{i,j}$ is the distance between cell i and j, v_{max} is the maximum drone speed, $\mathbf{G}$ is the set of cells to be visited, and M is the number of drones.

- *Percentage connectivity* (ψ) is the percentage of time the drones are connected to the GCS over possibly a multi-hop relay chain averaged over mission time and number of drones and is given by [48]

$$\Psi = \frac{1}{T}\frac{1}{M}\sum_{t=1}^{T}\sum_{m=1}^{\mathbf{M}}\Omega_{m,t} \tag{3.2}$$

where T is total number of timesteps and $\Omega_{m,t}$ is the binary value of connectivity of UAV m to GCS at timestep t.

- *Maximum (Φ_{max}) and mean (Φ_{mean}) disconnected timesteps* correspond to the maximum and average timesteps the drones are disconnected from the GCS (i.e., they are isolated) and they are given by:

$$\Phi_{max} = \max_{t=1}^{T}\sum_{m=1}^{M}\Gamma_t^m \tag{3.3}$$

$$\Phi_{mean} = \frac{1}{T}\sum_{t=1}^{T}\sum_{m=1}^{M}\Gamma_t^m \tag{3.4}$$

where

$$\Gamma_t^m = \begin{cases} 1, & \text{if } m \text{ is isolated at } t \\ 0, & \text{otherwise} \end{cases}$$

- *Maximum mean time between visits* Λ is proposed as the maximum of the mean time (in seconds) elapsed between consecutive visits to each cell regardless of the drone ID performing the visit. Given that $n_{visits} > 1$, Λ is defined as

$$\Lambda = \max(\lambda_i, i \in \mathbf{G}) \tag{3.5}$$

where

$$\lambda_i = \frac{\sum_{i=1}^{n_{visits}-1}\gamma[i]}{n_{visits}-1}$$

and

$$\gamma_i = (|\beta_i[t] - \beta_i[t+1]|), \forall t \in [1, 2, ..., n_{visits}-1]$$

with

$$\beta_i = (t \text{ if } \alpha_{i,v,t} = 1,\ \forall v \in [1, 2, ..., n_{visits}])$$

and

$$\alpha_{i,v,t} = \begin{cases} 1 & \text{if cell is visited for } v^{\text{th}} \text{ time at timestep } t, \\ 0 & \text{otherwise} \end{cases}$$

3.3.2 Constraints

In this section, we introduce the constraints used in the proposed MOO framework and the benchmark models mTSP, TC and TCD

- *Number of speed violations*

$$S \leq S_{th}$$

where

$$S = \sum_{t}^{T}\sum_{i}^{G}\sum_{j}^{G}\sum_{m}^{M}[\chi^{m}_{i,j,t}(D_{i,j} > \sqrt{2}A) = 0], \tag{3.6}$$

- *Maximum mission time*

$$\tau \leq \tau_{th},$$

- *Minimum percentage connectivity*

$$\psi \geq \psi_{th},$$

The first constraint is to eliminate number of speed violations in the path sequence. A speed violation occurs at timestep t when a drone visits more than one cell between timestep $t-1$ and timestep t, so the maximum distance a drone can take between consecutive steps can not be more than the distance between two diagonal cells and since the cells are all squares, the equation becomes (3.6). The rest of the constraints listed above is to put a threshold in both mission time and percentage connectivity objectives to stop the MOO framework from converging to solutions more veered towards one objective.

3.4 Proposed and Benchmark Multi-Objective Optimization Problems

We propose two different formulations that use different combinations of the defined objective functions. Note that the design and implementation of the path planners are done in a modular manner and other combinations of objectives can easily be tested. To this end, we choose two formulations with and without revisit time optimization to analyze the impact of revisit requirements. To the best of our knowledge, it is the first time coverage time, connectivity to GCS, and cell revisit time are jointly considered in multi-UAV path planning.

3.4.1 Area Coverage Time, Percentage Connectivity, Max and Mean Disconnected Time Joint Optimization Model (TCD)

First method is proposed as a benchmark and does not consider time between visits in the formulation. The optimization problem is given as

$$\begin{aligned}
\text{Minimize} \quad & \tau, \Phi_{max}, \Phi_{mean} \\
\text{Maximize} \quad & \psi \\
\text{s.t.} \quad & S \leq S_{th}, \\
& \tau \leq \tau_{th}, \\
& \psi \geq \psi_{th} \\
& \text{transmission range} \leq r_c \\
& \text{Number of drones} = M \\
& \text{Number of visits per cell} = n_{visits}
\end{aligned} \tag{3.7}$$

Objective functions to be minimized are mission time (3.1), maximum disconnected timesteps (3.3), and mean disconnected timesteps (3.4), while the one to maximize is percentage connectivity (3.2). First three constraints are explained in Section 3.3.2 and the rest of the constraints are there to show the valuation of varying mission scenario parameters.

3.4.2 Area Coverage Time, Percentage Connectivity, Max and Mean Disconnected Time and Max Mean TBV Joint Optimization Model (TCDT)

This formulation is the same as the TCD Model explained in Section 3.4.1 with the addition of the minimization of time between visits objective function (3.5) subject to the same constraints.

$$\begin{aligned} \text{Minimize} \quad & \tau, \Phi_{max}, \Phi_{mean}, \Lambda \\ \text{Maximize} \quad & \psi \end{aligned} \tag{3.8}$$

With this novel formulation, our goal is to achieve a close to uniform distribution for time between visits for each cell such that the updates from different regions are reasonably apart.

3.4.3 Benchmark Models: Multiple Travelling Salesmen Problem (mTSP) & Area Coverage Time and Percentage Connectivity Joint Optimization Model (TC)

mTSP benchmark optimization problem only optimizes τ. The same constraints that we used in our proposed models *TCD* and *TCDT* are also valid with this optimization problem. The optimization problem is given as

$$\text{Minimize} \quad \tau$$

TC benchmark optimization problem jointly optimizes τ and ψ with the same constraints and it is given as

$$\begin{aligned} \text{Minimize} \quad & \tau \\ \text{Maximize} \quad & \psi \end{aligned}$$

3.5 Evolutionary Algorithm Solution for Multi-objective Multi-UAV Path Planning

In MOO formulations with conflicting objectives, a global optimum solution that optimizes all objectives simultaneously may not be found. However, a set of near-optimal solutions may be found. From these near-optimal solutions, a Pareto-front is then set where one can see the trade-offs between objective functions clearly. MOO problems can be solved using a variety of methods. Typically, the MOO problem is converted into single-objective optimization, e.g., using methods like weighted sum [82]. Since in our mission there is no prior knowledge of objective priorities, we opt to choose an MOO solver instead, to simultaneously optimize all objectives. To this end, we propose an NSGA-II based solution, and provide a set of Pareto-optimal solutions. NSGA-II employs a two-level ranking system, with the nondominated sorting genetic algorithm [49]. Algorithm parameters are given in Table 3.2. In Figure 3.5 the MOO solver process is explained. We added our proposed problem definitions (objective functions and constraints) and GA Operators to the built-in NSGA-II solver in PyMOO [81]. We explain the proposed GA operators next.

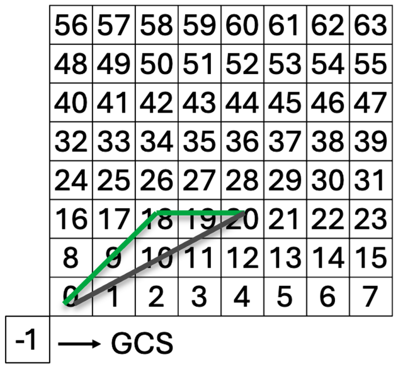
3.5.1 Sampling Operator

Given population size K, *our sampling operator* initializes a population object. Each chromosome in the population has two components: a path sequence and a set of start points with length M, first element of the set being 0. The path sequences are generated as a random permutation of $len(G) * n_{visits}$ cells. The path sequence is obtained by taking every element in the permutation result and taking $\mod len(G)$ of that element.The start points are also generated randomly and they allocate subpaths to UAVs.

3.5.2 Repair Operator

The proposed repair operator injects intermediate cells between each consecutive cell in the path component of each chromosome. If an intermediate cell is already in the updated path component n_{visits} times, then that cell does not get injected. The goal of this repair operator is to ease the process of reaching feasible solutions. In Figure 3.2, an example is given to illustrate the repair operator. The path component of the chromosome before repair is [0, 20], shown by the gray trajectory, and after repair, the path component becomes [0, 9, 18, 19, 20], shown by the green trajectory, with intermediate cells injected between cell 0 and cell 20. For the sake of illustration, we assume that the intermediate cells are not yet visited n_{visits} times.

Figure 3.2: *Pre-repair trajectory and post-repair trajectory*



3.5.3 Mutation Operators

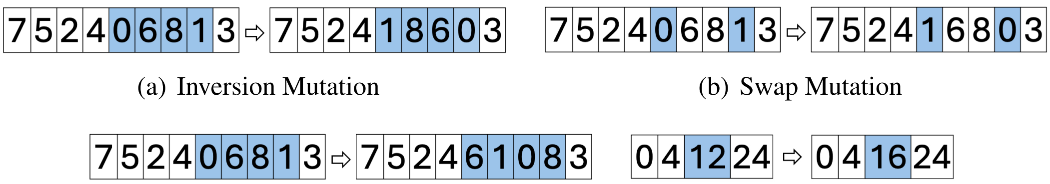
- *Inversion Mutation:* We take the path component of the chromosome, pick a random sub-path from that path, invert it and place it at the same position (index) of the original path component. Illustration can be seen in Figure 3.3 (a).

- *Swap Mutation:* We take the path component of the chromosome, pick two random indices and assign the value at the first index to the second index and vice-versa. Illustration can be seen in Figure 3.3(b).

