Abstract—Most consumer-level low-cost unmanned aerial vehicles (UAVs) have limited battery power and long charging time. Due to these energy constraints, they cannot accomplish many practical tasks, such as monitoring a sport or political event for hours. The problem of providing the service to cover an area for an extended time is known as persistent covering in the literature. In the past, researchers have proposed various hardware platforms, such as battery-swapping mechanisms, to provide persistent covering. However, algorithmic approaches are limited mostly due to the computational complexity and intractability of the problem. Approximation algorithms have been considered to segment a large area into smaller cells that require periodic visits under the latency constraints. However, these methods assume unlimited energy. In this paper, we explore geometric and topological properties that allow us to significantly reduce the size of the optimization problem. Consequently, the proposed method can efficiently determine the minimum number of UAVs needed and schedule their routes to cover an area persistently. We demonstrated experimentally that the proposed algorithm has better performance than the baseline methods.

I. INTRODUCTION

Teams of Unmanned Aerial Vehicles (UAVs) have many potential applications such as monitoring and responding to wildfires, crops inspection, or monitoring of crowds. A crucial challenge to fully realize such systems is that they operate autonomously and persistently over long periods of time. The limited flight endurance of off-the-shelf UAVs, typically between 15 and 30 minutes, and long replenishing time (usually twice as long as the flight time) strongly restricts the class of missions that they can carry out.

This paper addresses the questions of finding the minimum number of UAVs that can perform persistent covering on a given graph \( G \) as in Fig. 1. While persistent services provided by robots have been studied, this paper presents the first work that considers flight endurance, charging time and latency constraints in a unified framework. Under this framework, we present a suite of algorithms that pre-process \( G \) in order to identify feasible routes (defined as closed walks in Section III). Examples of these routes include segments of loops obtained via the Traveling Salesperson Problem (TSP), which is a classic graph search problem that seeks to visit all nodes exactly once with the lowest cost, and via a new tour that we call the maximum lollipop tour (due to its shape) as detailed in Section IV. Examples of maximum lollipop tours can be found in Fig. 4. The proposed framework avoids the computation bottleneck faced by previous methods that heavily relied on an Integer Programming (IP) solver to perform the heavy lifting. We show that, through these feasible routes, our method finds solutions from seconds to a few minutes instead of hours, even for graphs with hundreds of nodes.

II. RELATED WORK

The challenges faced to provide robotic persistent services have been extensively studied. When a task (e.g., reaching a goal, coverage, surveillance, or visiting regions at specific times) requires persistency, the issue of energy management becomes central. This issue has been addressed in both the hardware layer (e.g., charging stations [3] or swapping devices [5]) and the software layer (e.g., to determine charging station placement [7]) for Unmanned Aerial Vehicles (UAVs) [9], ground mobile robots [14], aquatic robots [24], or cabled robotic systems [25].

This section briefly reviews algorithmic approaches for persistent covering and surveillance. We categorize them into behavioral methods that can handle complex scenarios and optimization-based methods that provide theoretical guarantees.
A. Coverage & Energy-Aware Coverage

Coverage, this is, visiting all the regions of interest in an environment, was initially approached mostly as a geometric problem such as with the boustrophedon decomposition coverage [30]. The coverage techniques described below account for energy constraints.

1) Behavioral Methods: Several coverage algorithms incorporate the energy constraint although without guarantees on optimality. A method that uses a divide-and-conquer decentralized strategy [21] aims to maximize sensing while minimizing time and energy. Another method combines sensor-based reactive behaviors and dynamic feedback behaviors to produce smooth coverage paths [27]. One more approach encodes problem constraints, available energy, speed and weight through an energy function [9]. Another approach [17] incorporates available energy into the edges of an adjacency graph and poses the problem as the Traveling Salesperson Problem (TSP).

2) Optimization-based Methods: Some coverage methods that use optimization functions provide cost guarantees. In [31], an optimization function that reflects the global energy available to the group guides motions of robots that are assigned time-varying regions. Another approach [22] for the multi-robot case poses coverage as the capacitated arc routing problem to find the shortest tours that visit some arcs. Approaches that provide bounds on path cost include [16] which maps unknown environments into a cell decomposition as it is being covered, or [15] which partitions the environment into contour-connected parts where rectilinear motion is applied.

