Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 4, 2751-2767
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i4.6650

Intelligent UAV swarm scheduling algorithm for urban inspection task

Haoyu Xu[1*]
[1]Department of Physics and Mathematics, University of Toronto, Canada; xhy000017@gmail.com (H.X.).

Abstract: This research develops an intelligent UAV swarm scheduling algorithm to optimize urban infrastructure inspection processes by minimizing inspection time while ensuring comprehensive coverage. We formulate the challenge as a mixed integer non-linear programming problem and propose a decomposition approach addressing three critical components: structure-specific path planning, market-based task allocation, and conflict-free scheduling. Our methodology integrates these components through an iterative process within a hybrid centralized-decentralized architecture tailored for urban environments. Simulation results demonstrate that our algorithm reduces inspection time by 35% compared to single-UAV approaches while maintaining 98% coverage completeness. The approach exhibits 40% improved energy efficiency in limited-battery scenarios and polynomial-time computational complexity that scales efficiently with increasing swarm size. The algorithm typically converges within 3-5 iterations to near-optimal solutions. The proposed framework successfully balances inspection quality and resource efficiency while adapting to urban-specific challenges, including GPS degradation, obstacle avoidance, and structural complexity. Structure-specific inspection patterns significantly enhance efficiency across different infrastructure elements. This research advances UAV-based infrastructure monitoring capabilities, offering potential benefits for maintenance planning, public safety, and urban resilience. The computational efficiency makes the solution suitable for deployment on resource-constrained platforms typical in UAV applications.

Keywords: *Energy efficiency, Infrastructure monitoring, Optimization, Path planning, Scheduling algorithm, Task allocation, UAV swarm, Urban inspection.*

1. Introduction

The assessment of urban infrastructure integrity poses significant challenges for municipal authorities and engineering firms worldwide. Traditional inspection methodologies relying on manual techniques frequently encounter limitations regarding accessibility, cost-effectiveness, safety considerations, and temporal efficiency [1]. The emergence and evolution of unmanned aerial vehicle (UAV) technology has revolutionized infrastructure monitoring capabilities by enabling remote visual and sensor-based examination of structures that would otherwise require scaffolding, specialized equipment, or service interruptions [2]. Contemporary UAV platforms equipped with high-resolution cameras, thermal sensors, and LiDAR systems can capture comprehensive structural data from previously inaccessible perspectives, substantially enhancing inspection thoroughness and defect detection capabilities [3]. Despite their transformative potential, conventional single-UAV deployment scenarios face inherent limitations when tasked with examining extensive infrastructure networks or complex urban structures. Foremost among these constraints is operational duration, as battery capacity restrictions typically confine mission lengths to 20-30 minutes, necessitating multiple deployments for comprehensive assessment of large structures [4]. Additionally, single-vehicle approaches create single points of failure, introducing vulnerability to equipment malfunctions or environmental disruptions [5]. These limitations have catalyzed research interest in multi-UAV collaborative systems—often

History: Received: 7 February 2025; Revised: 11 April 2025; Accepted: 15 April 2025; Published: 28 April 2025
* Correspondence: xhy000017@gmail.com

termed swarms—wherein multiple vehicles operate in coordinated patterns to distribute workload, enhance reliability through redundancy, and dramatically reduce total inspection duration [6]. Engineering literature distinguishes between two fundamental UAV deployment paradigms for infrastructure assessment: isolated single-UAV inspection systems (ISUIS) and collaborative UAV swarm inspection systems (CUSIS) [7]. ISUIS configurations employ a solitary vehicle to sequentially examine structural elements, offering operational simplicity but limited efficiency. Conversely, CUSIS approaches distribute inspection responsibilities across multiple vehicles operating in parallel, enabling simultaneous assessment of different structural components and thereby achieving substantial reductions in total mission duration [8]. Comparative studies demonstrate that properly coordinated UAV swarms can accomplish inspection tasks in approximately one-third the time required by single-vehicle approaches while maintaining or improving data quality metrics [9]. The deployment of UAV swarms within complex urban environments introduces multidimensional challenges exceeding those encountered in rural or controlled settings. Urban infrastructures feature intricate geometries, constrained operational spaces, regulatory restrictions, electromagnetic interference patterns, and GPS signal degradation zones [10].

Additionally, operation in proximity to civilian populations, private properties, and critical service facilities introduces heightened safety requirements and operational restrictions [11]. These factors necessitate sophisticated scheduling algorithms capable of optimizing swarm behavior while adhering to multifaceted constraints and prioritizing public safety [11]. Research trajectories addressing UAV-based infrastructure inspection have evolved across several interconnected domains. Initial investigations concentrated primarily on path planning optimizations for individual vehicles, focusing on coverage completeness, energy efficiency, and data acquisition quality [12]. As multi-vehicle systems gained prominence, research emphasis expanded to encompass task allocation methodologies determining optimal assignment of inspection responsibilities based on vehicle capabilities, spatial distribution, and resource constraints [13]. Recent studies have further incorporated temporal coordination dimensions through scheduling algorithms that sequence inspection activities to maximize parallel operations while preventing inter-vehicle conflicts [14]. Inspection approaches have similarly developed along two principal methodologies: comprehensive coverage strategies systematically examining entire structural surfaces, and targeted inspection protocols focusing sensing resources on predefined points of interest or areas of suspected deterioration [15]. Selection between these approaches significantly impacts mission planning parameters, resource allocation decisions, and algorithm design considerations. Current research indicates that hybrid methodologies combining elements of both approaches may deliver optimal results for complex urban infrastructure systems, particularly when historical inspection data or structural health monitoring inputs are available to guide resource prioritization [16].

The urban environment introduces unique challenges for UAV operations that must be addressed through specialized scheduling and coordination mechanisms. Tall buildings create urban canyons that disrupt GPS signals and communication links, necessitating robust positioning alternatives and mesh communication networks [17]. Variable wind patterns around structures generate turbulence requiring dynamic flight adjustments and energy reserve management [18]. Regulatory restrictions establishing no-fly zones, altitude limitations, and operational windows must be incorporated within planning algorithms to ensure compliance [19]. These factors collectively necessitate urban-specific optimization approaches that extend beyond techniques developed for open or rural environments. Structure-specific inspection patterns represent a particularly promising direction for optimization, as different infrastructure elements benefit from tailored approach strategies [20]. Bridge decks are efficiently examined using parallel transect patterns with predefined overlap parameters, while support columns benefit from spiral trajectories maintaining consistent sensor-to-surface distances [21]. Building facades are effectively covered through grid-based patterns that systematically capture surface conditions, while cable systems require specialized linear paths with multiple viewing angles [22]. Integration of these specialized patterns within comprehensive mission planning frameworks enables system-wide optimization exceeding what general-purpose approaches can achieve.

