Hierarchical Coordination of UAVs for Dynamic Task Assignment in Large-Scale Traffic Surveillance Missions

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Abstract: This paper presents an hierarchical coordination architecture for a fleet of UAVs dedicated to road traffic surveillance over large urban areas. The system is built around a central drone, acting as a coordinator, which is responsible for monitoring the status of the fleet and dynamically assigning surveillance tasks in response to reported traffic events. To ensure scalability and responsiveness, our architecture combines a spatial clustering mechanism to partition mission area and distribute drones accordingly, with a receding horizon task assignment (RHTA) strategy within each sub-region. The fleet coordination requires designing specific trajectories for the central drone to ensure communication within the fleet and periodic updates of the surveillance information. This hybrid approach enables adaptive, region-based task allocation while preserving a global overview through the coordinator. Simulation results highlight the relevance and flexibility of the proposed coordination scheme when addressing dynamic and large-scale surveillance scenarios.

1 INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have emerged as a promising solution for traffic surveillance (Khan et al., 2020), (Butilă and Boboc, 2022). Thanks to their mobility, flexibility, and relatively low deployment cost, UAVs can provide rapid situational awareness over wide areas, complementing fixed infrastructure such as Closed-Circuit TeleVision (CCTV) (e.g. by (Kurdi, 2014)) or road sensors (Bernas et al., 2018), (Akhtar and Moridpour, 2021).

Road traffic surveillance is essential for enhancing urban mobility (Christodoulou and Kolios, 2020), ensuring safety, and responding effectively to incidents (Kiema et al., 2025). However, the real-time monitoring of large-scale road network remains a challenging task due to the complexity, and dynamic nature of urban traffic.

Many approaches have been suggested to use fleet of UAVs for coordinated surveillance application focusing on the multi-UAV task assignment, (Alqefari and Menai, 2025). These methods vary in terms of architecture (centralized, decentralized or hybrid), mission assumptions (static or dynamic task appearance), and task allocation logic such as greedy, clustering, auction-based. The coordination strategies in surveillance applications generally categorized into offline and online schemes. Offline approaches assume full knowledge of all tasks beforehand and often rely on formulations such as the multi-Traveling Salesman Problem (TSP) as proposed by (Luo et al., 2021); or on the Vehicle Routing Problem (VRP) in (Wang and Sheu, 2019). Online strategies can be time-triggered, based on periodic updates, or event-driven, where actions are triggered only when specific events occur. Event-driven coordination is particularly suited for dynamically assigning tasks as new incidents are reported or mission constraints evolve during execution. Several techniques have been explored for this purpose, including greedy nearest-neighbor dispatching, clustering-based assignment (Ma and Chen, 2023), and market-based methods (Ham and Agha, 2007).

Receding Horizon Task Assignment (RHTA) has emerged as a promising alternative for dynamic task allocation, capable of balancing reactivity and foresight. They consist in solving a local optimization problem over a finite prediction horizon, executing only the first action, and updating the plan at each decision step. Applications of RHTA have been proposed in both decentralized (Peterson et al., 2020) and centralized (Ma and Chen, 2023), (Cassandras and Li, 2003) frameworks, often integrating task allocation

