A Meta-Heuristic Approach for an Aerial-Ground Vehicle Path Planning Problem

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This study concerns the challenges of path planning and scheduling for multi-agent unmanned aerial vehicles (UAVs) operating under battery constraints while considering the presence of unmanned ground vehicles (UGVs) capable of recharging them. The objective is to efficiently coordinate UAVs and a UGV to maximize collected rewards by visiting nodes continuously in a 20 km x 20 km coverage area. The reward for each node is calculated based on the time difference between the last visit and the current visit, and the total nodes' reward contributes to the overall team score. The problem is a form of the Team Orienteering Problem (TOP), which is known to be NP-Hard. To solve this problem, we propose a new algorithm and simulation using a meta-heuristic approach. Specifically, our approach employs an advanced tabu search specialized in this problem with three improved tabu search stages: 2-point exchange, one-point movement, 2-opt cleanup, and two extra rearrange and reattach processes. It provides a feasible solution within a few minutes of computation time for large problems with accumulated nodes and rewards. Subsequently, our investigation uncovers a novel scheduling rule, which we apply to a demanding 72-hour mission schedule. Computational and simulation results demonstrate the algorithm's runtime, cumulative rewards, node visits, and charging schedules. The proposed approach is evaluated through simulations, further affirming its efficacy in addressing the challenges of path planning and scheduling for UAVs with battery constraints.

I. Nomenclature

UGV	=	Unmanned Ground Vehicle
UAV	=	Unmanned Aerial Vehicle
OP	=	Orienteering Problem
TOP	=	Team Orienteering Problem
AOI	=	Area of Interest
R_{TOP}	=	The Set of the Main Feasible Routes Which Have the Greatest Team Score
R_{NTOP}	=	The Set of the Remaining Routes Except for R_{TOP}

II. Introduction

Due to their diverse applications, unmanned vehicles have gained significant popularity in both the research and industrial sectors. These vehicles are essential for operations including site monitoring, moving object tracking, and search and rescue. In this paper, we aim to address the challenges of path planning and scheduling for multi-agent unmanned aerial vehicles (UAVs) with battery constraints, while considering the presence of unmanned ground vehicles (UGVs) capable of recharging them[1]. The objective is to efficiently coordinate UAVs and a UGV to maximize collected rewards by visiting nodes within battery constraints in a 20 km x 20 km coverage area. We assume prior knowledge of the four areas of interest (AOIs), three depots (A, B, and C), and a predetermined route connecting them.

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The UGV is equipped with two charging pads on top, enabling it to recharge three UAVs while on the road. Over 72 hours, the UGV travels along the road network, charging the UAVs to continue so that they can fly their routes continuously without ever fully discharging [2]. Our primary focus will be on the path-planning and time-scheduling stages for the UAVs and a UGV.

The proposed issue is closely related to the orientation problem (OP) which can be defined as a combination of two well-known problems, the Traveling Salesman problem (TSP) [3] and the Knapsack problem. In OP, a single vehicle is tasked with visiting multiple destinations within a given time frame, aiming to maximize the accumulated value within a specified budget. The primary objective of Orienteering is to identify closed tours that cover multiple targets while optimizing rewards based on time or distance constraints. Typically, it is not feasible to visit all targets. The Team Orienteering Problem (TOP) [4] represents a variant where multiple agents participate to maximize the overall collected rewards.

The proposed problem also considers area coverage and time scheduling, introducing additional complexities not observed in TOP. Unlike general path planning algorithms, which focus on visiting discrete destinations, our problem involves interconnected destinations that are constrained by predefined routes. Given the high complexity of the presented problem and the involvement of multiple vehicles, an efficient simulator is required to swiftly assess various planning algorithms. There are many simulators already out there but using them directly in our problems can take a long time for researchers to model the problem, especially in rare cases. We can employ no existing models for the subject under discussion. So, in this work, we'd like to develop a new simulator with a proposed heuristic for this problem.

Our employment of the Team Orienteering Problem (TOP) approach enables us to identify the feasible path, although this problem falls under the category of NP-hard. [5] Based on the work by Tsiligirides (1984) [6], we introduce a meta-heuristic algorithm that offers a promising solution. Furthermore, to evaluate its effectiveness in addressing the scheduling issue, we propose a tabu search heuristic which has recently been put forward and compared with other approaches [7] [8].

We present computational results and simulation results that illustrate the algorithm's runtime, variations in cumulative rewards, and whether AOI visits and continuous charging schedules are met. The key contributions of the paper are:

- Apply advanced Orienteering Problem in Tabu Search of Meta-heuristics for Optimal/Feasible Solutions
- Time Scheduling with Battery Constraints for vehicles to get the most team score (reward)
- Devise a way to reach the furthest AOI within battery constraints

The paper is organized as follows: In Section 2, we provide a comprehensive definition of the problem at hand. After, in Section 3, we introduce and elaborate on our proposed heuristic, offering insights into its key components. The simulation results, highlighting the outcomes and observations, are presented, and thoroughly discussed in Section 4. Finally, we draw conclusive remarks and insights in the concluding section, summarizing the key findings and outlining potential future directions for research and development.