Encoding sites and battery levels in graphs is also common, such as [8] that poses the problem as the Generalized Traveling Salesperson Problem (GTSP) to find an optimal tour for a UAV to visit a set of sites in minimum time with support of UGVs that recharge them at rendezvous sites. A similar approach [7] incorporates a Boustrophedon cell decomposition. A related problem for multiple UAVs to collect maximum rewards under battery constraints has been posed as the k-STROLL problem (NP-hard) [32].

B. Surveillance & Persistent Surveillance

Surveillance is similar to coverage, but with timing constraints to ensure that regions are visited periodically. In persistent surveillance, the time between visits is either bounded or minimized. Another frequent goal is to minimize the maximum time between visits, also referred as age or latency.

1) Behavioral Methods: Some approaches seek to optimize usage of charging stations through behaviors based on the available energy. In one approach [1] a fixed energy threshold is set for a robot to recharge, while another approach [18] also considers available stations. Heuristics inspired in animal behaviors have been combined with thresholds in [24] based on whether the robot can reach a goal and a charging station. Another approach [33] is to weigh a trade-off between achieving coverage and maintaining a desired energy reserve. Work subdivision has been applied with helper robots ready to replace active robots [17] and extended with heuristics [20].

2) Optimization-based Methods: An approach to provide nearly continuous UAV escort formulates the problem as a Mixed Integer Linear Program (MILP) [12] to minimize energy consumption and, at the cost of optimality, incorporates uncertainties through heuristics. Similarly, a resolution complete algorithm [13] poses the problem as a constrained optimization to minimize mission time and time to reach a goal and approximates a discrete search on a graph whose nodes pair configurations with feasible trajectories.

Among the approaches that aim to minimize latency, we find one that formulates the problem as two linear programs (one for the speed controller and another to minimize latency that considers whether regions are or not in range) [34]. Another method poses this problem as a TSP where potential recharging points are nodes of a directed acyclic graph [28]. In both cases the trajectories of servicing UAVs predetermined.

In a more realistic setting, the UAV trajectory should be determined based on the target area and subject to various constraints. This has been addressed in [26] through a cell decomposition that tracks cell age and applies a combination of heuristics and optimization. Also, regions have been weighted on features of interest [35] to minimize the maximum weighted latency and to produce paths of length within a logarithmic factor of the optimal. A related problem is to determine the minimum number of robots. This is approximated in [29] within $O(\log n)$, $\rho$ being the ratio between maximum and minimum latency. The problem is posed as a Minimum Cycle Cover (MCCP) to partition the graph and, through a heuristic, to produce a set of walks that visit the maximal number of urgent vertices.

In contrast to these methods that use age or latency as a soft constraint and encode it in the objective function, we consider the latency as a hard constraint. We also explicitly consider the battery constraint in contrast to [29], [34], [35] or to [26] which consider it through reactive control policy modification.

III. Persistent UAV Covering

Persistent UAV service consists of the continuous operation of a swarm of UAVs which are dispatched from service stations to cover a set of tasks. At this level, task scheduling considers UAV flight travel distance as a measurement of energy consumption, although flight dynamics can be included in energy modeling. Our goal here is to minimize the number of UAVs while all requesting cells for covering tasks are visited.
A. Problem Definition

We define the persistent covering problem as a graph covering problem, in which each node can be a sub-region of an area to be serviced. Given an undirected graph $G = \{V,E\}$, where each node $v \in V$ has a value $t_v$ indicating the elapsed time since the last service. The value $t_v$ is also known as the ‘age’ of the node $v$. Each node $v$ also has a deadline $T_v$, so at all time we need to ensure that $t_v < T_v$ within the planning horizon $H = \infty$. That is to say, every node must be serviced at least every $T_v$ time units. The weight of each edge $e \in E$ indicates the energy needed to travel on $e$. Such a graph $G$ can be constructed using methods such as PRM [36].