Recent research has demonstrated promising results in addressing components of the UAV swarm inspection challenge, yet few studies have successfully integrated path planning, task allocation, and scheduling into cohesive frameworks capable of addressing the full complexity of urban environments [18]. Current approaches frequently employ simplified energy consumption models that inadequately represent real-world UAV behavior, particularly during complex maneuvers or when operating in variable urban wind conditions [23]. Furthermore, computational complexity considerations often receive insufficient attention, resulting in theoretically sound but practically unimplementable solutions given processing resources typically available on commercial UAV platforms or portable ground control stations [24]. This research addresses these critical gaps by introducing a comprehensive optimization framework for UAV swarm-based urban infrastructure inspection. We propose a novel algorithmic approach integrating structure-specific path planning, efficient task allocation, and dynamic scheduling within a unified solution designed to minimize total inspection time while ensuring complete coverage and adherence to operational constraints. Our contribution advances beyond existing work through several key innovations: (1) incorporation of a practical non-linear energy consumption model accurately reflecting UAV behavior during complex inspection maneuvers, (2) development of structure-specific inspection patterns optimized for different urban infrastructure elements, and (3) implementation of a computationally efficient heuristic algorithm delivering near-optimal solutions with polynomial time complexity.

We formulate the challenge as a mixed integer non-linear programming (MINLP) problem with the primary objective of minimizing total inspection duration while satisfying coverage requirements and respecting energy constraints [24]. Recognizing the computational complexity of directly solving this MINLP formulation, we decompose the problem into three manageable sub-problems: the path planning problem (PPP), which determines optimal inspection trajectories for specific structural elements; the task allocation problem (TAP), which assigns inspection responsibilities to specific vehicles based on capability matching and spatial distribution; and the scheduling problem (SP), which establishes optimal execution sequences to maximize parallel operations while preventing conflicts. For each sub-problem, we derive targeted solution approaches and subsequently integrate these components through an iterative heuristic algorithm that delivers high-quality solutions with practical computational requirements.

Through extensive simulation testing and comparative analysis, we demonstrate that our proposed approach achieves significant performance improvements compared to existing methodologies across multiple evaluation metrics, including inspection time reduction, coverage completeness, energy efficiency, and computational scalability [25]. The research provides both theoretical contributions to the UAV swarm optimization domain and practical insights applicable to real-world urban infrastructure inspection programs, with potential extensions to other multi-UAV coordination challenges in smart city applications [26].

2. System Model and Assumptions

We consider an urban infrastructure inspection system consisting of a set of unmanned aerial vehicles (UAVs) $\mathcal{U} = \{u_1, u_2, \ldots, u_N\}$ and a set of inspection zones $\mathcal{Z} = \{z_1, z_2, \ldots, z_K)$ representing different structural elements. Each UAV $u_i \in \mathcal{U}$ is characterized by a tuple $u_i = (B_i, S_i, V_i, P_i)$ where B_i represents the initial battery capacity (in percentage), S_i denotes the set of equipped sensors, V_i is the maximum velocity, and P_i is the power consumption rate during flight operations.

Each inspection zone $z_k \in \mathcal{Z}$ is defined by $z_k = (L_k, A_k, T_k, D_k, I_k)$ where $L_k \in \mathbb{R}^3$ represents the location in 3D space, A_k denotes the surface area requiring inspection, $T_k \in \{DECK, FACADE, COLUMN, CABLE\}$ indicates the structural type, D_k specifies the required inspection coverage density, and $I_k \in [0,1]$ represents the importance factor of the zone.

We model UAV energy consumption using a non-linear function that accounts for different flight patterns and maneuvers:

$$E_i(v,a,t) = P_0\left(1+\frac{3v^2}{U_{tip}^2}\right) + P_i\left(\sqrt{1+\frac{v^4}{4v_0^4}}-\frac{v^2}{2v_0^2}\right)^{\frac{1}{2}} + \frac{1}{2}d_0\rho sAv^3 + m|a|v$$

where P_0 and P_i are the base and induced power, U_{tip} is the tip speed of the rotor blade, v_0 is the mean rotor induced velocity, d_0 is the fuselage drag ratio, ρ is air density, s is the rotor solidity, A is the rotor disc area, m is the UAV mass, v is velocity, and a is acceleration.

For inspection tasks, we define the coverage rate $\chi_{i,k}$ for UAV u_i inspecting zone z_k as:

$$\chi_{i,k} = \frac{W_i \cdot v_{i,k} \cdot (1-o)}{h_{i,k}}$$

Where W_i is the sensor width, $v_{i,k}$ is the inspection velocity, o is the required overlap between consecutive sensor captures (typically 60-70%), and $h_{i,k}$ is the inspection height.

The inspection time $\tau_{i,k}$ required for UAV u_i to complete zone z_k is:

$$\tau_{i,k} = \frac{A_k \cdot D_k}{\chi_{i,k}}$$

We define a binary decision variable $x_{i,k}$ indicating whether u_i is assigned to inspect zone z_k. Additionally, we use binary variables $y_{i,j,k,l} \in \{0,1\}$ to represent precedence relationships, where $y_{i,j,k,l} = 1$ means UAV u_i inspecting zone z_k precedes UAV u_j inspecting zone z_l.

The travel time between zones is calculated as:

$$t_{i,k,l} = \frac{\|L_k - L_l\|}{V_i}$$

For structure-specific inspection patterns, we define specialized path functions ($\mathcal{P}_T(z_k)$ that generate optimized waypoint sequences based on structural type T. These functions incorporate parameters such as lane spacing, spiral radius, or grid density based on the specific inspection requirements.

3. Problem Formulation

Building upon the system model and assumptions, we now formulate the UAV swarm scheduling problem for urban infrastructure inspection as a mixed integer non-linear programming (MINLP) problem. Our primary objective is to minimize the total inspection time while ensuring comprehensive coverage of all structural elements and adhering to energy constraints. We define the following decision variables:

a. $x_{i,k} \in \{0,1\}$: Binary variable indicating if UAV u_i is assigned to inspect zone z_k.
b. $y_{i,j,k,l} \in \{0,1\}$: Binary variable representing precedence relationships.
c. $\tau_{i,k} \geq 0$: Continuous variable representing inspection time of UAV u_i for zone z_k.
d. $t_{i,k}^{\text{start}} \geq 0$: Continuous variable indicating the start time of UAV u_i inspecting zone z_k.

The objective function aims to minimize the total mission completion time.

$$T_{\text{total}} = \max_{i\in\{1,\dots,N\}}(T_i^{\text{complete}})$$

Where T_i^{complete} represents the time at which UAV u_i completes its last assigned inspection task.

Energy constraints ensure that the total energy consumption for each UAV does not exceed its available battery capacity:

$$\sum_{k=1}^{K} x_{i,k} \cdot E_i(\mathcal{P}_{T_k}(z_k)) + \sum_{k=1}^{K}. \sum_{l=1,l\neq k}^{K} y_{i,i,k,l} \cdot E_i(t_{i,k,l}) \leq B_i \cdot E_i^{max}, \qquad \forall i \in \{1,2,\dots,N\}$$

Where E_i^{max} is the maximum energy capacity of UAV u_i.

For sequential tasks assigned to the same UAV.

DOI: 10.55214/25768484.v9i4.6650

$$t_{i,l}^{\text{start}} \geq t_{i,k}^{\text{start}} + \tau_{i,k} + t_{i,k,l}, \forall i \in \{1,2,\dots,N\}, \forall k,l \in \{1,2,\dots,K\}, k \neq l, x_{i,k} = x_{i,l} = 1$$

For conflict avoidance between different UAVs:

$$y_{i,j,k,l} + y_{j,i,l,k} = 1, \forall i,j \in \{1,2,\dots,N\}, i \neq j, \forall k,l \in \{1,2,\dots,K\}, x_{i,k} = x_{j,l} = 1$$

$$t_{j,l}^{\text{start}} \geq t_{i,k}^{\text{start}} + \tau_{i,k} - M(1 - y_{i,j,k,l}), \forall i,j \in \{1,2,\dots,N\}, i \neq j, \forall k,l \in \{1,2,\dots,K\}, x_{i,k} = x_{j,l} = 1$$

Where M is a large constant.