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and trajectory planning into a single loop.
Among centralized online approaches, cloud-based architectures have received particular attention in recent years (Allahbakhsh et al., 2019). In such systems, task assignment decisions are made by a remote cloud server with access to global mission data. These architectures offer computational scalability and facilitate fleet-wide optimization, but rely heavily on continuous connectivity. As a result, they may suffer from latency and reduced robustness in scenarios with intermittent communication or infrastructure limitations. An alternative approach consists in hierarchizing the fleet and attributing specific features to one of the UAV, (Xu et al., 2021). This enables fast and flexible deployment at the cost of designing different trajectories depending on the role attributed to the UAVs.
Despite these advances, relatively few approaches decouple high-level task assignment from low-level control, or address centralized RHTA in event-driven scenarios triggered by real-time incident reports. In the following, we propose a centralized coordination strategy that explicitly separates high-level task allocation from low-level trajectory execution. Task assignment is handled by a Receding Horizon Task Allocation (RHTA) mechanism, which is triggered upon the appearance of new Points of Interest (PoIs). A PoI refers either to a predefined location associated with a potential traffic incident requiring surveillance, or to a real-time incident report provided by traffic applications such as Waze (Waze Mobile Ltd., 2024).
A Model Predictive Control (MPC) scheme (Rawlings et al., 2017) is employed for the guidance of the fleet, with mission-specific objectives. The coordinating UAV applies MPC to optimize its repositioning strategy based on fleet connectivity, enabling effective supervision and continuous information updates. Meanwhile, the other UAVs use local MPC controllers to efficiently reach and monitor their assigned PoIs, with surveillance-focused criteria; the detailed implementation of the other UAV control is discussed in a separate study.
The key contributions of this work are as follows:
- **Architectural separation of concerns**: The RHTA handles task decisions at the fleet level, while each UAV locally manages its motion through a low level MPC. This modularity enhances scalability, flexibility and facilitates implementation.
- **Hierarchical control structure**: A high-altitude UAV supervises the fleet and acts as a coordination hub, continuously repositioning itself to maintain communication with as many spotter UAVs as possible, while simultaneously managing task distribution and global awareness.
- **Event-driven dynamic assignment**: Unlike periodic planning schemes, our RHTA mechanism is activated only upon the appearance of new PoIs, typically reported through real-time traffic platforms such as Waze. This makes the system reactive and communication-efficient.
- **Hybrid planning approach**: We combine an initial offline spatial clustering of PoIs for load balancing and regional assignment, with an online, event-driven task reassignment mechanism based on RHTA, allowing UAV tasking to adapt dynamically to real-time incident reports and fleet availability.
The remainder of this paper is organized as follows. Section 2 formulates the problem and presents the UAV model and mission constraints. Section 3 details the proposed coordination strategy, including the initial spatial clustering, the online task assignment mechanism, and the central UAV's route planning strategy. Simulation results and evaluation metrics are provided in Section 4. Finally, Section 5 concludes the paper and outlines future work directions.

2 PROBLEM STATEMENT

We consider a UAV-based surveillance system for road traffic monitoring over a large urban area called $\mathcal{Z}$. In this zone, **N** points can be distinguished as Points of interest (PoI) which correspond to locations of incident occurences. They are located at $X_i\ (x,y)$ for $i = 1,\ldots,\mathbf{N}$. An *a priori* probability of incident $P(IC)$ and a class index indicating the type of incidents most likely to occur are associated to each PoI. The area is represented as a graph $\mathcal{G}(X_i, \mathcal{R}_{i,j})$, where nodes correspond to *PoI* locations and $\mathcal{R}_{i,j}$ represents the connecting line between nodes.
The fleet of drones is structured hierarchically. A central UAV, denoted uav_0, operates at high altitude and is in charge of coordinating the fleet, managing the task assignments, and maintaining the global awareness of the mission state. The remaining drones, referred as spotter UAVs, uav_i, $i = 1,\ldots,n_d$ operate at a lower altitude and are responsible for observing the assigned *PoI*s using a downward-facing camera for incident detection. Each spotter drone has physical and operational constraints, including a bounded velocity v_{max}, limited flight autonomy t_{limit}, and a hovering time above the *PoI*, t_h. Communication between the central UAV and the spotter UAVs must be maintained throughout the mission, subject to a maximum communication range constraint R_{com}.
The mission objectives are threefold: *(i)* to maximize the coverage of high-priority PoIs under time and energy constraints, *(ii)* to dynamically reassign tasks in

response to evolving mission conditions, *(iii)* to maintain a scalable and modular coordination framework suitable for large-scale deployments.