III. Problem Definition

Consider a map spanning a 20 x 20 km^2 area, which includes 3 depots and 4 areas of interest (AOIs). The problem involves conducting 3 mission types over 72 hours: Persistent monitoring of a the road network, visiting predetermined mobile convoy points at a specific time, and visiting the AOIs. The setup includes 3 unmanned aerial vehicles (UAVs) and 1 unmanned ground vehicle (UGV). The UGV has two charging pads on top, enabling simultaneous wireless recharging of two UAVs. The UGV can recharge at depot A. The UGV's average speed is 4.5 m/s, but when the UAVs are charging on top, their speed reduces to below 1 m/s. Each UAV has an average speed of 15 m/s and can fly at this speed for 20 minutes, utilizing a 4000mAh 22.2V Li-po battery. Due to the lack of communication between the UGV and UAVs while the UAVs are airborne, a schedule must be determined in advance for the UGV and UAVs to meet at the next rendezvous point.

A UGV has operational constraints by the road network and needs the accurate setup of input data in a critical aspect of their functioning. Our approach involves the calculation of rewards for each coordinate, arranged in a connected graph to form a road network, as illustrated in Figure1. The road network in the figure diverges into three distinct directions from a central point. In practical scenarios, UGVs are typically assigned specific missions. However, in

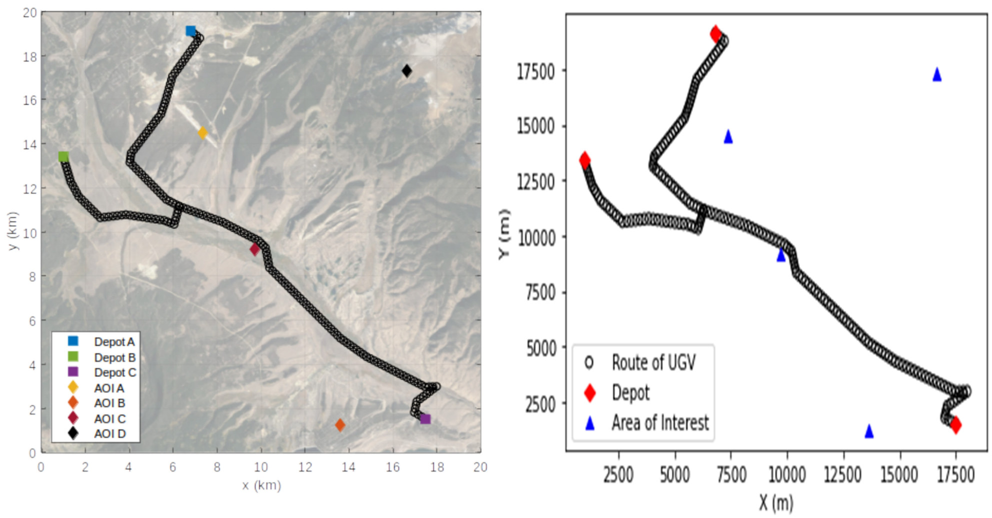

Fig. 1 Area coverage scenario within a 20 x 20 km map; 3 depots and 4 areas of interest are shown among a road network (black)

our current simulation, we have devised a unique strategy for the UGV's behavior. It departs from Depot B and, upon reaching the central point, undergoes a counterclockwise change in direction relative to the departure point, facilitating continuous forward movement.

Let V be the set of control points and E be the set of edges between points on V. Then $G = (V, E)$ is a complete graph. Each point i in V has a score $s_i \geq 0$ associated with it. The method of calculating scores s_i is described in detail in the reward section below. The initial starting point is vertex 1 and the ending point is vertex n, and these points are determined by UAVs and a UGV's rendezvous point considering the schedule. Because we have three UAVs and they all move within their battery constraints as planned, each UAV has different starting and ending points after the initial start. Each edge in E has a non-negative cost c_{ij} associated with it, where c_{ij} is the distance between the two points. For the M-member TOP, we need to find a set of M paths that maximizes the total team score.

A. Reward Definition (Team score)

Each point i's associated score is calculated based on the time difference between the last and the current visits, and the total node rewards contribute to the overall team score. The total score for a mission is the sum of the integrals of the scores of each node:

$$\Delta t = Time_{recent} - Time_{last}$$

$$\dot{S}_i^{(1)} = \frac{(\Delta t)^2}{30^2}$$

$$S = \sum_{i=1}^{N} \int_0^T \frac{(\Delta t)^2}{30^2} dt$$

where N is the total number of nodes, and T is the total mission duration. The integral is a piece-wise function with discontinuities at any time a node is visited(and thus that segment of the function has a new $t_{last,i}$ and $\dot{S}_i^{(1)}$ resets to zero at that point). This can be written in more compact notation given the series $\tau_0^i, \tau_1^i, \ldots, \tau_M^i$, where each UAV has different starting and ending points. After the initial start at the beginning of the mission (typically 0), τ_M^i is the time at the end of the mission (T), and $\tau_1^i, \ldots, \tau_{M-1}^i$ are the times when node i is visited, in ascending order. The team score then becomes:

$$S = \sum_{i=1}^{N} \sum_{j=1}^{M} \frac{1}{2700} \left(\tau_j^i - \tau_{j-1}^i\right)^3$$

We emphasize those real-world orienteering events contain many issues that are not addressed in this study or the cited literature.

