Energy-Constrained UAV-UGV Cooperative Systems: A Bilevel Framework for Routing in Multi-Agent Teams

BY

MOHAMMAD SAFWAN MONDAL
Bachelor of Engineering, Jadavpur University, 2021

THESIS

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Defense Committee:

Pranav A. Bhounsule, Chair and Advisor, Department of Mechanical and Industrial Engineering, University of Illinois Chicago
Selva Nadarajah, Department of Information and Decision Sciences, University of Illinois Chicago
James D. Humann, DEVCOM Army Research Laboratory

To,

my Mother, Father, Sabana, and my beloved grandparents—Dadu, Nana, and Nanima,

whose unwavering love and wisdom have shaped my journey,

and have given me the courage to dream beyond boundaries,

without them, I would not be here today.

মা, আব্বা, সাবানা এবং আমার প্রিয় দাদু, নানা ও নানিমাকে,

যাদের নিঃস্বার্থ ভালোবাসা ও সমর্থন আমার পথচলা গড়ে তুলেছে, স্বপ্ন দেখার সাহস জুগিয়েছে,

যাঁদের ছাড়া আমি আজ এখানে পৌঁছাতে পারতাম না ।

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SUMMARY

Unmanned Aerial Vehicles (UAVs) support a wide range of applications across various domains, including logistics, disaster response, infrastructure inspection, environmental monitoring, and smart city management. In these areas, UAVs offer rapid deployment, flexible mobility, and high-resolution data acquisition, significantly enhancing the capabilities of autonomous systems. However, despite these advantages, UAV operations remain fundamentally constrained by limited onboard energy capacity and restricted payload capabilities. These limitations hinder the ability of UAVs to sustain long-duration missions or cover large spatial areas, particularly when required to revisit multiple locations or maintain persistent surveillance.

To address these operational constraints, this thesis proposes a cooperative framework that facilitates synergistic interaction between UAVs and Unmanned Ground Vehicles (UGVs). UGVs act as mobile recharging platforms, allowing UAVs to periodically land and refuel without returning to fixed charging stations, thereby extending mission endurance and operational range. This UAV-UGV collaboration is particularly well-suited for time-sensitive missions in large, unstructured, or hazardous environments.

The core contribution of this thesis is a bi-level optimization framework that jointly plans routes for both the UAV and UGV in a coordinated single UAV-UGV system. At the upper level, a Minimum Set Cover (MSC) algorithm identifies optimal UAV recharging locations, which guide the UGV's road-constrained path, solved as a Traveling Salesman Problem (TSP). At the lower level, the UAV's routing is decomposed into subproblems, each modeled as an

Energy-Constrained Vehicle Routing Problem with Time Windows (E-VRPTW) and solved using constraint programming to ensure timely task completion and synchronized rendezvous with the UGV.

The framework was evaluated on 30 synthetic task scenarios of varying scales. Results show that the cooperative strategy reduces mission time by 10–30% and energy consumption by 15–50% compared to UGV-only baselines. Additionally, comparisons between greedy and constraint programming-based methods highlight the latter's superior performance in complex, high-density settings.

To validate real-world applicability, a hardware testbed was developed using a DJI Tello UAV and a Raspberry Pi-powered omnidirectional UGV. Deployed in a 4 $\times$ 4 meter lab with 12 task points, the system used motion capture for high-precision localization. The UAV autonomously executed tasks and repeatedly landed on the moving UGV for recharging, closely matching simulation results.

Overall, this thesis presents a computationally efficient and experimentally validated planning framework for energy-constrained, cooperative UAV-UGV missions. The contributions lay a strong foundation for future research in dynamic multi-agent coordination, learning-based adaptive routing, and real-world deployments in surveillance, logistics, and disaster response operations.

CHAPTER 1

INTRODUCTION

The integration of Unmanned Aerial Vehicles (UAVs) has significantly expanded the capabilities of autonomous systems, offering speed, flexibility, and high-resolution data collection across various domains. UAVs have found widespread applications in delivery logistics, disaster response, environmental monitoring, infrastructure inspection, and smart city management, demonstrating their potential to transform transportation, surveillance, and other critical decision-making processes.

One of the most impactful applications of UAVs is in delivery logistics. Companies such as Amazon [1], UPS [2], Alphabet's Wing [3], and DHL [4] have launched drone-based delivery programs to reduce delivery time and costs. By bypassing traffic congestion and geographical barriers, UAVs enable on-demand, high-speed deliveries, particularly beneficial in urban centers and remote regions. A compelling example is Zipline's medical drone delivery system, which has revolutionized healthcare logistics in Rwanda and Ghana by ensuring timely delivery of blood, vaccines, and essential medical supplies [5]. During the COVID-19 pandemic, UAVs further proved their value by transporting medical supplies, patient samples, and quarantine materials while minimizing human contact [6]. These real-world deployments underscore UAVs' ability to overcome infrastructure limitations and deliver time-sensitive goods more efficiently.

Beyond logistics, UAVs play a crucial role in disaster response and humanitarian aid. Their rapid deployment and ability to access hazardous or hard-to-reach areas make them invaluable in emergencies such as earthquakes, wildfires, and floods. After the 2023 Turkey-Syria earthquake, for example, UAVs equipped with thermal imaging sensors helped locate survivors trapped under rubble, significantly accelerating rescue operations [7]. During wildfire outbreaks, UAVs assist with real-time fire mapping, enabling firefighters to develop more effective containment strategies [8, 9]. In flood-prone regions, UAVs have been used to monitor rising water levels, guide evacuations, and deliver emergency supplies. A notable case is the 2018 Kerala floods in India, where drones were deployed to locate missing persons and assess damage [10]. These applications highlight UAVs' effectiveness in enhancing situational awareness and supporting crisis management in disaster-stricken environments.

In the realm of traffic monitoring and urban mobility, UAVs contribute to reducing congestion, improving road safety, and optimizing transportation systems [11, 12]. Cities like Singapore have piloted UAV-based surveillance systems to collect real-time data on traffic patterns, accident sites, and road hazards [13]. This data enables transport authorities to dynamically adjust traffic signals, dispatch emergency responders, and implement proactive congestion control measures. Such aerial monitoring is particularly valuable in densely populated urban areas, where traditional ground-based monitoring is often limited.

Despite their immense potential, Unmanned Aerial Vehicles (UAVs) face significant operational challenges, primarily due to limited energy capacity and payload restrictions. Unlike ground-based vehicles, UAVs are highly energy-constrained, with typical battery life ranging from 10 to 60 minutes. This limits their ability to conduct extended missions, as frequent returns to charging stations disrupt operations and reduce overall efficiency. Additionally, their limited payload capacity restricts the transport of heavy cargo, further constraining their use in logistics and rescue missions. These limitations highlight the need for integrated solutions, most notably, collaboration with Unmanned Ground Vehicles (UGVs).

UGVs complement UAVs by serving as mobile charging platforms, enabling UAVs to land and recharge on-site rather than returning to fixed stations. This capability supports continuous operations, especially for long-duration surveillance, delivery, or reconnaissance tasks. Beyond recharging, UGVs provide logistical support by transporting and deploying multiple UAVs, facilitating coordinated multi-drone missions over large areas. They also act as mobile data centers, collecting and transmitting real-time information gathered by UAVs, thereby enhancing communication and mission coordination. In critical scenarios like search and rescue, this synergy is especially valuable, UAVs can rapidly scan disaster zones and identify survivors, while UGVs deliver medical aid, assist in debris removal, or help evacuate affected individuals, resulting in a more comprehensive emergency response.

Real-world implementations of UAV-UGV cooperative systems are increasingly explored across sectors such as agriculture, infrastructure inspection, construction site monitoring, and disaster response [14–16]. These applications leverage the aerial perspective and agility of UAVs with the payload capacity and endurance of UGVs to enable tasks such as precision farming, coordinated site surveys, autonomous material transport, and persistent surveillance in hazardous environments.

1.1 Challenges of heterogeneous UAV-UGV cooperative systems

While UAV-UGV collaboration offers a promising solution to overcome individual platform limitations, coordinating these heterogeneous systems presents several challenges due to their fundamentally different operational characteristics. UAVs are agile and capable of rapidly reaching remote locations but are constrained by limited energy capacity, necessitating frequent recharging. UGVs, in contrast, offer longer endurance and greater payload capacity, making them suitable as mobile charging stations and logistical support units. However, their dependence on predefined road networks and limited mobility in unstructured terrain restrict their flexibility. The disparity in mobility and endurance between UAVs and UGVs introduces complex coordination requirements. Effective cooperation demands intelligent routing strategies that account for UAV energy limitations, UGV road-constrained accessibility, and overall mission goals. Poorly coordinated routing can result in premature UAV energy depletion, frequent interruptions for recharging, or delayed UGV support, thereby degrading mission efficiency and increasing operational costs.

These challenges are further compounded in dynamic environments, where real-time adaptability is essential. Robust planning frameworks must dynamically allocate tasks and coordinate vehicle movements based on evolving mission priorities, real-time energy levels, and environmental conditions. Optimizing recharging schedules and rendezvous points is critical to maintaining mission continuity and minimizing unnecessary energy consumption. The problem becomes increasingly complex in multi-UAV and multi-UGV scenarios, where joint optimization of UAV flight paths, UGV routes, energy models, and recharging logistics must be performed. Such planning is computationally intensive, especially when considering scalability, communication delays, and the need for real-time decision-making.

1.2 Contributions

1.2.1 Bi-Level Optimization Framework for UAV-UGV Cooperative Routing

The first contribution of this thesis is the development of a bi-level optimization framework for cooperative UAV-UGV routing, which efficiently integrates energy-constrained UAV operations with road-bound UGV support. The framework addresses the heterogeneous mobility of both vehicles to enable optimal routing and recharging coordination. In the first stage, a minimum set cover algorithm identifies UAV recharging stops, which guide UGV routing formulated as a Traveling Salesman Problem (TSP). The second stage decomposes the UAV's routing into subproblems using task allocation, each solved as an instance of the Energy-Constrained Vehicle Routing Problem with Time Windows (E-VRPTW).

This approach improves energy efficiency, reduces UAV downtime, and enhances mission performance. Evaluated across 30 task scenarios of varying scales, the framework achieves a 10–30% reduction in mission time and a 15–50% decrease in energy consumption compared to UGV-only operations. Chapter 3 details these contributions and results.

1.2.2 Hardware Validation in a Lab-Scale UAV-UGV System

To validate the framework, a proof-of-concept hardware deployment was conducted in a controlled lab environment using a DJI Tello UAV and a Raspberry Pi-powered omnidirectional UGV with a custom landing pad. The testbed included a 4 m $\times$ 4 m area with 12 task points and a mapped road network. A motion capture system provided real-time localization, and wireless communication enabled synchronized planning between the UAV, UGV, and a centralized mission planner. The UAV, constrained to 50 seconds of flight endurance, autonomously landed on the moving UGV for recharging. The experiments demonstrated successful mission execution under energy constraints, with accurate rendezvous and minimal deviation from simulated routes, confirming the practical feasibility of mobile UAV recharging and coordinated routing.

This validation highlights the real-world potential of the proposed system for applications in surveillance, logistics, and search-and-rescue. Further details are presented in Chapter 4.

CHAPTER 2

BACKGROUND

UAV-UGV collaborative systems have attracted considerable interest for their potential to improve operational efficiency and support complex autonomous missions across diverse fields. [14]. By leveraging the complementary strengths of aerial and ground vehicles, these systems enable tasks that surpass the capabilities of individual platforms. Applications include construction site monitoring and preparation [16], pursuit and tracking of dynamic targets [17], and large-scale visual data acquisition [18]. Key technological advances driving these systems include vision-based autonomous control [16,18], decentralized coordination strategies [17], and pattern recognition for enhanced cooperation [18].

A core challenge in UAV-UGV collaboration lies in optimizing cooperative routing to ensure synchronized task execution while accounting for energy constraints, mobility differences, and inter-vehicle dependencies. UAVs, despite their agility and wide coverage, are limited by battery capacity, requiring periodic recharging. UGVs, on the other hand, operate on road networks but offer extended endurance and the ability to serve as mobile refueling stations. This interdependence introduces a complex routing problem that demands efficient coordination to minimize mission time, optimize recharging schedules, and maximize area coverage. The problem closely relates to classical Vehicle Routing Problems (VRPs) and Traveling Salesman Problems (TSPs), widely studied in transportation, logistics, and multi-agent systems in robotics.

2.1 UAV-UGV Cooperative Routing in Transportation

The integration of UAV-UGV cooperation in transportation and logistics is closely linked to the Truck-Drone Coordinated Delivery Problem, commonly formulated as the Vehicle Routing Problem with Drones (VRP-D) or the Traveling Salesman Problem with Drones (TSP-D). In an early contribution to this domain, Murray and Chu [19] developed a Mixed Integer Linear Programming (MILP) formulation aimed at optimizing last-mile hybrid truck-drone parcel delivery, demonstrating notable improvements in both cost-effectiveness and operational efficiency. Building on this foundation, Bouman et al. [20] proposed an exact solution approach for TSP-D using dynamic programming, enabling the resolution of instances involving up to 16 delivery locations. Similarly, Chen et al. [21] explored UAV-UGV delivery systems where UAVs performed aerial deliveries while UGVs traveled along predefined road networks, ensuring seamless integration between aerial and ground-based transportation.