2.1 UAV Model

We consider a simplified discrete-time kinematic model of an UAV operating in a three-dimensional environment. The dynamics is modelled as a double integrator, which is discretized for practical integration.
The state vector at time step k is defined as $\mathbf{x}_k = [\mathbf{p}_k, \mathbf{v}_k]^T \in \mathbb{R}^6$, where the UAV position is given by $\mathbf{p}_k = [x_k, y_k, z_k]^T$, and $\mathbf{v}_k = [v_k^x, v_k^y, v_k^z]^T$ denotes its linear velocity in the 3D coordinates in the reference frame.
The control input $\mathbf{u}_k = [u_k^x, u_k^y, u_k^z]^T \in \mathbb{R}^3$ corresponds to the accelaration command in each direction. The discrete-time dynamics over a sampling period of time Δ_t are given by eq. 1:

$$\mathbf{x}_{k+1} = \begin{bmatrix} \mathbf{p}_k + \Delta_t \cdot \mathbf{v}_k + \frac{1}{2}\Delta_t^2 \cdot u_k \\ \mathbf{v}_k + \Delta_t \cdot \mathbf{u}_k \end{bmatrix} \tag{1}$$

which is expressed in the state-space form as:

$$\mathbf{x}_{k+1} = A\mathbf{x}_k + B\mathbf{u}_k \tag{2}$$

with:

$$A = \begin{bmatrix} I_3 & \Delta_t I_3 \\ 0 & I_3 \end{bmatrix}, B = \begin{bmatrix} \frac{1}{2}\Delta_t^2 I_3 \\ \Delta_t I_3 \end{bmatrix} \tag{3}$$

For the MPC design, we take into account the physical limitations of the drones such as maximum accelerations, as well as the control rate bounds to ensure feasible and safe trajectories by avoiding aggressive maneuvers.

3 GLOBAL APPROACH

The surveillance targets, referred to as Points of Interest (*PoI*s), correspond to locations on road segments or intersections associated with a non-zero probability of incident occurrence. These PoIs are assumed to be known *a priori*, either extracted from historical data (e.g. open datasets reporting road traffic statistics (ONISR, 2024)) or derived from traffic applications such as Waze, which provide real-time alerts. The coordination strategy unfolds in two layers: *(1)* Initial deployement layer section 3.1 and *(2)* Reactive task allocation layer section 3.2. Moreover, the description of the central uav route planner is given in section 3.3.

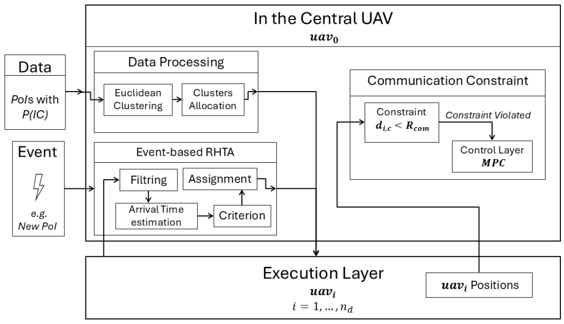


Figure 1: Functional architecture of the proposed coordination strategy, executed within the central UAV uav_0. The system combines data-driven clustering, event-triggered task reassignment, and communication-aware control to supervise a fleet of spotter drones (uav_i).

3.1 Spatial Clustering for Regional Assignment

To efficiently distribute surveillance tasks across the UAV fleet, we perform an initial spatial partitioning of the Points of Interest (PoIs). Let $\mathcal{C}$ be the set of known *PoI* positions X_i, and let n_d be the number of required spotter UAVs, each with a limited flight endurance $t_{\text{limit},j}$. Let T_i denote the estimated time required for a UAV to travel from the center of the area to PoI i, hover for observation, and return. The total required time to cover all *PoI*s is approximated by $\sum_{i=1}^{N} T_i$, which allows estimating the minimum number of UAVs needed as:

$$n_d = \frac{\sum_{i=1}^{N} T_i}{\min(t_{\text{limit},j})} \tag{4}$$

The set $\mathcal{C}$ is then partitioned into n_d spatial clusters (Rokach and Maimon, 2005) using the standard k-means algorithm briefly reminded here. We minimize the intra-cluster variance:

$$\mu_i = \arg\min_{\mu_i} \left(\sum_{i=1}^{n_d} \sum_{X_j \in \mathcal{C}_i} \|X_j - \mu_i\|^2 \right) \tag{5}$$