B. Scheduling charging rate

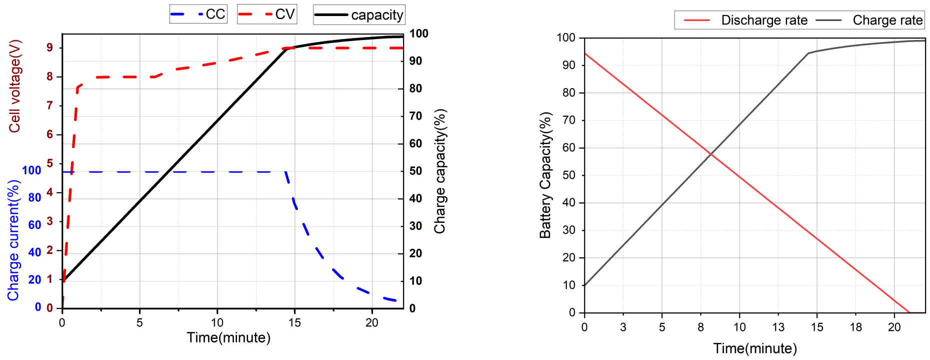

Fig. 2 UAV battery charging(left) and discharging(right) graph

The power transfer mechanism assumes a 10% allowance to accommodate battery voltage drop and other operational inefficiencies. The power transfer sequence involves a consistent current delivery from the initial charge until reaching 94.6% of the overall capacity, amounting to 94% of the remaining 90%. This phase operates at a 3.5C charge rate, equivalent to 14A. The duration required to transition from the 10% minimum power threshold to 94.6% spans approximately 14.4 minutes. Battery capacity until 94.6% is calculated: (4,000mAh - 400mAh) * 94% = 3,384mAh.

$$\begin{aligned} Charging\ Time &= \frac{Battery\ Capacity(Ah)}{Charge\ Current(A)} \\ &= \frac{3.38Ah}{14A} = 0.24\ hours = 14.4\ minutes \end{aligned} \tag{1}$$

Beyond 94.6% capacity, the charging process shifts to a constant voltage mode, initiating a slower charging rate. The battery charging data for the UAV is visually represented on the left side of Figure2. Regarding discharging behavior, the UAV maintains a maximum speed of 16 m/s. This translates to an anticipated maximum flight range of 18.32 km, achievable within 19.1 minutes of flight time, or a maximum endurance of 23.0 minutes for covering a distance of 13.52 km. Our assumptions are based on an average UAV speed of 15 m/s and an average discharge rate of 4.5% per minute at this speed. The battery discharging profile of the UAV is depicted on the right side of Figure2.

Based on the derived charging and discharging calculations above, Figure3 illustrates a graph demonstrating the recurrent cycle of the battery's discharge and subsequent recharge patterns. The graph shows the battery is discharged every minute from 100% and then it starts to be recharged promptly up to 94%, which aligns with a section conducive to swift recharging via constant current charging. Observing the charge and discharge within minute intervals revealed consistent patterns amidst the irregular charge and discharge sequences. The top-left graph displays the drone's recharge cycle, the drone discharges 2 minutes to 20 minutes after the start of the flight and recharges later. Based on recurring shapes within the data, the graph was divided into three types. The top-right graph indicates a recharge cycle after 2 to 7 minutes of the flight, while the bottom-left graph signifies recharging intervals after 8 to 14 minutes of the flight. The bottom-right graph portrays recharging intervals after 15 to 20 minutes of the flight. Notably, these graphs exhibit a repetitive charge/discharge cycle recurring every 6-7 minutes, consistently within a 1% error margin.

Leveraging this revelation, we formulated an iterative schedule for three UAVs, designed to cyclically repeat these patterns over 72 hours. This scheduled repetition ensures optimized battery charge cycles, maximizing operational efficiency and sustaining the UAVs' continuous functionality.

IV. A Meta-Heuristics approach

The Team Orienteering Problem (TOP) presents an advancement over conventional Orienteering Problems (OP), enabling multiple vehicles to concurrently gather rewards while commencing and concluding their paths from a common origin. Nevertheless, the conventional notion dictating a group of vehicles to traverse from one singular location to another was incompatible with our specific problem context, defined by the existence of only two charging pads moving in the mapped area. In light of this constraint, we devised a methodology that transcended the confines of fixed starting

