UAV Swarm Scheduling for Large-Scale Coordination: Applications, Challenges, Opportunities

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The rapid advancement of unmanned aerial vehicle (UAV) swarm systems has enabled their deployment in large-scale applications such as disaster response, environmental monitoring, logistics, and communication networks. In these scenarios, effective scheduling and coordination of UAV swarms are critical for mission success, particularly under complex spatiotemporal constraints. This paper provides a comprehensive survey of scheduling and planning algorithms for large-scale UAV swarm coordination under spatiotemporal

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constraints. The unique challenges posed by these constraints are analyzed, and state-of-the-art algorithms, including sampling-based, graph-based, mathematical optimization-based, and learning-based methods, are systematically evaluated. In addition, two representative application domains—sensing and communication—are investigated to demonstrate how spatiotemporal constraints shape algorithm design and performance. Furthermore, this paper also explores the key challenges faced by UAV swarms and proposes corresponding future research directions, which are crucial for advancing the development of this field. This survey aims to serve as a foundational reference for researchers and practitioners developing scalable coordination and planning solutions for UAV swarms.

CCS Concepts: • **Computer systems organization → Sensor networks**; **Robotic autonomy**; • **Computing methodologies → Multi-agent planning**; **Robotic planning**; • **Hardware** → *Sensor applications and deployments.*

Additional Key Words and Phrases: path planning, robotics, internet of things, Unmanned Aerial Vehicle, sensor networks, wireless sensor

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1 Introduction

Recent advancements in unmanned aerial vehicle (UAV) technology and swarm intelligence have significantly broadened the application scope of UAV swarm systems. By leveraging distributed coordination among multiple UAVs, swarm systems have demonstrated remarkable capabilities in a wide range of domains, including military operations [122], disaster response [204], environmental monitoring [55], precision agriculture [165], and intelligent transportation systems [5]. Compared to individual UAVs or small-scale systems, large-scale UAV swarms exhibit superior task efficiency, broader spatial coverage, and greater adaptability to handle complex missions in dynamic and uncertain environments [50]. These advantages make UAV swarms an indispensable tool for addressing modern challenges such as real-time disaster relief and large-area environmental sensing.

In large-scale UAV swarm systems, the incorporation of **spatiotemporal constraints** is critical to mission success. These constraints describe the temporal urgency, spatial coverage, and environmental dynamics that influence UAV swarm coordination. Different applications impose distinct spatiotemporal requirements on UAV operations. For instance, disaster relief missions demand real-time responsiveness and localized task execution, requiring UAVs to rapidly assess damage and deliver aid to critical zones [72]. In contrast, environmental monitoring focuses on long-term data collection and extensive area coverage, where UAVs must optimize sensing trajectories over extended periods [38, 39, 112]. Similarly, precision agriculture requires high-resolution sensing to monitor individual crops and detect anomalies at a fine spatial scale [227], whereas urban traffic surveillance emphasizes continuous updates and wide-area monitoring to track congestion patterns in real time [24, 150]. Furthermore, dynamic environments, such as rapidly evolving disaster zones or shifting agricultural conditions, introduce additional challenges, requiring UAV swarms to adapt their coordination strategies based on real-time data. Effectively integrating spatiotemporal constraints into UAV swarm scheduling ensures efficient resource allocation, minimizes conflicts, and enhances overall mission performance [66]. Conversely, failing to account for these constraints can lead to inefficient task assignments, suboptimal coverage, increased energy consumption, and even mission failures.

The design of scheduling and planning algorithms plays a pivotal role in enabling UAV swarm coordination under spatiotemporal constraints [10]. These algorithms are responsible for assigning tasks to individual UAVs, determining efficient flight paths, and ensuring that the swarm operates collaboratively to achieve mission objectives [49]. However, the challenges associated with scheduling and planning are significantly amplified in large-scale UAV swarms. The sheer number of UAVs and tasks results in a combinatorial explosion of possible task assignments and path configurations [169]. Additionally, the dynamic and uncertain nature of real-world environments—such as weather variability [171], unexpected obstacles [142], and communication delays [13] further complicates the problem. Traditional scheduling and planning approaches, which often rely on centralized control or heuristic methods, struggle to scale effectively to large swarms or adapt to dynamic environments [3]. This necessitates the development of innovative algorithms that are not only computationally efficient but also capable of handling the high-dimensional [4], adaptive [95], and uncertain nature of UAV swarm operations [186].

Incorporating spatiotemporal constraints into scheduling and planning introduces several critical challenges. First, UAV swarm missions often involve dynamic environments where task priorities and locations may change unpredictably, requiring real-time updates to schedules and flight paths [95, 200]. Second, coordinating large-scale UAV swarms requires balancing competing objectives such as task timeliness, energy efficiency, and spatial coverage, which often conflict. For example, meeting strict time constraints may increase energy consumption, while optimizing for broad-area coverage can delay responses to high-priority tasks [159, 182]. Third, ensuring **safety and robustness** in dense or dynamic environments is challenging, as UAVs must avoid collisions and tolerate failures without disrupting overall coordination [3, 141]. Finally, UAVs operate under **strict resource constraints**, including limited battery life and computational capacity, necessitating lightweight and decentralized scheduling approaches [163]. Addressing these challenges requires novel algorithms that seamlessly integrate spatiotemporal constraints to ensure **scalability, adaptability, and robustness** in real-world UAV swarm operations.

This survey addresses a critical gap in the existing literature by providing a comprehensive review of scheduling and planning algorithms for large-scale UAV swarms operating under spatiotemporal constraints. Unlike previous surveys that primarily focus on specific algorithmic paradigms or static scheduling problems, this work examines a broader range of methodologies and dynamic mission scenarios. Instead of adopting a rigid taxonomy, this work analyzes how different types of spatiotemporal constraints, such as task urgency, area coverage requirements, and environmental dynamics, shape algorithmic design and system performance. State-of-the-art scheduling approaches, including sampling-based [153], graph-based [103], mathematical optimization-based [81], and learning-based techniques [19], are comparatively assessed to highlight their respective strengths and limitations. In addition, two representative application domains—*sensing* and *communication*—are investigated to illustrate the practical implications of spatiotemporal constraints. In sensing tasks, UAVs must optimize flight paths to maximize coverage while minimizing energy consumption and redundancy. In communication networks, UAVs function as aerial relays or base stations, requiring adaptive scheduling to maintain connectivity and ensure efficient data transmission in dynamic environments.