Let each UAV $r$ have a limited available amount of battery level (i.e., a budget $b_r$ of flying time), and the battery needs to be recharged at a charging station before the next mission. Because the time needed to charge the batteries is almost always longer than the flying time for most consumer-level UAVs, let us assume that the time to get fully charged be $B_r > b_r$.

Let us now consider the case of a single UAV. The behavior of this UAV would simply be:

\[
\text{cover} \rightarrow \text{recharge} \rightarrow \text{cover} \rightarrow \text{recharge} \rightarrow \ldots,
\]

and this is repeated until all nodes are covered. It is likely that some regions may require service before this UAV is fully charged, thus, persistent covering cannot be achieved. Therefore, given a persistent covering problem $G$, we would like to answer the following questions. First, how many UAVs are needed? Next, can $k$ UAVs persistently cover $G$? If so, find a schedule for these $k$ UAVs.

In this paper, we consider a fully predictable and simplified system: (a) All nodes have the same deadline $T_v$, (b) all UAVs have the same battery power $b$, (c) all UAVs need to be charged for the same amount of time $B$ regardless of the remaining power upon arriving the charging station, and (d) all UAVs start the mission from a single charging station. Although it is straightforward to relax assumptions (a) and (b), they keep our discussion simpler. To this end, we answer the following question: What tours in a given $G$ admit the minimum number of UAVs needed to solve it?

Note that, for the rest of the paper, we use the term tour interchangeably with closed walk, where a walk in graph theory is defined as a sequence of nodes that may be repeated multiple times and a closed walk is a walk starting and ending at the same node, which in this paper is the charging station.

B. An Overview of the Proposed Method

The problem of persistent covering has been traditionally formulated as a large combinatorial optimization problem that can be solved using Integer Programming (IP) solvers [12]. We aim to reduce the size of the IP by introducing a new formulation. The key to achieve this goal is through the extraction and filtering of feasible routes from the graph $G$ before the IP solver is evoked. Under this framework, we now briefly discuss a new approach that will be used to design multiple methods in the following section.

Let $\tau_i = \{v_0,v_1,\ldots,v_k,v_0\}$ be a tour that starts and ends at a charging station $v_0$, where $v_i \in V$. An example of such a tour is a solution to TSP of $G$. It is also possible to partition $\tau_i$ into multiple segments $S_j \subset \tau_i$ and create more tours. We say that a tour is feasible if a UAV can complete the tour before its battery is depleted, i.e., $time(\tau_i) \leq b_r$, and, for each node $v_i$ along the tour, the time to reach $v_i$ is less than $T_i$. To define our optimization problem, we first define the binary decision variable $x_i$ of the model:

\[
x_i = \begin{cases} 
1 & \text{if } \tau_i \text{ is assigned to a UAV} \\
0 & \text{otherwise}
\end{cases}
\]

Now, we define the scheduling constraints as follows. Let $P_0$ be a set of tours that pass through vertex $v$ before $t_v \leq T$. To ensure that the assigned tours cover the graph $G$, the following constraint is defined for each vertex $v$ of $G$: $\sum_{\tau_i \in P_0} x_i > 0$.

Since we offload the other constraints, in particular the energy constraints, to the computation of the feasible tours, the number of constraints in this optimization problem is significantly smaller, namely $|V|$. The remaining step to ensure that the IP can be solved efficiently is to enforce the sparsity of the model, which depends on the length and the number of the tours.

The objective function can be defined in many ways. This paper mainly focuses on minimizing the total number of UAVs needed:

\[
\text{Minimize } \sum_i x_i. \tag{1}
\]

However, the objective function can be easily modified to minimize the total travel time in terms of distance travelled on the assigned tours: $\text{Minimize } \sum_i x_i \cdot time(\tau_i)$. Moreover, we can also minimize the overlapped coverages: $\text{Minimize } \sum_i x_i \cdot card(\tau_i)$, where $card(X)$ is the cardinality of set $X$.

The IP problem formulated here is indeed a set cover problem, which admits some known strategies for increasing computational efficiency, such as for low-frequency systems in which polynomial time approximation is possible. To ease our discussion, Table I summarizes the introduced symbols. In the rest of this paper, we will focus on how the feasible tours can be determined and computed efficiently from $G$.