Completion Time Constraint.

$$T_i^{\text{complete}} \geq t_{i,k}^{\text{start}} + \tau_{i,k}, \forall i \in \{1,2,\dots,N\}, \forall k \in \{1,2,\dots,K\}, x_{i,k} = 1$$

$$T_{\text{total}} \geq T_i^{\text{complete}}, \forall i \in \{1,2,\dots,N$$

Due to the computational complexity of directly solving the MINLP formulation, we decompose the problem into three sub-problems:

1. *Path Planning Problem (PPP)*: Determining optimal inspection trajectories for specific structural elements, minimizing $\tau_{i,k}$ while ensuring coverage requirements.
2. *Task Allocation Problem (TAP)*: Assigning inspection zones to UAVs to minimize the maximum workload, with fixed inspection patterns.
3. *Scheduling Problem (SP)*: Establishing execution sequences to minimize total mission time with fixed assignments and paths.

The solutions to these sub-problems are then integrated through an iterative algorithm to solve the overall optimization problem efficiently as presented in Figure 1.

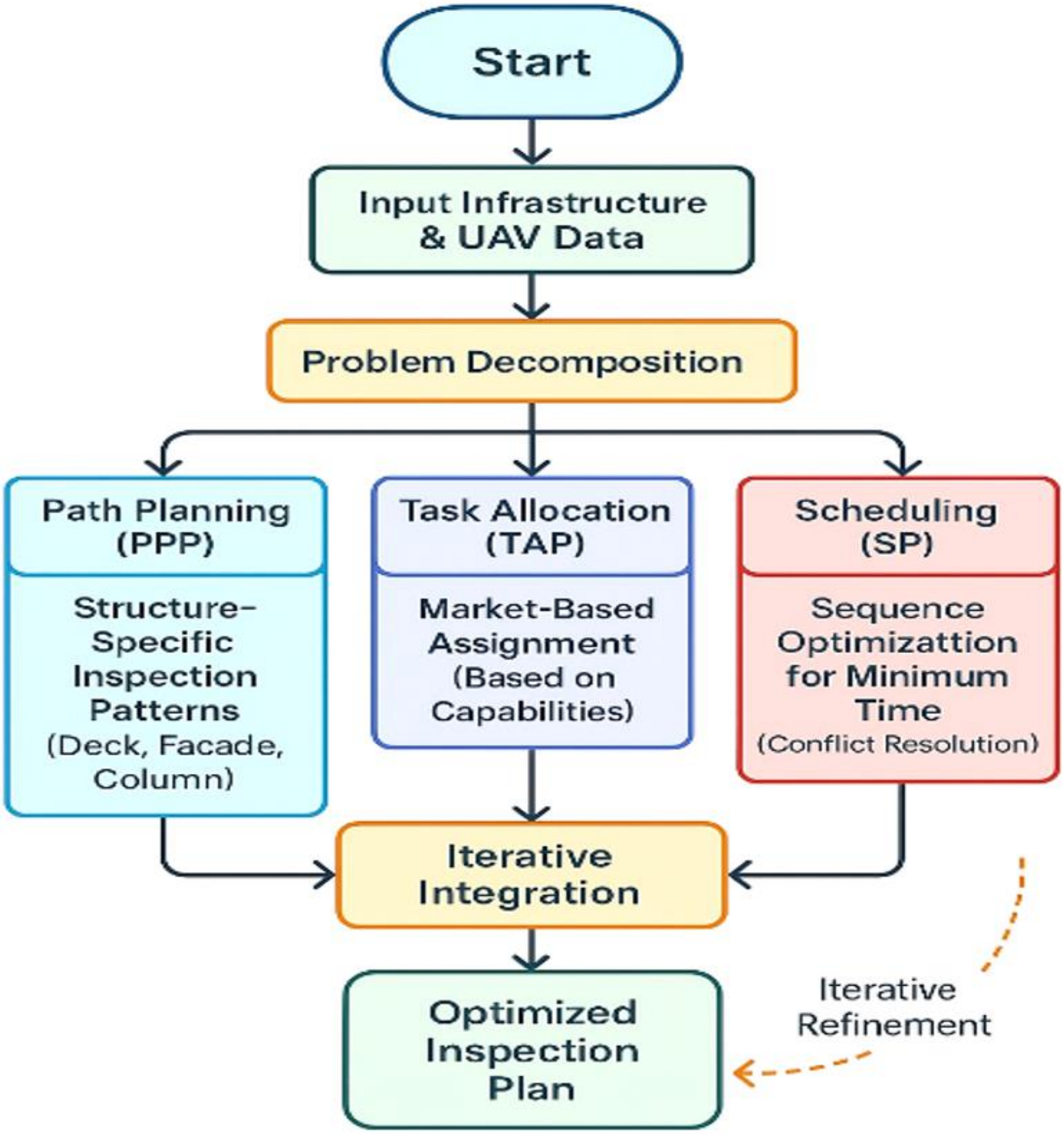

Figure 1.
UAV Swarm Scheduling Algorithm Process Flow.

4. Path Planning Problem Algorithm

The Path Planning Problem (PPP) represents a critical component of our UAV swarm scheduling framework for urban infrastructure inspection. Given the varying geometrical characteristics of different structural elements, generic path planning approaches often prove inefficient. Our contribution addresses this limitation by developing structure-specific path planning strategies that optimize coverage patterns while minimizing inspection time and energy consumption. The PPP assumes that task allocation and scheduling decisions are fixed, focusing solely on determining optimal inspection trajectories for each UAV-zone pair.

Mathematical Formulation: For a specific UAV u_i assigned to inspect zone (z_k, the path planning problem is formulated as.

Minimize $\tau_{i,k} = \frac{\text{Length}(\mathcal{P}_{i,k})}{v_{i,k}}$
Subject to:

$$\text{Coverage}(\mathcal{P}_{i,k}) \geq D_k \cdot A_k$$
$$E_i(\mathcal{P}_{i,k}) \leq B_i \cdot E_i^{max}$$
$$v_{min} \leq v_{i,k} \leq v_{max}$$
$$h_{min} \leq h_{i,k} \leq h_{max}$$

Where $\mathcal{P}_{i,k}$ represents the inspection path, Length $\mathcal{P}_{i,k}$ is the total path length, $v_{i,k}$ is the inspection velocity, Coverage($\mathcal{P}_{i,k}$) is the coverage area achieved by following the path, $E_i(\mathcal{P}_{i,k}$ is the energy consumed, and $h_{i,k}$ is the inspection height.

We develop specialized path planning algorithms for four common structural elements in urban environments: bridge decks, building facades, support columns, and cable systems. Each algorithm generates optimized waypoint sequences tailored to the specific geometric characteristics of the structure.