The key contributions of this survey are as follows:

- A comprehensive and systematic survey of scheduling and planning algorithms for large-scale UAV swarms operating under diverse spatiotemporal constraints is provided, addressing a critical gap in the existing literature.
- The effects of different spatiotemporal constraints, such as task urgency, coverage requirements, and environmental dynamics, on algorithmic design and system performance are analyzed, offering a structured perspective on the associated challenges.
- The strengths and limitations of state-of-the-art scheduling approaches, including sampling-based, graph-based, mathematical optimization-based, and learning-based methods, are evaluated, with emphasis on their suitability for different mission settings.

- Two key application domains, *sensing* and *communication*, are examined to illustrate the practical implications of spatiotemporal constraints and to assess the effectiveness of existing solutions in these contexts.
- Key challenges and future research directions are outlined, including simulator optimization, dataset diversification, the integration of artificial intelligence technologies, and security and privacy protection in UAV swarm systems.

By addressing these dimensions, this survey provides a comprehensive reference for developing scalable and effective UAV swarm coordination under spatiotemporal constraints. The paper is organized as shown in Fig. 1: Section 2 outlines the methodology and related works; Section 3 reviews UAV swarm scheduling and spatiotemporal requirements; Section 4 covers modeling, objectives, and algorithms; Sections 5 and 6 analyze sensing and communication planning with detailed structure presented by Fig. 8 and 9; and Section 7 discusses challenges and future directions.

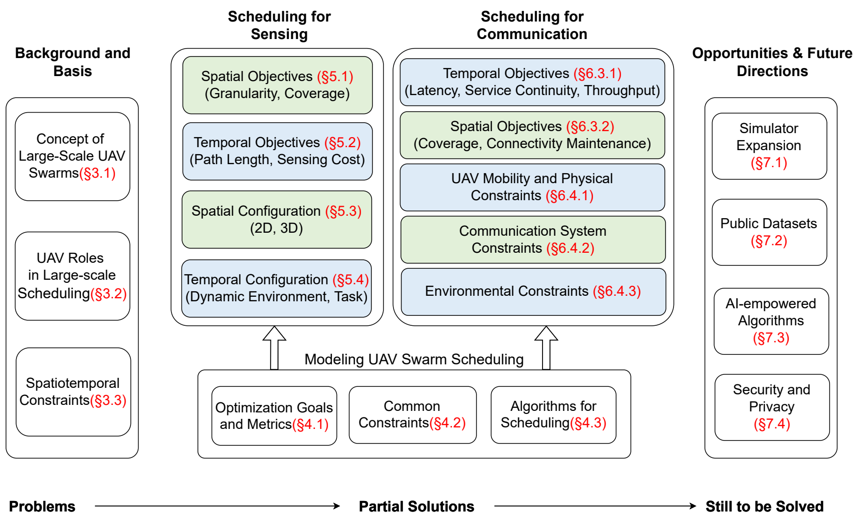

Fig. 1. The figure visualizes topics that discussed in this survey

2 Survey Methodology and Related Surveys

2.1 Survey Methodology

This survey methodology involves a comprehensive review and analysis of literature on scheduling and planning algorithms for large-scale UAV swarms under spatiotemporal constraints. The reviewed literature spans roughly the past decade, a period characterized by rapid progress in UAV swarm autonomy driven by advances in intelligent robotics and networked sensing. To ensure relevance and quality, this survey focuses on high-impact, peer-reviewed publications from leading venues in artificial intelligence, robotics, autonomous systems, and multi-agent research. A structured search across major scientific databases identified studies on UAV swarm coordination, task scheduling, multi-UAV mission planning, spatiotemporal-constrained optimization, and path planning within broader scheduling and decision-making frameworks. The overall survey process is illustrated in Fig. 2.

- **Keyword Selection:** Relevant works were retrieved through a structured search using terms such as "UAV swarm coordination," "multi-UAV task scheduling," "spatiotemporal mission planning," "scalable UAV swarm systems," and "collaborative autonomy."

- **Inclusion Criteria:** Papers were included if they (1) addressed UAV swarm scheduling or task allocation (e.g., mission scheduling, task assignment, cooperative planning); (2) incorporated spatiotemporal constraints in formulations or solutions (e.g., real-time decisions, spatial coverage, resource optimization); and (3) proposed algorithms or frameworks for large-scale UAV swarms emphasizing scalability, robustness, and adaptability.
- **Categorization and Analysis:** Selected papers were organized along two axes: (1) Algorithmic Approach including sampling-based, graph-based, optimization-based, or learning-based methods; and (2) Spatiotemporal Constraint Handling methods for managing timeliness and spatial granularity, as outlined in Section 1.

This structured methodology ensures a comprehensive and transparent literature selection process of the field, capturing state-of-the-art developments, identifying critical research gaps, and outlining future directions for UAV swarm scheduling under spatiotemporal constraints.

2.2 Related Surveys

Table 1. Comparison of previous surveys on UAV scheduling and planning algorithms.

Ref.	Year	Main Features	Learning-based Algo.	Collab.	Large-scale Context	Sensing	Comm.	Navig.
[162]	2019	3D path scheduling and planning for UAVs						✓
[6]	2020	Taxonomy of UAV scheduling approaches	✓				✓	✓
[146]	2020	Classification of cooperative heterogeneous robot tasks		✓	✓			
[161]	2021	Modeling traditional algorithms across scales			✓			✓
[117]	2022	UAV scheduling in communication networks	✓	✓	✓		✓	
[11]	2023	Task scheduling for multi-robot systems	✓	✓				✓
[116]	2023	Categorizes UAV scheduling algorithms based on algorithmic and functional levels	✓	✓	✓			✓
This Work	**2025**	**Comprehensive scheduling framework incorporating sensing, communication, and hierarchical task structures**	✓	✓	✓	✓	✓	✓