Subsequent studies have refined these models to further enhance operational efficiency and task execution strategies. Ha et al. [22] focused on minimizing the total operational cost of hybrid drone-truck systems, proposing the TPS-LS heuristic, which balances cost efficiency and delivery speed. Liu et al. [23] introduced a two-stage routing framework for UAV-UGV parcel delivery, leveraging nearest-neighbor and cost-saving heuristics to optimize both the truck's primary route and the UAV's aerial path. These research efforts highlight the significant benefits of UAV-UGV cooperative routing, particularly in e-commerce logistics, medical supply deliveries, and emergency response scenarios. Mbiadou et al. [24] formulated an iterative two-step heuristic to solve the Parallel Drone Scheduling Traveling Salesman Problem (PDSTSP), demonstrating improvements in computational efficiency. Schermer et al. [25] introduced a two-stage heuristic approach, which integrates a route-first cluster-second methodology with optimization techniques to minimize overall mission time.

2.2 UAV-UGV Cooperative Routing in Robotics

From a robotics multi-agent systems perspective, UAV-UGV coordination is framed as a distributed planning and decision-making problem, requiring autonomous collaboration, real-time communication, and adaptive mission execution. Early research on fuel-constrained vehicle routing primarily focused on UAVs operating with fixed recharging stations. Levy et al. [26] applied Variable Neighborhood Search (VNS) and Variable Neighborhood Descent (VND) heuristics to optimize multi-UAV routing with predefined recharging depots. Sundar et al. [27] extended this work by developing Mixed-Integer Linear Programming (MILP) models, utilizing off-the-shelf solvers to determine optimal UAV paths under energy constraints. Venkatachalam et al. [28] proposed a two-stage stochastic optimization model for multi-drone routing under fuel constraints, incorporating refueling stations and target locations to minimize total fuel consumption or travel distance. To address the computational complexity of finding optimal solutions, they employed the Sample Average Approximation (SAA) method and developed a heuristic approach to handle large-scale instances, demonstrating the robustness of their model through computational experiments.

Unlike depot-based recharging, Maini et al. [29, 30] introduced a UAV-UGV cooperative routing framework, where a UGV functions as a mobile refueling station for a fuel-limited UAV. Their two-stage optimization approach involved first identifying refueling depots along the

UGV's trajectory, followed by solving UAV and UGV routes using an MILP formulation. Later developments introduced receding horizon strategies for dynamic recharging and real-time route adaptation, further enhancing operational efficiency in unstructured environments. Beyond recharging-focused studies, Li et al. [31] explored UAV-UGV cooperative path planning by formulating a two-level memetic algorithm (Two-MA) that accounts for UGV speed limitations, UAV endurance, and communication constraints, significantly reducing mission execution time while ensuring effective coordination between UAVs and UGVs.

Recent studies have further extended UAV-UGV cooperative routing to multi-agent systems, introducing multi-UAV coordination with single or multiple UGVs. Mammarella et al. [32] examined UAV-UGV collaboration in precision agriculture, emphasizing their potential for optimizing in-field operations through autonomous navigation and collaborative task execution. Their proposed multi-phase approach was designed to enhance agricultural productivity in complex, unstructured terrains, such as sloped vineyards, by integrating sensor fusion, autonomous control, and adaptive mission planning. Manyam et al. [33] focused on communication-constrained UAV-UGV routing, formulating an MILP-based branch-and-cut algorithm to ensure reliable UAV-UGV rendezvous scheduling. Similarly, Luo et al. [34] extended UAV-UGV routing to a two-echelon system, developing a binary integer programming model for coordinating UAV refueling and mission execution. Ropero et al. [35] introduced a hybrid optimization approach, incorporating combinatorial optimization techniques and genetic algorithms to efficiently solve the UGV refueling problem for sustained UAV operations.

Experimental validation remains a critical aspect of UAV-UGV coordination research, bridging the gap between theoretical optimization models and real-world feasibility. Several studies have demonstrated UAV-UGV collaboration in hardware testbeds and outdoor field deployments. Nigam et al. [36–38] implemented persistent surveillance algorithms in stochastic environments, validating them through real-world UAV flight tests. Frew et al. [39] demonstrated UAV-UGV cooperation for road-following, obstacle avoidance, and convoy protection, highlighting the effectiveness of these systems in autonomous navigation scenarios. Wu et al. [40] developed a prototype UAV-UGV wireless recharging system, demonstrating the feasibility of on-demand mobile recharging. Karapetyan et al. [41] extended these efforts to coverage path planning, using a Clearpath Jackal UGV and a VOXL m500 UAV to showcase how heuristic-based optimizations reduce rendezvous overhead and increase UAV operational efficiency.

2.3 Our Previous Work and Contributions

Building upon existing UAV-UGV cooperative routing research, our prior work introduced a three-tiered heuristic framework designed to optimize multi-agent coordination and improve computational efficiency in UAV-UGV mission planning. Ramasamy et al. [42] proposed an approach that integrates K-means clustering to identify UGV waypoints, a Traveling Salesman Problem (TSP) formulation for optimizing UGV routes, and a Vehicle Routing Problem (VRP) with capacity constraints, time windows, and dropped visits to determine UAV paths. Their findings demonstrated that constraint programming solvers are highly efficient, solving UAV-UGV routing problems with up to 25 mission points and four UAVs in under a minute. The study further revealed that constraint programming approaches outperformed MILP solvers in terms of speed, achieving computational gains of 7–30 times faster, though at the cost of a 4–15% sub-optimality gap. In our previous research [43], we expanded upon these findings by exploring parameter tuning techniques using Genetic Algorithms (GA) and Bayesian Optimization (BO). Our study demonstrated that optimized heuristic parameters significantly enhance solution quality, enabling more robust and scalable UAV-UGV coordination strategies. The results showed that fine-tuned heuristics reduced overall mission completion time and improved energy efficiency.

CHAPTER 3

COOPERATIVE MULTI-AGENT PLANNING FRAMEWORK FOR FUEL CONSTRAINED UAV-UGV ROUTING PROBLEM

Overview: Unmanned Aerial Vehicles (UAVs), adept at aerial surveillance, are often constrained by their limited battery capacity. Refueling on slow-moving Unmanned Ground Vehicles (UGVs) can significantly enhance UAVs' operational endurance. This paper explores the computationally complex problem of cooperative UAV-UGV routing for vast area surveillance, considering speed and fuel constraints. It presents a sequential multi-agent planning framework aimed at achieving feasible and optimally satisfactory solutions. By considering the UAV fuel limit and utilizing a minimum set cover algorithm, we determine UGV refueling stops. This, in turn, facilitates UGV route planning as the first step. Through a task allocation technique and energy-constrained vehicle routing problem modeling with time windows (E-VRPTW), we then achieve the UAV route in the second step of the framework. The effectiveness of our multi-agent strategy is demonstrated through the implementation on 30 different task scenarios

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across three different scales. This work provides significant insight into the collaborative advantages of UAV-UGV systems and introduces heuristic approaches to bypass computational challenges and swiftly reach high-quality solutions.

3.1 Introduction

Over the past decade, unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs) have seen a surge in applications across various sectors, from military and civilian uses [23, 44, 45] to intelligence gathering, surveillance, reconnaissance tasks [46, 47], search and rescue operations [48], and agricultural activities [49]. UAVs, known for their cost-effectiveness, ease of control, and high maneuverability, are ideal for quickly scanning or surveying vast areas, yet their application to larger-scale problems is limited by their short battery lifespan and small payload capacity. In contrast, UGVs, equipped with a large payload capacity and extended battery life, can withstand lengthier task duration. Nevertheless, obstacles such as challenging ground terrain, limited visibility, and slower movement speed often compromise their efficacy, frequently resulting in incomplete task completion. To counteract these individual drawbacks, a cooperative routing strategy involving both UAVs and UGVs can be employed, enhancing the operation coverage speed and task endurance. For instance, in a persistent surveillance problem, UAV can visit a set of distant task points while being periodically refueled by the UGV, which acts as a mobile refueling depot. Simultaneously, the UGV can cover task points along the road network, thus reducing the UAV's workload and ensuring the operation's swift completion. By focusing on such a **UAV-UGV cooperative vehicle routing problem**, this study aims to find approximate near-optimal solutions in quick runtime that account for the UAV's fuel constraint and the UGV's speed and terrain limitations. The goal is to devise strategic collaborative routes between the UAV and UGV that enable effective UAV recharging by the UGV, ensuring a complete visit to designated task points in the shortest possible time.

3.1.1 Related works

Extensive research has been conducted on the cooperative routing of UAVs with ground vehicles across the field of Robotics and Transportation. In Transportation, the Truck-Drone coordinated delivery problem, analogous to the UAV-UGV cooperative routing problem is conceptualized as a variation of the Vehicle Routing Problem with Drones (VRPD) [50] or the Traveling Salesman Problem with Drones (TSP-D) [51]. Here, Murray and Chu [19] introduced a Mixed Integer Linear Programming (MILP) formulation, supplemented by heuristics, for a hybrid truck-drone parcel delivery system optimized for last-mile delivery, leveraging the advantages of both truck and drone. Similarly, Chen et al. [21] explored path planning for heterogeneous robot systems, including UGVs and UAVs, for urban parcel delivery, where UGVs navigate along road networks and UAVs transfer parcels from UGVs to customers. Bouman et al. [20] contributed an exact solution approach to the Traveling Salesman Problem with Drones (TSP-D) using dynamic programming, capable of solving problems with up to 16 customers. Furthermore, Ha et al. [22], inspired by Murray and Chu [19], aimed to minimize the total operational cost of a drone-truck delivery system, proposing a MILP formulation and a heuristic called TPS-LS, providing a cost-focused perspective alongside the efficiency-driven approaches in drone-truck collaborative routing.

Similarly, in Robotics, Levy et al. [26] explored the routing problem for multiple fuel-constrained UAVs with access to several static recharging depots, employing rapid variable neighborhood descent (VND) and variable neighborhood search (VNS) heuristics to generate viable solutions for a large number of problem instances. Extending this problem for multiple fuel-constrained vehicles with multiple depots, Sundar et al. [27] developed a mixed-integer linear programming model (MILP), which they solved optimally using a standard MILP solver. In contrast to fixed recharging stations, Maini et al. [29] addressed a cooperative routing problem involving a single UAV-UGV system, where the UGV has the ability to recharge the UAV while in transit on a road. They proposed a greedy heuristic for determining the meeting points for recharging along the UGV route and later used a MILP model to solve both UAV and UGV routes. Continuing the work, Manyam et al. [33] examined the cooperative routing of air and ground vehicle teams considering communication constraints, framing the problem as a MILP model and developing a branch-and-cut algorithm to solve it optimally. Several researchers have delved deeper into the UAV-UGV cooperative vehicle routing problem, exploring it in a tiered, two-echelon manner [52]. For instance, Luo et al. [34] introduced a binary integer programming model, supplemented by two heuristics, to tackle the two-echelon cooperative routing problem. Similarly, Liu et al. [53] devised a two-stage, route-focused framework for a parcel delivery system utilizing a truck and a drone, aiming to optimize both the truck's primary route and the associated drone's aerial routes. To quickly generate a feasible solution, they developed a hybrid heuristic combining nearest-neighbor and cost-saving strategies. Robert B. Anderson [54] investigated the impact of different objective functions and the split vehicle routing problem (SVRP) over the classical VRP in the routing and control of unmanned aerial vehicles (UAVs) for payload delivery and aerial reconnaissance missions. Ropero et al. [35] presented a hybrid UAV-UGV system designed to cooperatively visit a set of target points, with the UAV periodically recharged by the UGV at refuel stops. They employed a classical combinatorial approach combined with Genetic algorithm metaheuristics to identify refuel stops in the preliminary stages and thereby solve the routing problem with a genetic algorithm. In a related problem, Seyedi et al. [55] and Lin et al. [56] proposed a scalable and robust approximation algorithm for persistent surveillance tasks by energy-constrained UAVs and UGVs. However, their methodologies rely on forming uniform UAV-UGV teams and partitioning the environment among them, which can compromise the solution quality of the cooperative routes.

Significant experimental efforts have been conducted in UAV routing problems. Nigam et al. [37, 38] explored scalable control techniques for UAVs engaged in persistent surveillance within uncertain stochastic environments using a hardware testbed. Frew et al. [39] demonstrated road following, obstacle avoidance, and convoy protection in flight tests involving two UAVs, while Jodeh et al. [57] provided an overview of cooperative control algorithms for heterogeneous UAVs developed by the Air Force Research Laboratories (AFRL). Extensive UAV flight testing has also been conducted in indoor lab-scale setups by Boeing's Vehicle Swarm Technology Laboratory (VSTL) [58,59] and MIT's RAVEN laboratory [60]. Wu et al. [40] developed a prototype UAGVR (Unmanned Aerial and Ground Vehicle Recharging) system that addresses the limited battery life of UAVs by enabling on-demand wireless recharging via a UGV, demonstrating its feasibility in extending UAV operation time through experimental validation and the creation of a cooperative mission planning algorithm. In UAV routing, Yu et al. [61] focused on planning and executing UAV tours incorporating both stationary and mobile recharging stations, such as UGVs, to minimize mission time. This work is significant for its validation through both simulations and proof-of-concept experiments using a custom UAV and a Clearpath Husky UGV, effectively demonstrating the feasibility of these coordinated recharging strategies in real-world scenarios. Karapetyan et al. [41] demonstrated practical deployment in coverage path planning for an energy-constrained UAV and UGV, with the UGV acting as a mobile recharging station. Using a VOXL m500 drone and a Clearpath Jackal ground vehicle, their heuristic method significantly reduced rendezvous overhead compared to a greedy approach, showcasing the system's robustness from algorithm development to real-world execution.