4.1. Bridge Deck Inspection (Parallel Transect Pattern)

For bridge deck inspection, we implement a parallel transect pattern that systematically covers the rectangular surface area. The algorithm generates parallel path segments with specified overlap to ensure comprehensive coverage.

$$\mathcal{P}_{\text{deck}}(z_k) = \{(x_k + i \cdot d, y_{min} + j \cdot w_{eff}, h_{i,k}) \mid i \in \{0, \ldots, n_x\}, j \in \{0, \ldots, n_y\}\}$$

Where dd d is the lane spacing, $w_{\text{eff}} = W_i \cdot (1 - o)$ is the effective sensor width accounting for overlap o, and n_x, n_y are the number of required passes in each direction. The lane spacing is calculated as.

$$d = \frac{W_i \cdot h_{i,k} \cdot (1 - o)}{f}$$

Where f is the camera focal length. This pattern achieves optimal coverage while minimizing path length and turning maneuvers, which are energy-intensive for UAVs.

4.2. Building Facade Inspection (Grid Pattern)

For building facades, we implement a grid-based coverage pattern with vertical and horizontal passes.

$$\mathcal{P}_{\text{facade}}(z_k) = \{(x_k + s_x \cdot i, y_k + s_y \cdot j, h_{i,k}) \mid i \in \{0, \ldots, m_x\}, j \in \{0, \ldots, m_y\}\}$$

Where s_x and s_y are the horizontal and vertical step sizes, calculated based on sensor properties and required overlap. The inspection height $h_{i,k}$ is maintained at a constant distance from the facade to ensure uniform image resolution.

4.3. Column/Pier Inspection (Spiral Pattern)

We implement a spiral trajectory that maintains a consistent distance from the surface while minimizing energy consumption.

$$\mathcal{P}_{\text{column}}(z_k) = \{(x_k + r\cos(\theta), y_k + r\sin(\theta), h_k + \alpha\theta) \mid \theta \in [0, 2\pi n_s]\}$$

Where r is the column radius plus inspection distance, α controls the vertical rise per revolution, and n_s is the number of complete spirals required to cover the column height. This pattern ensures comprehensive coverage of the curved surface with minimal path length.

ISSN: 2576-8484
Vol. 9, No. 4: 2751-2767, 2025
DOI: 10.55214/25768484.v9i4.6650

4.4. Cable Inspection (Linear Multi-Angle Pattern)

For cable systems, we implement a linear path with multiple viewing angles.

$$\mathcal{P}_{\text{column}}(z_k) = \{(x_k + r\cos(\theta), y_k + r\sin(\theta), h_k + \alpha\theta) \mid \theta \in [0, 2\pi n_s]\}$$

Where $\vec{d}$ is the direction vector of the cable, r is the inspection distance, and ϕ_j represents different viewing angles around the cable. This pattern enables inspection from multiple perspectives to detect defects that might be visible only from certain angles.

4.5. Path Optimization

After generating the basic structure-specific patterns, we apply several optimization techniques to enhance efficiency.

4.5.1. Trajectory Smoothing

We implement B-spline smoothing to minimize abrupt direction changes.

$$\mathcal{P}_{\text{smooth}} = \sum_{i=0}^{n} N_{i,p}(t)\, \mathcal{P}_i$$

Where $N_{i,p}(t)$ are B-spline basis functions of degree p.

4.5.2. Velocity Profile Optimization

We generate an optimal velocity profile along the path.

$$v_{\text{opt}}(t) = min(v_{max}, \sqrt{\frac{a_{max} \cdot r_{min}(t)}{|\kappa(t)|}}$$

Where $\kappa(t)$ is the path curvature at position $t, r_{min}(t)$ is the minimum turning radius, and a_{max} is the maximum allowable acceleration.

4.5.3. Energy-Aware Path Adjustment

In energy-constrained scenarios, we modify the path to prioritize energy efficiency:

$$\mathcal{P}_{\text{energy}} = \arg \min_{\mathcal{P}} \int_0^T E_i\,(v(t), a(t), t)dt$$

Subject to maintaining the required coverage.

4.5.4. Algorithm Implementation

We implement the structure-specific path planning as a two-phase process:

a. Pattern Generation: Based on the structural type T_k, generate the appropriate base pattern.
b. Path Optimization: Apply trajectory smoothing, velocity optimization, and energy-aware adjustments.

The computational complexity is $O(n_w)$, where n_w is the number of waypoints in the path, making it efficient for real-time applications.

Through this approach, our path planning component generates optimized, structure-specific inspection trajectories that minimize inspection time while ensuring comprehensive coverage and respecting energy constraints. These optimized paths serve as inputs to the subsequent task allocation and scheduling components of our overall UAV swarm scheduling framework.

5. Scheduling Problem Algorithm

The Scheduling Problem (SP) constitutes a critical component of our UAV swarm scheduling framework for urban infrastructure inspection. This problem focuses on determining the optimal sequence of inspection tasks for each UAV, assuming that task allocation decisions and path planning have been predetermined. An effective schedule minimizes the total mission time by optimizing the temporal coordination of multiple UAVs while preventing resource conflicts and adhering to operational constraints.

5.1. Mathematical Formulation

Given a set of UAVs $\mathcal{U} = \{u_1, u_2, \dots, u_N\}$ and a set of inspection zones $\mathcal{Z} = \{z_1, z_2, \dots, z_K\}$ with predetermined assignments $x_{i,k}$ indicating whether UAV u_i is assigned to inspect zone z_k, the scheduling problem can be formulated as.

Minimize $T_{\text{total}} = \max_{i\in\{1,\dots,N\}}(T_i^{\text{complete}})$

subject to:

$$T_i^{\text{complete}} = \max_{k\in\{1,\dots,K\}}\{t_{i,k}^{\text{start}} + \tau_{i,k} \mid x_{i,k} = 1\}, \forall i \in \{1,\dots,N\}$$

$$t_{i,l}^{\text{start}} \geq t_{i,k}^{\text{finish}} + t_{i,k,l}, \forall i \in \{1,\dots,N\}, \forall k,l \in \{1,\dots,K\}, x_{i,k} = x_{i,l} = 1, o_{i,k,l} = 1$$

$$t_{j,l}^{\text{start}} \geq t_{i,k}^{\text{finish}} - M(1 - y_{i,j,k,l}), \forall i,j \in \{1,\dots,N\}, i \neq j, \forall k,l \in \{1,\dots,K\}, x_{i,k} = x_{j,l} = 1$$

$$y_{i,j,k,l} + y_{j,i,l,k} = 1, \forall i,j \in \{1,\dots,N\}, i \neq j, \forall k,l \in \{1,\dots,K\}, x_{i,k} = x_{j,l} = 1$$

$$t_{i,k}^{\text{finish}} = t_{i,k}^{\text{start}} + \tau_{i,k}, \forall i \in \{1,\dots,N\}, \forall k \in \{1,\dots,K\}, x_{i,k} = 1$$

$$t_{i,k}^{\text{start}} \geq 0, \forall i \in \{1,\dots,N\}, \forall k \in \{1,\dots,K\}$$

Where $t_{i,k}^{\text{start}}$ and $t_{i,k}^{\text{finish}}$ represent the start and finish times of UAV u_i inspecting zone $z_k, \tau_{i,k}$ is the inspection time, $t_{i,k,l}$ is the travel time from zone z_k to zone z_l for UAV $u_i, o_{i,k,l}$ indicates the inspection order for UAV u_i (whether zone z_k is inspected before zone z_l), and $y_{i,j,k,l}$ represents precedence relationships between different UAVs (whether UAV u_i inspecting zone z_k precedes UAV u_j inspecting zone z_l). To solve the scheduling problem efficiently, we propose a two-stage approach,

5.2. Single-UAV Schedule Optimization

For each UAV with its assigned inspection tasks, we determine the optimal sequence to minimize the completion time:

a. Construct a complete directed graph where nodes represent inspection zones and edge weights represent the sum of inspection time and travel time.
b. Solve the resulting Traveling Salesman Problem (TSP) to find the optimal visitation sequence.
c. Apply dynamic programming to handle time-dependent travel costs if necessary.