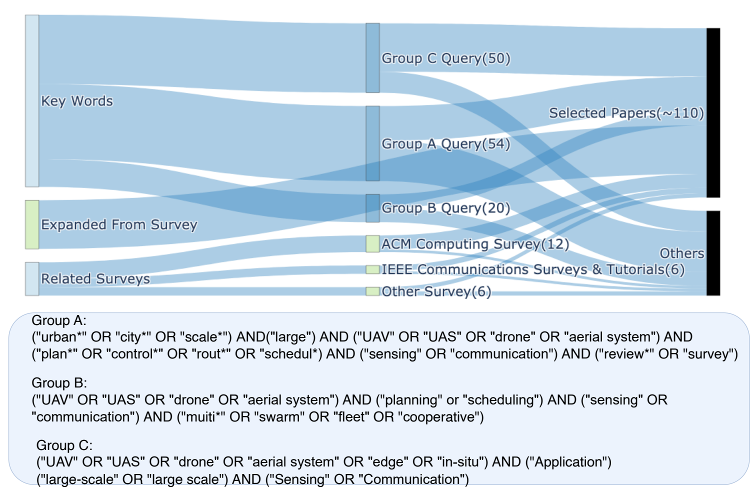

Fig. 2. The figure visualizes the search and conduct process for this survey

Table 2. Comparison of previous surveys on collaborative UAV systems

Ref.	Year	Main Features	Auto. Tasks	Scalability	Robustness	Spatio-temporal Constraints
[94]	2021	Methods for balancing exploration and exploitation in multi-agent and multi-robot systems		✓	✓	
[3]	2022	Path planning for multi-robot formation systems, highlighting formation control strategies and decision-making approaches		✓		
[89]	2023	UAV swarm task allocation algorithms for precision agriculture	✓		✓	
[25]	2024	Computational Intelligence based UAV swarm networking and collaboration, covering both networking and cooperative tasks	✓	✓	✓	
This Work	**2025**	**Comprehensive analysis of scheduling and planning for large-scale UAV coordination under spatiotemporal constraints**	✓	✓	✓	✓

2.2.1 Surveys on UAV Scheduling and Planning Algorithms. Several surveys have explored UAV scheduling and planning, each with a distinct focus, such as path planning, cooperative task execution, or algorithmic classification. However, most prior works concentrate on either navigation-centric planning or communication-specific scheduling, lacking a unified framework that integrates diverse mission objectives. In contrast, this survey provides a comprehensive analysis of UAV swarm scheduling from the perspective of sensing and communication, two fundamental applications that impose distinct requirements on scheduling strategies. Table 1 summarizes key prior surveys in this domain. Early works such as Song et al.[162] and Aggarwal et al.[6] primarily focus on path planning and navigation, categorizing scheduling approaches but without explicitly addressing large-scale UAV swarm coordination. Rizk et al.[146] and Antonyshyn et al.[11] extend their analysis to cooperative multi-agent systems, incorporating learning-based methods but without a dedicated focus on UAV-specific scheduling. More recent surveys such as Luo et al.[117] and Luo et al.[116] examine UAV scheduling within communication networks, emphasizing algorithmic classification but without systematically considering sensing-related scheduling challenges or mission-level task structures.

Unlike prior surveys, this work examines sensing and communication as core application domains, each with distinct scheduling challenges. Sensing-driven scheduling emphasizes spatial–temporal coverage under dynamic priorities, while communication-driven scheduling focuses on link management to maintain connectivity and optimize data transmission under evolving topologies. This survey offers a holistic view of how these domains impact UAV coordination. While most surveys concentrate on low-level tasks like path optimization, this work emphasizes higher-level scheduling structures such as task allocation, resource optimization, and mission prioritization. This hierarchical approach is crucial for large-scale UAV swarm operations, where decisions must balance individual UAV constraints with system-wide efficiency. By linking algorithmic scheduling with mission-driven coordination, this survey offers a more structured, application-aware analysis of UAV swarm scheduling strategies.

2.2.2 Surveys on Large-Scale Collaborative UAV Systems. Research on large-scale collaborative robotic systems has attracted broad interest, with surveys covering coordination, task allocation, and swarm intelligence. Most, however, adopt a general multi-robot perspective—spanning ground, aerial, and underwater platforms—while overlooking the unique challenges of large-scale UAV swarms, such as spatiotemporal constraints, wireless limitations, and UAV-specific resource restrictions. Table 2 contrasts prior surveys with the contributions of this work. Kwa et al. [94] reviewed exploration–exploitation trade-offs in multi-agent systems, focusing on scalability and robustness but not UAV-specific airspace challenges. Abujabal et al. [3] examined path planning in multi-robot formations, emphasizing formation control and decision-making, yet without addressing scalability or robustness in UAV swarm coordination. Recent surveys have begun incorporating UAV-specific considerations. Karampelia et al. [89] studied UAV swarm task allocation in precision agriculture, focusing on autonomous execution without addressing scalability or dynamic scheduling under real-world constraints. Similarly, Cao et al. [25] explored computational intelligence for UAV swarm networking and collaboration, but did not delve into spatiotemporal scheduling challenges in large-scale operations.

In contrast to prior surveys, this work offers a comprehensive analysis of large-scale UAV coordination under spatiotemporal constraints. Unlike general multi-robot surveys, this survey focuses specifically on UAV swarm scheduling, addressing unique challenges like airspace congestion, energy-aware task scheduling, and real-time adaptation to dynamic mission demands. This work also examines how spatiotemporal constraints, such as mission deadlines and spatial coverage, impact UAV scheduling strategies—an aspect often overlooked in previous works. Unlike ground-based robotic systems, UAV swarm operations rely on wireless communication and decentralized control, which introduce challenges such as communication latency, link disruptions, and coordination complexities. This survey highlights how these factors affect UAV swarm scheduling, providing a fresh perspective on large-scale UAV deployments. Additionally, this paper emphasizes energy-aware scheduling, given the stringent power constraints that influence mission planning and task execution. By integrating these UAV-specific challenges, this work presents a structured, application-driven view of UAV swarm coordination, setting it apart from existing surveys.

3 Background and Basis

3.1 Overview of Large-Scale Swarm Collaboration

Large-scale swarm collaboration refers to the coordinated operation of a large number of autonomous agents, such as UAVs, to achieve complex tasks that are beyond the capabilities of individual agents. In such systems, UAVs work together to complete missions that require high levels of adaptability, scalability, and robustness [33, 211]. The importance of large-scale swarm collaboration lies in its ability to address challenges in dynamic and uncertain environments [179], where tasks often require diverse capabilities, efficient resource allocation, and robust communication. Applications of large-scale swarm collaboration span a wide range of domains, including disaster monitoring [90], environmental sensing [60, 69, 224], urban planning [125, 218], logistics [100], military operations [175], and communication networks [187]. For instance, UAV swarms can be deployed for rapid disaster response, such as assessing damage after earthquakes or floods. In logistics, UAVs enable efficient delivery systems in urban areas, while in environmental sensing, they provide scalable solutions for large-scale data collection and monitoring.