where μ_i denotes the centroid of cluster $\mathcal{C}_i$ and X_j the PoI locations. Initialization is done by randomly sampling n_d centroids within the area. Each PoI is assigned to the closest centroid, and they are updated iteratively as:

$$\mu_i = \frac{1}{|\mathcal{C}_i|} \sum_{X_j \in \mathcal{C}_i} X_j \tag{6}$$

Once the clusters $\mathcal{C}_i$ are formed, each characterized by its centroid μ_i, the candidate cluster i is allocated to the closest available UAV based on euclidean distance between the UAV position X_{uav} and the cluster centroid μ_i:

$$j^* = \arg\min_j \|\mu_i - X_{uav_j}\| \quad \text{with } i, j = 1, \ldots, n_d; \tag{7}$$

j^* is the UAV assigned to cluster C_i. This clustering serves as an initial spatial decomposition of the mission space, allowing each uav_i to focus on a specific region. Within each cluster, the initially known PoIs are scheduled using a route optimization strategy enabling each UAV to plan an efficient surveillance path. The detailed design and evaluation of this task allocation process have been addressed in a different study. Within a cluster, the uav_i performs three main tasks: *(i)* hovering above PoIs to collect observational data, *(ii)* collecting and updating incident information based on visual inspection, and *(iii)* rallying PoIs during the mission. When a traffic incident is detected or reported in real time; the central UAV manages the integration and reassignment of these new tasks online using a Receding Horizon Task Allocation (RHTA) mechanism.

3.2 Online Receding Horizon Task Allocation

During the mission, an event which can be defined as the dynamic appearance or disappearance of PoIs, for instance upon receiving a real-time traffic incident report through an external source such as Waze. In addition, onboard observations performed by the spotter UAVs during their hovering tasks can also lead to the confirmation, creation, or removal of PoIs, dynamically updating the incident probability map. These PoIs, which were not part of the initial spatial clustering, require prompt integration into the mission plan. To handle such events, the central UAV triggers an Online RHTA mechanism. This mechanism is activated only while an event is detected rather than following a fixed time schedule, thereby making the system event-driven. At each triggering event, the central UAV evaluates the status of all spotter UAVs to determine which one is the most suitable to handle this new task i.e reaching and overseeing the newly reported or removed PoI. The online RHTA follows the steps below:

(1) Pre-filtering of PoI: A PoI is integrated into the task allocation process only if its incident probability $P(IC)$ exceeds a predefined threshold $P(IC)_{\min}$. The threshold is not fixed globally, but varies depending on the average number of incident reports in the corresponding region. The adaptive thresholding ensures that areas with low traffic activity are not penalized by an overly strict filtering, while busy areas are protected against noise from uncertain or weakly confirmed reports. This pre-filtering step avoids disturbing the UAV fleet coordination due to uncertain or weakly confirmed incident reports.

(2) Filtering of available UAVs: UAVs currently executing a hypothesis test (i.e., hovering over a PoI to validate the presence or absence of an incident) are excluded from the candidate list. For UAVs rallaying a PoI, we compute their estimated time of arrival $t_{\text{ETA},j}$. A UAV is considered interruptible only if this value exceeds a switching threshold t_{switch}. This avoids reassigning a drone that is near completing its current mission.

(3) Computation of effective arrival time: For each eligible UAV j, we compute the total time before it can reach the new PoI:

$$t_{\text{eff},j} = t_{\text{free},j} + t_{\text{path},j} \tag{8}$$

where $t_{\text{path},j}$ is the estimated time needed to reach the new *PoI* from its future position and $t_{\text{free},j}$ is given by:

$$t_{\text{free},j} = \begin{cases} 0, & \text{if the UAV is idle,} \\ \frac{d_{rem}}{\mathbf{v}_{average}} + t_h, & \text{if rallying a PoI.} \end{cases} \tag{9}$$

where t_h is the hovering time, d_{rem} is the remaining distance form the current location to the PoI, and $\mathbf{v}_{average}$ is the average drone velocity.