- *Scramble Mutation:* We take the path component of the chromosome, pick a random sub-path from that path, shuffle it and place it at the same position (index) of the original path component. Illustration can be seen in Figure 3.3(c).

- *Start Point Mutation:* We take the start point component of the chromosome, pick one random start point and randomly assign another start point depending on the start points at the previous and next indices. First element of the start points cannot be chosen since it is set to 0. If the last start point is chosen, next start point is considered as $len(G) * n_{visits}$. Illustration can be seen in Figure 3.3(d).

Figure 3.3: *Mutation operators*



(a) Inversion Mutation (b) Swap Mutation (c) Scramble Mutation (d) Start Point Mutation

3.5.4 Crossover Operator

Crossover operation produces two offspring chromosomes from two parent chromosomes. Procedure is as follows: We select a sub-path from parent 1 and copy it to the same position in the offspring chromosome then we delete every gene in the chosen sub-path from parent 2 and copy the remaining genes in the same order to the remaining index positions of the offspring chromosome. That is how we generate the path component of offspring 1. We do the same with changing the roles of the parents and generate the path component of offspring 2 that way. The start points component of offspring 1 is the same as parent 1 and the start points component of offspring 2 is the same as parent 2. It is illustrated in Figure 3.4.

Figure 3.4: *Order crossover*

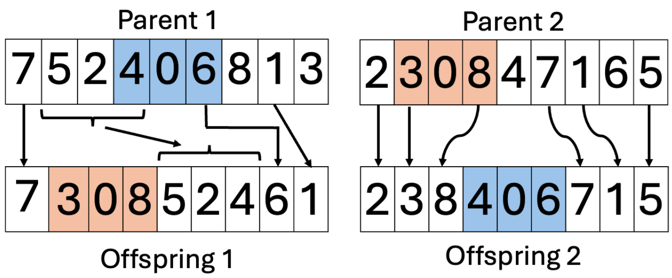


Figure 3.5: *Flowchart of the genetic algorithm process, depicting the key stages from initial population generation to termination.*

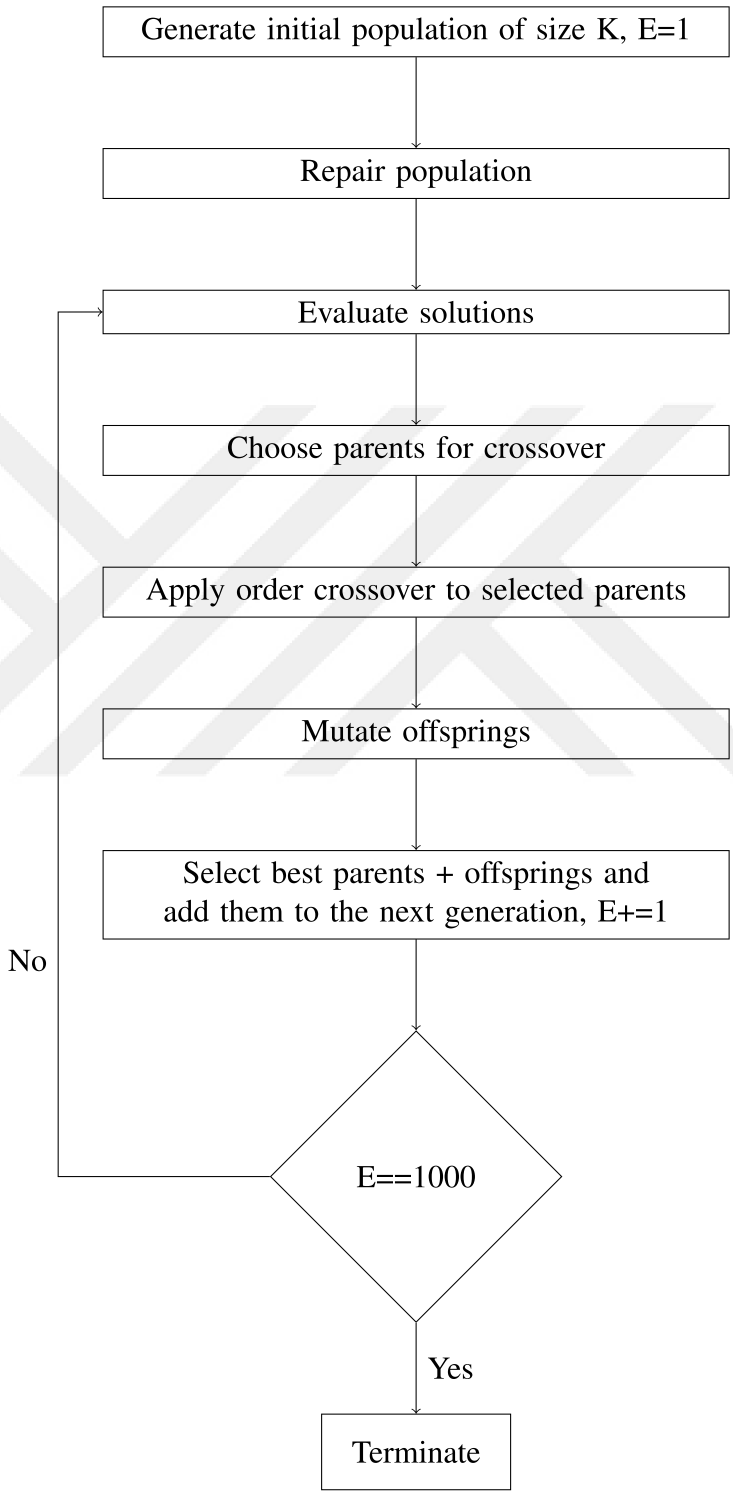


Table 3.2: *Multi-UAV multi-visit path planning: genetic algorithm (NSGA-II) parameters and values*

Parameter	**Definition**	**Value**
$\boldsymbol{K}$	Population size	300
$\boldsymbol{E}$	Number of generations	1000
$\boldsymbol{\mu}_{\text{inversion}}$	Inversion mutation probability	40%
$\boldsymbol{\mu}_{\text{scramble}}$	Scramble mutation probability	30%
$\boldsymbol{\mu}_{\text{swap}}$	Swap mutation probability	30%
$\boldsymbol{\mu}_{\text{startpoints}}$	Start point mutation probability	40%
$\boldsymbol{\mu}_{\text{crossover}}$	Order crossover probability	90%

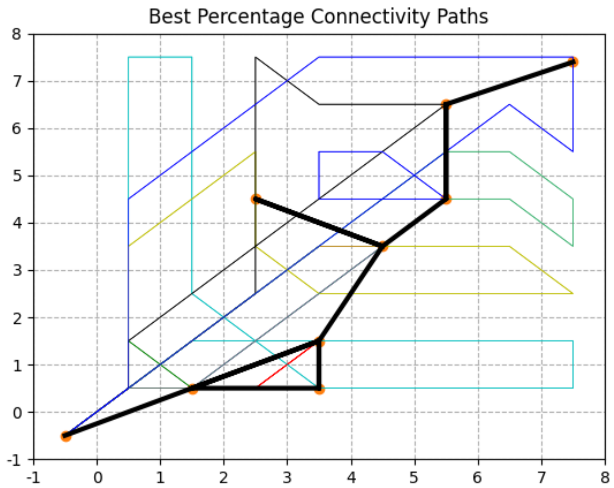
3.6 Results and Discussions

In this section, simulation results for the proposed path planning algorithms are presented for the parameters given in Table 3.3 and pareto optimal outcomes are provided for the NSGA-II parameter values given in Table 3.2. These values were chosen according to the convergence time to valid and desirable solutions. Note that NSGA-II returns a set of solutions (not a single solution). Therefore, in the following, we present results corresponding to paths with best objective function values. The simulations are run on Apple M1 chip with 16 GB of RAM utilizing the open source Python library PyMOO [81]. Average runtimes for $TCDT$ are 23, 27, 28, 33 minutes for 4, 8, 12, 16 drones respectively and for TCD, average runtimes are 15, 16, 26 and 30 minutes.

Table 3.3: *Multi-UAV multi-visit path planning: scenario parameters and values*

Parameter	**Definition**	**Value**
$\boldsymbol{G}$	Set of disjoint cells	{0,1,...,63}
$\boldsymbol{A}$	Cell Side Length	50m
$\boldsymbol{M}$	Number of Drones	{4,8,12,16}
$\boldsymbol{r}_c$	Transmission range	$\{2, 2\sqrt{2}\}$A
$\boldsymbol{n}_{visits}$	Number of visits	{1,2,3}

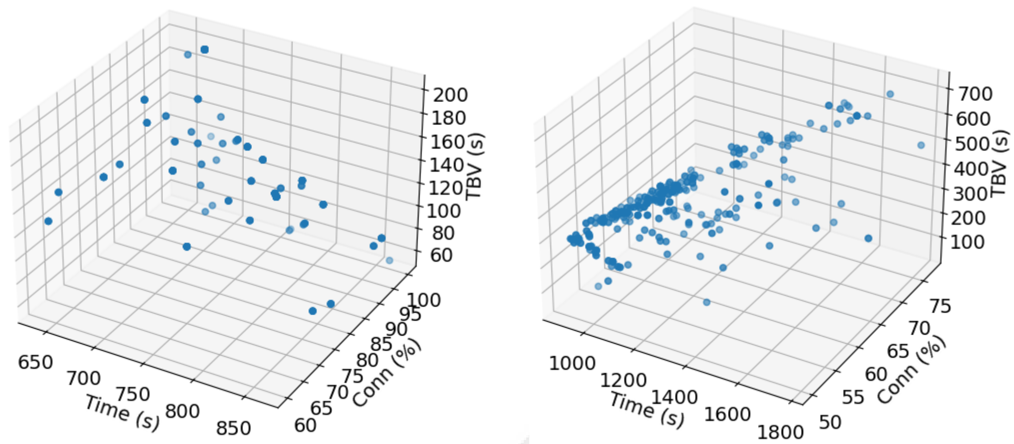
Figure 3.6: *Percentage connectivity optimized multi-UAV multi-visit path plan snapshot for $M = 8$ drones, $r_c = 2\sqrt{2}$ cells, $n_{visits} = 3$ visits*



3.6.1 Sample Solutions

Snapshot for the best percentage connectivity path for $M = 8$, $r_c = 2\sqrt{2}$ cells, $n_{visits} = 3$ is given in Figure 3.6. The flown paths are shown in colored solid lines. The current position of the drones and the GCS location (lower-left corner) are marked with orange dots, and the corresponding network connectivity graph at this instant is shown by the black lines, indicating full connectivity. To illustrate the diversity of the obtained solutions, we provide the Pareto-fronts for 2 cases, with high and low spatial density, respectively, in Figure 3.7 (a) and (b). Observe that the Pareto-optimal solutions are distributed across the exploration space. The results illustrate various trade-offs. For instance, as connectivity improves, mission time increases since the drones tend to hover to provide connectivity to their team members and hence cause delays in terms of mission duration. On the other hand, the decrease in time between visits also leads to longer mission times.