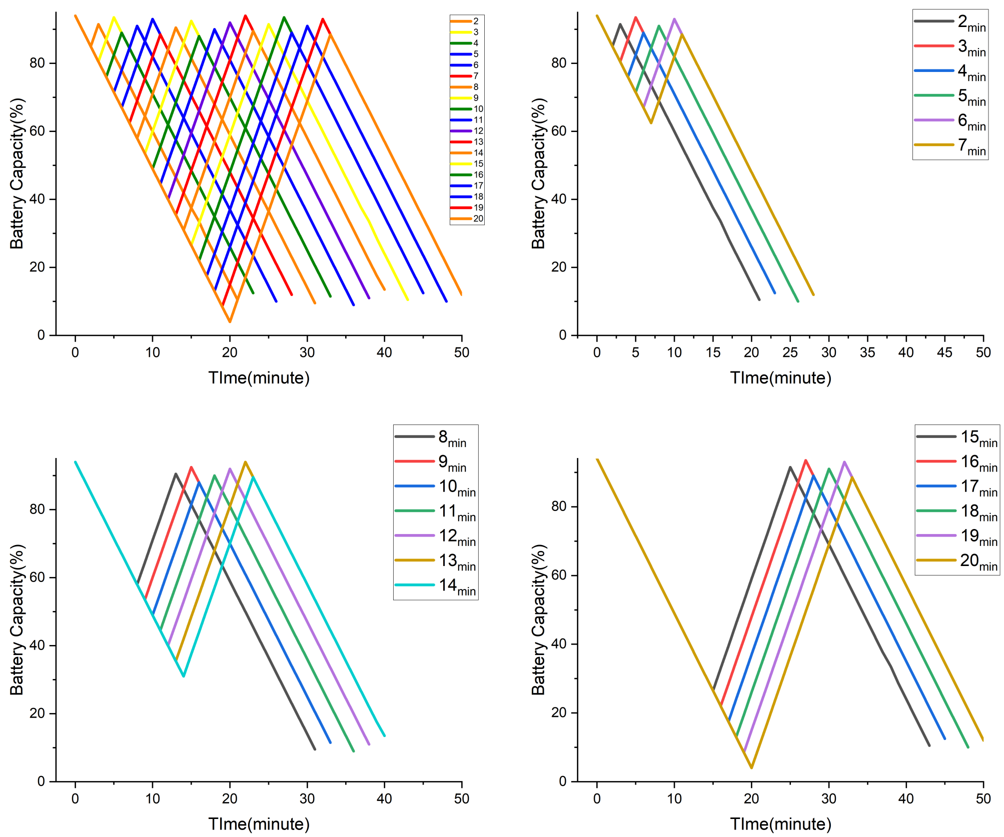

Fig. 3 UAV's recharging cycle after 2 to 20 minutes of flying.

and ending points, aiming to generate an array of team scores across multiple temporal instances. This adaptive approach allowed us to get feasible team scores extensively with prescribed movement between changing starting points and ending points. For an understanding of the distinctions between OP, TOP, and the suggested approach, please refer to Table 1.

In this section, we present a new meta-heuristic for the TOP that yields high-quality routes in a fast computation time and is simple to comprehend and apply. Our heuristic consists of four sequential stages: A greedy insertion heuristic, Improvement, Tabu-search, and Reattachment. Initially, the greedy insertion heuristic is employed to establish the primary routes. We define R_{TOP}, the set of main feasible routes that have the greatest team score. R_{NTOP} is the set of remaining routes except for R_{TOP}. To initialize the route, we draw an ellipse over the entire set of points by using the starting and ending points as the two foci and we only consider the points within the ellipse. The temporal limitation, denoted as T_{max}, corresponds to the major axis length of the ellipse, defined as the product of the UAVs' average speed and their flying duration.

Following this, iterative improvement steps are implemented to enhance the feasibility of the routes. Subsequently, the tabu-search heuristic is employed to navigate away from local optima. Finally, considering the feature of the given problem, a concluding reattachment step is integrated. This step allows for the merging of overlapping routes, particularly when similar routes are reiterated within a single route so that there is no confusion in the previous heuristic algorithm.

	Orienteering Problem(OP)	Team Orienteering Problem(TOP)	Meta-heuristic TOP
Number of vehicles	One vehicle	Multi vehicles	Multi vehicles
Number of trips	One-time trip	One-time trip	Multiple trips
Destination	Fixed	Fixed	Moving
Starting point	One point	The same point to all vehicles	Various points
Ending point	Another point	Another same point to all vehicles	Various points

Table 1 The differences between OP, TOP, and the new meta-heuristic

A. Greedy insertion heuristic

According to a predetermined schedule, we know the UAV's flight starting point and the rendezvous point (ending point) where subsequent UAV and UGV interactions occur. In a greedy way, we interlink target points. Our approach involves a step-by-step addition of points within the defined ellipse, spanning between the starting and ending points. The arrangement of the route is organized by using the two-opt process. When the results satisfy the temporal constraint denoted by T_{max}, it is classified as a path. As the initial route R_{TOP}, we identify the set of M paths with the highest team score; the $team\ score$ is the total of the scores of these paths.

The greedy insertion heuristic operates under the assumption that all points are positioned within a two-dimensional Euclidean space, a condition consistent across all test scenarios addressed in this paper. This heuristic initialization forms the foundation for subsequent optimization processes within the proposed meta-heuristic approach

B. Improvement

In the process of improvement, we hope to find a better route through repeated comparisons. We call it improved if UAV visits more targets, or if cost c_{ij} is reduced even after visiting the same number of targets.