(4) Scoring Function. A global cost function is evaluated for each candidate UAV:

$$f_j = \alpha \cdot t_{\text{eff},j} - \beta \cdot P(IC) + \gamma \cdot \left(1 - \frac{t_{\text{residual},j}}{t_{\text{limit},j}}\right) \tag{10}$$

where:
- $t_{\text{eff},j}$ (eq. 9) represents the effective time for UAV j to finish the current mission, reach the new PoI and start observations. It promotes responsiveness by encouraging the assignment of tasks to UAVs that can act quickly.
- $P(IC)$ is the probability of incident occurrence at the PoI, which gives priority to higher-risk locations by reducing the overall cost.
- $t_{\text{residual},j}$ is the UAV's remaining flight time, and the term $\left(1 - \frac{t_{\text{residual},j}}{t_{\text{limit},j}}\right)$ penalizes UAVs with limited remaining energy to favor tasking UAVs with sufficient endurance.

The weighting coefficients α, β, and γ allow balancing the relative importance of responsiveness, incident criticality, and energy robustness. After the pre-filtering step based on the minimum reliability threshold $P(IC)_{\min}$, the coefficient β can be tuned to reflect that all considered *PoI*s have already met an acceptable reliability level.

(5) Assignment: The UAV j with the lowest cost is selected and assigned to the new PoI (eq. 11):

$$j^* = \arg\min_j f_j \tag{11}$$

The selected UAV updates its trajectory accordingly via its low level MPC controller, integrating the new task into its current flight plan.

3.3 Route Planner and Control Layer

The uav_0 implements a connectivity-aware MPC strategy that proactively adapts its position within the surveillance area. The objective is to maximize the communication robustness with the uav_i while minimizing unnecessary motion.

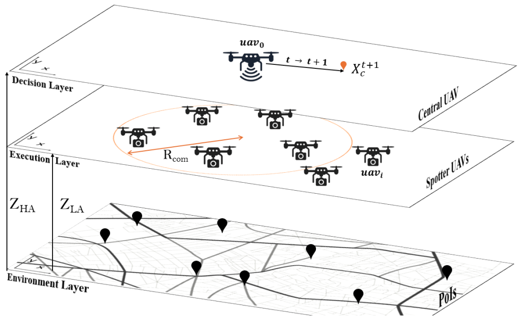


Figure 2: Representation of the UAV coordination architecture.

3.3.1 Connectivity-Based Cost Function

As information is fed back from the spotter drones to the central, it is essential to ensure uninterrupted communication between the uav_0 and uav_i for a designated period of time t_{com}. The connectivity-based function J_c qualifies the expected level of communication in the fleet over a prediction over the prediction horizon N_p (eq. 12). This cost penalizes large distances between uav_0 and uav_i, especially for those that have not communicated recently (weighting ratio eq. 13).

$$J_c = \sum_{k=0}^{N_p-1} \left\| \mathbf{x}_c(k) - \frac{1}{\sum_{i=1}^{n_d} \rho_{w,i}(k)} \sum_{i=1}^{n_d} \rho_{w,i}(k)\mathbf{x}_i(k) \right\|^2 \tag{12}$$

where :

- $\mathbf{x}_c^k = [x_c^k, y_c^k, z_c^k]^T$, $\mathbf{x}_i^k = [x_i^k, y_i^k, z_i^k]^T$ represents respectively the predicted position of the central UAV and the spotters at step k,
- $\rho_{w,i}^k$ is the dynamic weight prioritizing uav_i being disconnected for a longer period of time (eq. 13),
- R_{com} is the communication constraint.

$\rho_{w,i}$ is defined as:

$$\rho_{w,i} = \left(\frac{t_{elapsed,i}}{t_{com}} \right)^2 \tag{13}$$

where $t_{elapsed,i}$ is the time since the last communication with uav_i, and t_{com} is the maximum allowed time without communication.

Eq. 13 ensures that the uav_0 encouraged to reposition toward uav_i at risk of losing contact, or which has not been in contact for a long time.