Figure 3.7: *NSGA-II sample Pareto fronts*



(a) $M = 12$, $r_c = 2\sqrt{2}$ cells, $n_{visits} = 3$

(b) $M = 4$, $r_c = 2$ cells, $n_{visits} = 3$

3.6.2 Objective Function Values

In this section, the best values the NSGA-II solver returns in terms of objective functions and a comparison with benchmark schemes that optimize mission time only under connectivity constraint mTSP and that optimize mission time and connectivity TC under connectivity and mission time constraints are given. We present results for mission time, percentage connectivity and maximum mean time between visits for various scenarios. We omit the disconnected time results; but it is important to note that they are aligned with the percentage connectivity results as expected. The subscripts in the legends correspond to the number of visits.

Figure 3.8 shows the best values for mission time (τ), percentage connectivity (ψ) and mean disconnected timesteps (Φ_{mean}) for $r_c = 2$ and $r_c = 2\sqrt{2}$. We omit the best values for Φ_{max} because they are aligned with the values for best Φ_{mean}.

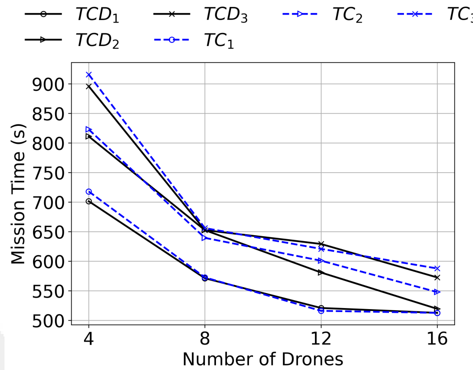
First, we look at the mission time comparison in parts (a) and (b). From these plots, we can see similar results as expected, since both models have τ optimization in them. If we compare values for different n_{visits} (i.e. 1 visit, 2 visits and 3 visits), we see the merit of our proposed multi-visit paradigm over the traditional multi-tour approach where the same 1 visit tour is repeated n_{visits} number of times.

Finally, in parts (c),(d),(e) and (f), superiority of the proposed TCD model over the benchmark TC model in terms of *mean disconnected timesteps* with similar performance in terms of *percentage connectivity to GCS* can be observed. Thus, it is safe to say that we can get a more diverse set of pareto-optimal solutions with the TCD model. Furthermore, we see better performance in percentage connectivity values as n_{visits} increases, so we can also say that multi-visit solutions perform better than multi-tour solutions in terms of percentage connectivity values as well since in multi-tour solutions, the percentage connectivity values will be the same as the same tour is repeated multiple times. The boost we get in disconnected time objective functions will be important in the next chapter, Chapter 4 because it helps with drone-drone and drone-GCS information sharing, however, it is not important in the scope of this chapter.

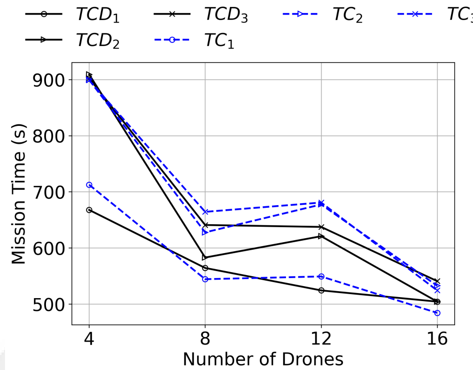
Figure 3.9 (a) and (b) show the best mission time results versus number of drones for $r_c = 2$ and $r_c = 2\sqrt{2}$ cells, respectively. Results show that the proposed TCDT fairs good in terms of mission times in comparison to mission time optimized mTSP. When r_c is small the performance gain is more significant when the number of required visits increases. When r_c is increased to $2\sqrt{2}$ the performance of all schemes come within 200 s of each other TCDT taking the lead. Addition of Λ in the optimization leads to longer mission times in comparison to TCD, since the paths the drones can take are further restricted; e.g., it makes sense to revisit the farther regions from the GCS fast (even in consecutive time steps) to avoid long jumps, but Λ parameter might not allow that.

Figure 3.9 (c) and (d) show the best percentage connectivity values versus number of drones for $r_c = 2$ and $r_c = 2\sqrt{2}$, respectively. Observe that, as expected, as spatial density increases (due to r_c or M), the connectivity significantly improves. When $M = 4$, 2-cell connectivity range is not sufficient to keep the drones connected to GCS at

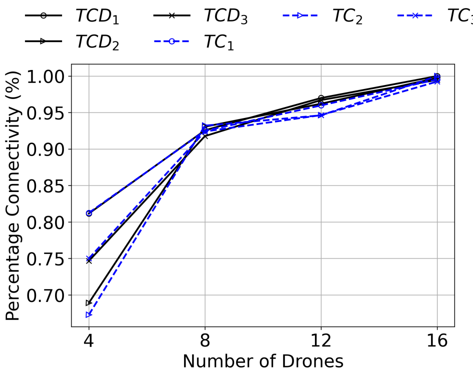
Figure 3.8: *Best objective values for various parameters TC vs TCD*



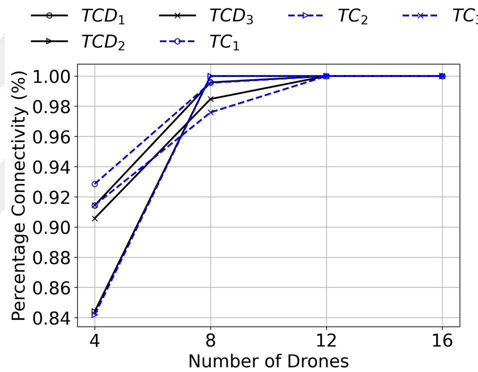
(a) Mission Time for $r = 2$ cells



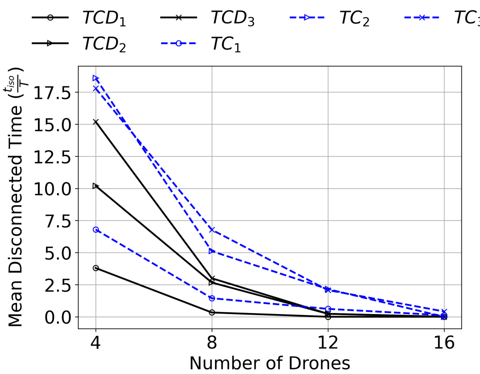
(b) Mission Time for $r = 2\sqrt{2}$ cells



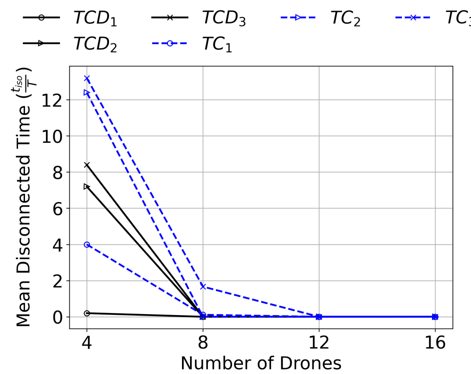
(c) Percentage Connectivity for $r = 2$ cells



(d) Percentage Connectivity for $r = 2\sqrt{2}$ cells

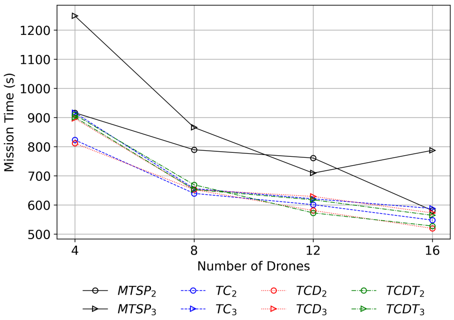


(e) Mean Disconnected Timestep for $r = 2$ cells

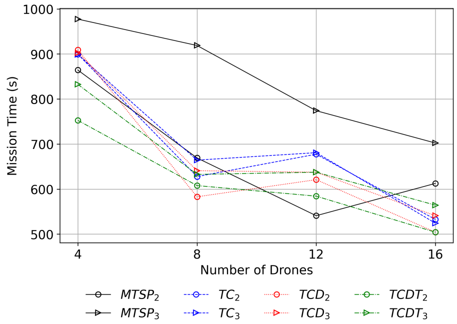


(f) Mean Disconnected Timestep for $r = 2\sqrt{2}$ cells

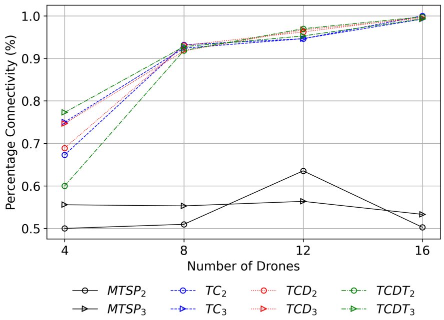
Figure 3.9: *Best objective values for various parameters TCDT vs TCD vs TC vs mTSP*