3.2 UAV Roles in Large-scale Scheduling

3.2.1 UAVs as Mobile Sensing Platforms. UAVs have emerged as promising platforms for large-scale mobile sensing due to their high mobility, flexibility, and adaptability [132, 209]. Compared with traditional ground-based sensors or satellites, UAVs can access hard-to-reach areas and dynamically adjust flight paths based on real-time information or mission requirements [35]. Equipped with diverse sensing modalities, UAVs enable the collection of spatially distributed data, supporting environmental monitoring as well as spatial reasoning and decision-making with advanced artificial intelligence (AI) techniques [102, 210, 219].

3.2.2 UAVs as Data Collection Stations. In addition to their role as mobile sensing platforms, UAVs can also serve as data collection stations in large-scale sensing scenarios. UAVs can act as relay points, gathering data from ground-based sensors or other UAVs and transmitting it to a central processing unit [84]. This functionality is particularly useful in situations where direct communication between sensors and the central unit is limited due to distance or obstacles. By acting as data collection stations, UAVs can extend the range and coverage of sensing networks, enabling efficient data aggregation and transmission.

3.2.3 UAVs as Communication Nodes. UAVs can also play a crucial role as communication nodes in large-scale sensing applications. In scenarios where traditional communication infrastructure may be limited or unavailable, such as in remote areas or disaster-stricken regions, UAVs can establish temporary communication networks [29]. By acting as aerial communication nodes, UAVs can facilitate data exchange between ground-based sensors, other UAVs, and control centers. This capability enhances the overall connectivity and coordination within the sensing network, enabling real-time data sharing and decision-making [192].

3.3 Classification of Spatiotemporal Requirements

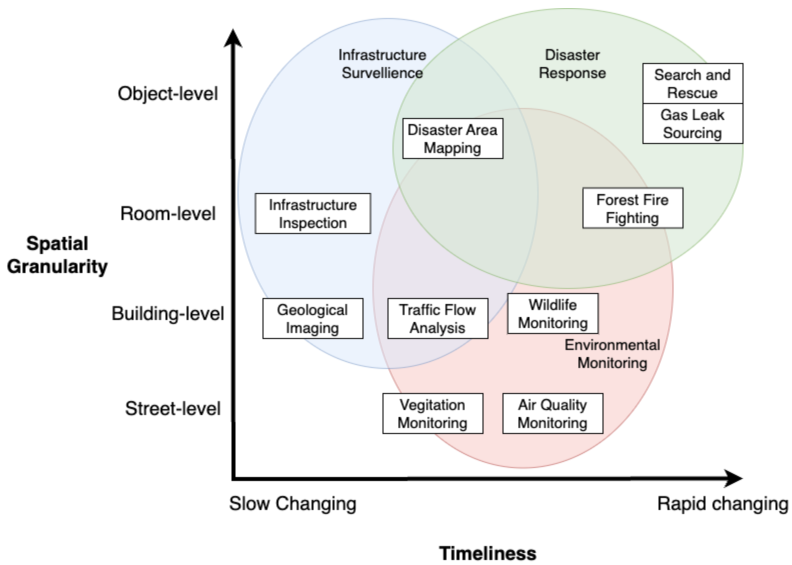

Fig. 3. The figure visualizes the spatio-temporal requirements of these applications. The placement of the applications within the figure indicates their specific spatio-temporal characteristics and requirements.

Spatiotemporal constraints play a crucial role in UAV swarm scheduling and planning, directly impacting task prioritization, mission feasibility, and execution strategies. These constraints encompass multiple factors, including task urgency, spatial coverage requirements, and environmental dynamics, all of which must be carefully considered to ensure efficient and scalable UAV swarm coordination. Proper characterization of these constraints is essential for aligning UAV operations with real-world mission demands and optimizing resource allocation. Fig. 3 depicts applications with specific spatio-temporal requirements.

3.3.1 Temporal Dimension. From a temporal perspective, tasks can be classified by timeliness. Low-timeliness (LT) tasks permit flexible scheduling and are common in missions without urgent demands, such as environmental monitoring [60], terrain mapping [130], and periodic data collection [191]. High-timeliness (HT) tasks, by contrast, require immediate or real-time responses in time-critical scenarios, including search and rescue [120], disaster response [76], traffic monitoring [137], and military operations [114]. This temporal classification is central to defining task urgency and guiding swarm resource allocation.

3.3.2 Spatial Dimension. Beyond temporal requirements, tasks can also be categorized by spatial granularity. Fine-granularity (FG) tasks require precise interaction with specific targets, such as package delivery [17], target tracking [184], and infrastructure inspection [126]. Coarse-granularity (CG) tasks instead prioritize wide-area coverage, as in environmental sensing [60], agricultural monitoring [214], and large-scale disaster assessment [144].

3.3.3 Spatiotemporal Combinations. The interplay of temporal and spatial requirements yields four spatiotemporal categories, offering a systematic lens on UAV swarm operations. Low-timeliness and fine-granularity (LT-FG) tasks involve slow-changing object-level operations (e.g., wildlife monitoring [178], infrastructure inspections [126]), requiring spatial precision but allowing flexible scheduling. Low-timeliness and coarse-granularity (LT-CG) tasks address slow-changing region-level operations (e.g., environmental monitoring [60], climate data collection [15]), prioritizing broad coverage over strict timing. High-timeliness and fine-granularity (HT-FG) tasks involve rapidly changing object-level operations (e.g., target identification, precision strikes [114]), demanding both real-time response and spatial accuracy. High-timeliness and coarse-granularity (HT-CG) tasks concern rapidly changing region-level operations (e.g., traffic surveillance [137], disaster response [76], search-and-rescue [120]), where timely coverage of large areas is crucial.