3.3.2 Event-Triggered Repositioning Strategy

For energy consumption consideration, the central drone (uav_0) has to move only when the communication is degraded within the fleet (eq. 15). At each time step, we monitor the elapsed communication time ($t_{elapsed,i}$) for each spotter. The repositionning is trigerred based on a temporal indicator t_{conn} defined as:

$$t_{\text{conn}} = \frac{1}{n_d} \sum_{i=1}^{n_d} t_{elapsed,i}^{\varepsilon} \tag{14}$$

The parameter $\varepsilon \geq 1$ is a tuning exponent that increases the influence of longer delays (outliers). A new optimization problem is solved, when eq. 15 is satisfied.

$$t_{\text{conn}} > t_{com}^{\lambda} \tag{15}$$

where t_{com} denotes the maximum tolerable period of time without communication with uav_0, and $\lambda \in [0, \varepsilon[$ is a parameter. The two tuning parameters choice must be done following the condition $\varepsilon > \lambda$. The sensitivity of the repositioning mechanism depends directly on the choice of these two parameters, which control the threshold and responsiveness of the triggering condition.

3.3.3 MPC Connectivity Optimization Problem

When repositioning is needed (eq. 15), the optimization criterion (eq. 16) allows to determine its further actions :

$$\min_{\mathbf{u}(0:N_p-1)} J_{\text{MPC}} = J_c + \sum_{k=0}^{N_p-1} \mathbf{u}(k)^T R \mathbf{u}(k) \tag{16}$$

subject to the system dynamics (eq. 2) over the prediction horizon N_p and following constraints:

$$\mathbf{x}_c^{\min} \leq \mathbf{x}_{c,k} \leq \mathbf{x}_c^{\max} \qquad \forall \quad k \tag{17}$$

$$\mathbf{u}^{\min} \leq \mathbf{u}_k \leq \mathbf{u}^{\max} \qquad \forall \quad k \tag{18}$$

where:

- $\mathbf{u}_k$ is the control input at step k,
- R is a positive definite matrix weighting control effort minimization,
- $\mathbf{x}_c^{\min}$ and $\mathbf{x}_c^{\max}$ represent the lower and upper bounds on the state vector. The position limits correspond to the size of the environment and the velocity limits are set according to the maximum speed allowed along each axis.

The optimization problem (eq. 16) is solved using a Quadratic Programming (QP) solver.

4 SIMULATION AND RESULTS

The effectiveness of the proposed coordination architecture is presented in this section.

4.1 Simulation Setup

The surveillance zone is modeled as a square area of $1500 \times 1500\ \text{m}^2$, within which a set $\mathcal{C}$ of Points of Interest (PoIs) is randomly distributed. Each PoI is associated with 2D coordinates X_i, a probability of incident occurrence $P(IC)$, and a type of incident. Three incident classes are considered in the scenario: *accident*, *traffic congestion*, and *pothole*.
All UAVs follow the dynamic model defined in section 2.1. The spotter UAVs have a limited flight time of $t_{\text{limit}} = 30$ min and a sensing range defined by a Field of View (FoV) of 30 m. Communication between drones is constrained by a maximum range $R_{\text{com}} = 300$ m.
Given the autonomy of the UAVs and the area to supervise, four low-altitude spotter drones uav_i, flying at a fixed altitude $Z_{LA} = 20$ m, and one high-altitude central UAV uav_0 (blue line in fig. 3) flying at $Z_{HA} = 30$ m. When assigned to observe a PoI, a UAV hovers above it for a fixed duration $t_h = 120$ s. In all simulations, the number of PoIs is set to $\mathbf{N} = 55$, with random placement and incident probability sampled uniformly. $t_{elasped,i}$ of all uav_i are also randomly initialized to test the response of the system and $\varepsilon = 3$, $\lambda = 2$.
For simplicity and clarity of analysis, the simulations are carried out in a two-dimensional environment.
We aim to illustrate the effectiveness of the centralized task assignment strategy, the benefits of spatial clustering, and the role of the central UAV in maintaining communication and coordination efficiency.

4.2 Results Analysis

To validate the proposed coordination architecture, we conducted a series of numerical simulations. We first present a single, illustrative mission scenario to provide a qualitative understanding of the system's behavior. Subsequently, we present a comprehensive Monte Carlo analysis to quantitatively assess the strategy's robustness against various forms of uncertainty.