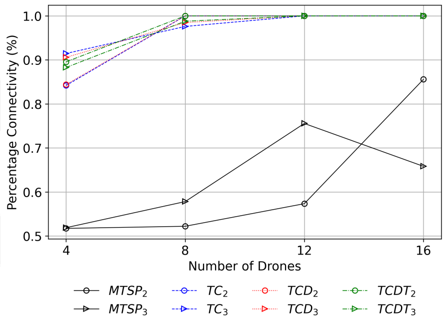
(a) Mission Time $r = 2$ cells



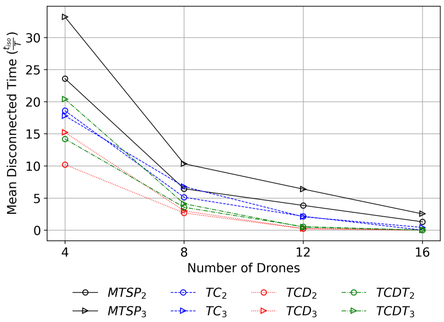
(b) Mission Time $r = 2\sqrt{2}$ cells



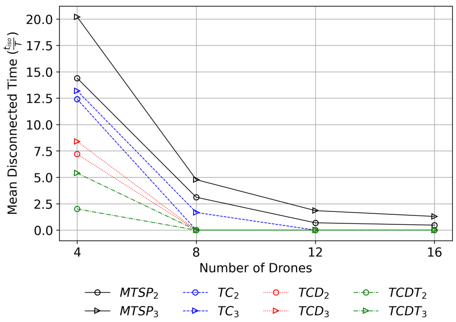
(c) Percentage Connectivity $r = 2$ cells



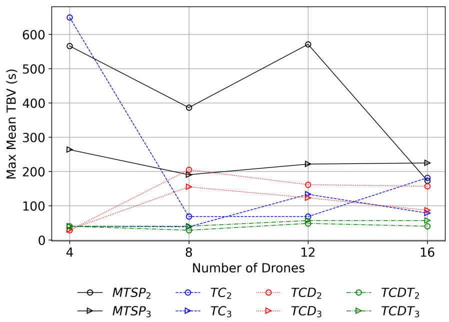
(d) Percentage Connectivity $r = 2\sqrt{2}$ cells



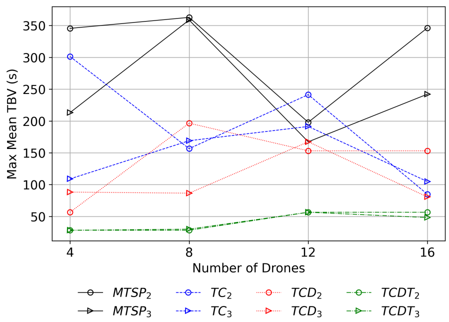
(e) Mean Disconnected Time $r = 2$ cells



(f) Mean Disconnected Time $r = 2\sqrt{2}$ cells



(g) Max mean time between visits $r = 2$ cells



(h) Max mean time between visits $r = 2\sqrt{2}$ cells all times; but, nevertheless a ψ value between 60% and 80% is possible. The connectivity-optimum paths tend to utilize drones as hovering relays to create a relay-drone backbone. Although the connectivity looks good, note that this will come as a cost in terms of mission time. Especially, when M is low, even if only one drone is reserved as a hovering relay, the remaining area will be covered in a longer time due to less available drones for search. As expected, connectivity-optimized schemes have a significantly higher percentage connectivity than mTSP. Even if M is high, mTSP does not reach full connected state, as the node locations are optimized toward coverage, which leads to nodes located far away from each other, hence disconnected. These results are aligned with the mean disconnected time (Φ_{mean}) results presented in Figure 3.9 (e) and (f) since percentage connectivity and disconnectivity are inversely proportional.

Finally, Figure 3.9 (g) and (h) show the best Λ values versus M for $r_c = 2$ and $r_c = 2\sqrt{2}$, respectively. Observe that the gain we get in the optimization of maximum time between visits objective is far greater than the loss we get in the optimization of both mission time and percentage connectivity with the exception of a few worst-case scenarios (i.e. $M = 4$, $r_c = 2$ cells, $n_{visits} = 2$) where percentage connectivity drops from close to 70% to 60%. Enforcing revisits tend to create redundancy which benefits connectivity. However, without constraining the time between visits some regions might be revisited with a significant delay (observe the TCD, TC, and mTSP results), which might not be acceptable if vital information needs to be updated, e.g., in case of disaster. Beyond a certain M both connectivity and mission time will not improve significantly, but the results show that among the best connectivity-coverage paths, there can still be better distribution of drones to provide good update frequency.

3.7 Summary

In this chapter, we propose a multi-drone path planning approach that simultaneously optimizes *mission time*, *percentage connectivity*, *maximum disconnected time*, *mean disconnected time* and *maximum mean time between visits* among a group of drones tasked with exploring an unknown area visiting each cell a specified n_{visits} number of times to mitigate uncertainty due to imperfect onboard sensing or to enable sensed data updates. The multi-drone path planning problem has been formulated as a novel multi-objective optimization problem. To solve the optimization problem, an NSGA-based multi-objective evolutionary algorithm was proposed, consisting of custom sampling, repair, mutation, and crossover operators. We used our solver to test two models as well as benchmarks. We showed the difference in objective value performances for each of the models and the trade-offs between *maximum mean time between visits* objective and the other objectives. We showed that while there is a range of solutions to choose from, TCDT can provide reasonable connectivity and time between visits values, while not significantly increasing the mission time with respect to the benchmark mTSP.

4. COOPERATIVE MULTI-TARGET SEARCH IN UAV SWARMS UNDER SENSOR AND CONNECTIVITY LIMITATIONS

In this chapter, we propose a sensor model to be used in cooperative multi-target search involving imperfect sensing and dynamic information exchange. We use the multi-UAV paths from the results of Chapter 3 and test the detection time, inform time and mission time metrics. Our results show that by considering cell revisit times as well as connectivity in the path planning, the target detection time can be improved by 60% and we can achieve instant GCS inform post-detection in realistic, uncertain environments.

4.1 Introduction

In this chapter, we consider a multi-target search mission, where multiple UAVs work as a team and cooperatively search an unknown area, exchanging information within the swarm and with a GCS under connectivity constraints and sensing uncertainties. For this mission, we propose a multi-objective multi-UAV path optimization framework that jointly optimizes coverage, connectivity, and revisit times within the context of multi-target search missions with imperfect sensing and dynamic information exchange. To this end, we integrate probabilistic occupancy updates and inter-UAV information sharing mechanisms into our path planning strategy to avoid redundant revisits. We consider the search area as a grid consisting of equal-sized cells, where a known number of stationary targets are randomly distributed. For a successful mission, we first determine the minimum number of visits required to maximize target detection probability given a certain sensor uncertainty model and detection threshold. We then use the required number of visits in our multi-UAV path planner to optimize target detection time and mission success probability, while maintaining connectivity. During the mission, the UAVs that are within the same clique (i.e., that are connected to each other over possibly multi-hop links) merge their target probability maps, while informing the GCS as soon as possible. Once all targets are detected and known to a UAV, it flies back to the GCS continuously sharing information. When all UAVs are back at the GCS, the mission is completed. We compare the detection time, inform time and mission success probability of our jointly optimized path planners with benchmarks that do not consider connectivity constraints and/or revisit quality. Our results show the superiority of the proposed model in terms of target detection time, inform time and mission time metrics compared to the benchmark coverage-only and coverage and connectivity only optimizations. We complete 1000 runs in our simulations and the proposed model shows up to 60% improvement in inform time compared to the benchmark. In terms of inform time, our proposed model achieves instant inform after detection while inform time of 35 seconds is observed on average in the coverage-optimized paths even at higher transmission ranges. In terms of detection time, we see up to 100% improvement and in terms of mission time, we observe up to 200% improvement.

In Section 4.2, we explain our system model, namely the multi-UAV mission including mission and sensing parameters and models we used for sensing, map merging and communication and our performance metrics. In Section 4.3, MOO frameworks used for generating ready multi-UAV paths are explained. In Section 4.4, results are discussed where various multi-UAV paths' performance on our performance metrics are compared and finally in Section 4.5, the chapter is concluded summarizing our work in this chapter.

4.2 System Model

In this section, we define the multi-UAV cooperative search mission, the models we use for sensing and required number of visits for detection [3] and information merging [15], and finally, we define the performance metrics we used related to target detection. Mission scenario and sensor parameter definitions are given in Table 4.1.