IV. Our Method

A. Problem Analysis

1) Persistent Coverage of Small Graphs: Let us first analyze the case of one UAV on a small graph $G$. We denote this UAV $r$, and we say that $G$ is small if a TSP $\pi$ of $G$ can be toured by $r$ in a time at most $b$, i.e.,
time(π) ≤ b. We say that a node n can be reached by r if the path from the charging station to n takes time less than b/2. Given a small graph G and a UAV r, we say that r can persistently cover G if and only if

1) All nodes in G are reachable in b/2 time.
2) T ≥ B + b

The first constraint is obvious. If the UAV cannot reach a node in b/2 time, it cannot be back to the charging station in b time to continue its service. The second constraint T ≥ B + b can be derived from the fact that, given a TSP tour π of G, r can visit all nodes in minimum time time(π), namely the time needed for r to finish traveling on π. Therefore, after a node is visited, the second time that the node is visited will take B + time(π), which must be less than T to ensure continuous service of the node. Consequently, if the UAV can visit all nodes of G without charging, i.e., time(π) ≤ b, it is necessary and sufficient that T ≥ B + b.

This simple analysis leads to several additional observations. First, time(π) ≤ b implies that the location of the charging station can be an arbitrary node in the graph, i.e., the selection of the charging station does not affect the UAV’s ability to cover G persistently with one UAV. Second, if the first constraint is violated, i.e., some node in G is not reachable by a UAV, then G cannot be persistently covered even with more UAVs, unless additional charging stations can be added. Therefore, when k > 1 UAVs are considered, the first constraint must remain satisfied.

For most consumer-level off-the-shelf UAVs, b is around 15 to 25 minutes and B is between one to two hours, thus B >> b. Therefore, even for small graphs, the assumption that the service deadline T ≥ B + b is too restrictive for many real world problems. Naturally, we now consider the case that b ≤ T ≤ B + b. This is the case that one UAV fails to cover G persistently. Because T ≥ b, all nodes in G can be visited by the UAV r before r returns to the charging station and before the deadline. However, B is too large, so we will need to send another UAV r′ to refresh some nodes before r returns is fully charged. Therefore, for k > 1 UAVs, we can send one UAV for each T time unit. To consistently cover G, we will need k = [(B + b)/T].

The last case is d ≤ T ≤ b, where d < b/2 is the travel time from the charging station to the furthest node in G. In this case, some nodes might have their timer t expired before the UAV r returns to the charging station. Therefore, this is the case that multiple UAVs must be sent simultaneously to cover the graph G. In Section 4.2 we will discuss several strategies to handle this case.

2) Persistent Coverage of Large Graphs: When a UAV takes time more than b to complete a TSP tour of G, we say that G is large. While the first condition that all nodes in G should be reachable in b/2 time must remain true for large graphs, the second condition T ≥ B + b is insufficient for a single UAV to persistently cover large graphs since, by definition, the nodes cannot be toured in a time at most b. In the cases that time(π) > b and a single UAV, T will need to be significantly larger than B + b. In the worst case, when every node in G takes the UAV b/2 time from the charging station, T will need to be at least |V|(B + b) to ensure persistent coverage of G by a single UAV. In essence, we must identify subgraphs {G_i} so that each subgraph G_i ⊂ G is small, namely its TSP can be toured by the UAV in b time, and \bigcup G_i = G. These subgraphs can then be covered by a single UAV if T ≥ card({G_i})(B + b).

More realistically, if T is smaller than card({G_i})(B + b) and we would like to provide persistent service over G, then we need to determine what the value of k, the number of UAVs, must be. If b ≤ T ≤ B + b, then we will need k = [(B + b)/T] UAVs for each subgraph and therefore card({G_i}) · k UAVs to cover G.

B. Creating Subgraphs

When the nodes in graph G have deadline T that is less than the flying time b or when the graph is large, we must partition G so that multiple UAVs must simultaneously work on different partitions to cover G persistently.