4.2.1 Illustrative Mission Scenario

To provide a qualitative overview of the system in operation, a representative mission is depicted in Fig. 3. In this scenario, the fleet is tasked with surveying a set of randomly distributed *PoI*s, with dynamic events occurring during the mission.The simulation is initialized with one spotter UAV exceeding the communication timeout threshold t_{com} (fig. 4), thereby stress-testing the event-triggered repositioning mechanism. As a result of the presented approach (fig. 3), we get more than 70% spatial coverage with the flight time constraint. A spatial coverage means that all *PoI*s (static and dynamic) were visited. Furthermore we have an average detection-to-service delay below 70s for all visited *PoI*s. With a low number of repositioning of the uav_0 $N_{rep} = 3$, the event-triggered strategy proves its effectiveness while keeping the fleet connected for 90% of the mission time (fig. 4). N_{rep} varies accordingly to t_{com}. More strict t_{com} (fig. 4b) leads to more repositioning $N_{rep} = 7$. This first result shows as that the central-UAV repositioning underline that the central MPC (section 3.3.3) is invoked only when connectivity genuinely degrades, thereby saving global energy.

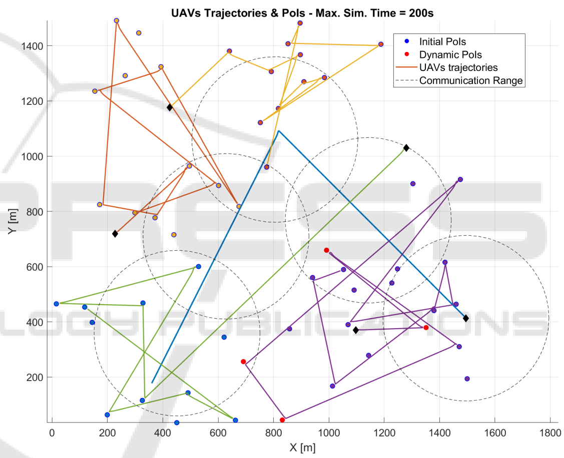
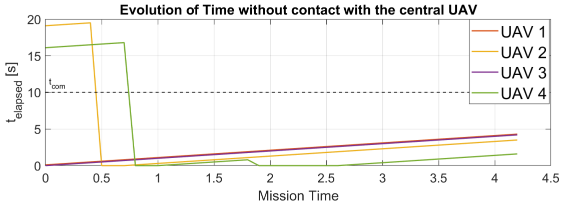


Figure 3: Mission overview – Executed trajectories of the central UAV, with 4 uav_i. The central UAV periodically re-positions to maximise fleet connectivity while spotters visit their local PoIs. The circle represents the communication constraint R_{com}.

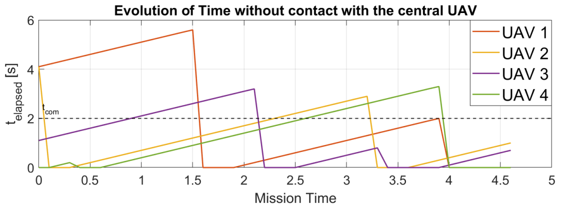
4.2.2 Monte Carlo Robustness Analysis

While a several and isolated run illustrates feasibility, a comprehensive Monte Carlo analysis was performed to rigorously evaluate the system's performance under uncertainty. The analysis consisted of 100 simulation runs for each of two distinct scenarios, each designed to challenge a specific aspect of the architecture's robustness.

Scenario A:
This scenario addresses the challenge of deployment uncertainty. The initial spatial disposition of the spotter UAVs was randomized in each of the 100



(a)



(b)

Figure 4: Time since last contact for each spotter UAV during the mission. The dashed horizontal line marks the communication limit $t_{\text{com}} = 10$s in (a) and $t_{\text{com}} = 2$s in (b). Spikes above this threshold trigger the MPC-based repositioning of the central UAV; the quick return below the limit confirms that connectivity is promptly restored.

runs. The objective is to verify that the strategy's performance is not contingent on a favorable or manually selected starting configuration, but is robust across a wide spectrum of initial fleet deployments.
The results for scenario A (fig. 5) provide strong quantitative evidence of the strategy's robustness. The system's effectiveness is confirmed by a high fleet-wide connectivity rate, which exceeded 95% in over 70% of the tested scenarios. This high performance was achieved with significant efficiency, requiring a mean of only 1.76 repositioning maneuvers per mission, which validates the parsimonious nature of the event-triggered approach. Furthermore, the system demonstrated consistent reactivity, allowing a reliable and prompt recovery from communication loss.