Table 4.1: *Multi-UAV multi-visit cooperative search: scenario and sensor parameters*

Parameter	Definition
M	Number of UAVs
N_t	Number of targets
n_{visits}	Number of visits
G	Set of disjoint cells
r_c	Communication range in cells
$\tau_{detection}$	Detection time in seconds
τ_{alo}	Time at least one drone knows all targets in seconds
τ_{inform}	Inform time in seconds
τ	Mission time (Time All UAVs are back at GCS) in seconds
ρ	Mission success (detection of all targets) probability
B	Cell occupancy threshold
p	Detection probability
q	False alarm probability
P_0	Initial occupancy probability of each cell
$P_{i,c,t}$	Occupancy probability of cell c at time t in the occupancy grid/map of drone i

4.2.1 Multi-UAV Mission

In this work, the goal is detection of N_t randomly distributed targets in an unknown area. To this end, M UAVs take off from GCS and fly pre-defined optimized paths at the same altitude. The pre-planned paths will be introduced in the next section. The UAVs are equipped with onboard sensors used to detect targets (e.g., disaster victims, damaged areas, critical infrastructures, etc) and mesh-capable wireless interface to exchange information with other UAVs and the GCS. The mission area is represented as a grid of G equal-sized grid cells. The size of each cell depends on the ground sensor coverage of the onboard UAV sensors. During the mission, at each cell, the UAVs share information such as positions, target status, target probability map, etc. As soon as the confidence level in N_t locations is above a pre-defined threshold, B, the mission is over. The UAVs with this knowledge fly back to the GCS.

4.2.2 Sensing, Map Merging and Communication Models

We assume that all UAVs and the GCS have their own occupancy grids (probabilistic search maps) with occupancy probabilities between 0 and 1. The probabilities are computed for each cell and correspond to the probability that a target is present in a given cell. At each time step, each UAV takes one measurement at a given cell, determine whether a target is present or not, update its probabilistic search map, share its measurement history with its connected component (UAVs or GCS over single or multiple hops), and update its own map if necessary given the other UAVs shared history.

4.2.2.1 Sensing Model Used for Updating Cell Occupancy Probabilities

The sensing model is defined based on detection and false alarm probabilities: (i) p = Prob{target is detected/there is a target} and q = Prob{target is detected/there is no target}. The occupancy probability update is dependent on the prior occupancy probability and sensor characteristics p and q. Each UAV keeps a list of known sensor measurement values (1 for target presence and 0 for target absence) and the corresponding timestamp. While at a given point in time, each UAV might have a different list, by sharing the measurements and the timestamps, we aim to synchronize the search maps of all UAVs as they meet each other. The current occupancy probability for cell c at the UAV i is computed using Bayesian rule [3]:

$$P_{i,c,t} = \begin{cases} \frac{pP_{i,c,t-1}}{pP_{i,c,t-1}+q(1-P_{i,c,t-1})}, & \text{if sensor value is 1.} \\ \frac{(1-p)P_{i,c,t-1}}{(1-p)P_{i,c,t-1}+(1-q)(1-P_{i,c,t-1})}, & \text{if sensor value is 0.} \end{cases}$$

where $P_{i,c,t}$ and $P_{i,c,t-1}$ represent the occupancy probability of cell c in the occupancy map of drone i at time steps t and $t-1$, respectively. We set the initial occupancy probabilities at mission start, $t = 0$, to 0.5.; i.e., we assume that there is no prior information.

4.2.2.2 Communication Model

We assume a disc model for communication; i.e., we assume that two nodes are connected to each other if they are within r_c of each other. This assumption is based on our experimental results, where UAVs are equipped with a multi-antenna setup that provides omnidirectional radiation [83]. Each node keeps an adjacency matrix; i.e., list of its neighbors and correspondingly its reachable nodes. As soon as the transmission range condition is satisfied, position and sensor measurement history can be exchanged.

4.2.2.3 Number of Required Visits to Each Cell

Due to sensing uncertainty, each cell may need to be visited multiple times. The required number of visits depends on the desired confidence B and sensor model and can be determined from the Bayesian update rule as follows [3]:

$$m \geq \frac{\log\left(\frac{P_0(1-B)}{B(1-P_0)}\right)}{(1-p)\log\frac{1-q}{1-p} + p\log\frac{q}{p}} \tag{4.1}$$

where P_0 is the initial occupancy probability for a given cell and m is the minimum number of visits required to detect a target in a cell, given there is a target.

4.2.3 Performance metrics

The performance of various path planners are measured in terms of the following parameters.

- *Detection time* ($\tau_{detection}$) is defined as the time all targets are detected. For this metric, we do not require any node, including the GCS, to know of all targets. Detection is defined as $P_{i,c,t} \geq B$ at N_t cells, where B is the preset threshold, corresponding to the required confidence in target detection probability.

- *Time at least one drone knows all targets* (τ_{alo}) is defined as the time at which at least one UAV has $P_{i,c,t} \geq B$ for all N_t targets.

- *Inform time* (τ_{inform}) is defined as the time the GCS knows of all targets.
- *Mission time* (τ) is the time from take-off till all UAVs return to GCS.
- *Success probability* (ρ) is the success rate across all simulated missions.

4.3 Multi-UAV Path Planning for Multi-Target Detection

In this chapter, we test the performance of our novel MOO frameworks *TCD* and *TCDT* which we introduce under Section 3.4, in (3.7) and (3.8), respectively on our performance metrics mentioned in this chapter (i.e. $\tau_{detection}$, τ_{alo}, τ_{inform}, τ) and compare them to our benchmark models mTSP and TC. We study the benefits of multi-visit path planning and information merging paradigms and then we compare our proposed models to the benchmark models which all include multi-visit path planning and information merging. As multi-UAV paths, we take the paths that has the best perfomance in certain objectives.

To illustrate the impact of choice of optimization parameters, information merging, as well as joint optimization we compare the following path planners:

- *Multi-tour mTSP*: This path planner corresponds to mTSP. The goal is to minimize mission time (τ) under connectivity constraints for one tour (single visit) only; i.e., the mission planner doesn't consider sensing uncertainty. UAVs are not capable of merging their maps; i.e., each UAV sends their maps to the GCS, where the information is merged and detection decisions are made, At the end of a tour, if all targets are not found, the UAVs fly the same paths for another round, until detection is completed; with the chosen sensing parameters, at least 3 tours are required.
- *Multi-tour mTSP with merging*: This planner allows the UAVs to share and merge maps on-the-fly. The formulation is same as the previous planner. The goal is to see the impact of onboard merging on the mission parameters.

- *Multi-visit mTSP*: This planner considers sensing uncertainty and incorporates the minimum number of visits into the optimization problem as a constraint. So, the formulation becomes minimization of τ, such that $n_{visits} = 3$ and percentage connectivity is greater than 0.5 (in addition to the other constraints in (3.7)). For this method, the UAVs are not capable of merging their maps; i.e., each UAV sends their maps to the GCS, where the information is merged and detection decisions are made. When all targets are found, GCS calls the UAVs back.

- *Multi-visit mTSP with merging*: This planner allows the UAVs to share and merge maps on-the-fly. The formulation is same as the previous planner. The goal is to see the impact of onboard merging on the mission parameters.

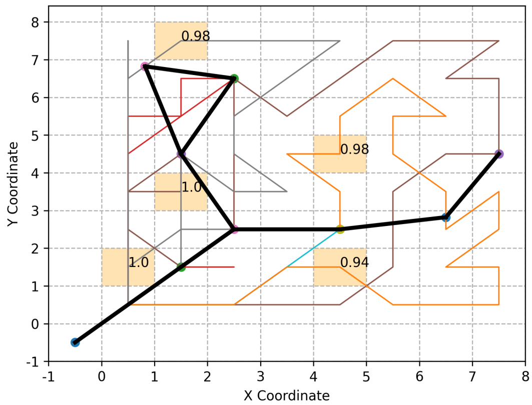
- *TCD*: Our proposed planner introduced in Section 3.4.1 which jointly optimizes mission time (τ), percentage connectivity (ψ) and max (Φ_{max}) and mean (Φ_{mean}) disconnected times, also returns several Pareto optimal solutions. Among the returned path, we pick the path with best τ and best Φ_{max}. The algorithms are denoted as *TCD Best τ Path* and *TCD Best Φ_{max} path* respectively in the figure legends.

- *TCDT*: Our proposed planner introduced in Section 3.4.2 which jointly optimizes τ, ψ, Φ_{max}, Φ_{mean} and time between visits (Λ), also returns several Pareto optimal solutions. Among the returned path, we pick the path with best τ, best Φ_{max} and best Λ. The algorithms are denoted as *TCDT Best τ Path*, *TCDT Best Φ_{max} path* and *TCDT Best Λ path* respectively in the figure legends.

4.4 Results and Discussions

In this section, we analyze the performance of the proposed path planner for various scenarios. $N_t = \{3, 5\}$ targets are randomly distributed in an 8x8 grid, where each cell in the area correspond to a 50mx50m ground coverage. Each scenario is run for 1000

Figure 4.1: *Multi-UAV cooperative search path snapshot for $M = 8$ drones, $r_c = 2\sqrt{2}$ cells, $N_t = 5$ targets*



runs. The maximum speed of the UAVs is set to 2.5m/s. M UAVs are initially located at the GCS, with wireless interface with range $r_c = \{2, 2\sqrt{2}\}$ cells, sensing equipment with $p = 0.8$ and $q = 0.2$. The detection threshold B is set to 90%. The number of required visits is set to 3 accordingly from (4.1). The initial cell occupancy probabilities are set to 0.5; i.e., we have no prior knowledge of target locations.

Figure 4.1 shows a snapshot of the mission plan obtained from the output of the proposed TCDT algorithm. It is the multi-UAV path plan with the best percentage connectivity performance for $M = 8$ drones, $r_c = 2\sqrt{2}$ cells. We used this multi-UAV path plan for the simulation of multi-UAV cooperative search mission with $N_t = 5$ targets. Planned paths are shown, as well as the network graph at the chosen time instant. There are 5 targets with detection probabilities ranging from 0.94 to 1; i.e., all targets are detected and the UAVs are on the way home. Targets are marked in yellow and probability map values are given. The colored solid lines are the optimized paths. Solid black lines show the network graph.