1. Two points exchange

The two-point exchange operation involves the sequential selection of two points at a time from different two routes. By iterating from the first to the last point within the routes present in R_{TOP}, these points are then exchanged with corresponding points located in the routes from the first to the last within R_{NTOP}. Upon execution of this exchange, an evaluation is conducted to assess if the modification results in an augmented team score. If the exchange fails to yield a better movement in the route, we explore alternative feasible movements that minimize the cost. Conversely, if the route adjustment improves the team score, the modifications are added to the solution set. The objective of the two-point exchange operation is to continuously optimize the routes by exploring and implementing point exchanges that elevate the overall team score, thus refining the solution within the optimization framework.

2. One-point movement

The one-point movement operation involves the relocation of individual points within the predefined T_{max} ellipse. This process is about shifting one point, successively moving from the first point to the last within the ellipse, and positioning it ahead of another selected point. These points are chosen sequentially from the initial to the final points within both the R_{TOP} and R_{NTOP} routes. Upon executing this relocation, we check if this adjustment makes the team score better. When the team score demonstrates improvement consequent to the modification, the better solution is added to the resultant solution set. The one-point movement operation aims to iteratively refine the routes by examining individual point movements that potentially enhance the overall team score, thereby contributing to the ongoing optimization process within our proposed heuristic framework.

3. Route optimization (two-opt)

We use a two-step procedure in the route optimization stage to fix complicated routes. The basic 2-opt procedure consists of repeatedly switching two edges in a route to improve its quality. The main goal of this procedure is to reduce the length of R_{TOP} in order to make advantageous spaces for the insertion of points from R_{NTOP} into R_{TOP}. The 2-opt process's iterative structure makes it possible to continuously improve routes, which promotes a methodical decrease in route complexity. Through the strategic exchange of edges between routes, this optimization technique aims to reduce the complexity of the routes, which in turn helps to combine and improve R_{TOP} and R_{NTOP} in our developed heuristic algorithm.

4. Rearrange: Route refinement

Routine route optimization execution frequently faces certain obstacles that result in less-than-ideal routes and inefficiencies in operations:

- It often replicates a similar path without accounting for gaining coordinate points.
- Occasionally, it overlooks certain coordinates during transitions, creating gaps in the paths.
- Inefficiencies arise when coordinates are revisited repeatedly, resulting in back-and-forth movement

To address these issues, we present a crucial "Rearrange" procedure. By resolving the inefficiencies from earlier stages, this step is essential to increasing path effectiveness.

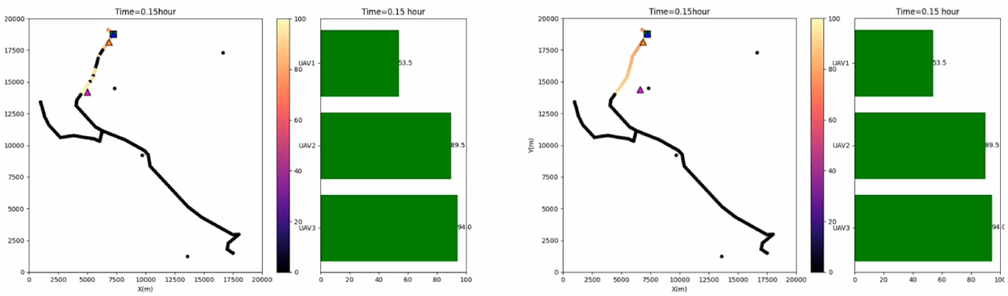

Fig. 4 Before(left) and after(right) rearrangement process

For instance, when examining destination points 1 and 2 in R_{TOP}, a comparison is made with the target data. An additional point "A" is located near the directional vector that runs from point 1 to point 2 in the target data if points 1 and 2 are not contiguous. Next, we place point "A" in between points 1 and 2. The altered path is then carefully examined to make sure the T_{max} condition is met. After the identified point "A" is satisfied, it is moved from R_{NTOP} and placed in the route between points 1 and 2. This strategic process aims to streamline route execution, notably reducing repetitive execution time while expediting the accumulation of higher team scores. By leveraging targeted point insertions, this method substantially enhances route optimization, culminating in improved efficiency within the algorithmic framework. We can see the importance of the rearrangement step in the Figure.4.

C. Tabu search (Re-initialization)

We employ a tabu search strategy in an effort to determine the best possible set of routes that maximize the team score. By using this method, we can identify differences within the structure of R_{TOP} without significantly changing its overall structure. We can depart from local optima thanks to this nuanced exploration, which makes it easier to work toward global optima.

A key of this approach involves a strategy where a specified number of k points are systematically removed from one point to the number of k points by its loop within R_{TOP}. Subsequently, this process is iterated k-times to remove additional points, which are then strategically inserted into paths within R_{NTOP}. This careful wrangling strengthens the solution set as a whole and facilitates the exploration of global optima.

Our goal is to iteratively improve the team score by applying these modifications and working toward the best possible outcome over time. The tabu search mechanism's re-initialization phase coordinates intentional changes, stepping up the search for the best possible solution inside the heuristic framework.