In our previous works [42, 62, 63], we explored a hierarchical, bi-level optimization framework for the cooperative routing of multiple fuel-limited UAVs and a single UGV. The outer level of this framework employed K-means clustering to determine UGV visit points, which were then connected using a Traveling Salesman Problem (TSP) approach to establish the UGV route. On the inner level, using the determined UGV path, we formulated and solved a vehicle routing problem that accounted for capacity constraints, time windows, and dropped visits for the UAV. Further expanding on this work, we demonstrated that optimizing heuristic parameters using Genetic Algorithm (GA) and Bayesian Optimization (BO) methods could lead to substantial improvements in solution quality [43, 64]. Given the intricacy of this problem, exact methods of solving this combinatorial optimization problem or generalizing a solution framework for diverse scenarios pose significant challenges. In this research endeavor, we propose a generalized multi-agent cooperative framework for addressing this fuel-constrained UAV-UGV cooperative routing problem. The key contribution of our study is the creation of **a heuristics-based, multi-staged framework** aimed at facilitating a rapid solution to the two-echelon UAV-UGV routing problem, considering fuel and speed constraints. To this end, our novel contributions include the following:

1. The proposed framework utilizes a sequential optimization strategy with a task allocation technique. Coupled with the constraint programming-based formulations, it can provide an effective solution for fuel constrained UAV-UGV cooperative routing problems within a quick time.

2. A task allocation technique based on the minimum set cover algorithm is proposed, which breaks down the entire problem into smaller subproblems, leading to a substantial simplification of the problem-solving process.

3. Our formulation of a constraint programming-based vehicle routing problem accommodates time windows, and fuel constraints, thereby enabling swift solutions for each subproblem.

4. We present extensive computational results on different kinds of scenarios to affirm the effectiveness and robustness of our proposed framework. This underscores the practicality of our framework in a diverse set of real-world applications.

The rest of the article is structured as follows: Section 3.2 presents the problem statement, section 3.3 illustrates the framework methodology and solution heuristics. Section 3.4 introduces the experiments of different random instances in three different scales and shows the results part, offering a concrete view of our findings. The results are analyzed in section 3.5 and finally, section 3.6 presents the conclusion and outlines future works.

3.2 Problem Description

The problem objective is to configure an optimal cooperative route for a team comprising a UAV and UGV to visit a set of n task points $\mathcal{M}_n = \{m_0, m_1, ..., m_n\}$ in a euclidean space (see Figure 3a). The UAV $A \equiv (v^a, F^a, \mathcal{P}^a)$ and the UGV $G \equiv (v^g, F^g, \mathcal{P}^g)$ have heterogeneous vehicle characteristics; with the UAV having a higher velocity, i.e. $v^a > v^g$ but lower fuel capacity than that of the UGV, i.e. $F^a < F^g$. They also differ in their power consumption profiles (Equation 3.1, Equation 3.2), with the UAV demonstrating greater energy efficiency per unit distance traversal when operating at standard speeds (see Figure 1).

$$\mathcal{P}^a = 0.0461{v^a}^3 - 0.5834{v^a}^2 - 1.8761v^a + 229.6 \tag{3.1}$$

$$\mathcal{P}^g = 464.8v^g + 356.3 \tag{3.2}$$

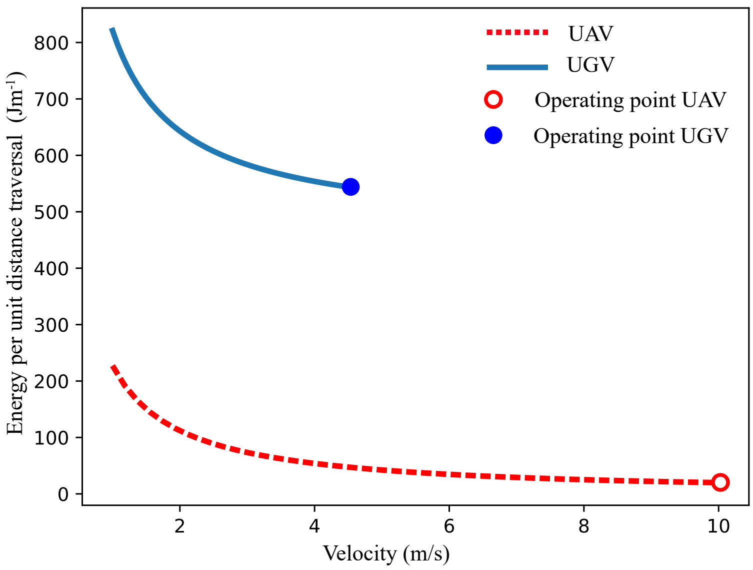


Figure 1: Energy consumption per unit distance traversal of UAV & UGV

For the study, we specifically consider a multi-rotor UAV, and a large wheeled robot as UGV, with vehicle parameters modeled after the existing works [65, 66]. Furthermore, the proposed framework can accommodate other types of UAVs and UGVs with proper modeling of their characteristics. For instance, the framework can be extended to include quadrupedal-legged robots as UGVs or fixed-wing drones and VTOL (Vertical Take-Off and Landing) hybrid drones as UAVs, acknowledging their fuel efficiency for extended endurance. The task points can be visited by a free flyover of the UAV, τ^a or a visit by the UGV along the road network, τ^g. The cost of travel between a pair of task points is equal to the time of traversal between them $t_{ij} = t_j - t_i$. Both the UAV and UGV commence their journeys from the same starting depot and return to it upon completion. The total task duration is the time span from when the first vehicle departs the depot until the last one returns. Due to having a limited battery capacity, the UAV has to get recharged periodically from the UGV, which acts as a mobile recharging depot, or from the starting depot (which acts as a fixed recharging depot) besides visiting the task points. The recharging time of the UAV at the UGV is not instantaneous, it depends upon the amount of fuel consumed by the UAV. Since the fuel capacity of the UGV is significantly larger compared to the UAV, it is assumed to be infinite to simplify the problem.

With all these above configurations, we have to find the time optimal cooperative route, $\tau = \tau^a \cup \tau^g$ between the UAV and UGV for visiting all the task points at least once; given the UAV will never run out of fuel. A typical sequence for this cooperative route can be as follows: Both the UAV and UGV commence their journey from the starting depot and visit several task points. As they proceed, the UGV will reach an appropriate location to recharge the UAV. After recharging, both vehicles will resume their task, continuing to visit task points until they reach the next recharging stop. This pattern will continue until all task points have been visited, after which both the UAV and UGV will return to the starting depot to conclude their task. However, for an optimal cooperative route, it is important to figure out:

1. Suitable refueling stop locations $\mathcal{M}_r = \{m_0^r, m_1^r, ..., m_n^r\}$, **where** the UAV and UGV will rendezvous for recharging.

2. Appropriate time intervals during the task **when** the UAV and UGV will meet at the refuel stops i.e, i.e, $t_i^r \ \forall \ m_i^r \in \mathcal{M}_r$.

3. Optimal routes for the UAV, τ^a and UGV, τ^g based on the determined refuel stop locations m_i^r and time intervals t_i^r to cover the entire task scenario in the quickest possible time.

3.3 Methods

We have devised a two-tiered optimization framework (as depicted in Figure 2) for executing this fuel-constrained cooperative routing between the UAV and UGV. This framework is inspired by the "UGV First, UAV Second" heuristic approach for UAV-UGV cooperative routing [35, 67].

At the first stage of this framework, we utilize a ***UGVPlanner*** to establish the route $\tau^g = (X^g, T^g)$ for the UGV. Here, X^g and T^g are the spatial and temporal components of the UGV route τ^g. This route is constructed by identifying appropriate recharging stations $\mathcal{M}_r$ and formulating the UGV's movement along the road network accordingly. The UGV's navigation is a combination of two-step processes. The initial phase involves movement along waypoints on the road network to cover the task points, while the second phase necessitates waiting for the UAV at the recharging stops.

At the second tier of the framework, the ***UAVPlanner*** devises the route $\tau^a = (X^a, T^a)$ for the UAV. Here, X^a and T^a are the spatial and temporal components of the UAV route τ^a. The formation of this UAV route significantly relies on the UGV route τ^g created at the outer level of the framework. Because of the slower speed of the UGV, the ***UAVPlanner*** takes into consideration the *availability* time window constraint at the refuel stops. This planning approach effectively divides the entire scenario into a series of manageable subproblems, each of which can be solved by modeling it as an energy-constrained vehicle routing problem with time window constraints (E-VRPTW).

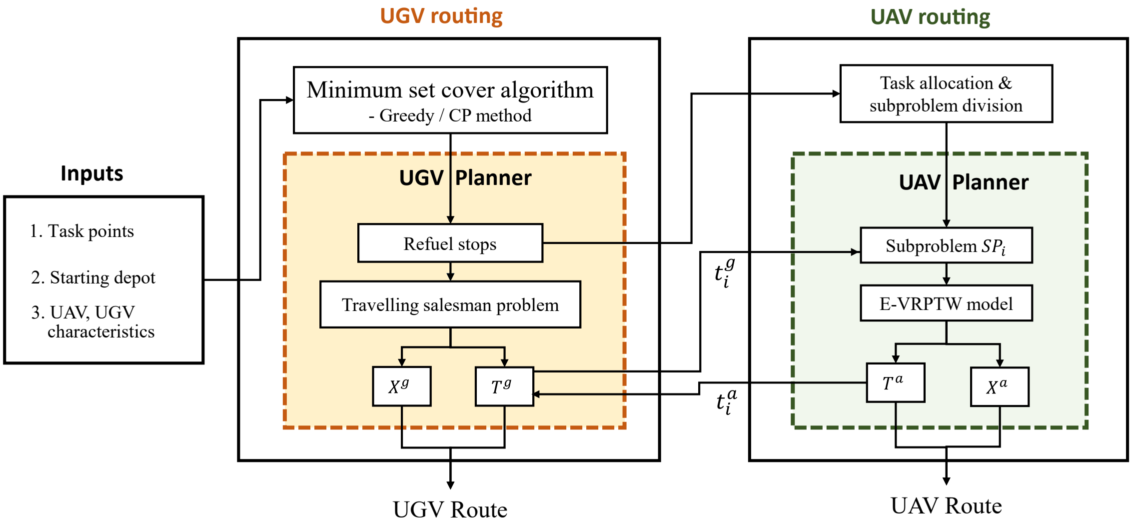


Figure 2: proposed framework

3.3.1 UGV routing

At the outer level of the proposed framework, the initial objective is to determine suitable recharging rendezvous locations $\mathcal{M}_r$ for the UAV-UGV system. Subsequently, an optimal route τ^g is generated for the UGV, taking into account the refuel stop locations $\mathcal{M}_r$ and its operational speed v^g in the ***UGV-Planner***. Previous research by Maini et al. [29, 30] emphasized the importance of including refueling stops within the UAV's fuel coverage radius to ensure a viable route in fuel-constrained cooperative routing problems. It was also noted that minimizing the number of recharging instances can reduce the time spent on recharging and minimize the detour required in the UAV's route, resulting in a faster cooperative route. With these aforementioned considerations, we implement the minimum set cover algorithm (MSC) to find out minimum number of refueling stops and their locations $\mathcal{M}_r$ that cover the entire task scenario. The minimum set cover problem has been extensively studied [68, 69], and various methods, including greedy approaches [29, 70] have been proposed. However, we come up with an alternative constraint programming formulation for solving the minimum set cover problem in the context of the cooperative routing problem.

3.3.1.1 Minimum set cover algorithm

1. **Greedy heuristics approach** :

   The minimum set cover algorithm is an NP-hard problem; however, through greedy heuristics, the complexity of the problem can be reduced significantly. In the context of the cooperative routing problem to find optimal refuel stops through the greedy algorithm, we start with the task points $\mathcal{M}_n$ that needed to be covered, the fuel capacity F^a of the UAV and the starting depot m_0 of the scenario. Our goal is to obtain the smallest possible subset of $\mathcal{M}_n$ that can act as refueling stops $\mathcal{M}_r$. As shown in Algorithm 1, the greedy algorithm includes the stating depot m_0 as the first refueling stop m_0^r, then it sequentially adds the task points m_i which covers the maximum number of other task points into the refueling stop set m_i^r until all the points are covered (lines 4-8).

   Greedy heuristics can quickly generate optimal result for a minimum set cover problem. But in many situations, a minimum set cover problem can have multiple optimal results for a particular scenario; because we are implementing a bilevel optimization framework, it is important to take into account the other optimal solutions of the outer level algorithm. As it is not possible to acquire all the optimal solutions through greedy heuristics, we used the constraint programming method, which can generate multiple optimal results (if any) in a quick span of time.