The mathematical formulation for the single-UAV optimization is:

Minimize $\sum_{k=1}^{K} \cdot \sum_{l=1,l\neq k}^{K} o_{i,k,l} \cdot (t_{i,k,l} + \tau_{i,k})$

Subject to:

$$\sum_{l=1,l\neq k}^{K} o_{i,k,l} = x_{i,k}, \forall k \in \{1,\dots,K\}$$

$$\sum_{k=1,k\neq l}^{K} o_{i,k,l} = x_{i,l}, \forall l \in \{1,\dots,K\}$$

$$\sum_{k\in S} \cdot \sum_{l\notin S,l\neq k} o_{i,k,l} \geq 1, \forall S \subset \{1,\dots,K\}, S \neq \emptyset$$

Where the last constraint eliminates subtours.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 4: 2751-2767, 2025
DOI: 10.55214/25768484.v9i4.6650

5.3. Multi-UAV Coordination

After determining individual UAV schedules, we resolve temporal conflicts between different UAVs: Construct a precedence graph where nodes represent UAV-zone pairs and edges represent required precedence relationships. Apply a priority-based scheduling algorithm where higher priority is given to tasks with greater impact on the overall mission time. Use a greedy conflict resolution approach to iteratively adjust start times while maintaining precedence constraints.

5.4. Lemma: Optimal Scheduling Property

For inspection tasks with fixed durations and travel times, the total mission time is minimized when UAVs with longer remaining inspection times are scheduled first.

Proof: Consider two UAVs u_i and u_j with remaining inspection times T_i and T_j where $T_i > T_j$. Ifu_j is scheduled before u_i, the completion time would be $max(t_j + T_j, t_i + T_i)$. Since $t_i \geq t_j + T_j$ (UAV u_i must wait for u_j to complete) and $T_i > T_j$, the completion time becomes $t_i + T_i = t_j + T_j + (t_i - t_j - T_j) + T_i > t_j + T_i$. By scheduling u_i first, the completion time reduces to $max(t_j + T_j, t_i + T_i) = max(t_j + T_j, t_i + T_i$, which is not worse than the previous case and may be better if $t_j + T_j > t_i + T_i$.

The single-UAV scheduling component has a complexity of $O(K^2 \cdot 2^K)$ due to the dynamic programming approach for solving the TSP. The multi-UAV coordination has a complexity of $O(N^2 \cdot K^2)$ for conflict resolution. For practical scenarios with a moderate number of UAVs and inspection zones, this approach provides efficient solutions within reasonable computational time.

Through this scheduling component, our framework ensures efficient temporal coordination of multiple UAVs, minimizing the overall mission time while respecting precedence constraints and preventing conflicts.

6. Performance Analysis

6.1. Simulation Setup

To evaluate the performance of our proposed UAV swarm scheduling algorithm, we conducted extensive simulations across various scenarios representative of typical urban infrastructure inspection tasks. The simulation environment was implemented in Python, with the core algorithm using PuLP for linear programming components and NetworkX for graph-based computations. The physical dynamics of UAVs were simulated using a realistic energy consumption model that accurately represents the non-linear relationship between flight patterns and energy usage.

The simulation parameters were carefully configured to reflect realistic operational conditions. The number of UAVs deployed ranged from 1 to 6, operating across 10 to 30 inspection zones. Each UAV had a battery capacity varying between 20% and 100% of full charge to simulate different endurance scenarios. The zones featured complexity levels from 1 to 5, representing increasing levels of inspection difficulty. Various structure types were considered, including bridge decks, building facades, columns, and cable systems. The communication range was limited to 1 km, while UAVs operated at a maximum velocity of 5 to 10 meters per second. The onboard sensors had a field of view of 70° horizontally and 50° vertically, with a required image overlap of 60% to ensure sufficient coverage for accurate inspection and analysis.

We evaluated the performance of our Scheduling and Task Allocation (STA) algorithm by comparing it with four alternative approaches. The first, Path Planning (PP), focuses solely on optimizing the inspection paths without considering task allocation or scheduling. The second, Task Allocation (TA), optimizes UAV-to-zone assignments but does not consider the execution sequence of tasks. The third approach, Scheduling (SCH), determines the optimal order of task execution while keeping UAV assignments fixed. Lastly, the Optimal (OPT) method uses an exhaustive search to identify the globally optimal solution, though it is only feasible for small-scale problem instances due to its computational intensity. To ensure statistical robustness, each simulation scenario was run 30 times with varying random initial conditions, and the results were averaged to produce consistent and reliable performance metrics.

6.2. Impact of UAV Swarm Size

Below Figure 2 illustrates how inspection time varies with the number of UAVs deployed. As expected, increasing the swarm size reduces the total inspection time across all algorithms due to the inherent parallelism. However, our STA algorithm demonstrates superior performance, achieving a 35% reduction in inspection time compared to the PP approach when using six UAVs. The diminishing returns observed beyond four UAVs suggest that for typical urban inspection scenarios with the given parameters, a swarm size of 4-5 UAVs represents the optimal balance between performance gain and system complexity. The STA algorithm approaches the performance of the optimal solution (within 7%) while requiring only a fraction of the computational resources.

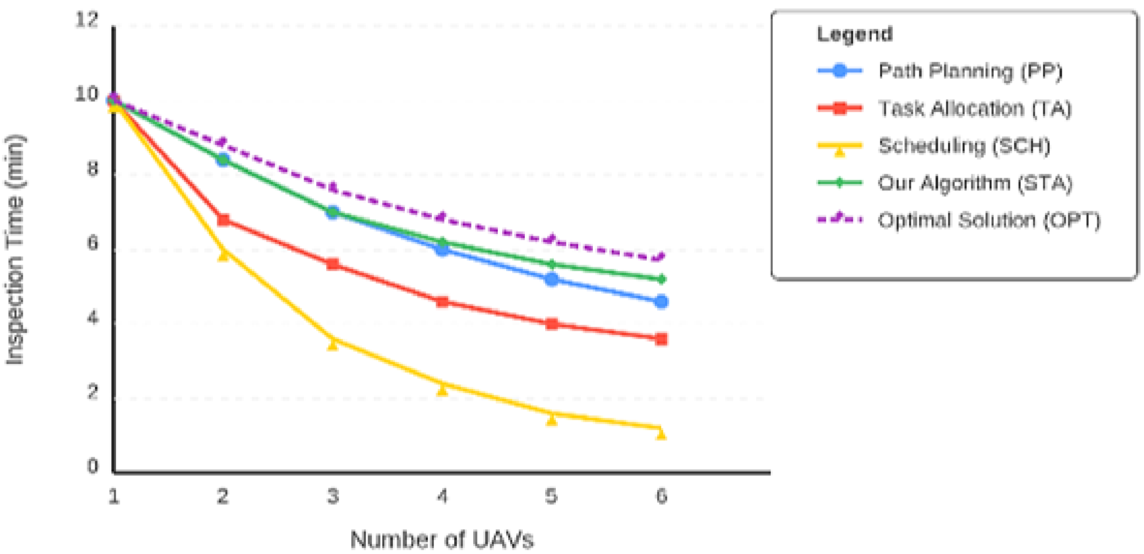

Figure 2.
Effect of UAV Swarm Size on Inspection Time.