D. Reattachment

The heuristic algorithm is restricted in that it cannot return to coordinates that have already been visited within a path. This restriction guarantees path consistency, but it sometimes makes it difficult for the UAV to navigate around a target effectively, even when a nearby route provides sufficient access to the target. In order to overcome this difficulty, we add the "Reattachment" procedure at the end of our algorithm. The goal of this procedure is to greatly increase the efficiency of route creation by combining multiple acceptable routes into one.

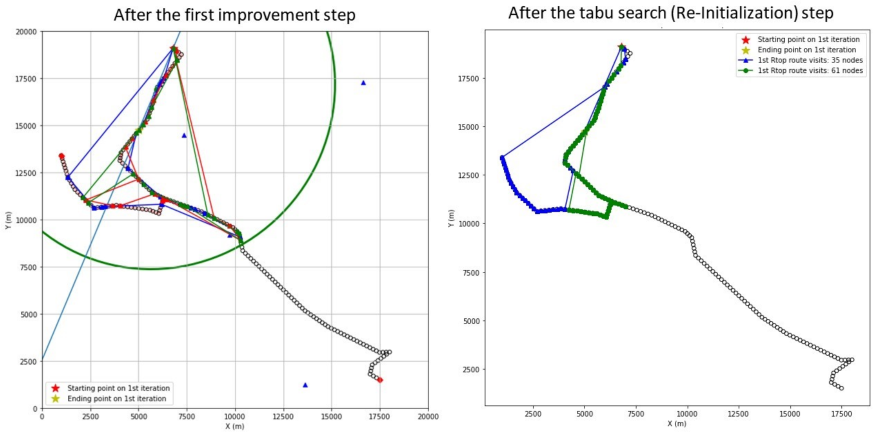

Fig. 5 Initial route(left) and after Tabu search(Re-initialization)(right)

The main goal of this phase is to eliminate the constraints of redundant paths. In the final route, when the UAV flies close to the target data, the "Reattachment step" changes UAV paths slightly adjusted to make it possible to fly to the target data even though it has been there in the same route. Because of this strategic integration, the UAV can navigate around targets more skillfully, improving both route efficiency and path planning capabilities. The capabilities of the solution set are increased by this algorithmic refinement, which goes beyond simple route optimization to include thorough path planning techniques, improving the UAV's navigation around targets. The final integration pseudo code encapsulating these procedures is shown in Algorithm 1.

Algorithm 1 A Meta-heuristic for TOP

Step 1. Initialization

Perform initialization

Set *team score* = team score of the initial solution

Step 2. Improvement

For $k = 1, 2, ..., K$

For $i = 1, 2, ..., I$

Perform two-point exchange

Perform one-point movement

Perform route optimization(two-opt)

Perform rearrange

If no movement has been made above, end I loop

If a better solution has been obtained, reset the $team\ score$

End I **loop**

If no new *team score* is obtained in 5 iterations, then go to **Step 3**

Perform Tabu search (reinitialize for k points)

End K **loop**

Step 3. Tabu search reinitialize and redo Step 2 once more.

Step 4. Reattachment

V. Simulation Results

This section discusses the results of our implementation. Simulation results for a team of 3 UAVs and 1 UGV were performed on a previously developed multi-agent simulator [1] in Python, on a Ubuntu 18.04 laptop computer with an Intel i7-7700HQ processor and 16 GB of RAM. The following assumptions were made:

- All UAVs are initially fully charged. They start from Depot B.
- UGV is assumed to have infinite energy and depots are not used presently.
- The landing and takeoff times of UAVs are not taken into consideration.
- The unmanned team was deployed with the proposed algorithm for a 72-hour period, during which different parts of the road network in the corridor scenario were visited.

Initially, a comparison between our proposed approach and Dijkstra's greedy algorithm will be delineated. Following this comparison, an in-depth presentation and discussion of the simulation results obtained from the 72-hour full simulation will be provided.

A. Algorithm comparison to Dijkstra's greedy algorithm

In this section, we compare the proposed meta-heuristic algorithm with Dijkstra's algorithm [9], a traditional greedy method (designed to find the shortest path in a weighted graph), in order to assess how well they perform in the problem domain. Dijkstra's algorithm uses a greedy approach that could result in local optima for our problem. On the other hand, our algorithm has benefits, particularly in situations where sequential decision-making is important.

A comparison of the two algorithms' respective performances is evaluated by looking at the simulation runtime and cumulative rewards. Table 2 explores how changing certain parameters—specifically, the quantity of targets and UAVs—affects the length of the simulation. The research looks into the effects of changing the number of targets, which are divided into subsets of 10, 20, and 30, similar to the changes shown in Figure 6. The quantity of UAVs is divided into groups of one, two, and three at the same time. Predetermined UGV driving routes and a constant UGV count are maintained as constants. This investigation aims to clarify the algorithms' performance, scalability, and efficiency while illuminating how flexible they are in various operational contexts.