2. **Constraint programming method :**

   To determine the minimum number of refueling stops $\mathcal{M}_r$ required to cover the entire task scenario ($\mathcal{M}$), we employ linear integer programming and utilize a constraint programming method (CP method) for solving. The problem is modeled using binary decision variables, x_j (indicating

Algorithm 1: Greedy Minimum Set Cover Algorithm

Input: Task points $\mathcal{M}$, UAV fuel limit F^a, starting depot m_0

Output: Refueling stops $\mathcal{M}_r$

Initialize refueling stops $\mathcal{M}_r \leftarrow \{m_0^r = m_0\}$

Initialize remaining tasks $\mathcal{T} \leftarrow \mathcal{M}$

Compute initial coverage $C_0 \leftarrow \{m_i \in \mathcal{T} \mid \|m_i - m_0^r\| < 0.5F^a\}$

Remove covered tasks $\mathcal{T} \leftarrow \mathcal{T} \setminus C_0$

while $\mathcal{T} \neq \emptyset$ **do**

  Select next refueling stop $m_{i_{\max}}^r \leftarrow \arg\max\ Covered(m_i^r)$

  Update refueling stop set $\mathcal{M}_r \leftarrow \mathcal{M}_r \cup \{m_{i_{\max}}^r\}$

  Compute new coverage $C_{\max} \leftarrow \{m_i \in \mathcal{T} \mid \|m_i - m_{i_{\max}}^r\| < 0.5F^a\}$

  Remove covered tasks $\mathcal{T} \leftarrow \mathcal{T} \setminus C_{\max}$

whether a task point is chosen as a refueling stop) and y_{ij} (indicating whether a task point m_i is assigned to a refueling stop m_j^r). The objective function (Equation 3.3) aims to minimize the total number of refueling stops. Constraint Equation 3.4 ensures that each task point m_i is assigned at least one refueling stop m_j^r. Constraint Equation 3.5 ensures that a task point m_i can be allocated to a refueling stop m_j^r only if the refueling stop is selected. Furthermore, constraint Equation 3.6 guarantees that a task point m_i is assigned to a refueling stop m_j^r only if the refueling stop falls within the fuel coverage radius of the UAV, allowing for a round trip from the refueling stop.

$$\text{Objective: } \min \sum_{m_j^r \in \mathcal{M}_r} x_j \tag{3.3}$$

Subject to,

$$\sum_{m_j^r \in \mathcal{M}_r} y_{ij} \geq 1,\ \forall\ m_i \in \mathcal{M} \tag{3.4}$$

$$y_{ij} \leq x_j,\ \forall\ m_i \in \mathcal{M} \text{ and } \forall\ m_j^r \in \mathcal{M}_r \tag{3.5}$$

$$y_{ij} = 0,\ \text{if } d_{ij} > 0.5F^a,\ \forall\ m_i \in \mathcal{M} \text{ and } \forall\ m_j^r \in \mathcal{M}_r \tag{3.6}$$

$$y_{ij}, x_j \in \{0, 1\} \tag{3.7}$$

We use Google's OR-Tools Constraint programming solver (CP-SAT solver [71]) to solve the above linear integer formulation. It is possible to record all the solutions if there are multiple optimal solutions through the solver. Once, the optimal refuel stops $\mathcal{M}_r$ are obtained from the MSC algorithm, it is sent to the ***UGVPlanner*** to construct the UGV route $\tau^g = (X^g, T^g)$ based on it.

3.3.1.2 UGV Planner

Upon identifying the refueling stop locations $\mathcal{M}_r$ using the minimum set cover algorithm, the ***UGV-Planner*** proceeds to map out a feasible UGV route for the overall task through a sequential phase process (see Algorithm 2). Initially, it connects the refueling stops optimally on the road network by solving a simple Travelling Salesman Problem (TSP), which yields the spatial components $X^g \in \tau^g$ of the UGV route, denoting the sequence x_i^g in which the task points on the road network will be visited. Next, the planner calculates the temporal components $T^g \in \tau^g$ of the UGV route till the first refuel stop, which details the time instances at which the UGV will visit those task points. We operate under the assumption that the UGV will not wait at any task point, except at the refueling stops. Therefore, the arrival times at the task points are computed based on the UGV's constant operational speed v^g (line 4). This also gives the UGV's arrival time at the refueling stops (line 7), which serve as an *availability* time window constraint in the ***UAVPlanner***. Utilizing the UAV's arrival time at the first refuel stop and the recharging time $\mathcal{R}_t$ (contingent on the UAV's fuel consumption level) from the UAV's route in subproblem 1, we can estimate the UGV's waiting time at the first refuel stop (line 9), which is taken into account when computing the temporal component of the UGV route up to the next refuel stop. This process is reiterated until the UGV arrives at the final refuel stop.

At the end of this process, the temporal components are integrated with their respective spatial components to provide a comprehensive UGV route, outlining the sequence in which the UGV visits the task points and their corresponding time instances.

Algorithm 2: UGV Planner

Input: Refuel stops $\mathcal{M}_r \leftarrow MSC$, UGV velocity v^g, starting depot m_0
Output: UGV route $\tau^g = (X^g, T^g) = [(x_i^g, t_i^g)]$

```
UGV navigation waypoints X^g ← TSP(M_r, m_0, v^g)
Initialize UGV route τ^g = [(x_0^g, t_0^g)]
for x_i^g ∈ X^g do
    t_i^g = t_{i-1}^g + (x_i^g − x_{i-1}^g) / v^g
    τ^g.append((x_i^g, t_i^g))
    if x_i^g ∈ M_r then
        Send t_i^g to UAVPlanner
        Receive t_i^a, R_t from UAVPlanner
        t_i^g = t_i^a + R_t
        τ^g.append((x_i^g, t_i^g))
```

3.3.2 UAV routing

At the inner level of the proposed framework, we split the full task scenario into subproblems, taking information about the refuel stops provided by the ***UGVPlanner***. A task allocation technique is employed to assign distinct task points to each subproblem. These subproblems are then individually addressed by formulating them as Energy Constrained Vehicle Routing Problems with Time Windows (E-VRPTW).

3.3.2.1 Allocation of task points

Given the scenario and the obtained refuel stops $\mathcal{M}_r$ from the MSC algorithm, we can divide the entire problem into $r-1$ number of subproblems (r = number of refuel stops with starting depot) with an assumption that UGV travels only between two refuel stops in each subproblem. For the subproblem SP_i, the origin node is refuel stop m_{i-1}^r and the destination node is refuel stop m_i^r. The subproblems are assigned with separate task points. The UAV task points covered by the destination refuel stop m_i^r

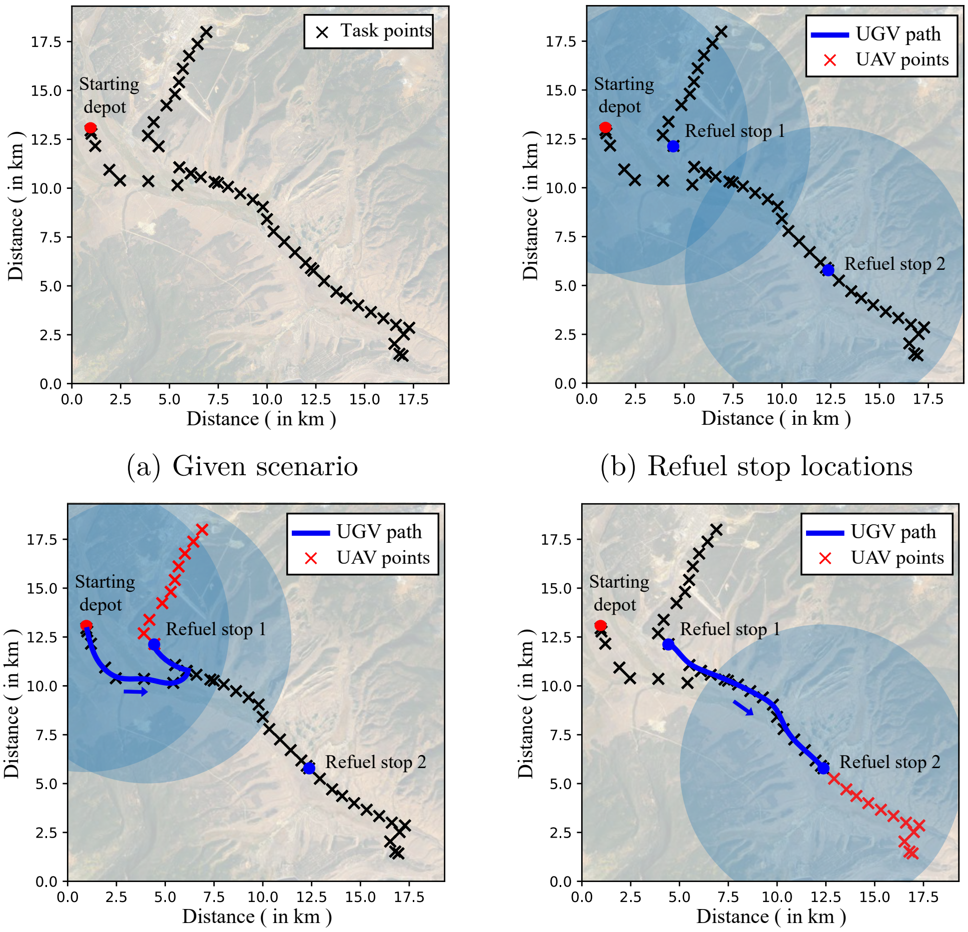
are assigned to that subproblem SP_i. Only, for the first subproblem SP_1 the task points covered by both origin m_0^r and destination node m_1^r is assigned to it.

Figure 3 demonstrate the process of subproblem division and task allocation. Figure 3b shows the refuel stops obtained from minimum set cover algorithm which are taken into account for UGV route construction. Based on refuel stops, the first subproblem (Figure 3c) is created by taking the starting depot as the origin node and the refuel stop 1 as the destination node. The UAV task points covered by origin node (starting depot) and destination node (refuel stop 1) are assigned for subproblem 1. Similarly, the second subproblem (Figure 3d) is created by taking the refuel stop 1 as origin node and refuel stop 2 as destination node and the task points covered by the destination node (refuel stop 2) are assigned for this subproblem.

Now in the subproblems, the destination nodes m_i^r have an *availability* time window constraint because UAV can recharge only when the UGV has already reached the refuel stops. This *availability* time period t_i^g is obtained from the ***UGVPlanner*** and taken in account while modelling the subproblems as energy constrained vehicle routing problem with time window constraints (E-VRPTW).

3.3.2.2 E-VRPTW formulation

The formulation of the E-VRPTW can be described with a graph theory. Consider an undirected graph $G = (V, E)$ where V is the set of vertices $V = \{S, 0, 1, 2, ...D\}$ and E is the set of edges between the vertices i and j as $E = \{(i, j) \parallel i, j \in V, i \neq j\}$. The non-negative arc cost between the vertices i and j is expressed as t_{ij} and x_{ij} is a binary decision variable whose value will be 1 if a vehicle travels from i to j, and 0 otherwise. The UAV will start from refuel stop S and meet the UGV at destination



(a) Given scenario

(b) Refuel stop locations

(c) Subproblem 1

(d) Subproblem 2

Figure 3: a) Given scenario with task points and starting depot b) Refuel stops in UGV route obtained from minimum set cover algorithm; the blue circles are indicating the radial coverage of the UAV c) Subproblem 1 with allocated UAV task points, here UGV travels between starting depot and refuel stop 1 d) Subproblem 2 with allocated UAV task points, here UGV travels between refuel stop 1 and refuel stop 2.

stop D. We then formulated the objective function of the E-VRPTW problem with fuel constraint, time window constraint, optional node constraints as follow:

$$\min \sum_i \sum_j t_{ij} x_{ij}, \quad \forall i, j \in V \tag{3.8}$$

$$\sum_{j \in V} x_{ij} = 1, \quad \forall i \in V \setminus \{S, D\} \tag{3.9}$$

$$\sum_{i \in V} x_{ij} = 1, \quad \forall j \in V \setminus \{S, D\} \tag{3.10}$$

$$\sum_{j \in V} x_{Sj} = \sum_{i \in V} x_{iD} = 1 \tag{3.11}$$

$$f_j^a \leq f_i^a - (\mathcal{P}^a(v^a) t_{ij} x_{ij}) + L_1 (1 - x_{ij}), \quad \forall i, j \in V \setminus \{S, D\} \tag{3.12}$$

$$f_j^a = F^a, \quad \forall j \in D \tag{3.13}$$

$$0 \leq f_j^a \leq F^a, \quad \forall j \in V \tag{3.14}$$

$$t_j \geq t_i + (t_{ij} x_{ij}) - L_2 (1 - x_{ij}), \quad \forall i, j \in V \tag{3.15}$$

$$t_{j,start} \leq t_j \leq t_{j,end}, \quad \forall j \in D \tag{3.16}$$

$$x_{ij} = 0, \quad \forall i \in D, \forall j \in V \tag{3.17}$$

$$x_{ij} \in \{0, 1\}, \quad \forall i, j \in V \tag{3.18}$$

$$f_i > 0, \quad f_i \in \mathbb{R}_+, \quad \forall i \in V \tag{3.19}$$

$$t_i > 0, \quad t_i \in \mathbb{Z}, \quad \forall i \in V \tag{3.20}$$

$$L_1, L_2 > 0, \quad L_1, L_2 \in \mathbb{R}_+ \tag{3.21}$$

The objective of Equation 3.8 is to minimize the total time spent by the UAV. Constraints in Equation 3.9 and Equation 3.10 represent flow conservation, where the inflow should equal the outflow at any of the task point vertices. Following that, constraint in Equation 3.11 represents flow conservation for start and end vertices, where the number of UAVs leaving the start vertex must equal the number of UAVs arriving at the end vertex. The Miller-Tucker Zemlin (MTZ) formulation [72] for sub-tour elimination is the constraint in Equation 3.12. The MTZ constraint ensures that each node is visited sequentially by keeping track of values such as fuel capacity and power consumption of the UAV corresponding to each node. It ensures that if a node is visited twice, the constraint is broken. This constraint allows the UAV's energy not to be fully drained out while eliminating loops. L_1 denotes a large number in this constraint. This constraint activates only when there is a flow between vertices i and j and drains the UAV energy based on the time taken between the two vertices. The $\mathcal{P}^a$ represents the UAV's power consumption curve during traversal.

According to constraint Equation 3.13, if the vertex is the destination stop (recharging stop), the UGV must refuel the UAV to its full capacity F^a. Constraint Equation 3.14 states that the UAV's fuel should be between 0 and maximum fuel capacity F^a at any vertex in V. The cumulative arrival time at the j^{th} node is equal to the sum of the cumulative time at the node i, t_i and the travel time between nodes i and j, t_{ij}. Here, L_2 is a large number that aids in the elimination of sub-tours in Equation 3.15.