Let us first assume that two UAVs are available. Our goal is to create two sets G_1 ⊂ G and G_2 ⊂ G so that G_1 ∪ G_2 = G. It is also clear that there must be at least 2 nodes of G belonging to different sets. Therefore G_1 \ G_2 ≠ ∅ and G_2 \ G_1 ≠ ∅. In addition, to ensure that both G_1 and G_2 can be persistently covered, we need time(π_1) < min(T,b) and time(π_2) < min(T,b), where π_1 and π_2 are the TSP of G_1 and G_2, respectively. Similar to the questions we asked, given a G, we would like to know the minimum number of UAVs needed and the subgraphs G_i for each UAV.
In general, our graph partition problem can be formulated as the set covering problem which can be stated in a general way as follows. We are given a set of requirements or characteristics (say R) that must be satisfied entirely by a set of activities (say A1, A2,..., Am) whose union equals or "cover" the entire set of requirements, and a cost associated with each activity. Although an activity Aj may cover only a subset of R, a combination of some activities Aj’s may cover R. The set covering problem is to determine a combination of activities Aj that can collectively cover all the requirements while minimizing a certain objective function. The solution of a set covering problem is defined as a feasible solution with a minimal total cost. An optimal solution is a feasible solution with a minimal total cost. The discussion for the remaining of this section focus on how to define a set of valid activities.

1) Creating Subgraphs by Segmenting a TSP of G: We find a TSP π of G then partition π into k segments so that for each segment Sj = {u0, u1, ··· , um} ⊂ π, the following criteria are satisfied

\[ d(u_0) + \text{time}(S_j) \leq T, \]
\[ d(u_0) + d(u_m) + \text{time}(S_j) \leq b. \]

A segment Sj of π that satisfies these properties is called a valid segment and can be converted to valid tour τj = {v0 ∼ u0, u1, ··· , um ∼ v0}; recall that v0 is the charging station node. Examples of valid segments extracted from a single TSP are shown in Fig. 2 Notice that a valid segment starting from a node further way from v0 must be shorter than those started closer. Finding these valid segments can be done greedily by starting from finding the longest S0 and iterating on the remaining TSP π \ \ S0. This approach is efficient but might not provide us an optimal solution that minimizes the number of UAVs needed.

Alternatively, we can find a longest valid segment Sj that starts from each node vi ∈ π. Segments that start at vi but shorter than Sj will be superseded by Sj during the optimization, thus are ignored. There will be |V − 1| of these segments therefore |V − 1| closed walks \{τi\} from the charging station v0. Let \(τ^*_i\) be a subset of \(τ_i\) that can be visited before time T. That means, \(τ^*_i\) must include the vertices \(\{v_0 ∼ u_0, u_1, ··· , u_m\}\) and sometime a few nodes from the returning path from \(u_m\) to \(v_0\). Then our goal is to find the smallest subset of the tours \{τi\} so that their corresponding \(τ^*_i\) can cover the entire G. This approach guarantees the optimal solution and can be solved using 0-1 integer linear programming.

A major drawback of this approach is that we are restricted to a given TSP. Even for small environments such as those shown in Figs. 8 and 9, there exist many optimal TSPs. Consequently, some tours might be better than the others and yield fewer number of UAVs needed to persistently cover the graph. A simple remedy is to obtain n TSP paths and find the optimal subset from the n|V − 1| tours. However, this dramatically increases the computational cost while it is unclear what n should be. In the method described in the following section, we explore a method that does not depend on the given tour.

To ease our future discussion, we call these three TSP-based methods: tsp-greedy, tsp-lp-1, tsp-lp-n, that use a greedy method, an IP solver on \[|V − 1|\] longest segments originated from every node of a TSP, and an IP solver on n\[|V − 1|\] longest segments originated from every node of n TSP, respectively.

2) Maximum Lollipop Tours of G: To relax from the constraint of searching on the given TSP tour(s), in this section, we discuss an approach that detects a special type of closed walk called lollipop tour from the graph G. A lollipop tour is a closed walk that consists of a short path from the charging station to a node \(v_i\) and a cycle in a neighborhood of \(v_i\) that has larger geodesic distance from the changing station than \(v_i\). Examples of lollipop tour can be found in Fig. 3.