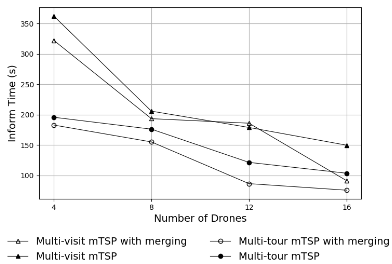
Figures 4.2 (comparison of mTSP schemes with $r_c = 2$ cells), 4.3 (comparison of mTSP schemes with $r_c = 2\sqrt{2}$ cells), 4.4 (comparison of mTSP, TCD and TCDT models with $r_c = 2$ cells) and 4.5 (comparison of mTSP, TCD and TCDT models with

$r_c = 2\sqrt{2}$ cells) show the durations of different phases of our search and rescue mission for $N_t = 3$ targets and $N_t = 5$ targets. Since the mission success probability is 1 for all cases; i.e., 3 visits are sufficient for correct detection, we omit these results.

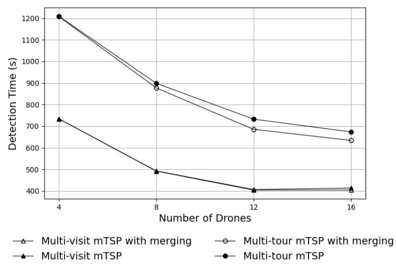
First, from Figures 4.2 and 4.3, we analyze the benefits of the multi-visit path planning proposed in Chapter 3 opposed to multi-tour path planning where the drone paths generated for single visit on each cell are repeated n_{visits} times and the information merging algorithm proposed in this chapter opposed to mTSP schemes where there is no information merging. When we observe (b) and (f), we see similar performance in terms of detection time between all mTSP schemes. When we look at (c) and (g), we see a consistent performance boost in τ_{alo} from mTSP schemes with no merging to mTSP schemes with merging. Finally, observing inform time metrics in (a) and (e), we see a performance boost, albeit a slight one, from multi-tour mTSP with no merging scheme to multi-tour mTSP with merging scheme. Overall, in our search and rescue simulations for our mTSP schemes, we observe improvements in inform time and τ_{alo} metrics from *multi-tour mTSP with no merging* to *multi-visit mTSP with merging* (both multi-visit and merging paradigms provide significant boost over multi-tour and no merging respectively). We also see slight improvements in detection time, especially when we compare *multi-tour mTSP* and *multi-tour mTSP with merging*. The improvements we get in all phases of the mission leads to better mission times (observe (d) and (h)), hence improving the efficiency of a search and rescue mission.

Now that we have analyzed the significance of our proposed multi-visit and information sharing paradigms, we discuss the impact of simultaneously optimizing mission time and connectivity from Figures 4.4 and 4.5, we compare the best objective paths obtained from our solutions using mTSP, TCD and TCDT models. Observe from inform time plots in (a) and (e) that mTSP schemes perform worse than (at times more than doubling) even the best τ paths of TCD and TCDT, especially, in sparser scenarios, with low

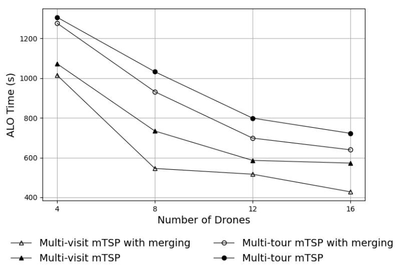
Figure 4.2: *mTSP schemes performance comparison for $r_c = 2$ cells*



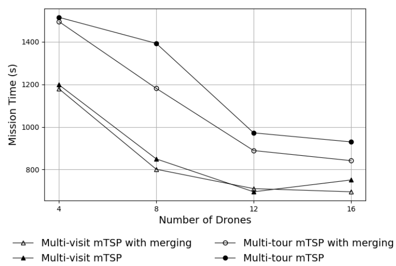
(a) τ_{inform}, $N_t = 3$



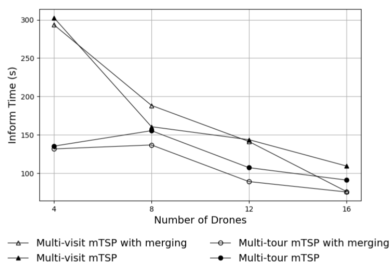
(b) $\tau_{detection}$, $N_t = 3$



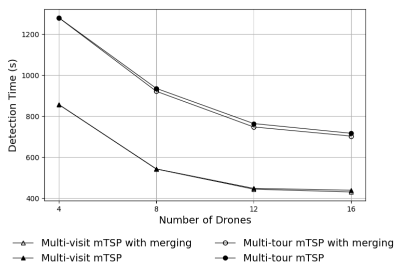
(c) τ_{alo}, $N_t = 3$



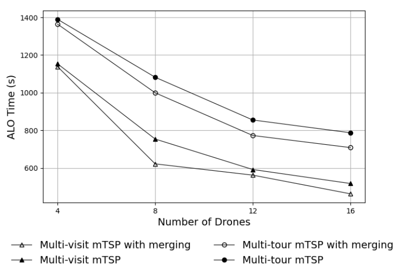
(d) τ, $N_t = 3$



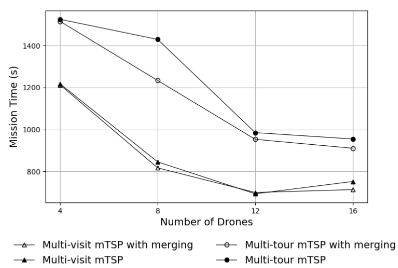
(e) τ_{inform}, $N_t = 5$



(f) $\tau_{detection}$, $N_t = 5$

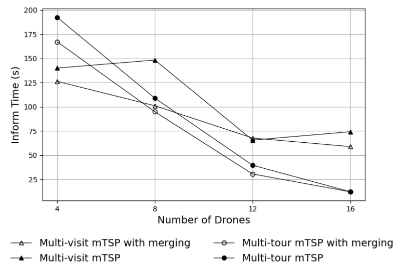


(g) τ_{alo}, $N_t = 5$

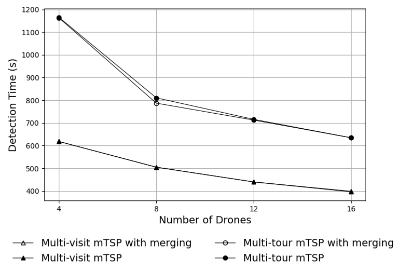


(h) τ, $N_t = 5$

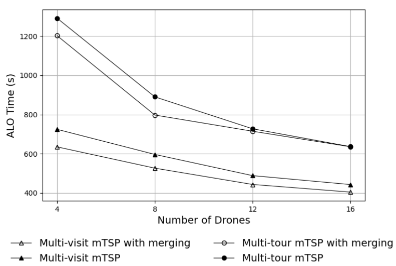
Figure 4.3: *mTSP schemes performance comparison for* $r_c = 2\sqrt{2}$ *cells*



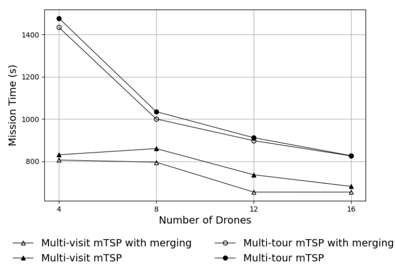
(a) $\tau_{inform}, N_t = 3$



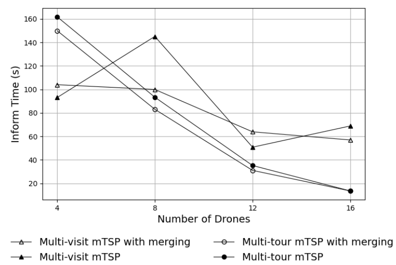
(b) $\tau_{detection}, N_t = 3$



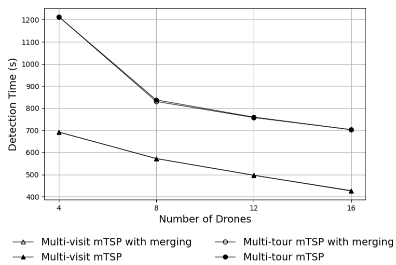
(c) $\tau_{alo}, N_t = 3$



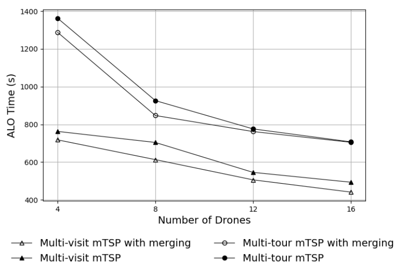
(d) $\tau, N_t = 3$



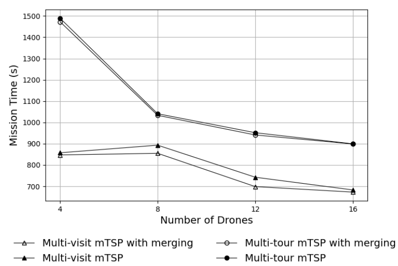
(e) $\tau_{inform}, N_t = 5$



(f) $\tau_{detection}, N_t = 5$



(g) $\tau_{alo}, N_t = 5$



(h) $\tau, N_t = 5$

M and/or low r_c. The best Φ_{mean} and best Λ paths perform best among all schemes as expected, since the UAVs stay connected to the GCS most of the time and maximum mean time elapsed between visits to each cell is as small as possible. We observe that number of targets only slightly affect the inform times, whereas when r_c is increased, the network becomes more connected and schemes other than best ψ paths perform similarly.

Futhermore, when we observe the τ_{alo} metrics from parts (c) and (g), we see a similar trend to inform time metrics in parts (a) and (e), however, we see the best τ paths taking the lead over the best Φ_{mean} paths. At low r_c, best Λ paths gain precedence over best Φ_{mean} paths at high M while at high r_c, there is a more consistent superiority of the best Λ paths over the best Φ_{mean} paths.