Equation 3.16 imposes a time window constraint, instructing the vehicle to visit the destination node within its time window. This means the UAV is allowed to visit the destination node only after the UGV has arrived, as the UAV can only be recharged following the UGV's arrival. However, the UGV can arrive early at refueling stops, and the difference between its arrival and the UAV's landing determines the UGV's recharge waiting time. The constraint in Equation 3.17 indicates that there should be no flow once the vehicle reaches the end node and the route will end there. Equation 3.18 is a binary decision variable in charge of flow between the edges. The continuous decision variable, Equation 3.19, monitors the fuel level at any node and has zero as the lower bound value. Equation 3.20 denotes the integer decision variable that computes the cumulative time of the UAV's route and has a lower bound of zero. To solve the E-VRPTW model with its associated constraints, we utilize Google's OR-Tools CP-SAT solver [71], known for its effectiveness in solving the Traveling Salesman Problem (TSP) and

Vehicle Routing Problem (VRP) via constraint programming (CP). The OR-Tools solver combines search tree strategies, local search techniques, and metaheuristics to efficiently find good approximate optimal solutions. Our choice of Google's OR-Tools is driven by its rapid solution capabilities, particularly in heuristic implementations for TSP and VRP problems. At the core of OR-Tools lies the CP-SAT solver, which uses a *DecisionBuilder* for managing decision variables. This involves selecting which variable to assign next and determining the value to assign. It applies the *Path Cheapest Arc Strategy* for an initial feasible solution, starting from the "start" node and connecting to the nearest subsequent node until the route is complete. OR-Tools then refines this solution through local search, using a move operator to explore feasible, cost-effective configurations, continuing until no further improvements can be made. We also set an execution time limit of $T_s = 60$ seconds for the solver to generate a solution within a feasible time frame.

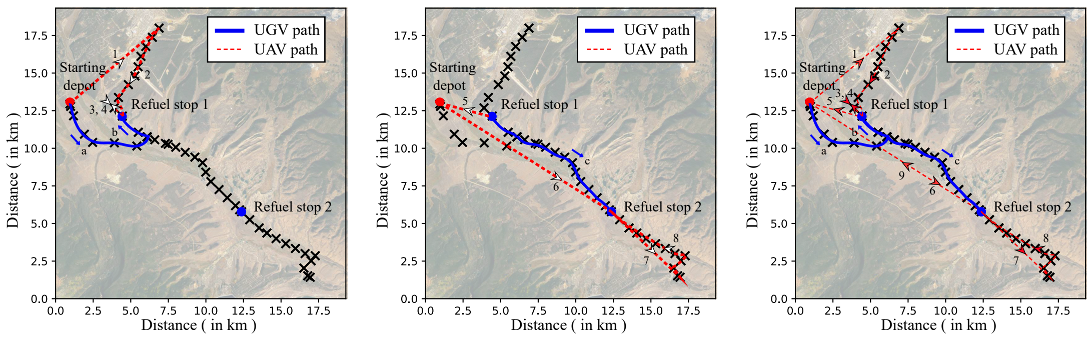
3.3.2.3 UAV Planner

Algorithm 3: UAV Planner

Input: Set of subproblems $\mathcal{S} = [SP_i]$ from Task Allocation
Output: UAV route $\tau^a = (X^a, T^a) = [(x_i^a, t_i^a)]$

1 Initialize $\tau^a = [\ ]$
2 **for** $SP_i \in \mathcal{S}$ **do**
3     $t_i^g \leftarrow UGVPlanner$
4   Send t_i^g to SP_i
5     $(x_i^a, t_i^a), \mathcal{R}_t \leftarrow EVRPTW$
6   τ^a.append(x_i^a, t_i^a)
7   Send $t_i^a, \mathcal{R}_t$ to UGVPlanner

By solving this E-VRPTW for subproblem SP_i, ***UAVPlanner*** gets the optimal UAV route τ^a, (both spatial component X^a and temporal component T^a); i.e, $\tau^a = (X^a, T^a) = [(x_i^a, t_i^a)]$, as well as the time instance t_i^a at which the UAV will arrive at the refuel stop m_i^r to recharge with the UGV and the recharging time $\mathcal{R}_t$ of it, which is dependent on its fuel consumption level. These information are fed back to the ***UGVPlanner*** again to calculate the UGV *availability* time window for next subproblem SP_{i+1}. This reciprocal and iterative process (line 3 - 7 in Algorithm 3) between the ***UAVPlanner*** and



(a) solution of subproblem 1 (b) solution of subproblem 2 (c) entire solution

Figure 4: a) UAV-UGV routes from subproblem 1 b)UAV-UGV routes from subproblem 2 c) UAV-UGV routes for entire task scenario after combining subproblem 1 & 2. The animation can be found at http://tiny.cc/3wgnxz

UGVPlanner is what facilitates the cooperative route for the entire task scenario. In Figure 4a and Figure 4b, we got the routes for the UAV and the UGV which are combined together to get the complete routes of UAV and UGV for the entire task scenario (Figure 4c).

The proposed algorithm's overall time complexity is determined by the execution time limit T_s set for solving the E-VRPTW subproblems, rather than by traditional algorithmic complexity measures. The overall time complexity of the proposed algorithm inherently depends on the fixed time limit (T_s) set for the solver to address each individual E-VRPTW subproblem. As the problem sizes increase, the number of subproblems (s) grows linearly. Consequently, the overall time complexity of the framework can be considered as scaling with $s \times T_s$. This approach ensures that the algorithm operates within practical bounds of time, making it suitable for applications where a predictable execution time is crucial.

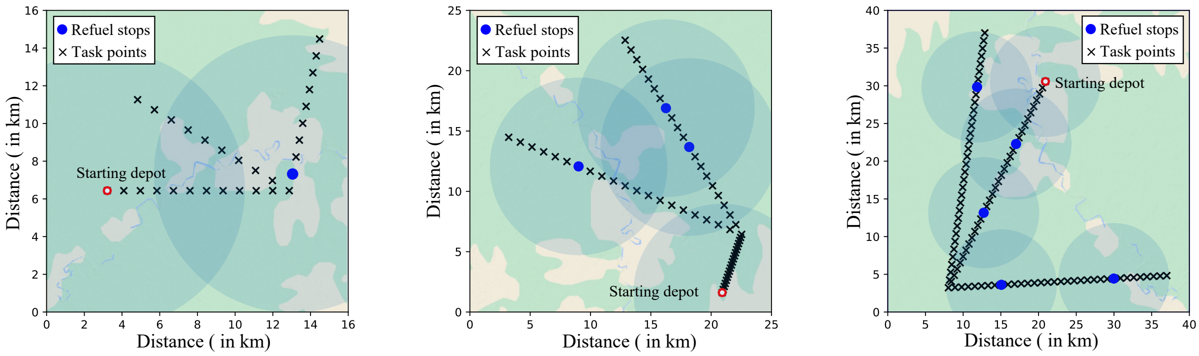
3.4 Results

We implement the proposed framework across diverse random task scenarios to evaluate its proficiency. The task scenarios, generated at three distinct scales, help us investigate the impact of UAV fuel capacity on the overall routing process. In these tests, we compare the results of the greedy and constraint programming methods when applied to the outer-loop baseline of our proposed framework.

Additionally, to ascertain the upper limit of the performance metrics, we also construct a UGV-only route in each scenario, which facilitates the assessment of the practicality and advantages of the cooperative UAV-UGV route in each specific scenario. In each problem scenario, it is assumed that the UAV and UGV commence their journey from a fixed starting depot with constant speeds of 10 m/s and 4.5 m/s respectively and UAVs have fuel capacity of 287.7 kJ [65].

3.4.1 Design of experiments

The efficacy of our proposed framework is tested across numerous random task scenarios generated at three separate scales. We design the scenarios such that the farthest task point from the starting depot is always outside the UAV's radial coverage, guaranteeing that at least one refueling stop is necessary for the UAV to complete the task. To substantiate the robustness and adaptability of the suggested methodology, we experiment with three distinct scales of task instances, as exhibited in Table I. We introduce a *scale factor*, a non-dimensional number, to represent the relationship between the scenario map size and the UAV's radial fuel coverage area. Three examples of scenarios from three different scales are shown in Figure 5.



(a) small scale scenario (b) medium scale scenario (c) large scale scenario

Figure 5: Sample scenarios with starting depot, task points, and the obtained refuel stops from minimum set cover algorithm. Radial circles represent the UAV's coverage area from the refuel stops. As the task scenario's scale increases, both the number of task points and the number of refueling stops grow proportionally.

$$\textit{scale factor} = \frac{\text{Area of scenario}}{\text{UAV coverage area on a single charge}} \tag{3.22}$$

For each instance, two types of cooperative routes (if different) are generated by employing the Greedy method and the CP method at the outer loop of the suggested framework. The UGV-only route (UGV operates alone) is also determined for the specific scenarios. There is no benchmark solution exists to this specific problem due to its complex combinatorial nature. Hence, we treat the UGV-only route as the baseline method for comparison. Comparison is made between the cooperative route and UGV only route, which signifies the impact of cooperation between UAV and UGV on the task execution. The total task completion time and total energy consumption are treated as the metrics for the evaluation of routes.

3.4.2 Time metrics

In Table II, the total task completion time of the route obtained by the three aforementioned methods has been displayed. For all instances in the small-scale scenarios, cooperative routing with the constraint programming method in the framework's outer loop is proved more time-efficient than the UGV-only routing. The task completion time for UGV-only routes is reduced by approximately 6% to 40% through the cooperation between the UAV and UGV in small-scale scenarios. Although cooperative routing with the Greedy method in the outer loop baseline doesn't perform as well as the CP method, it is more

TABLE I: Specifications of task Scenario

Scale	Map size	*scale factor*	No. of task points
Small	16 km x 16 km	1.5	30
Medium	25 km x 25 km	3	60
Large	40 km x 40 km	9	100

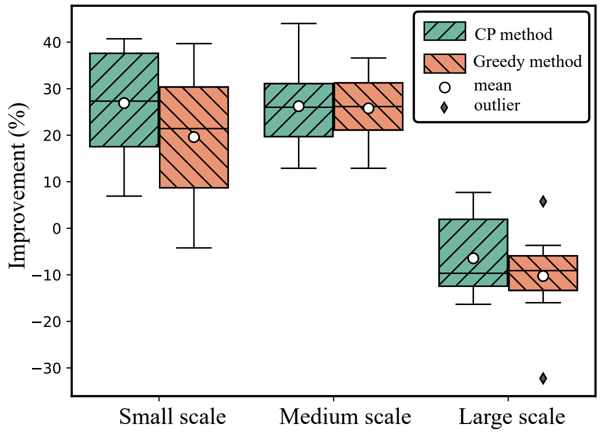


Figure 6: Time metrics across three different scale of scenarios

time-efficient than the UGV-only route in most instances. As the only exception, for scenario 10 on a small scale, the Greedy method can't improve the task completion time through the operative route.

For medium-scale scenarios, the task completion time is improved by 12% up to 45% through the CP method-based cooperative routing, while for the Greedy method-based cooperative route, the improvement range is 12% up to 30%. The cooperative route is more economical than the UGV individual route for most scenarios with the CP method at the outer loop. However, the improvement range is less than that in the small-scale scenarios.

However, for most large-scale scenarios, the cooperative route can't improve the total task completion time, making the UGV-only route the optimal choice. Figure 6 depicts the improvement in the total task completion time achieved by the cooperative route with the CP method and the Greedy method at the outer loop of our framework over the UGV-only route for three types of scenarios.

3.4.3 Energy metrics

The total energy consumed by the UAV and UGV during the routing process is also analyzed across the same scenarios, and depicted in Table III. The improvement percentage reflects the relative gain in total energy consumption that is achieved through UAV-UGV cooperation. The results confirmed that cooperative routing is more energy-efficient than UGV-only routing. Among the cooperative routing methods, the CP method applied in the outer loop outperformed the Greedy method.

For the small-scale instances, cooperative routing enables energy savings ranging from 28% up to 58%. For medium-scale scenarios, the improvement ranges from 40-55%, while for large-scale scenarios, the range is between 8-37%. This data affirms that cooperative routing, particularly when employing the CP method in the outer loop, can significantly enhance energy efficiency across a variety of scenarios (see Figure 7).