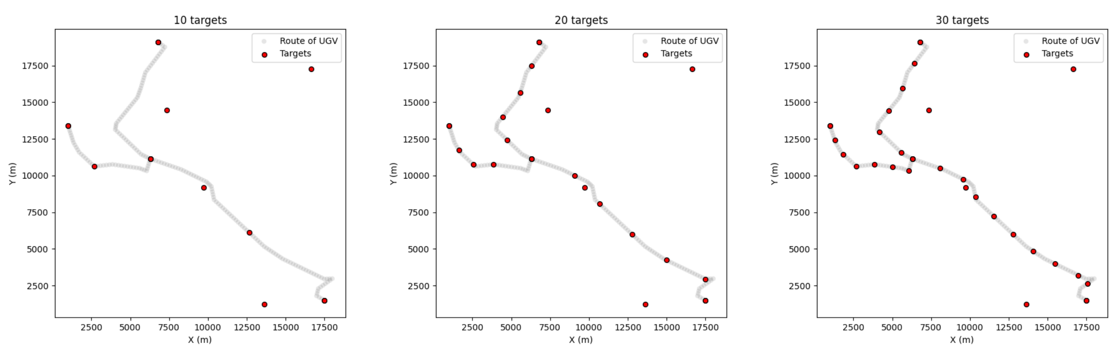

Fig. 6 Subsets of 10, 20, and 30 targets

In Table 2, the simulation results reveal a runtime of 104 minutes. Notably, the Greedy (Dijkstra's) algorithm exhibits a repetitive back-and-forth pattern due to its inherent limitations, and it couldn't find a feasible solution to this problem. Lacking a tabu-search mechanism to explore global optimization opportunities, this algorithm primarily relies on greedy strategies, restricting its exploration range considerably. This confined exploration range impedes its ability to efficiently navigate the extensive scope of this problem. Consequently, despite Dijkstra's algorithm demonstrating faster runtime performance compared to our proposed algorithm, its constrained exploration capability renders it less suitable for addressing the complexities inherent in scenarios with a larger number of targets. This constraint highlights how flexible and efficient our suggested algorithm is, especially when target quantities are larger, as our algorithm performs better and is better suited to handle the problem's extensive exploration requirements.

B. 72 hours simulation results

In the culminating simulation phase, our methodology successfully navigated a continuous sequence of 198 predetermined target coordinates, employing a coordinated fleet comprising three UAVs and one UGV. The entirety

Increase the range for specific number of targets							
		10 targets		20 targets		30 targets	
		Time	Visited targets	Time	Visited targets	Time	Visited targets
Meta -Heuristic algorithm	1uav+1ugv	0.105ms	8	0.191ms	19	0.213ms	24
	2uavs+1ugv	0.398ms	15	0.433ms	38	0.491ms	45
	3uavs+1ugv	0.516ms	22	0.578ms	58	0.613ms	67
Greedy Dijkstra algorithm	1uav+1ugv	0.002ms	6	0.003ms	15	0.003ms	23
	2uavs+1ugv	0.005ms	12	0.006ms	29	0.006ms	43
	3uavs+1ugv	0.004ms	17	0.006ms	32	0.007ms	59

Table 2 Algorithm comparison results

of this computational endeavor spanned a mere 8.454 milliseconds, attesting to the efficiency and computational prowess of our devised approach. This notable accomplishment highlights the remarkable potential and resilience of our approach, demonstrating its effectiveness in quickly investigating and covering a wide range of target coordinates within a demanding operational window. The efficient cooperation between the UAVs and UGV, as well as their average speeds (1 m/s for UGVs and 15 m/s for UAVs), made a substantial contribution to the thorough and rapid exploration completed in this demanding time frame.

Four important snapshots from our simulation results are summarized visually in Figure 7. Every segment of the screen displays the co-operation of UAVs flying along their assigned flight paths and UGVs moving between target locations. Each screen's left portion shows the precise movement of UAVs flying over the airspace as UGVs drive on the ground below. If any of the three UAVs are not visible in the picture, some of them can be seen wirelessly charging on top of the UGVs.

On the other hand, the right portion of every screen provides a summary of the battery condition for each of the three UAVs. In this case, a green battery status indicates that the UAVs are in active flight, while a red indicator indicates that the UAVs are recharging at specific charging pads that are located atop the UGV. But in the first simulation result, a clear observation appears: the first UAV starts flying while the other two UAVs, which started from a fully charged state, do not start flying. Because they are not participating in active flight operations, these surviving UAVs maintain their green battery status in this scenario.

These results not only underscore the effectiveness of our approach but also highlight its potential for practical applications across various domains, showcasing its adeptness in handling large-scale operations and its potential for real-world deployment in scenarios demanding extensive coverage and precise navigation within defined parameters.

VI. Conclusion

In this work, we addressed the complex problems of path planning and scheduling for multi-agent UAVs that have limited battery by utilizing the existence of UGV that can recharge them inside a pre-established coverage region, where unmanned vehicles were required to continuously visit given targets to maximize team score. However, an important consideration is the battery constraint associated with each UAV. Additionally, a UGV is employed to recharge the UAVs by following a route.

Our study explored an intricate issue that is closely associated with the Team Orienteering Problem (TOP), combining factors such as battery limitations, time scheduling, and area coverage. In this endeavor, our suggested algorithm, which is based on meta-heuristics, showed impressive performance in path planning, especially when faced with limitations imposed by UAV battery life and connected destinations confined by pre-planned routes. Similar work on TOP in literature did not focus on different time constraints and different landing conditions for each vehicle. So we proposed a comprehensive solution that encompasses four phases: 1) Greedy insertion heuristic, 2) Improvement to optimize the route, 3) Tabu-search, and 4) Reattachment. To validate the effectiveness of our approach, we generated a problem instance and a simulator that accurately represents the scenario, including coverage zones, areas of interest, and general surveillance routes. We also applied our algorithms to this problem instance and obtained promising results over 72 hours.