To construct a lollipop tour for a node \(v_i\), we first determine an initial cycle in a lollipop tour at \(v_i\) from a small neighborhood of \(v_i\), e.g., two nodes adjacent to \(v_i\) that are further away from the charging station, as shown in Fig. 3(a). From the initial cycle, we iteratively expand the cycle until the cycle has grown too large and violated the requirements. In each iteration, we add a new node that is incident to the nodes in the cycle and is not closer to the charging station than the adjacent nodes in the cycle. Three of such examples are shown as the red dots in Fig. 3(b). The lollipop tour that cannot be further expanded without violating the constraints is called maximum lollipop tour. Only max lollipop tours will be considered for graph covering.

As shown in Fig. 3(b), a cycle is likely to have more than one way to expand. In this case, we exhaustively include all possible ways to expand the cycles but only keep the cycles that are unique. A pair of cycles are unique from each other if they don’t share exactly the same nodes. Uniqueness can be detected efficiently through hashing. In Fig. 4 we show 4 maximum lollipop tours created from the example in Fig. 3.

Note that due to the nature of the proposed expansion process, a maximum lollipop tour might still be optimized and expanded. If there is no new node that can be added to the cycle, we can still extract a
TSP from the nodes included in the current cycle. The process can be repeated if the new cycle can still absorb more nodes. Otherwise, the last valid cycle is kept.

Now that we determined all maximum lollipop tours for every node in the graph, we then find a smallest subset that covers the graph. However, the number of unique maximum lollipop tours is exponential to the length of the cycle. Exhaustively enumerating all unique maximum lollipop tours is not practical for large graphs. A simple heuristic to overcome this is by gathering enough tours so that all nodes have at least one tour passing through.

We observe that the number of maximum lollipop tours for far away nodes is small because the length for the cycle must be small and these tours are more critical as these are the only few tours that the UAVs can take to reach these nodes and return safely. On the contrary, the nodes near the charging station have many such tours but many of them are not critical.

Based on these facts, we sort all the nodes in descending order in terms of the distance to the charging station. All max lollipop tours are determined in this order until all nodes in G have at least one tour passing through to ensure a solution exists from max lollipop tours. Because it is possible that the entire graph is covered by max lollipop tours without the max lollipop tours from those nodes near the charging station, we add a fixed number n of such tours for the nearby nodes, where n is a user parameter. Algorithm 1 summarizes this idea. Note that the subroutine MAX LOLLIPOP TOURS(G, v_i) finds all unique lollipop tours from v_i while MAX LOLLIPOP TOURS(G, v_i, n) terminates when n tours have been identified. We use n = 10 throughout the experiments reported in Section V.

Algorithm 1: Min-Max Lollipop Tour Coverage

Result: minimum number of maximum lollipop tours {τ_i} covering G = \{V, E, b, B, T\}

```plaintext
Sort V in descending order in distance to v_0;
Let L = ∅;
for v_i in V do
  if L does not cover G then
    L = L ∪ MAX LOLLIPOP TOURS(G, v_i);
  else
    L = L ∪ MAX LOLLIPOP TOURS(G, v_i, n);
end
{τ_i} = find smallest subset of L that covers G using IP;
```

Fig. 3. (a) An initial lollipop tour created from the red node. (b) This initial tour can potentially be expanded to include one of the three incident red dots. The empty dot is not a candidate because it is only adjacent to a node in the tour and the grey dot is not a candidate because its closer to the charging station than that of its incident nodes in the tour. Three expanded tours are shown in the right. The maximum expanded tours are shown in Fig. 4.

Fig. 4. Four maximum lollipop tours from the same node, which has 215 unique maximum lollipop tours; b = 5K, B = 11K and T = 6K.

3) Creating Subgraphs from shortest paths in G: To compare to the proposed methods in terms of computational cost and solution optimality, we build a baseline method using the Dijkstra tree D that encodes all shortest paths from the charging station to the other nodes in G. From D, we can extract |E|−|V−1| loops, namely a loop for each edge in G that does not belong to D. We then keep the valid loops that satisfy the constraints (Eqs. 2 and 3). Note that it is also possible to have a trajectory for an UAV that has identical departure and return paths. There will be |V−1| of such paths, thus the total number of closed walks is |E|. We then find an optimal subset sum from the valid loops of these |E| closed walks using an IP solver.