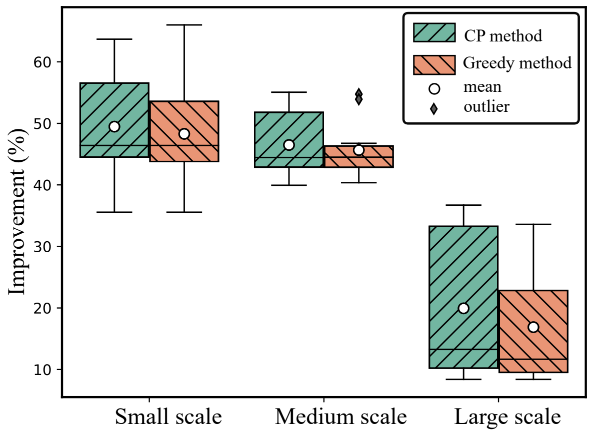


Figure 7: Energy metrics across three different scale of scenarios

TABLE II: Time metrics of different scenarios

Map Size	**Scenarios**	**Route Time (min.)**			**Improvement (%)**	
		Cooperative Routing		UGV only		
		Greedy Method	CP Method		Greedy Method	CP Method
Small scale	Scenario 1	200	210	249	19.68	15.66
	Scenario 2	91	82	133	31.58	38.35
	Scenario 3	117	115	194	39.69	40.72
	Scenario 4	153	153	178	14.04	14.04
	Scenario 5	148	148	159	6.92	6.92
	Scenario 6	222	222	289	23.18	23.18
	Scenario 7	190	149	196	3.06	23.98
	Scenario 8	128	128	198	35.35	35.35
	Scenario 9	222	210	303	26.73	30.69
	Scenario 10	223	128	214	-4.21	40.19
Medium Scale	Scenario 1	411	404	497	17.30	18.71
	Scenario 2	414	409	622	33.44	34.24
	Scenario 3	364	364	511	28.77	28.77
	Scenario 4	340	338	452	24.78	25.22
	Scenario 5	297	297	341	12.90	12.90
	Scenario 6	396	417	524	24.43	20.42
	Scenario 7	296	298	370	20.00	19.46
	Scenario 8	324	325	477	32.08	31.87
	Scenario 9	292	295	403	27.54	26.80
	Scenario 10	291	257	459	36.60	44.01
Large Scale	Scenario 1	461	407	438	-5.25	7.08
	Scenario 2	440	431	467	5.78	7.71
	Scenario 3	537	532	484	-10.95	-9.92
	Scenario 4	611	519	462	-32.25	-12.34
	Scenario 5	744	744	680	-9.41	-9.41
	Scenario 6	452	412	436	-3.67	5.50
	Scenario 7	655	701	607	-7.91	-15.49
	Scenario 8	682	684	588	-15.99	-16.33
	Scenario 9	620	620	570	-8.77	-8.77
	Scenario 10	613	604	537	-14.15	-12.48

TABLE III: Energy metrics of different scenarios

Map Size	**Scenarios**	**Total energy consumption (MJ)**			**Improvement (%)**	
		Cooperative Routing		UGV only		
		Greedy Method	CP Method		Greedy Method	CP Method
Small scale	Scenario 1	20.56	20.61	37.07	44.54	44.40
	Scenario 2	6.73	7.19	19.80	66.00	63.68
	Scenario 3	12.53	11.82	28.88	56.62	59.08
	Scenario 4	17.08	17.08	26.50	35.56	35.56
	Scenario 5	12.46	12.46	23.67	47.38	47.38
	Scenario 6	23.47	23.47	43.03	45.44	45.44
	Scenario 7	14.14	16.72	29.18	51.56	42.71
	Scenario 8	13.49	13.49	29.48	54.25	54.25
	Scenario 9	25.47	24.86	45.11	43.55	44.89
	Scenario 10	19.73	13.60	31.86	38.07	57.32
Medium Scale	Scenario 1	39.40	34.00	73.99	46.75	54.04
	Scenario 2	41.90	41.63	92.60	54.75	55.04
	Scenario 3	41.82	41.82	76.08	45.03	45.03
	Scenario 4	38.15	38.05	67.29	43.31	43.46
	Scenario 5	30.10	30.10	50.77	40.71	40.72
	Scenario 6	46.52	46.85	78.01	40.37	39.94
	Scenario 7	31.56	31.57	55.09	42.71	42.70
	Scenario 8	39.75	39.67	71.02	44.03	44.15
	Scenario 9	33.01	33.14	60.00	44.98	44.76
	Scenario 10	31.49	30.71	68.34	53.92	55.06
Large Scale	Scenario 1	43.63	41.27	65.21	33.09	36.71
	Scenario 2	46.17	45.35	69.53	33.59	34.78
	Scenario 3	62.94	62.67	72.06	12.66	13.03
	Scenario 4	56.05	59.50	68.78	18.51	13.50
	Scenario 5	92.74	92.74	101.24	8.39	8.39
	Scenario 6	49.15	42.32	64.91	24.28	34.81
	Scenario 7	81.63	64.41	90.37	9.68	28.73
	Scenario 8	80.17	79.96	87.54	8.42	8.66
	Scenario 9	75.80	75.80	84.86	10.67	10.67
	Scenario 10	72.37	71.89	79.95	9.48	10.07

3.4.4 Computational time

For real-time applications, the computational time of the vehicle routing problem is a crucial factor. The greedy method and the CP method, when implemented at the outer loop of the proposed framework, display notable differences in computational time. As shown in Figure 8, the greedy method requires substantially less computational time compared to the CP method. All our computations are performed in a Python 3.9 environment running on a 3.7 GHz Intel Core i9 processor with 48 GB RAM on a 64-bit Windows 10 operating system.

Given the subproblem division approach at the inner loop, the computational time increases for both the Greedy and CP methods as the scale of the scenarios increases. However, the Greedy method consistently outperforms the CP method, and the gap between their respective computational times grows in proportion to the scale of the scenario. This highlights the Greedy method's efficiency and its suitability for larger-scale scenarios that require rapid computations.

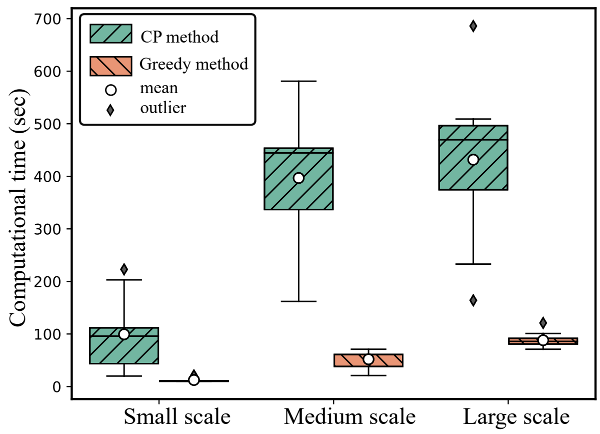


Figure 8: Computational time

3.4.5 Case study

As an illustrative example, we examine a real-world task site consisting of 44 task points spread across a 20 km $\times$ 20 km area, as presented in Figure 3a. The UAV and UGV both start their journey from

TABLE IV: Impact of the optimal solution of the cooperative routing on case study scenario.

Metrics	**Cooperative route**		**UGV only route**	**Improvement** (%)	
	CP method	Greedy method		CP method	Greedy method
Time consumption (min.)	200	272	233	14.16	-16.74
Energy consumption (MJ)	21.98	21.14	34.69	36.62	39.06

the starting depot and meet at refuel stops for recharging while visiting task points, determined by the minimum set cover algorithm in the UGV routing of the proposed framework. For comparison evaluation, we apply both the CP method and the Greedy approach to solve the minimum set cover algorithm. The cooperative routes obtained from both methods, as illustrated in Figure 9, are compared. We evaluate the total mission completion time and total energy consumption from the two cooperative routes, as shown in Table IV. Table IV also highlights the improvements achieved by UAV-UGV cooperation over the UGV-only route, which serves as an upper limit. Cooperative routing proves to be more energy-efficient than the UGV-only route. Both the CP method and the Greedy method at the outer loop show positive improvements, reducing total energy consumption in the mission by 36-39%. However, for total mission time, the Greedy method at the outer loop has a negative impact. This is due to the positioning of refuel stops (see trajectory in Figure 9*b*), which causes the UAV to take frequent detours (6 times) for recharging at the refuel sites, thereby elongating the total mission time. Conversely, appropriate refuel stop locations determined by the CP method (see trajectory in Figure 9*a*) enables the UAV to complete its route with fewer recharging detours (4 times), effectively reducing the total mission time.

3.5 Discussion

The scenario size and the geometric configuration of task points within a scenario critically influence the potential for improving total task completion time through cooperative routing. As observed in

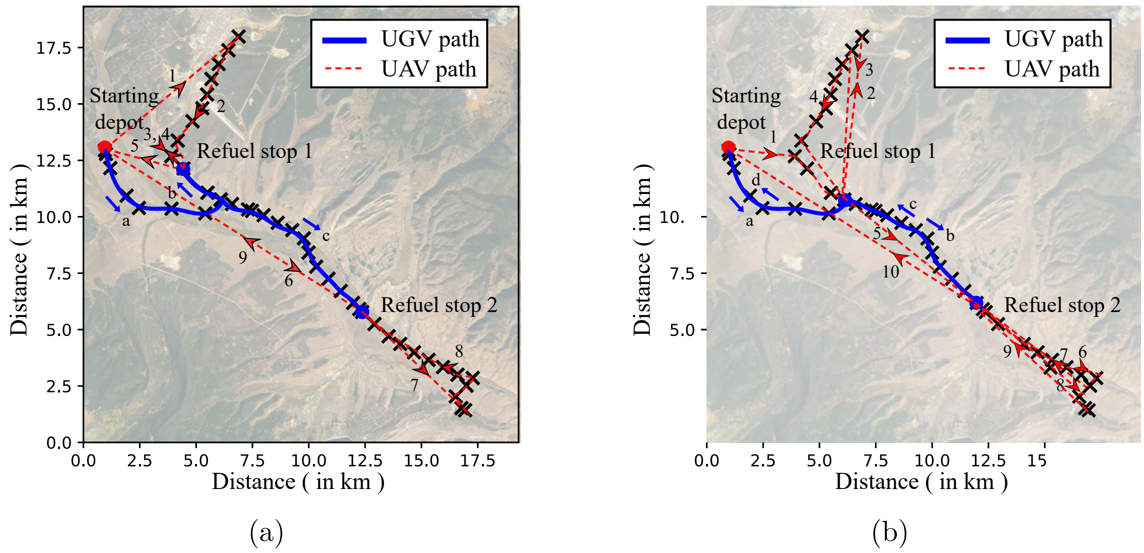


Figure 9: UAV & UGV trajectory obtained from bilevel optimization with Greedy and CP method at the outer loop. Numerical and alphabetical order shows the UAV and UGV motion respectively. a) CP method based trajectory b) greedy method based trajectory. The animation of the route can be found at http://tiny.cc/3wgnxz

Figure 6, there are positive improvement percentages for small and medium scale scenarios, but a negative trend emerges for large scale scenarios. The total time taken to complete the task via a cooperative route depends on three elements: UAV traversal time, UGV traversal time, and the waiting time of the UGV for UAV refueling. Conversely, the total task completion time for the UGV-alone route depends solely on the UGV traversal time, as it does not involve refueling.

When the UGV operates alone, it has to visit all task target points alone, leading to a significant UGV traversal time. This duration increases proportionally with the scale of the scenario, as demonstrated in Figure 10. This UGV traversal time can be reduced through cooperative routing, which divides the task points between the UAV and UGV. However, a drawback of cooperative routing is the addition of waiting time during which the UAV is refueled by the UGV.

In small and medium-scale scenarios, the number of task points is lower within smaller areas, resulting in fewer refueling stops. This configuration ensures that the extra waiting time at refueling stops never exceeds the reduction in UGV traversal time, leading to a shorter overall task completion time for the cooperative route compared to the UGV-alone route. However, in large-scale scenarios, where there are more refueling stops to cover a greater number of task points spread over a large area, the additional waiting time can surpass the decrease in UGV traversal time. This results in the cooperative route having a longer overall mission time than the UGV-alone route. Within the cooperative routing methods, the task point density significantly influences the performance of the CP method and the Greedy approach. If the task points are densely spread, having fewer refuel stops leads to fewer recharging detours for the UAV and reduced recharging waiting time. This configuration leads to a decreased overall task completion time for the CP method compared to the Greedy method, as the former is more effective in minimizing the number of refuel stops. Conversely, if task points are not densely clustered, fewer refueling stops may negatively impact the mission time, as the UAV might need to undertake more detours, thereby extending the overall mission duration. In such scenarios, the Greedy method tends to outperform the CP method.

In terms of energy consumption metrics, the cooperative route consistently outperforms the UGV-alone route, regardless of the scenario scale. This is because, as demonstrated in Figure 1, the UAV consumes five times less energy than the UGV per unit distance traveled, making the UGV the dominant influence on total energy consumption. Hence, the UGV-alone route, which involves a longer UGV traversal distance, consumes more energy than the cooperative route, where the UGV covers a smaller distance due to task division with the UAV.

Nevertheless, as the scale of scenarios increases, the gap in total energy consumption between the UGV-alone route and the cooperative route narrows. This is because in larger scenarios, despite cooperation with the UAV, the UGV must still cover a considerable distance to provide suitable refueling stops, leading to higher overall energy consumption.

The proposed framework can be implemented using a receding horizon approach to account for dynamic environmental changes, such as the random emergence of new task points, disappearance of old task points, and obstacle avoidance. Given that we assume UAVs and UGVs can communicate only during the recharging process, we propose updating the scenario map at every recharging instance to incorporate these changes. Consequently, the ***UGVPlanner*** can resolve the MSC problem to update the UGV route as necessary. Based on the revised UGV route, the UAV routes can be constructed by applying task allocation and the EVRPTW modeling within the ***UAVPlanner***, as described in Subsection 3.3.2. Dynamic planning proves extremely useful for continuous monitoring, disaster management, and traffic monitoring by capturing the most recent state of the environment. We recognize the potential of dynamic planning and suggest it as an avenue for future research in our study.