When we study the detection times in (b) and (f) on the other hand, we see some of the trends reversing. The mTSP and best Φ_{mean} and Λ paths perform significantly worse than the time optimized or time prioritized paths. Jointly optimized schemes lead to similar but better performance compared to mTSP (which minimizes mission time), when the best τ paths are chosen. As M increases, the detection times decrease, and r_c doesn't have much impact on time-optimized paths as expected, but improves the best Φ_{mean} and best Λ paths, especially at bigger M values since the network becomes well-connected allowing the nodes to spread out more improving detection performance.

Upon complete mission time observation from parts (d) and (h), we see the superiority of the best τ paths over the best Φ_{mean} paths and best Λ paths. At high r_c, the performance boost we get from best Φ_{mean} paths to best τ paths in terms of mission time gets significantly lower. The same goes for the relation between best Λ paths and the best τ paths, however, only at high M.

Furthemore, we look whether the gains due to connectivity and information merging, compensate for the loss due to staying connected. The importance of connectivity becomes more prominent when it comes to mission time. Only UAVs that know that all targets are found can return to GCS. If there are isolated nodes, which can happen when M or r_c is small, such nodes keep searching until they meet other nodes, or in the worst case, when they are in the range of GCS. Results show that the proposed best τ paths lead to the best solutions especially in low spatial density scenarios.

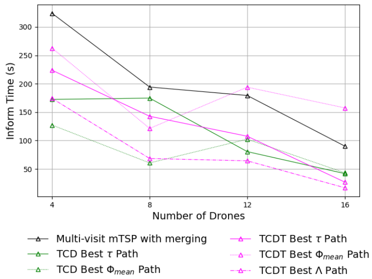
Finally, we study the performance of the best paths for each objective in the TCDT model to clarify which objective to take into account if the end user wants to improve a particular mission phase (inform, detection or complete mission) from Figures 4.6 and 4.7. When we observe the best τ paths, we see that they are more optimal towards the detection phase of the mission (see (b), (c), (f), (g)) as expected and they are also more optimal in terms of mission time (see (d) and (h)). When we look at the best ψ paths, we observe better performance in the inform phase of the mission (see (a) and (e)) followed closely by the best Φ_{mean} paths and when we observe the best Λ paths, we see similar performance to best ψ paths (high inform time performance) especially at low r_c. The same goes for scenarios where r_c and M values are high. Last but not least, we note that in overall mission time, the best τ paths and the best Λ paths have the best performance across all scenarios on average.

These results show that once the sensing model is mapped to required number of visits, and this number is incorporated into the mission plan, the mission success may be guaranteed and the UAVs can stay connected while looking for the targets. Allowing onboard information sharing and merging also helps improve the target detection mission.

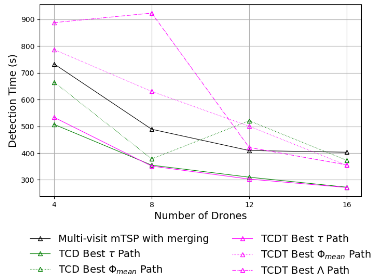
4.5 Summary

In this chapter, we proposed a sensor model and inter-UAV information sharing algorithm for multi-UAV cooperative search missions under imperfect sensing limitations. We ran multiple simulations of the mission under various scenarios and discussed the detection and inform time performance of the proposed sensor models and information

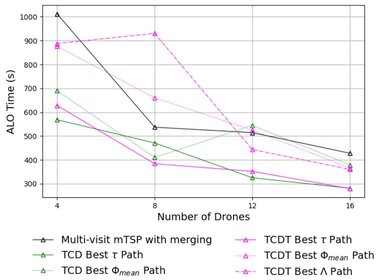
Figure 4.4: *Multi-visit mTSP with merging, TCD and TCDT models performance comparison for $r_c = 2$ cells*



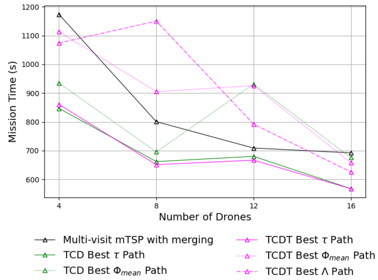
(a) $\tau_{inform}, N_t = 3$



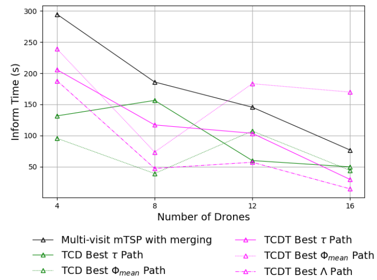
(b) $\tau_{detection}, N_t = 3$



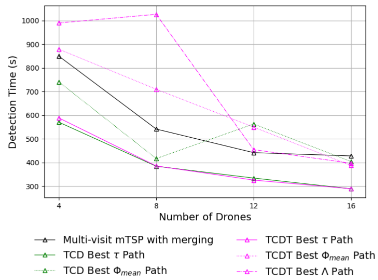
(c) $\tau_{alo}, N_t = 3$



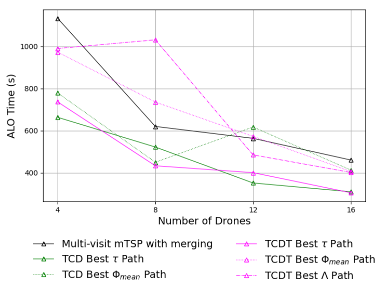
(d) $\tau, N_t = 3$



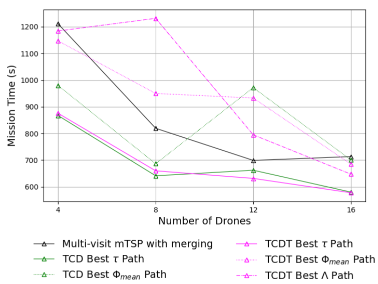
(e) $\tau_{inform}, N_t = 5$



(f) $\tau_{detection}, N_t = 5$

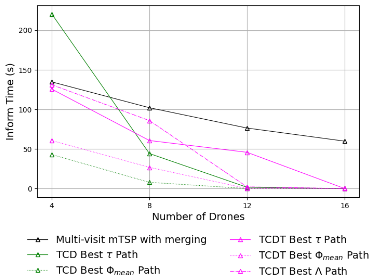


(g) $\tau_{alo}, N_t = 5$

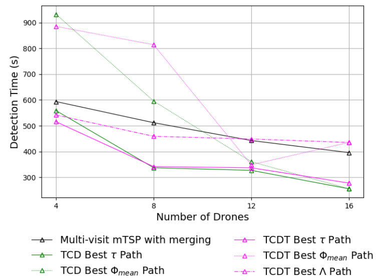


(h) $\tau, N_t = 5$

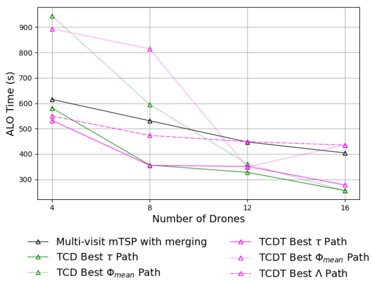
Figure 4.5: *Multi-visit mTSP with merging, TCD and TCDT models performance comparison for* $r_c = 2\sqrt{2}$ *cells*



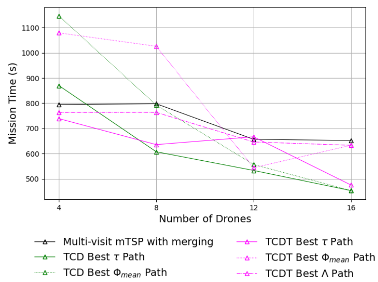
(a) $\tau_{inform}, N_t = 3$



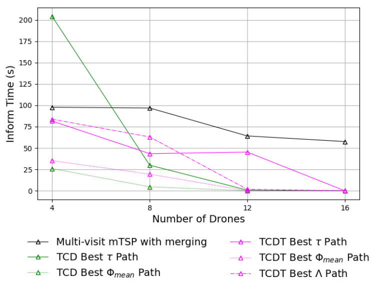
(b) $\tau_{detection}, N_t = 3$



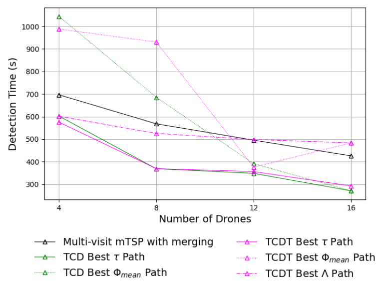
(c) $\tau_{alo}, N_t = 3$



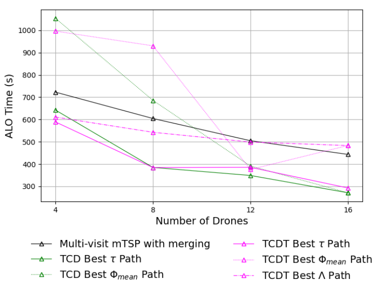
(d) $\tau, N_t = 3$



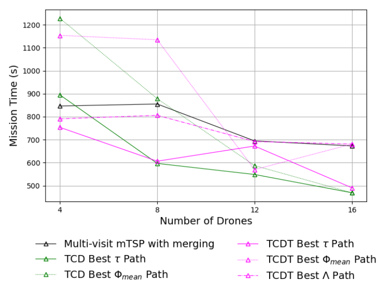
(e) $\tau_{inform}, N_t = 5$



(f) $\tau_{detection}, N_t = 5$

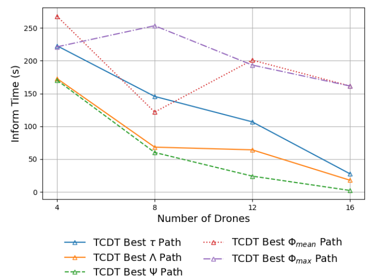


(g) $\tau_{alo}, N_t = 5$

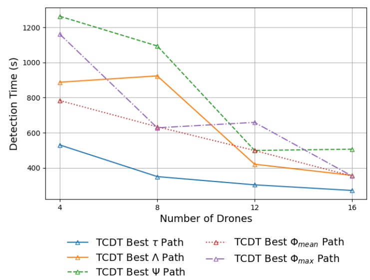


(h) $\tau, N_t = 5$

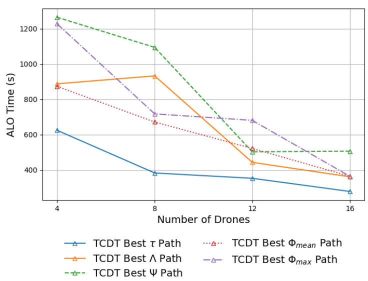
Figure 4.6: *TCDT best objective paths comparison for $r_c = 2$ cells*