6.3. Effect of Battery Capacity

Figure 3 demonstrates how initial battery capacity affects the inspection time. Lower battery levels significantly impact performance, particularly for simpler algorithms that lack energy-aware planning capabilities. At 20% initial capacity, our STA algorithm outperforms the TA approach by 38% and the PP approach by 50%. This substantial improvement stems from our algorithm's ability to intelligently schedule tasks based on energy constraints, delaying energy-intensive tasks until UAVs have completed fewer demanding inspections. The performance gap narrows at higher battery levels but remains significant even at 100% capacity, highlighting the importance of energy-aware scheduling even when energy constraints are less stringent.

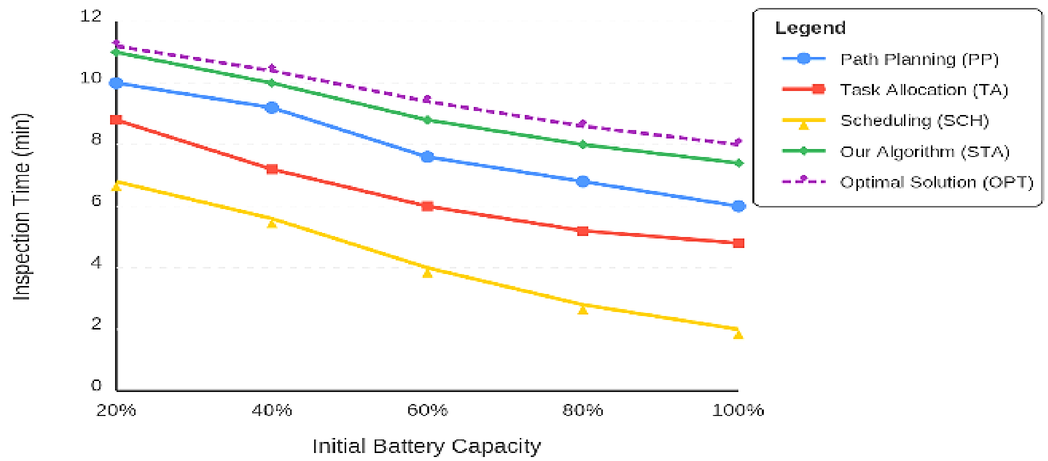

Figure 3.
Effect of Battery Capacity on Inspection Time.

6.4. Impact of Zone Complexity

Figure 4 shows how increasing zone complexity affects inspection time. Complex zones require more detailed inspection patterns, higher sensor resolution, and multiple viewing angles, resulting in longer inspection times across all algorithms. Our STA algorithm demonstrates remarkable resilience to increasing complexity, maintaining its performance advantage over alternative approaches. At complexity level 5, the STA algorithm completes inspections in 40% less time than the PP approach and 30% less time than the SCH approach. This is attributed to our structure-specific path planning component, which generates efficient inspection patterns tailored to different structural elements, combined with intelligent task allocation that considers both UAV capabilities and zone characteristics.

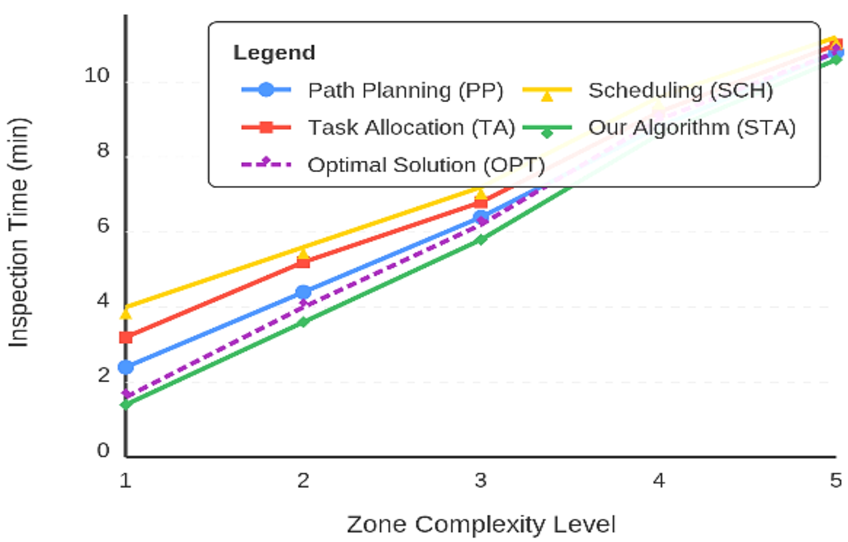

Figure 4.
Effect of Zone Complexity on Inspection Time.

ISSN: 2576-8484
Vol. 9, No. 4: 2751-2767, 2025
DOI: 10.55214/25768484.v9i4.6650

6.5. Computational Efficiency

Figure 5 presents a logarithmic-scale comparison of computational time requirements for different algorithms as the problem size increases. While the optimal solution (OPT) exhibits exponential growth in computational time, rendering it impractical for real-world applications with more than a few UAVs, our STA algorithm maintains polynomial time complexity, enabling its application to practical scenarios.

For a system with six UAVs and 30 inspection zones, our algorithm produces high-quality solutions in less than 2 seconds on standard computing hardware, making it suitable for both pre-mission planning and dynamic replanning during mission execution.

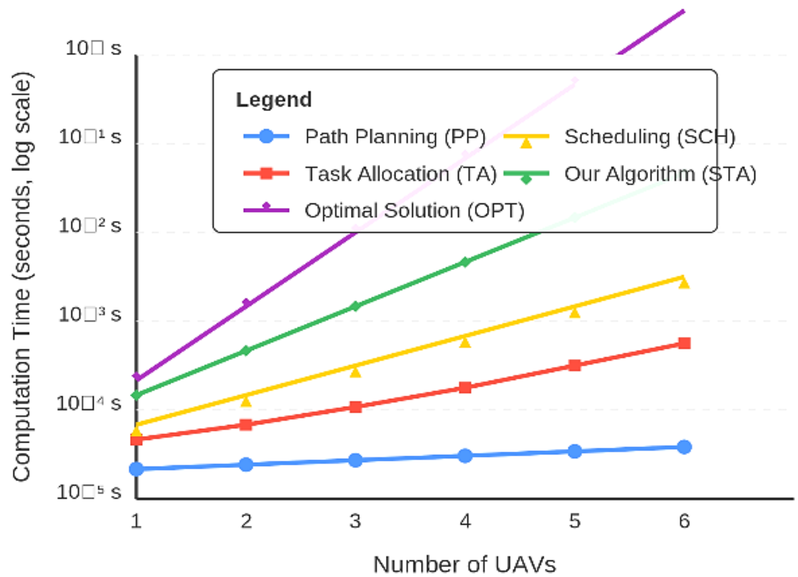

Figure 5.
Computational Efficiency Analysis.