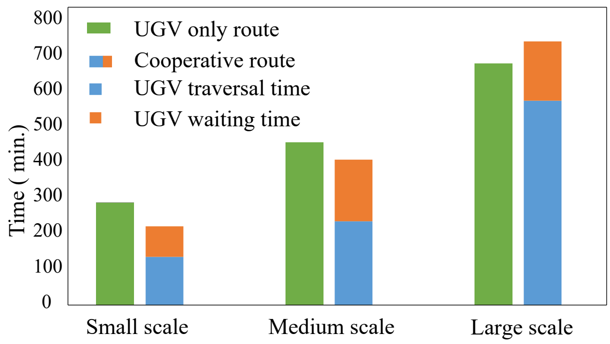


Figure 10: Cooperative routing Vs UGV-only route

3.6 Conclusion

In this work, we focus on a cooperative vehicle routing problem involving a multirotor UAV and a wheeled UGV team with fuel and speed constraints. Both vehicles are required to cover a set of assigned task points, with the UAV periodically recharging from the UGV to complete the task in the minimum possible time. Finding the optimal recharging rendezvous points, in terms of both location and timing, between the UAV and UGV is important to achieve an optimal route in this cooperative routing problem. We introduce a sequential optimization framework that operates in two primary steps.

The initial step involves the utilization of a minimum set cover algorithm to determine the locations for refueling stops. These identified locations serve as an input to the ***UGVPlanner***, which then creates the UGV route employing a Traveling Salesman Problem model. In the subsequent step, a task allocation technique is employed to partition the entire problem into smaller, more manageable subproblems. The ***UAVPlanner*** then develops the UAV route by framing these subproblems as instances of the Energy-Constrained Vehicle Routing Problem with Time Windows constraints (E-VRPTW).

Our framework has been successfully applied to 30 distinct task scenarios across three different scales, showcasing its effectiveness and practicality. The cooperative routes resulting from our framework have been benchmarked against the UGV-only routes for the same scenarios that serve as an upper limit for comparison. The results reveal substantial improvements, with time consumption reduced by 10-30% and energy consumption diminished by 15-50% in most instances through the cooperative routing. In the future, we will expand the framework for persistent surveillance of the task points and consider stochasticity in the scenarios. Insights from this study suggest a potential enhancement of leveraging the UGV's idle waiting times during refueling to establish a mobile recharging rendezvous, which will be a focal point in our subsequent investigations. Additionally, we intend to refine our approach by incorporating reinforcement learning techniques to tackle this UAV-UGV cooperative routing problem, thereby providing an additional benchmark for future comparative analyses.

CHAPTER 4

LAB-SCALE HARDWARE VALIDATION OF A BI-LEVEL UAV-UGV COOPERATIVE ROUTING FRAMEWORK

Overview: Unmanned Aerial Vehicles (UAVs) are well-suited for aerial surveillance due to their agility and rapid coverage capabilities. However, their limited battery capacity significantly constrains their operational endurance. To extend flight time, UAVs can be periodically recharged by Unmanned Ground Vehicles (UGVs), which navigate along predefined road networks. This cooperative UAV-UGV routing problem introduces computational challenges due to differences in vehicle speed, mobility constraints, and energy limitations. While prior studies have demonstrated the efficacy of heuristic-based routing strategies in simulation, real-world feasibility remains a critical aspect for practical deployment. This study presents the proof-of-concept hardware deployment of our bi-level UAV-UGV cooperative routing framework, evaluating its performance in a controlled lab-scale environment. The proposed approach employs a minimum set cover algorithm to determine optimal UGV refueling locations, followed by a traveling salesman problem (TSP) formulation to optimize the UGV's route. The UAV's trajectory is planned using an energy-constrained vehicle routing problem with time windows (E-VRPTW), ensuring efficient task execution while maintaining synchronized recharging with the UGV. Experimental validation was conducted using a UAV-UGV testbed, where the UAV autonomously executed its mission

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Parts of this chapter is taken from published conference article:
Mondal, M. S., Ramasamy, S., Humann, J. D., Reddinger, J. P. F., Dotterweich, J. M., Childers, M. A., & Bhounsule, P. (2023, December). Optimizing fuel-constrained uav-ugv routes for large scale coverage: Bilevel planning in heterogeneous multi-agent systems. In *2023 International Symposium on Multi-Robot and Multi-Agent Systems (MRS)* (pp. 114-120). IEEE.

while periodically landing on a mobile UGV for simulated refueling. A high-precision motion capture system provided real-time tracking and feedback control, ensuring accurate trajectory execution. The results demonstrated strong alignment with simulation-based predictions, confirming the robustness of the framework in achieving coordinated UAV-UGV operations under real-world constraints. Experimental data and further details can be accessed at http://tiny.cc/vancvz.

4.1 Introduction

This chapter presents the experimental validation of the proposed bi-level optimization framework for UAV-UGV cooperative routing, assessing its feasibility beyond computational evaluations. While simulations provide valuable insights into theoretical performance, real-world deployment introduces additional complexities such as aerodynamic disturbances, localization inaccuracies, communication latency, and dynamic environmental factors. To bridge the gap between simulation-based validation and practical applicability, a proof-of-concept hardware implementation was conducted in a controlled lab-scale testbed. The experimental setup involved an autonomous UAV-UGV team executing a cooperative routing strategy under constrained energy conditions. The UAV, subject to endurance limitations, relied on the UGV for periodic refueling while carrying out its assigned mission. The UGV, constrained to road networks, simultaneously optimized its traversal path to facilitate timely recharging rendezvous. This real-world implementation enabled a comprehensive assessment of key operational aspects, including UAV trajectory adherence, precision landing for recharging, synchronization of movement, and the robustness of the task allocation strategy. By evaluating cooperative routing under realistic conditions, the experiment aimed to validate the framework's effectiveness in ensuring continuous mission execution while minimizing UAV downtime. The motion capture system provided high-precision localization feedback, allowing for real-time corrections and adjustments to trajectory deviations. Through multiple experimental trials, the study examined the reliability of refueling coordination, the impact of real-world dynamics on UAV-UGV interactions, and the extent to which the proposed optimization strategy aligns with its simulated counterpart. The results of this validation provide critical insights into the practical challenges and performance limitations of UAV-UGV coordination, offering a foundation for further refinements in energy-efficient multi-agent routing. This chapter details the experimental setup, mission execution, performance analysis, and key observations, ultimately reinforcing the feasibility of deploying UAV-UGV teams for real-world autonomous operations.

4.2 Experiment design

The most stringent way of validating a framework is by hardware demonstration. Hardware testing of our surveillance planning framework was crucial given its complexity. We utilized a small-scale lab scenario with a UAV and UGV to test our proposed framework, aiming for full autonomy where each robot independently locates, plans, and executes its route, leveraging its sensing, processing, and communication capabilities. Developing this experimental system was challenging due to the integration of software, hardware, and communication. The individual elements of the hardware architecture are detailed separately (see Figure 11) as follows:

1) **Hardware:** In our experiment, we used the DJI Tello quadcopter as our UAV, a lightweight drone (80 g) with basic flight stabilization and trajectory capabilities, which can also achieve higher autonomy via an external ground-based computer using its telemetry and video feed. Our UGV was a Raspberry Pi controlled omnidirectional car with a landing pad for UAV recharging.

2) **Control & communication:** A wireless 2.4 GHz 802.11n WiFi connection was used to communicate with the drone. The approach makes use of the official Tello SDK 2.0. The UDP port is used to send text messages to the drone programming interface. To create the application, we used the SDK and the low-level Python library DJItelloPy. Wireless wifi communication was also established with the Raspberry Pi for controlling the UGV.

3) **Central manager:** The final component of our system is a centralized manager, which runs our proposed bi-level optimization framework to generate routes for the UAV and UGV based on the

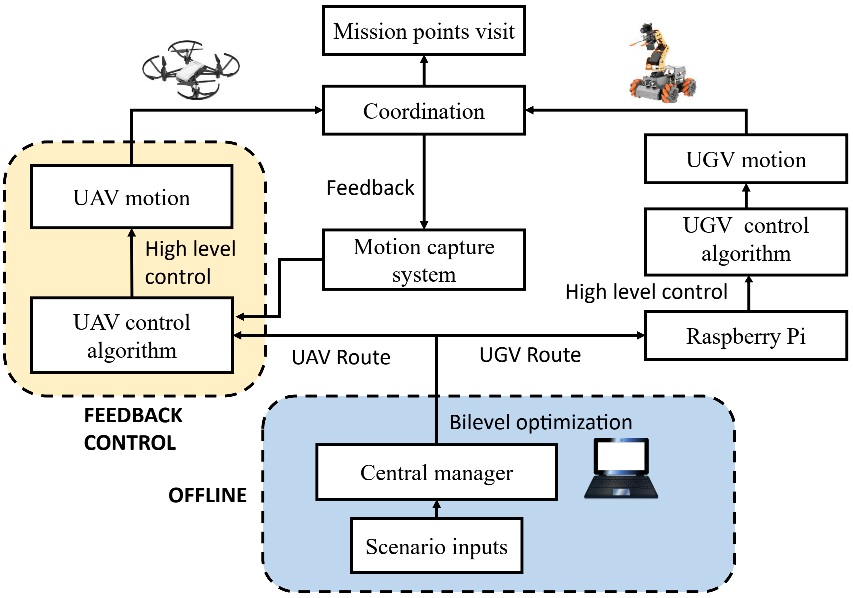

Figure 11: Hardware architecture

given scenario. It assigns tasks and monitors progress via a motion capture system. The UGV and the UAV relies on feedback control from the central system for precise navigation and successful recharging landings on the UGV.

4.3 Experimental scenario and mission execution

The experiments were conducted in the *Robotics and Motion Lab* at the *University of Illinois Chicago*, in a designated flight area equipped with a high-precision motion capture system. This system served as a reference for the position of reflective markers placed on both the quadrotor (UAV) and the ground vehicle (UGV), enabling real-time localization. The positional data of the vehicles were captured at a rate of 100 Hz, with a latency of less than 9 ms, ensuring precise tracking of their movements throughout the experiment.

The experimental testbed was designed to replicate a constrained fuel-limited UAV-UGV routing problem within a 4 m $\times$ 4 m area. A mission scenario was created by defining 12 distinct task points for the UAV, while a structured road network was mapped for the UGV. A flight endurance constraint was introduced by limiting the UAV's flight time to 50 seconds per recharge cycle. The UAV and UGV were programmed to operate at speeds of 0.20 m/s and 0.15 m/s, respectively, reflecting their real-world mobility characteristics. Due to the endurance limitation, the UAV was required to periodically land on the UGV for recharging to successfully complete its mission. However, no actual recharging took place; instead, it was hypothesized that the UAV was instantly refueled upon landing on the UGV. The UGV's road network was intentionally designed to be challenging, with the farthest mission points requiring the UAV to operate near its endurance limits, thereby testing the robustness of the proposed cooperative routing framework. The mission execution followed these sequential steps:

1. **UGV route planning:** A minimum set cover algorithm was employed to determine optimal refueling stop locations, which were then used to construct the UGV's travel path using a Traveling Salesman Problem (TSP) model.

2. **UAV route optimization:** Given the UGV's refueling stops, the UAV's trajectory was optimized as an Energy-Constrained Vehicle Routing Problem with Time Windows (E-VRPTW), ensuring synchronized refueling rendezvous with the UGV.

3. **Autonomous task execution:** The UAV autonomously executed its mission by sequentially visiting designated task points while periodically landing on the UGV for refueling. The motion capture system continuously tracked both vehicles, providing real-time position updates to enable feedback-based corrections and mitigate any landing drift or trajectory deviations.

4.4 Experimental results and performance evaluation

To evaluate the reliability of the proposed bi-level UAV-UGV cooperative routing framework, multiple trials were conducted under identical mission settings. Given mission point locations and road

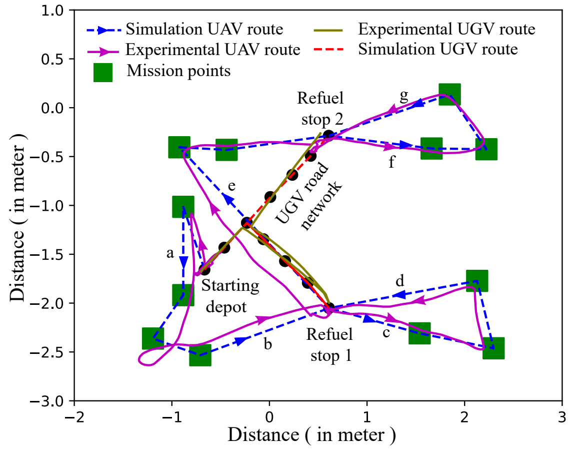

Figure 12: Comparison between simulation and experimental results. In the trajectory, the alphabetical order represents the direction of motion of the UAV

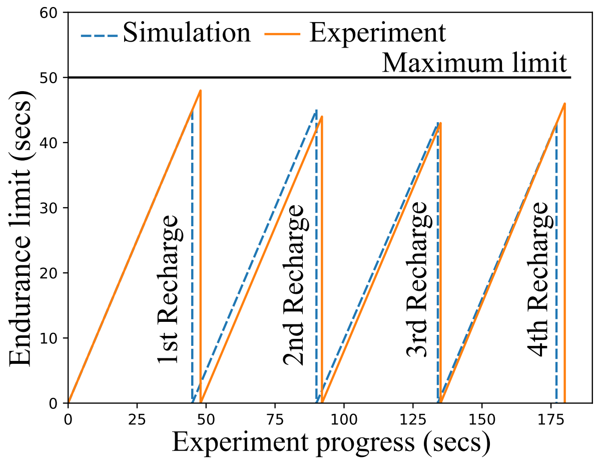

Figure 13: Comparison between simulation and experimental results for the fuel depletion of the UAV

constraints, the outer loop computed the UGV's refueling schedule and route, while the inner loop generated an energy-efficient UAV path synchronized with the UGV's trajectory. A centralized manager transmitted these plans and monitored execution.

A motion capture system enabled precise real-time tracking and feedback control, allowing the UAV to maintain its planned route despite minor deviations from aerodynamic disturbances. As shown in Figure 12, all trials resulted in successful rendezvous and coordinated mission completion.