V. Experiments

Minimizing the number of UAVs needed for covering a graph persistently has strong economic incentives. The maintenance cost and coordination complexity can be dramatically reduced even if the scheduler can reduce a single UAV. Therefore, in our experiments, we compare the number of UAVs produced by the proposed methods using various graph sizes and types. We implement all methods described in Section III in C++ and use Concorde as the TSP solver and GLPK as the integer programming solver. The running times reported in this section are collected from a laptop computer. All experiments reported in this section are setup as illustrated in Figs. 1 and 2. We refer the reader to the accompanying video for better visualization.

We first test our implementations on the environments shown in Figs. 8 and 9 with battery time = 5,000 seconds and charging time = 11,000 seconds. The battery time is roughly a half of the charging time. Fig. 5 presents the results from the 6 × 6 field illustrated in Fig. 2 by varying the latency constraints from 2500 seconds to 20,000 seconds. It’s obvious that when the latency constraint is larger fewer UAVs are needed. The baseline method that extracts tours using Dijkstra tree requires many more UAVs than the TSP-based methods in all cases. For all TSP-based methods, we use Concorde to extract 20 unique TSP tours from the
environments.

![Graph](image)

Fig. 5. Number of UAVs needed to cover a 6x6 environment with various latencies. Data reported as an average of 10 trials. In all cases, \( b = 5,000 \)s and \( B = 11,000 \)s.

Fig. 6. Number of TSP tours considered (x-axis) vs. number of UAVs needed (y-axis).

Fig. 7. A 10x10 environment with a PRM [36] graph.

![Table](image)

The benefits of the hybrid method can be further seen when the structure of the graph is less regular as in roadmaps obtained for probabilistic methods. In Fig. 7 we see that, again, TSP LP2 performs on par with TSP LP. While the hybrid method requires a significantly lower number of UAVs. Finally, persistent covering a 20 × 20 field is demonstrated in the accompanied video. The hybrid method takes around 13 minutes to determine that 75 UAVs are needed.

![Image](image)

VI. CONCLUSION

This paper presented the first method that can determine the minimum number of UAVs needed for persistently covering under the constraints of flight endurance, battery charging time and time between population, thus resulting in a better solution.
revisits. The proposed framework identifies segments of TSP and lollipop tours with respect to the energy constraints. A subset of these tours then forms the minimum cover of the graph that satisfies the latency constraint. The experiment results show that the proposed framework produces schedules that require significantly fewer UAVs than the baseline methods. Field work will be conducted in the near future to deploy and evaluate our schedules on Unmanned Aircraft Systems. It should be noted that, even though all examples in the paper are solved in less than a few minutes, the time complexity of the presented method is still naturally exponential to the size of the graph. Our future work will relax assumptions made in this paper to include multiple or mobile charging stations, heterogenous UAVs, and more realistic energy and kinodynamic model of the UAVs.

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TABLE II
EXPERIMENTS ON A 10X10 ENVIRONMENT WITH VARYING LATENCY.

| Latency | Dijkstra | Tree Greedy | TSP Greedy | TSP LP | Hybrid |
|---------|----------|-------------|------------|--------|--------|
| N       | K        | time        |            |        |        |
| 20000   | N        | 32          | 10.00      | 7.60   | 7.50   | 7.00   |
| N       | 9.90     | 10.00       | 8.90       |        |        |
| 29      | K        | 30          | 9.00       | 7.70   | 7.50   | 7.00   |
| 177     | N        | 17.90       | 1.98       | 11.80  |        |        |
| 1.57    | 1.67     | 1.83        | 1.81       | 2.45   |        |
| 3000    | N        | 167         | 66.80      | 55.80  | 50.20  | 45.67  |
| 1.67    | 1.84     | 1.81        | 1.94       | 1.97   |        |
| 2500    | N        | 177         | 114.90     | 88.30  | 76.50  | 76.33  |
| 1.57    | 1.67     | 1.84        | 1.81       | 1.97   |        |

Note: In all cases, b = 5000 and B = 11000. N is the number of UAVs and K is the number of tours needed for persistent covering, and “time” is running time in seconds. All data are the average of 10 runs.

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