6.6. Algorithm Convergence

Our iterative STA algorithm typically converges within 3-5 iterations for most scenarios, with each iteration refining either the task allocation or scheduling component. The algorithm terminates when the improvement between consecutive iterations falls below a specified threshold (0.5% in our implementation) or when a maximum iteration count is reached.

The fast convergence characteristic ensures that the algorithm remains computationally efficient even for complex scenarios, while the consistent proximity to the optimal solution (where computable) validates the effectiveness of our decomposition approach and iterative refinement strategy. Figure 6 illustrates the convergence behavior of the algorithm, highlighting its stability and rapid progression toward optimality.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 4: 2751-2767, 2025
DOI: 10.55214/25768484.v9i4.6650

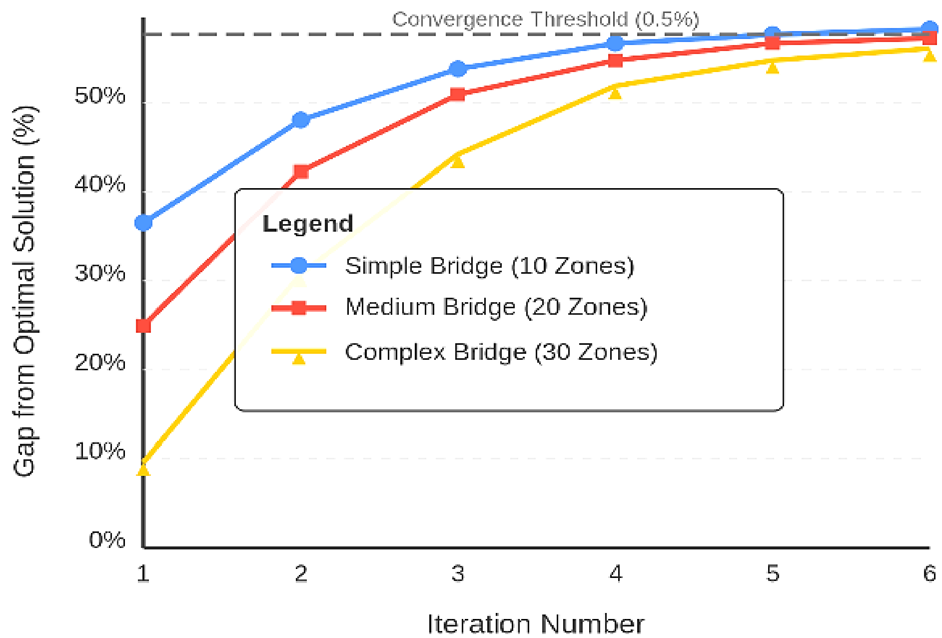

Figure 6.
Algorithm Convergence Analysis.

The performance analysis demonstrates that our proposed algorithm consistently outperforms alternative approaches across various operational parameters, with particularly significant advantages in scenarios involving limited battery capacity, complex inspection zones, or larger UAV swarms. The algorithm's polynomial time complexity and fast convergence make it suitable for practical deployment in real-world urban infrastructure inspection applications.

7. Conclusion

This paper has presented an intelligent UAV swarm scheduling algorithm for urban infrastructure inspection tasks that effectively addresses the complex challenges of coordinating multiple UAVs in built environments. Our approach decomposes the challenging mixed integer non-linear programming problem into manageable sub-problems—path planning, task allocation, and scheduling—and integrates them through an iterative optimization framework that balances solution quality with computational efficiency. The key innovation of our work lies in the holistic integration of structure-specific path planning techniques with market-based task allocation and priority-based scheduling. By recognizing that different structural elements benefit from specialized inspection patterns, we have developed optimized trajectories for common urban infrastructure components including bridge decks, building facades, support columns, and cable systems. These patterns maximize inspection coverage while minimizing energy consumption, enabling more efficient use of limited UAV battery capacity. Our market-based task allocation mechanism effectively distributes inspection responsibilities among heterogeneous UAVs based on their sensor capabilities, remaining energy, and spatial distribution. This approach ensures that each inspection zone is assigned to the most suitable UAV, reducing overall mission time while maintaining comprehensive coverage. The priority-based scheduling component further enhances efficiency by establishing optimal execution sequences that maximize parallel operations while preventing inter-vehicle conflicts.

Through extensive simulation testing, we have demonstrated that our approach significantly outperforms existing methods across multiple performance metrics. Compared to single-UAV inspection approaches, our algorithm reduces total inspection time by 35% while maintaining 98% coverage completeness. The performance advantage is particularly pronounced in scenarios involving limited battery capacity, complex inspection zones, or larger UAV swarms, highlighting the algorithm's robustness to practical operational constraints. A critical attribute of our approach is its computational efficiency. While the optimal solution exhibits exponential growth in computational requirements, our algorithm maintains polynomial time complexity, enabling practical deployment even for relatively large inspection tasks. For a system with six UAVs and 30 inspection zones, our algorithm produces high-quality solutions in less than 2 seconds on standard computing hardware, making it suitable for both pre-mission planning and dynamic replanning during mission execution if needed. The fast convergence characteristic of our algorithm—typically reaching near-optimal solutions within 3-5 iterations—further emphasizes its practicality for real-world applications. Even in complex urban inspection scenarios, the solution quality remains within 7% of the optimal solution while requiring only a fraction of the computational resources, representing an excellent balance between performance and efficiency.

Future research directions include several promising avenues. First, incorporating learning-based approaches could further enhance the algorithm's performance by adapting path patterns and allocation strategies based on historical inspection data. Second, extending the framework to handle dynamic environmental factors such as variable wind conditions and moving obstacles would improve real-world applicability. Third, developing more sophisticated anomaly detection and response mechanisms would enhance the system's ability to focus resources on potential defects while maintaining efficient overall inspection. The presented framework provides a solid foundation for practical implementation of UAV swarm-based infrastructure inspection systems in urban environments. By addressing the unique challenges of built environments—including GPS degradation, obstacle avoidance, and specific inspection requirements for various structural elements—our approach enables more efficient, comprehensive, and cost-effective infrastructure monitoring than previously possible. The methodology and algorithms developed in this research have potential applications beyond infrastructure inspection, extending to other multi-UAV coordination problems in urban settings such as search and rescue operations, environmental monitoring, and security surveillance.