3.3.4 Impact of Spatiotemporal Constraints. Spatiotemporal constraints, defined by task urgency and spatial precision, are central to UAV swarm scheduling and planning. They shape task prioritization, resource allocation, and path design, creating challenges in balancing efficiency, responsiveness, and scalability. Temporal constraints dictate urgency: high-timeliness tasks (e.g., disaster response [76], search-and-rescue [120]) demand immediate action, whereas low-timeliness tasks (e.g., environmental monitoring [60]) allow flexible execution. Spatial constraints define granularity: fine-granularity tasks require precise navigation to specific targets, while coarse-granularity tasks emphasize broad coverage. Their interplay complicates task allocation under limited energy and communication resources. Path planning is equally shaped by these constraints. High-timeliness tasks require fast route optimization, while fine-granularity tasks necessitate accurate trajectories. These needs often conflict with energy efficiency and coverage, motivating multi-objective optimization. Recent advances in reinforcement learning and heuristics have shown promise [123, 170]. The coupling of scheduling and path planning further intensifies complexity: scheduling decisions constrain feasible paths, while path outcomes reshape task assignments. Integrated frameworks are thus critical for robust swarm operation in dynamic environments where tasks and UAV states evolve.

4 Modeling UAV Swarm Scheduling and Planning

The modeling of scheduling and planning for UAV swarms is a critical foundation for enabling the efficient and reliable execution of missions. In the context of large-scale operations, scheduling refers to the allocation of tasks across a fleet of UAVs, while planning involves determining the optimal paths and strategies for task execution. Together, these processes aim to achieve mission objectives under a variety of constraints and uncertainties.

4.1 Optimization Goals and Metrics

The optimization of UAV swarm scheduling and planning is inherently multi-objective, reflecting the diverse requirements of real-world applications. Key objectives include minimizing the number of UAVs in resource-constrained scenarios, reducing energy consumption given limited onboard battery capacity, and shortening mission completion

Table 3. Comparison of Key Metrics in UAV Scheduling

Metric Name	Formula	Purpose	Advantages	Applications
Entropy	$H(X) = -\sum_{i=1}^{n} P(x_i) \log P(x_i)$	Measure of uncertainty in a system	Assess the level of uncertainty, prioritize high entropy regions	Exploration [57], Information acquisition [41]
Ergodic Metric	$\lim_{T\to\infty} \frac{1}{T} \int_0^T f(x(t))dt = \int \Omega f(x)\rho(x)dx$	Measure uniformity of coverage	Evaluate and optimize coverage uniformity	Environmental monitoring, surveillance
Average Coverage Rate	$r_t = \frac{f_t\left(\sum_{k=1}^{K} \Delta c_k^t\right)}{\sum_{i=1}^{N} \Delta e_i^t}$	Evaluate rate of effective coverage	Considers both coverage quality and energy expenditure	Efficient coverage of the area of interest
Coverage Fairness	$f = \frac{\left(\sum_{k=1}^{K} c_k\right)^2}{K\left(\sum_{k=1}^{K} c_k^2\right)}$	Quantify evenness in coverage distribution	Ensures uniformity in coverage among sensing agents	Communication Coverage [107]
Age of Information (AoI)	$\kappa_{t+1}^m = \begin{cases} 1, & \text{if updated} \\ \kappa_t^m + 1, & \text{otherwise} \end{cases}$	Quantify freshness of collected information	Minimizes information decay, prioritizes real-time updates	Disaster response [51], surveillance [104]
Aggregate System Throughput	$T_{\text{total}} = \sum_{i=1}^{N} T_i = \sum_{i=1}^{N} \frac{B_i}{\Delta t}$	Quantify total data delivery capability of the UAV swarm.	Clarify the communication bottleneck of practical deployment, enables QoS guarantees	Sensing applications [154], Communication [82], Joint systems [154]
Image Overlap Ratio	$O = 1 - \frac{df}{HW} = 1 - \frac{dp}{\text{GSD}\cdot w}$	Quantify common ground coverage between successive images	Ensures coverage and quality of sensing output	Agricultural applications [139], Photogrammetry [58]

time in time-critical tasks such as search and rescue or disaster response. Additional considerations involve minimizing flight path length to reduce energy usage and hardware wear, maximizing sensing coverage for reliable data collection, and ensuring safety and robustness through collision avoidance and resilience to failures or communication disruptions.

In addition to these objectives, several performance metrics are widely used to evaluate UAV swarm systems, as summarized in Table 3. Information-theoretic measures such as entropy and ergodicity quantify sensing uncertainty and spatial coverage uniformity, while metrics including coverage rate and coverage fairness assess the efficiency and balance of area monitoring across multiple UAVs. The age of information (AoI) further captures the freshness of collected data, which is particularly important for time-sensitive monitoring tasks such as disaster response and surveillance. At the communication level, aggregate throughput reflects the overall data delivery capability of the UAV swarm network and becomes critical in data-intensive sensing missions, such as LiDAR mapping, hyperspectral imaging, or large-scale visual monitoring, where sensing data volumes may exceed available communication capacity [154]. Higher transmission rates, however, may require additional bandwidth or communication power, thereby increasing energy consumption and creating trade-offs with other objectives. Another practical metric is the image overlap ratio, which measures the shared ground coverage between consecutive images and is essential for photogrammetric pipelines such as structure-from-motion and multi-view stereo reconstruction. Higher overlap improves reconstruction reliability but also increases the number of captured images, leading to longer flight time, greater energy consumption, and higher communication demand. Consequently, overlap constraints must be balanced with coverage efficiency, mission completion time, and communication throughput in UAV swarm scheduling [58].

In practical UAV swarm scheduling systems, performance metrics are inherently interdependent rather than optimized in isolation. Geometric sensing objectives, communication capacity, and resource constraints jointly shape overall system performance. The introduction of metrics such as aggregate throughput and image overlap further turns UAV planning into a cross-layer multi-objective optimization problem that simultaneously considers coverage quality, communication efficiency, information freshness, and energy consumption. Empirical studies illustrate these interactions. Reinforcement learning-based scouting strategies [217] adaptively increase sampling density in informative regions while avoiding

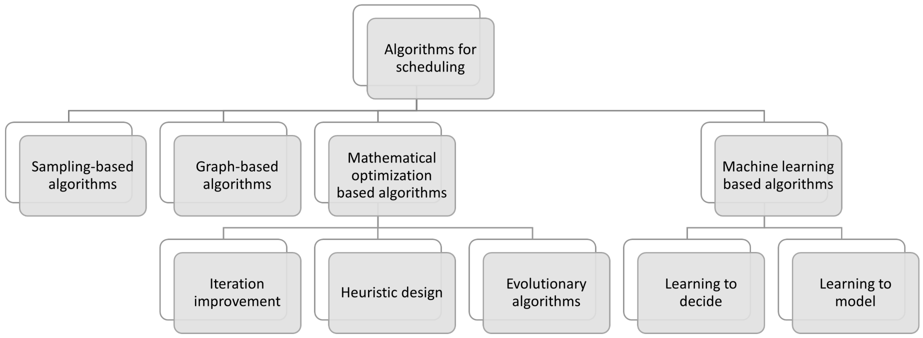

Fig. 4. Structure of Section 4.3. Branches of representative planning algorithms.