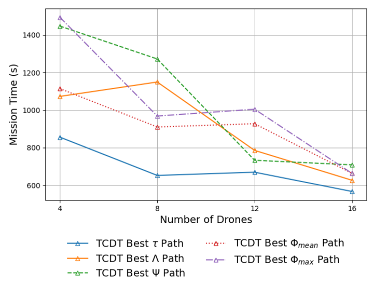
(a) τ_{inform}, $N_t = 3$



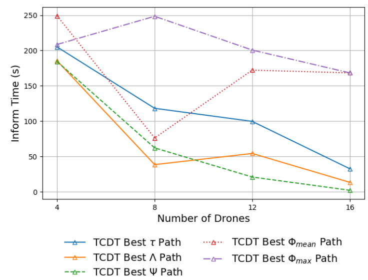
(b) $\tau_{detection}$, $N_t = 3$



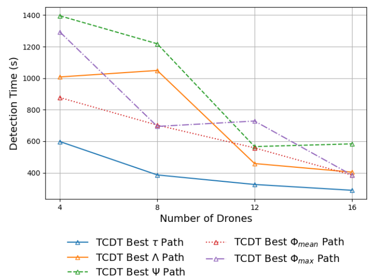
(c) τ_{alo}, $N_t = 3$



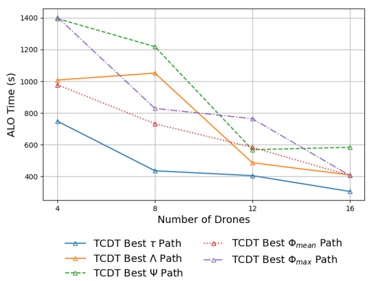
(d) τ, $N_t = 3$



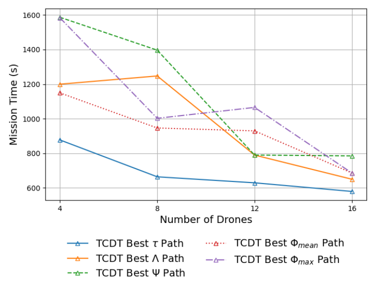
(e) τ_{inform}, $N_t = 5$



(f) $\tau_{detection}$, $N_t = 5$

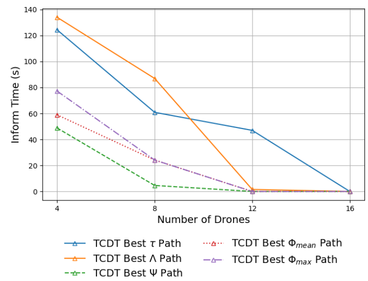


(g) τ_{alo}, $N_t = 5$

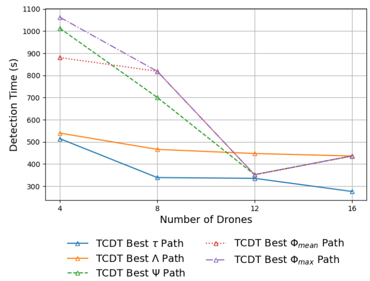


(h) τ, $N_t = 5$

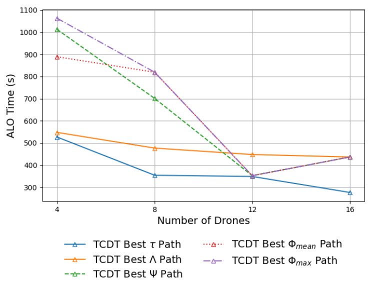
Figure 4.7: *TCDT best objective paths comparison for* $r_c = 2\sqrt{2}$ *cells*



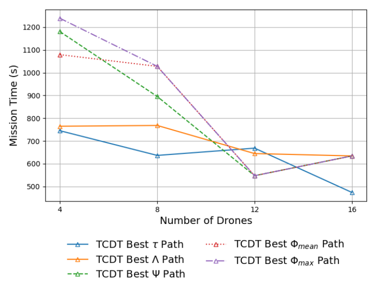
(a) τ_{inform}, $N_t = 3$



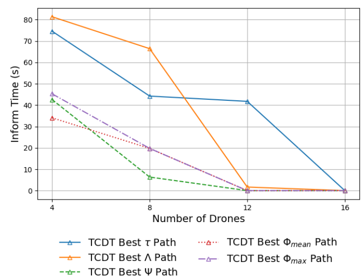
(b) $\tau_{detection}$, $N_t = 3$



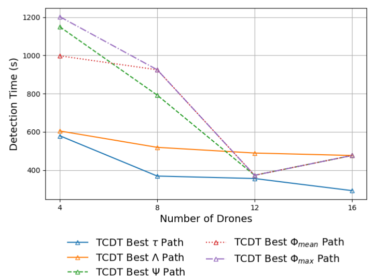
(c) τ_{alo}, $N_t = 3$



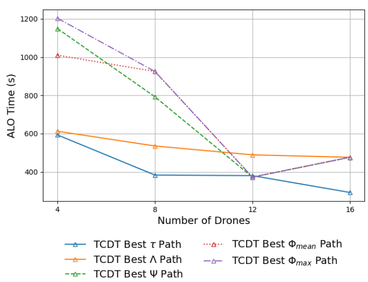
(d) τ, $N_t = 3$



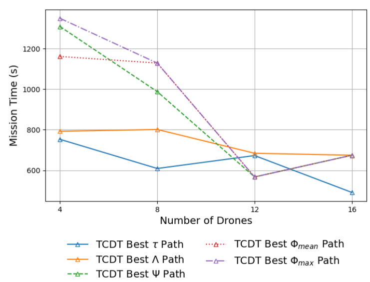
(e) τ_{inform}, $N_t = 5$



(f) $\tau_{detection}$, $N_t = 5$



(g) τ_{alo}, $N_t = 5$



(h) τ, $N_t = 5$

sharing algorithm using objective-optimal multi-UAV paths obtained from the TCDT path planning framework proposed in Chapter 3. We observed that the multi-UAV paths obtained in Chapter 3 offer varying target detection time and GCS inform time performance and we showed that the proposed sensor model and information sharing algorithm significantly improve the detection time and inform time performance of multi-UAV systems without incurring excessive travel cost.

5. CONCLUSIONS

In this thesis, we proposed a MOO framework that optimizes *cell revisit times* alongside of *area coverage time, topological connectivity to GCS* and *UAVs' disconnectivity from GCS* for the purpose of optimizing the efficiency and reliability of multi-UAV cooperative search missions under communication and sensing constraints. Reporting on the multi-UAV paths we gathered from our proposed MOO frameworks (TCD and TCDT), we provided a diverse solution set comprised of various multi-UAV path plans that offer trade-offs between each objective function and we presented plots showing the performance of the multi-UAV paths on each objective function considering various scenarios and showed that *the gain we achieve in cell revisit time performance outperforms the loss we suffer in area coverage time and connectivity*. Then, we tested the *target detection* and *GCS inform times* performance of the multi-UAV paths with the best objective function performance gathered from the proposed MOO frameworks against that of the benchmark models (mTSP and TC). We showed that the *target detection times can be improved by 60%* and *instantaneous GCS inform* can be achieved. Furthermore, we proved the *benefit of information merging and multi-visit paradigms* seperately by comparing *information merging against no information merging* and *multi-visit against multi-tour* in multi-UAV paths optimized for mTSP benchmark model.

We believe the work we propose in this thesis to be a big step toward the improvement of *time-critical cooperative search missions* in real world applications such as SaR. However, offline multi-UAV path generation has a few shortcomings. Foremost, in dynamic missions like cooperative search, it falls short in terms of robustness. Although the pre-planned paths are reliable at the known state of the mission environment, they lack adaptability to critical dynamic events such as bad weather conditions. Furthermore, in our methodology, all connectivity calculations are done at discrete timesteps (i.e. at times when each UAV reach their next waypoint simultaneously). Real-time connectivity implementation can improve the overall connectivity since time elapsed between discrete timesteps is quite large due to the large size of each cell and slow speed of the UAVs. Moreover, the addition of real-time connectivity calculations can lead to better target detection and GCS inform time performances since UAVs will be able to share information at any time instead of only at discrete timesteps.

Towards the betterment of our current implementation considering the shortcomings mentioned, future research will explore dynamic environments and real-time decision-making under uncertainty and intermittent connectivity to further enhance the adaptability and resilience of our multi-UAV system to further decrease mission time. Furthermore, to increase the adaptability of our methodology, we aim to deliver a GA-RL hybrid approach to generate more robust optimal multi-UAV paths and test these paths on time-limited targets.

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