The developed method produced simulation and computational results that highlight its accuracy in time scheduling,

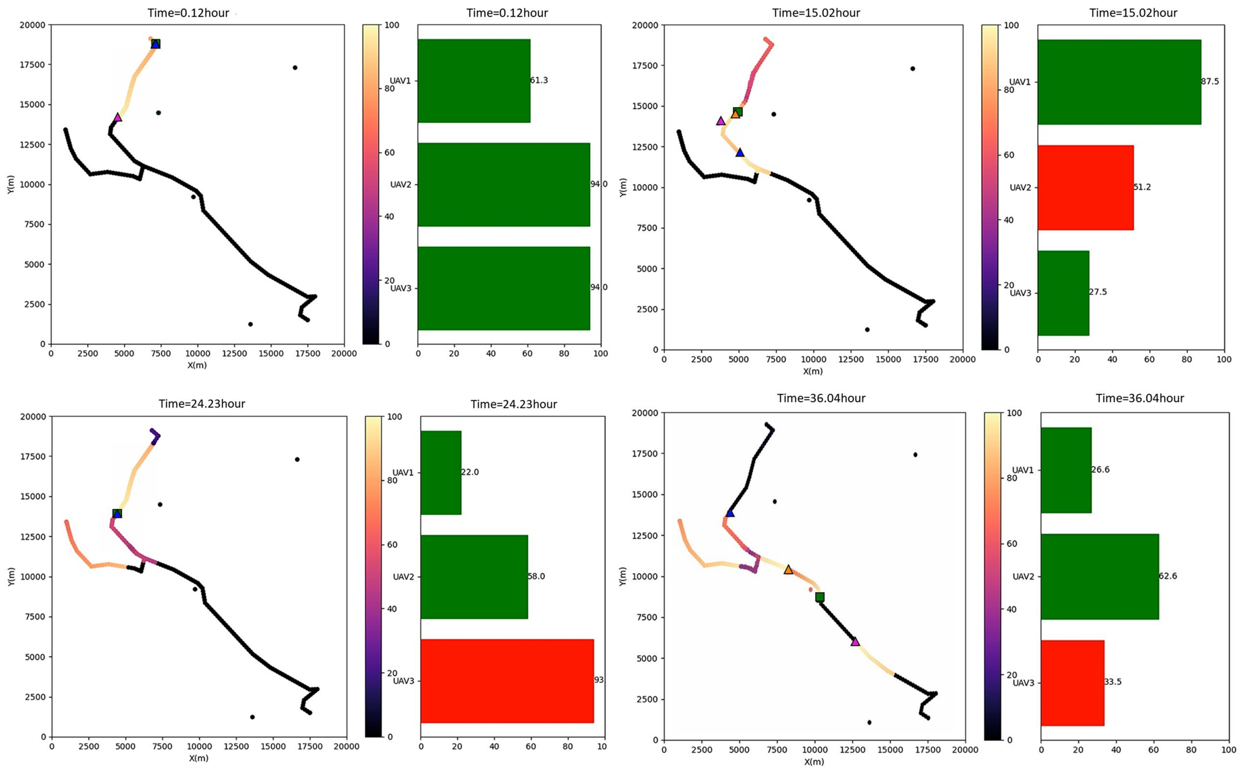

Fig. 7 Four Snapshots during the 72-hour simulation.

high computational efficiency, and a notable improvement in cumulative rewards. In particular, our approach enabled smooth synchronization between three UAVs and a UGV, leading to the navigation of a continuous series of 198 predefined target coordinates in an incredibly short computation time of 8.454 milliseconds. Moreover, our simulations conducted over a 72-hour period demonstrated the remarkable efficacy of our methodology, highlighting the concerted efforts of three UAVs that visited 38,962 targets with success. These successes attest to the flexibility, effectiveness, and scalability of our suggested methodology in handling the difficulties of in-depth investigation and accurate navigation within predetermined bounds.

Using sophisticated orienteering problem techniques within a Tabu Search-based meta-heuristic framework, scheduling tasks optimally under battery constraints to maximize team scores, and developing a novel technique that facilitates effective navigation to the farthest AOI within predetermined battery constraints are the main contributions of this research.

There are many future directions to further enhance and extend our research in the future. One issue is to deal with the situation that occurs in real life, where perfect information may not always be available. Future studies could investigate the incorporation of uncertainty factors about objects within the mapped area using new approaches like deep learning models to address this challenge. Furthermore, an essential component that needs to be taken into account in subsequent research projects concerns the real-world application and verification of our suggested methodology. This entails a more thorough examination that concentrates on possible collisions between the UAVs' flight paths—a factor that isn't specifically taken into account in our current study. Further research in these areas can open the door to more resilient, flexible, and workable solutions that go beyond

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