redundant coverage, thereby implicitly regulating overlap and communication demand. Similarly, adaptive multi-UAV deployment strategies [22] show that excessive sensing density can increase communication load and energy consumption, leading to earlier system bottlenecks. Overall, incorporating practical performance metrics highlights the need for cross-layer modeling and Pareto-aware optimization to balance coverage, information freshness, energy efficiency, fairness, communication capacity, and sensing reliability in large-scale UAV swarm systems.

4.2 Common Constraints

Beyond mission objectives, UAV swarm scheduling and planning must account for constraints arising from the environment and operational context. Terrain factors (e.g., urban obstacles, mountainous landscapes, restricted airspace) limit feasible flight paths; resource constraints (e.g., battery life, payload) restrict operational capacity; and communication constraints (e.g., range, bandwidth, disruptions) challenge coordination in large-scale or remote settings. Algorithmic constraints also matter, as scheduling methods must balance complexity, scalability, and adaptability. Among these, spatiotemporal requirements are particularly critical, defining task urgency and spatial precision. They shape prioritization and feasibility: strict temporal demands require highly responsive scheduling, while fine spatial accuracy necessitates precise path planning and localization. Incorporating spatiotemporal constraints into scheduling models is thus essential for effective UAV swarm operation in complex, dynamic environments.

4.3 Algorithms for Scheduling

Planning algorithms are essential for efficient and optimized UAV navigation in large-scale sensing applications [92, 157], guiding UAVs to feasible routes while accounting for terrain, obstacles, energy, and mission objectives. This section overviews path planning methods, categorized into Sampling-based (§4.3.1), Graph-based (§4.3.2), Optimization-based (§4.3.3), and Learning-based (§4.3.4) algorithms. This section also highlights the methods' distinct features, strengths, and limitations for collaborative UAV swarm operations (§4.3.6). Section 4.3.5 explains how these algorithms are mapped to the spatiotemporal task categories in Fig. 3 and Section 3.3, where varying temporal urgency and spatial granularity impose different computational and operational requirements on UAV swarm coordination.

4.3.1 Sampling-based Algorithms. These methods require prior knowledge of the workspace, typically represented mathematically and sampled into nodes, cells, or other forms. The environment is then mapped or randomly searched to obtain a feasible path. Sampling-based algorithms fall into two categories: active and passive [143]. Active methods, such as Rapidly-Exploring Random Trees (RRT), autonomously generate feasible paths to the goal. Passive methods, such as Probabilistic Roadmaps (PRM) [199], construct a roadmap between start and goal, after which a search algorithm selects the optimal path among many feasible options.

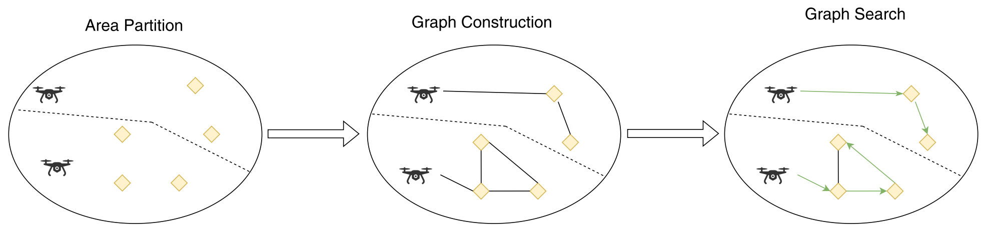

Fig. 5. A visualization of general steps in Graph-based Algorithm

4.3.2 Graph-based Algorithms. Graph-based algorithms plan paths by representing the environment as a graph and searching for optimal routes. The configuration space is discretized into nodes connected by edges, followed by graph search. Classical algorithms such as Dijkstra and A* are widely used in both static and dynamic environments.

Geometric Graph. Geometric graphs are a graph-based path planning method representing the environment with nodes (points) and edges (feasible paths). In large-scale sensing, they enable efficient area coverage while accounting for maneuverability. Their advantages include optimality in well-defined, static environments, simplicity, and ease of implementation. Notable works include Di Franco and Buttazzo [53], who minimized UAV energy consumption considering terrain, and Kusnur et al. [93], who minimized path length in dynamic settings.

Heuristical Shortest Path. Geometric graphs represent the environment with nodes (points) and edges (feasible paths) and are widely used for UAV path planning. In large-scale sensing, they support efficient area coverage while considering maneuverability. Advantages include optimality in static environments, simplicity, and ease of implementation. Key studies include Di Franco and Buttazzo [53], who minimized UAV energy consumption with terrain constraints, and Kusnur et al. [93], who minimized path length in dynamic scenarios. Schlotfeldt et al. [158] applied the ARA* algorithm for decentralized, anytime planning in multirobot active information gathering, pruning uninformative trajectories and providing suboptimality guarantees, demonstrating feasibility in target tracking under real-time constraints. Nieuwenhuisen and Behnke [127] employed D* for 3D MAV trajectory planning, ensuring onboard sensor coverage while balancing flight time under payload limits. Kusnur et al. [93] used ITSA* for search-based active sensing in goal-directed coverage tasks, independently planning robot and sensor trajectories in decoupled spaces and refining them via local joint-space search to maximize information gain.

Nearest Neighbour. The Nearest Neighbour Algorithm (NNA) is widely used for large-scale sensing, selecting the closest unvisited node at each step to efficiently cover an area. To reduce query complexity, data structures such as k-d trees [48] are often employed. Collins et al. [48] proposed SCoPP, a multi-robot coverage path planning algorithm that uses nearest-neighbor planning to generate time-efficient, workload-balanced paths while handling area discontinuities like no-fly zones. Yu et al. [207] addressed coverage for a UAV-UGV system by reducing the problem to the NP-hard Generalized Traveling Salesperson Problem (GTSP), enabling optimal path computation using a GTSP solver.