The endurance limit constraint was rigorously tested, with all trials confirming that the UAV's flight time per charge remained within the predefined limits. Figure 13 presents the recorded endurance trends, demonstrating that the UAV completed its designated tasks without exceeding operational constraints. The cooperative routing approach effectively minimized UAV downtime, enabling sustained mission execution with optimized refueling schedules. The UAV's synchronization with the UGV further ensured mission completion within the given energy constraints.

4.5 Comparison between simulation and experimental results

A direct comparison between the simulation-based trajectory planning and real-world experimental execution demonstrated strong alignment between planned and executed UAV-UGV routes. As shown in Figure 12, the experimental trajectory closely follows the simulated path, with only minor deviations due to real-world aerodynamic factors. The UAV consistently adhered to its scheduled recharging rendezvous, validating the effectiveness of the proposed task allocation and refueling strategy.

Further analysis of mission completion time and energy efficiency confirmed the robustness of the cooperative routing approach. The UAV successfully met its endurance constraints in all test trials, validating the framework's efficacy under fuel-limited conditions. Figure 14 highlights key instances of UAV-UGV coordination, where the UAV accurately landed on the UGV for recharging, demonstrating the feasibility of the proposed methodology. To account for real-world UAV dynamics, a buffer period was incorporated into the simulation model to adjust for variations in takeoff and landing times.

Overall, the experimental validation highlights the practical viability of the bi-level optimization framework, bridging the gap between theoretical planning and real-world deployment. Future work will extend these tests to larger environments and incorporate multi-UAV and multi-UGV teams to assess scalability and adaptability under dynamic mission conditions.

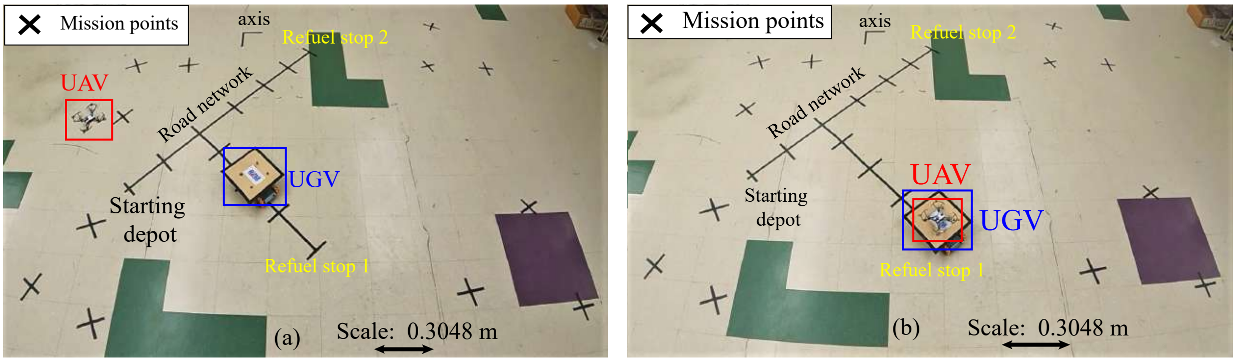

Figure 14: Experiment instances: a) UAV and UGV navigating to their designated locations. b) UAV landing on UGV for recharging.

4.6 Limitations and future directions

The experimental validation confirmed the feasibility of the proposed UAV-UGV cooperative routing framework for real-world deployment. Hardware tests demonstrated successful UAV-UGV synchronization, effective recharging coordination, and robust mission execution. However, several real-world challenges emerged that highlight directions for future work:

- **Landing precision:** Minor trajectory deviations caused by aerodynamic disturbances were observed. Although real-time feedback control mitigated these errors, improved landing precision is needed to enhance overall reliability.
- **Communication latency:** Wireless network delays introduced slight synchronization lags, potentially affecting time-sensitive refueling rendezvous. Future efforts should explore optimized, low-latency communication protocols for more reliable coordination.
- **Scalability:** The current framework is validated for a single UAV-UGV pair. Scaling it to multi-agent systems introduces additional complexity. Future work will focus on dynamic coordination strategies to enable seamless collaboration among multiple UAVs and UGVs in large-scale missions.

Addressing these limitations will be key to enabling autonomous UAV-UGV teams to perform real-time, energy-aware operations in complex and mission-critical environments.

4.7 Conclusions

This chapter presented the experimental validation of the proposed bi-level UAV-UGV cooperative routing framework through a lab-scale deployment involving a constrained energy-aware mission scenario. The real-world trials demonstrated the successful integration of planning, control, and feedback systems for synchronized UAV-UGV operations. Through precise trajectory tracking, autonomous task execution, and reliable recharging rendezvous, the framework showed strong alignment with its simulation counterpart, confirming its practical viability.

The results underscore the robustness and efficiency of the proposed approach in managing fuel-constrained UAV missions with UGV-assisted support. Key observations from the experiments, such as accurate mission completion within endurance limits and minimal trajectory deviations, highlight the effectiveness of the bi-level optimization strategy in enabling continuous, coordinated operations.

While the experiments affirm the feasibility of the system in controlled environments, identified challenges such as precision landing, communication latency, and scalability point to the need for further refinements. Addressing these limitations will be crucial for extending the framework to dynamic, large-scale, multi-agent deployments in real-world settings. The insights gained from this validation provide a solid foundation for future advancements toward fully autonomous, energy-efficient UAV-UGV collaboration in mission-critical applications.

CHAPTER 5

CONCLUSION

This study presented a bi-level optimization framework for UAV-UGV cooperative routing, addressing the operational challenges of fuel-constrained UAVs by leveraging coordinated refueling on mobile UGVs. The proposed methodology integrates a minimum set cover algorithm to determine optimal refueling stops, a Traveling Salesman Problem (TSP) model for UGV route planning, and an energy-constrained vehicle routing problem with time windows (E-VRPTW) for UAV trajectory optimization.

Computational results demonstrated significant improvements in mission efficiency, with reductions of 10–30% in total mission time and 15–50% in energy consumption compared to UGV-only routing. These findings highlight the effectiveness of cooperative UAV-UGV routing in minimizing UAV downtime and enhancing overall mission performance.

To validate the practical feasibility of the proposed framework, a hardware-in-the-loop proof-of-concept experiment was conducted in a controlled lab-scale testbed. The experimental setup consisted of an autonomous UAV-UGV team executing cooperative routing strategies under fuel constraints, with a high-precision motion capture system providing real-time localization for feedback-based trajectory corrections. The results exhibited strong alignment with simulation-based predictions, confirming the robustness of the proposed methodology in achieving synchronized UAV-UGV coordination.

Despite its success, certain real-world challenges were identified, including minor UAV trajectory deviations, requiring feedback control for precise landings, wireless communication latency, which affected synchronization, and scalability limitations in multi-agent deployments. Addressing these challenges is critical for enhancing UAV-UGV cooperation in dynamic environments and transitioning the framework toward real-world applications.

5.1 Future Work

While this study provides a validated framework for UAV-UGV cooperative routing, several key research directions remain open for further exploration:

- **Multi-UAV and Multi-UGV Coordination:** Extending the framework to larger agent teams to improve scalability in persistent surveillance and large-scale mission planning.
- **Adaptive Learning-Based Strategies:** Incorporating reinforcement learning to enable dynamic task allocation and adaptive route planning in real-time scenarios.
- **Field Deployment and Robustness Testing:** Transitioning from controlled lab experiments to outdoor environments with real battery recharging and external environmental disturbances.
- **Heterogeneous Robotic Platforms:** Expanding the approach to fixed-wing UAVs, quadrupedal UGVs, and VTOL systems for diverse mission requirements.

Overall, this work advances UAV-UGV cooperative routing by presenting a computationally efficient and experimentally validated framework. The findings contribute toward enabling autonomous UAV-UGV teams for applications in persistent surveillance, disaster response, and energy-aware multi-agent mission planning. Future research will focus on scaling the framework for large-scale deployments, improving decision-making under uncertainty, and integrating robust AI-driven control strategies for real-world implementation.

APPENDICES

Appendix A

Code Repository

The code for the planning framework presented in this thesis (Chapter 3) can be found at: https://github.com/imsafwan/bilevel_opt_uav_ugv_routing.

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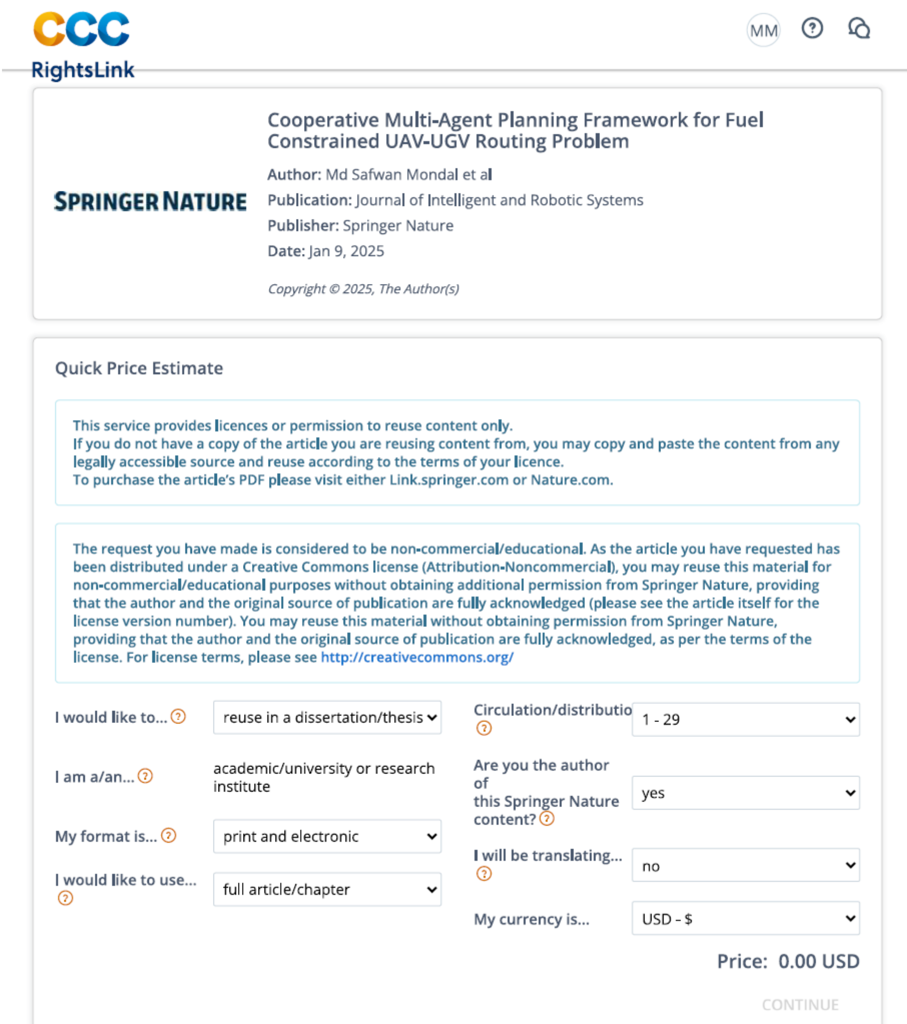

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VITA

MOHAMMAD SAFWAN MONDAL

EDUCATION	Ph.D., Mechanical Engineering, University of Illinois Chicago, Chicago, IL, USA, Cont. B.E., Mechanical Engineering, Jadavpur University, Kolkata, INDIA, 2021
EXPERIENCE	Teaching Assistant, University of Illinois Chicago 2025 – Cont. Research Assistant, University of Illinois Chicago 2021 – 2024 Summer Research Intern, Indian Institute of Technology Mandi May 2019 – July 2019
PUBLICATIONS	Mondal, Md Safwan, Subramanian Ramasamy, James D. Humann, James M. Dotterweich, Jean-Paul F. Reddinger, Marshal A. Childers, and Pranav A. Bhounsule. ”Cooperative multi-agent planning framework for fuel constrained uav-ugv routing problem.” Journal of Intelligent & Robotic Systems 111, no. 1 (2025): 1-17. Mondal*, Md Safwan, Subramanian Ramasamy, and Pranav Bhounsule. ”Risk-Aware Energy-Constrained UAV-UGV Cooperative Routing using Attention-Guided Reinforcement Learning.” 2025 IEEE International Conference on Robotics & Automation. (accepted) Mondal*, Md Safwan, Subramanian Ramasamy, James D. Humann, James M. Dotterweich, Jean-Paul F. Reddinger, Marshal A. Childers, and Pranav Bhounsule. ”An Attention-aware Deep Reinforcement Learning Framework for UAV-UGV Collaborative Route Planning.” In 2024 International Conference of Robots and Systems (IROS) Abu Dhabi, UAE.

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PRESENTATIONS **Conference Presentations**

2025 Robotics: Science and Systems

2025 IEEE International Conference on Robotics and Automation

2024 IEEE International Conference on Intelligent Robots and Systems

2024 IEEE International Conference on Unmanned Aircraft Systems

2023 IEEE International Symposium on Multi-Robot & Multi-Agent Systems

2022 IEEE International Conference on Unmanned Aircraft Systems

Poster Presentations

2025 Robotics: Science and Systems

2025 Midwest Robotics Workshop (MWRW 2025)

2025 IEEE International Conference on Robotics and Automation

2023 DST-NSF Joint Research and Development Projects Kick-off Workshop

AWARDS	Image of Research Award, Graduate College and University Library, University of Illinois Chicago, 2023
	Litvin Honor Award, University of Illinois Chicago, 2021