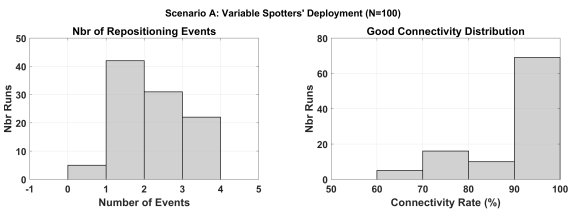


Figure 5: Performance Distributions for Scenario A (Variable Spotters' Deployment).

Scenario B:
This scenario is designed to evaluate the system's robustness to mission uncertainty. For each run, the entire map of PoIs was randomly regenerated. This tests the ability of the initial spatial clustering algorithm to handle varied mission geometries and ensures that the RHTA mechanism is effective across different task distributions.
The analysis of the performance metrics across all 100 simulations reveals that the coordination architecture demonstrated strong resilience when faced with these more complex mission geometries. Theses results are shown in fig. 6. First, the system adapted more frequently, as evidenced by the mean number of repositioning events, which rose to 2.05 per mission. This indicates that the controller actively compensated for the increased fleet dispersion and furthermore that the controller's reactivity remained consistent. Most significantly, the primary mission objective was largely achieved. In over 80% of cases, the good connectivity rate remained above 95%, proving that even with an imperfect initial assignment, the dynamic repositioning strategy can effectively compensate to ensure fleet cohesion.

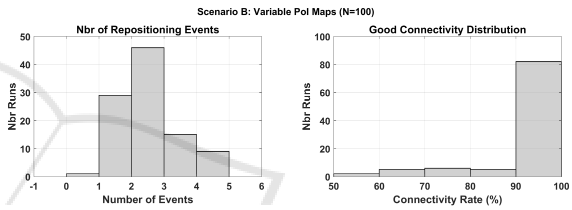


Figure 6: Performance Distributions for Scenario B (Variable PoI Maps).

4.3 Selective Desactivation Study

Although a full numerical ablation is left for future work, we provide here a qualitative assessment of the role of each module in the architecture.

- Without Spatial Clustering: All UAVs are allowed to compete for all PoIs. As a result, task overlap increases, especially in dense zones, and UAVs frequently select conflicting or suboptimal assignments. This leads to greater trajectory overlap and higher risk of conflicting trajectories. Moreover, the absence of regional decomposition reduces overall scalability and requires additional logic for conflict resolution, which is avoided in our modular approach.

- Without RHTA: The task assignment process is static per cluster and does not adapt to real-time incident appearance. UAVs will visit a pre-assigned lists of PoIs, regardless the appearance of new incident and the availability of nearby UAVs. This may result in slower response times for and missed opportunities to effectively oversee a new PoI. Although spatial clustering ensures workload balance at the start, the lack of reactivity penalizes the system under dynamic conditions.

5 CONCLUSION

In this paper, we proposed a centralized coordination architecture for UAV-based traffic surveillance, combining spatial clustering, event-driven task allocation, and a communication-aware guidance strategy for the central UAV. The proposed system is designed to remain scalable and responsive to real-time incident reports, while ensuring communication robustness and balanced task distribution across the fleet.
A particular focus was placed on how the central UAV uses a receding-horizon task assignment strategy to dynamically select its next positioning target, prioritizing fleet-wide communication. The resulting motion plan is executed via a Model Predictive Control scheme that guarantees constraint satisfaction and smooth trajectory tracking.
Further work includes design of spotters trajectories to follow the road maps to enhance patrolling efficiency and methods for realistic detection and identification of new PoIs.

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