4.3.3 Mathematical Optimization-based Algorithms. Graph-based algorithms model robots as points with acceleration and velocity constraints, limiting their ability to capture full environment and system dynamics. In contrast, optimization-based algorithms formulate path planning as an objective-driven problem, using techniques like gradient methods or genetic algorithms to minimize distance, maximize clearance, or reduce energy consumption. These methods can incorporate kinodynamic constraints and polynomial forms, enabling modeling of time-varying environments. Notable applications include Schlotfeldt et al. [158] and Wang et al. [183], optimizing runtime and path length, respectively. Key

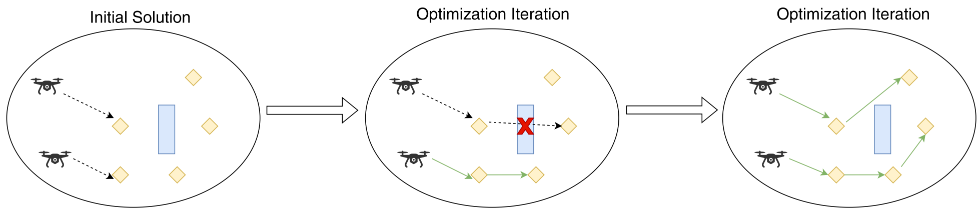

Fig. 6. A visualization of general steps in Optimization-based Algorithm

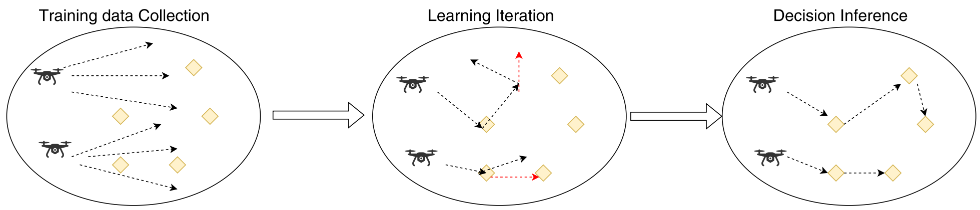

Fig. 7. A visualization of general steps in Learning-based Algorithm

factors include Iteration Improvement, which refines solutions through repeated updates, and Heuristic Design, which applies practical methods for efficient, though potentially suboptimal, solutions.

Iteration Improvement. Iteration Improvement refines an initial solution through repeated algorithmic application, guided by a cost function to progressively enhance solution quality. Schlotfeldt et al. [158] demonstrated this in a target-tracking scenario with three UAVs and five mobile targets, using an anytime planning algorithm to reduce suboptimality while respecting real-time constraints. Wang and Zhang [183] proposed a gradient and grouping (GGC) method for simple swarm robots, enabling self-organization and parallel area coverage without heavy computational resources, thereby enhancing iterative planning efficiency in unknown environments.

Heuristic Design. Heuristic design provides practical, though not always optimal, solutions for complex, large-scale sensing problems. In planning, heuristics enable efficient navigation over vast environments. For example, Sanchez-Fernandez et al. [156] introduced the Visibility-Based Path Planning (VPP) heuristic, allowing UAVs to monitor complex terrains by identifying hidden areas and maximizing visual coverage, achieving up to 98.7% coverage in Montes de Malaga Natural Park and 94.5% in Sierra de las Nieves National Park. Ahmed et al. [8] proposed an energy-efficient UAV method using heuristics to optimize paths while accounting for battery, terrain, and coverage, providing practical large-scale sensing solutions.

Evolutionary Algorithm. Evolutionary Algorithms (EAs) encompass methods such as Genetic Algorithm (GA) [174], Memetic Algorithm (MA), Particle Swarm Optimization (PSO) [46], Ant Colony Optimization (ACO) [32], and Shuffled Frog Leaping Algorithm (SFLA). Designed to tackle NP-hard problems with many variables, EAs use stochastic search inspired by natural evolution and social behaviors. GA, the first widely implemented EA, served as the basis for subsequent methods inspired by various natural processes.

4.3.4 Learning-based Algorithms. Learning-based algorithms leverage machine learning to improve path planning by learning from data or experience. Common approaches include reinforcement learning, imitation learning, and deep learning, which map environment states to optimal actions and adapt over time. Specifically, early work [21] demonstrates how reinforcement learning can be applied to decentralized multi-UAV coordination, establishing key frameworks for scalability, adaptation, and learning-based decision-making in swarm systems. While related to mathematical optimization, these methods focus on data-driven decision-making. Learning algorithms are categorized into Learning to Model, which predicts system behavior to guide planning, and Learning to Decide, which uses these models for action selection. Both categories enhance the efficiency and effectiveness of path planning.

Learning to Model. Learning-to-Model algorithms are classified into Recurrent Neural Networks (RNNs) and Q-Learning, both essential for large-scale sensing. RNNs process sequential data and capture temporal dependencies, enabling informed path planning to maximize data collection utility. Wei and Zheng [189] proposed an IPP algorithm combining RNNs and reinforcement learning, addressing reward dependencies and budget constraints, achieving faster convergence, superior optimality, and transferability across scenarios. Q-Learning, a model-free reinforcement learning method, estimates action values (Q-values) directly from experience without requiring an environment model. Wei [190] applied Q-Learning to multi-robot informative path planning, using independent and sequential rollout-based strategies that scale with robot number, match or outperform genetic algorithm baselines, reduce inference time, and generalize to varying budgets or initial positions. Together, RNNs and Q-Learning enhance adaptability and decision-making in dynamic, large-scale UAV operations.

Learning to Decide. Learning-to-Decide algorithms are categorized into Policy Gradient, Tree Search, and Submodular Optimization, all crucial for large-scale sensing. Policy Gradient optimizes decision-making by adjusting policy parameters based on expected reward gradients, adapting actions to the environment and past experience. Notable works include Liu et al. [105] (energy-efficient UAV planning), Wang et al. [180] (trajectory planning with 3D networks and multi-head attention), and Gong et al. [67] (Bayesian optimization for multi-UAV learning). Tree Search explores the solution space systematically; Ruckin et al. [149] combined Monte Carlo Tree Search (MCTS) with Convolutional Neural Networks (CNNs) for UAV data gathering, and Dai et al. [51] enhanced MCTS with a relational graph convolutional network (RGCN) and next-state prediction for improved planning. Submodular optimization leverages diminishing marginal gains to enable efficient greedy algorithms with theoretical guarantees, making it effective for near-optimal decision-making in large, complex sensing environments. A notable use of submodularity in learning-based algorithms is Prajapat et al. [136], who formulated multi-agent path planning as maximizing a monotone submodular reward under matroid constraints. They proposed the SAFEMAC algorithm, achieving near-optimal guarantees. By exploiting submodularity, SAFEMAC efficiently selects informative paths, maximizing cumulative reward while scaling well with the number of agents.