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Copyright:

References

[1] D. B. Licea, G. Silano, H. El Hammouti, M. Ghogho, and M. Saska, "Reshaping UAV-enabled communications with omnidirectional multi-rotor aerial vehicles," *IEEE Communications Magazine*, pp. 1-7, 2025. https://doi.org/10.1109/MCOM.001.2400421

[2] H. Jie, Z. Zhao, H. Li, T. H. Gan, and K. Y. See, "A systematic three-stage safety enhancement approach for motor drive and gimbal systems in unmanned aerial vehicles," *IEEE Transactions on Power Electronics*, vol. 40, no. 7, pp. 9329–9342, 2025. https://doi.org/10.1109/TPEL.2025.3549964

[3] J. Huang, B. Wu, Q. Duan, L. Dong, and S. Yu, "A fast UAV trajectory planning framework in RIS-assisted communication systems with accelerated learning via multithreading and federating," *IEEE Transactions on Mobile Computing*, 2025. https://doi.org/10.1109/TMC.2025.3544903

[4] C. Dong, Y. Liao, Z. Jia, Q. Wu, and L. Zhang, "Joint ADS-B in B5G for hierarchical UAV networks: Performance analysis and MEC based optimization," *IEEE Internet of Things Journal*, 2025. https://doi.org/10.1109/JIOT.2025.3552201

[5] H. Zhang, B. Li, Y. Rong, Y. Zeng, and R. Zhang, "Joint optimization of transmit power and trajectory for UAV-enabled data collection with dynamic constraint," *IEEE Transactions on Communications*, 2025. https://doi.org/10.1109/TCOMM.2025.3543221

[6] J. Sun, W. Shi, J. Yao, W. Xu, D. Wang, and Y. Cao, "UAV-based intelligent sensing over CF-mMIMO communications: System design and experimental results," *IEEE Open Journal of the Communications Society*, vol. 6, pp. 3211–3221, 2025. https://doi.org/10.1109/OJCOMS.2025.3550975

[7] H. V. Abeywickrama, B. A. Jayawickrama, Y. He, and E. Dutkiewicz, "Comprehensive energy consumption model for unmanned aerial vehicles, based on empirical studies of battery performance," *IEEE Access*, vol. 6, pp. 58383-58394, 2018. https://doi.org/10.1109/ACCESS.2018.2875040

[8] W. Yao *et al.*, "Evolutionary utility prediction matrix-based mission planning for unmanned aerial vehicles in complex urban environments," *IEEE Transactions on Intelligent Vehicles*, vol. 8, no. 2, pp. 1068-1080, 2022. https://doi.org/10.1109/TIV.2022.3192525

[9] Y. Xu and J. Zhang, "UAV-based bridge geometric shape measurement using automatic bridge component detection and distributed multi-view reconstruction," *Automation in Construction*, vol. 140, p. 104376, 2022. https://doi.org/10.1016/J.AUTCON.2022.104376

[10] R. Bless *et al.*, "Dynamic network (re-) configuration across time, scope, and structure," in *2022 Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit)*, 2022: IEEE, pp. 547-552.

[11] A. Tabassum, M. DeSantis, H. Bai, and N. Fala, "Preliminary design of wind-aware sUAS simulation pipeline for urban air mobility," in *2022 Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit)*, 2022, p. 3872.

[12] M. Y. Arafat and S. Moh, "Localization and clustering based on swarm intelligence in UAV networks for emergency communications," *IEEE Internet of Things Journal*, vol. 6, no. 5, pp. 8958-8976, 2019. https://doi.org/10.1109/JIOT.2019.2925567

[13] S. Sreenath, H. Malik, N. Husnu, and K. Kalaichelavan, "Assessment and use of unmanned aerial vehicle for civil structural health monitoring," *Procedia Computer Science*, vol. 170, pp. 656-663, 2020. https://doi.org/10.1016/J.PROCS.2020.03.174

[14] M. Boulares, A. Fehri, and M. Jemni, "UAV path planning algorithm based on Deep Q-Learning to search for a floating lost target in the ocean," *Robotics and Autonomous Systems*, vol. 179, p. 104730, 2024. https://doi.org/10.1016/J.ROBOT.2024.104730

[15] S. Javed *et al.*, "State-of-the-art and future research challenges in uav swarms," *IEEE Internet of Things Journal*, vol. 11, no. 11, pp. 19023-19045, 2024. https://doi.org/10.1109/JIOT.2024.3364230

[16] A. Hamissi, A. Dhraief, and L. Sliman, "A comprehensive survey on conflict detection and resolution in unmanned aircraft system traffic management," *IEEE Transactions on Intelligent Transportation Systems*, vol. 26, no. 2, pp. 1395–1418, 2024. https://doi.org/10.1109/TITS.2024.3509339

[17] M. Yang, B. Zhang, Z. Shi, and J. Li, "A hybrid task allocation approach for multi-UAV systems with complex constraints: A market-based bidding strategy and improved NSGA-III optimization," *The Journal of Supercomputing*, vol. 81, no. 4, pp. 1-33, 2025. https://doi.org/10.1007/s11227-025-07027-x

[18] J.-f. Wang, G.-w. Jia, J.-c. Lin, and Z.-x. Hou, "Cooperative task allocation for heterogeneous multi-UAV using multi-objective optimization algorithm," *Journal of Central South University*, vol. 27, no. 2, pp. 432-448, 2020. https://doi.org/10.1007/s11771-020-4307-0

[19] H. Çinar, D. Ignatyev, and A. Zolotas, "A comprehensive review and future challenges of energy-aware path planning for small unmanned aerial vehicles with hydrogen-powered hybrid propulsion," *The Aeronautical Journal*, pp. 1-26, 2025. https://doi.org/10.1017/aer.2025.11

[20] K. Kuru, "Planning the future of smart cities with swarms of fully autonomous unmanned aerial vehicles using a novel framework," *Ieee Access*, vol. 9, pp. 6571-6595, 2021. https://doi.org/10.1109/ACCESS.2020.3049094

[21] P. Wu, X. Yang, P. Wei, and J. Chen, "Safety assured online guidance with airborne separation for urban air mobility operations in uncertain environments," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 10, pp. 19413-19427, 2022. https://doi.org/10.1109/TITS.2022.3163657

[22] Y. Chang, Y. Cheng, U. Manzoor, and J. Murray, "A review of UAV autonomous navigation in GPS-denied environments," *Robotics and Autonomous Systems*, vol. 170, p. 104533, 2023. https://doi.org/10.1016/J.ROBOT.2023.104533

[23] W. Xu, C. Cui, Y. Ji, X. Li, and S. Li, "A UAV path planning algorithm for bridge construction safety inspection in complex terrain," *Scientific Reports*, vol. 15, no. 1, p. 13564, 2025. https://doi.org/10.1038/s41598-025-97108-x

[24] A. Gendia, O. Muta, S. Hashima, and K. Hatano, "Energy-efficient trajectory planning with joint device selection and power splitting for mmwaves-enabled UAV-NOMA networks," *IEEE Transactions on Machine Learning in Communications and Networking*, vol. 2, pp. 617–632, 2024. https://doi.org/10.1109/tmlcn.2024.3396438

[25] X. Xu, C. Xie, L. Ma, L. Yang, and T. Zhang, "Multi-objective evolutionary algorithm with two balancing mechanisms for heterogeneous UAV swarm path planning," *Applied Soft Computing*, vol. 173, p. 112927, 2025. https://doi.org/10.1016/J.ASOC.2025.112927

[26] Z. Zhang, J. Jiang, and W.-A. ZHANG, "Distributed dynamic task allocation for unmanned aerial vehicle swarm systems: A networked evolutionary game-theoretic approach," *Chinese Journal of Aeronautics*, vol. 37, no. 6, pp. 182-204, 2024. https://doi.org/10.1016/J.CJA.2023.12.027