4.3.5 Mapping algorithms categories to spatiotemporal quadrants. In general, tasks characterized by high timeliness (HT) require algorithms capable of rapid decision-making and online adaptation, making heuristic or learning-based approaches particularly suitable. In contrast, low-timeliness (LT) missions allow more computationally intensive optimization methods that can improve global efficiency. Similarly, fine-granularity (FG) tasks demand precise trajectory planning and target-level navigation, favoring optimization-based or sampling-based algorithms, while coarse-granularity (CG) tasks emphasize area coverage and scalability, where graph-based or coverage-planning methods are often preferred. Therefore, the algorithms discussed above can also be analyzed through the spatiotemporal framework shown in Fig. 3.

4.3.6 Summary for planning algorithms. Table 4 compares representative path planning algorithms for large-scale sensing. Sampling-based methods, such as Rapidly-exploring Random Trees (RRT) and Probabilistic Roadmaps (PRM), efficiently explore high-dimensional or partially unknown environments but may yield suboptimal paths and require

Table 4. Selected representative algorithms for planning

Paper	year	Spatial Granularity	Timeliness	Optimization Goal	Environmental Constraints	Algorithm Type
[53]	2015	Object-level	On demand	Energy consumption	Terrain and physical constraints	Graph-based
[105]	2018	Street-level	Periodic	Energy consumption	Communication constraints	Learning-based
[158]	2018	N/A	Real-time	Runtime	Terrain and physical constraints	Optimization-based
[127]	2019	Object-level	N/A	Turning maneuvers	Terrain and physical constraints	Graph-based
[207]	2019	Object-level	On demand	Completion time	Terrain and physical constraints	Graph-based
[189]	2020	N/A	N/A	Runtime	N/A	Learning-based
[48]	2021	N/A	N/A	Completion time	Terrain and physical constraints	Graph-based
[93]	2021	Object-level	N/A	Path length	Dynamic constraints	Graph-based
[180]	2021	Building-level	Periodic	Energy consumption	Terrain and physical constraints	Learning-based
[183]	2021	N/A	N/A	Path length	N/A	Optimization-based
[190]	2021	N/A	N/A	Runtime	N/A	Learning-based
[51]	2022	N/A	Real-time	Energy Consumption	N/A	Learning-based
[136]	2022	N/A	N/A	N/A	Terrain and physical constraints	Optimization-based
[149]	2022	Building-level	On demand	N/A	N/A	Learning-based
[151]	2022	Room-level	On demand	Runtime	Algorithm constraints	Learning-based
[156]	2022	Building-level	On demand	Path length	Terrain and physical constraints	Optimization-based
[8]	2023	Object-level	On demand	Energy Consumption	Terrain and physical constraints	Optimization-based
[67]	2023	Street-level	Periodic	Energy Consumption	Communication constraints	Learning-based

scenario-specific tuning. Graph-based algorithms perform well in static, well-defined environments due to their optimality and implementation simplicity. Optimization-based approaches, including gradient-based and evolutionary algorithms, handle dynamic environments with complex constraints. Learning-based methods provide strong adaptability by leveraging experience, making them suitable for complex and evolving scenarios, although they require high-quality training data and substantial computational resources.

5 Scheduling for Sensing

As illustrated in Fig. 8, this section shows how scheduling for sensing can be systematically analyzed from two complementary perspectives—optimization objectives and system configuration—since sensing missions must simultaneously determine what performance criteria to optimize (e.g., coverage, granularity, or sensing cost) and how the UAV system is structured to achieve these objectives in practical deployments.

5.1 Optimization Objectives

Based on objectives of optimization in scheduling for sensing–spatial granularity, spatial coverage, path lengths, and sensing costs–related works are organized into relevant categories.

5.1.1 Spatial Objectives. **Spatial Granularity.** For granularity prioritized UAV sensing systems, current works can be categorized into high-resolution scalar field sensing and high-resolution imaging.

Fine-Grained Scalar Field Sensing Coverage. [59] addressed fine-grained spatio-temporal sensing in Vehicular Urban Sensing (VUS) systems using sensors on for-hire vehicles (FHVs) and dedicated sensing vehicles (DSVs). Due to uneven

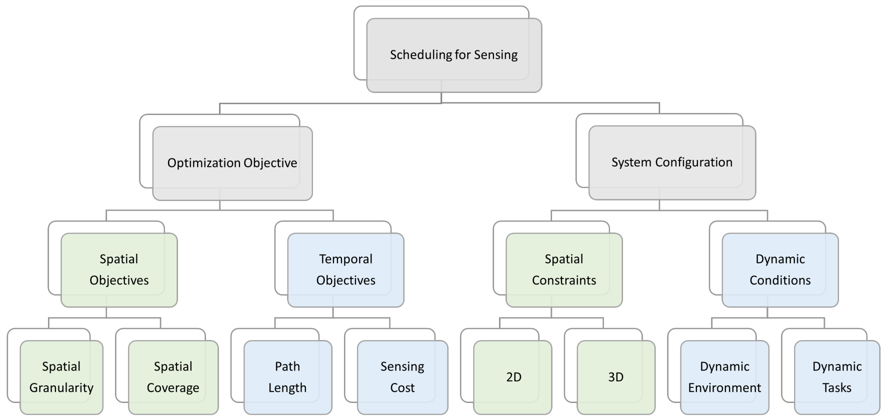

Fig. 8. Structure of Section 5. Scheduling for sensing.

FHV distribution, their coverage alone is insufficient. The proposed hybrid approach combines FHVs with DSVs, optimizing DSV repositioning to minimize long-term operational costs while ensuring comprehensive coverage. The problem is formulated as a stochastic dynamic program, solved using distributionally robust optimization, primal-dual transformation, and second-order conic programming to manage uncertainty and computational complexity. Validation with real-world Shenzhen taxi trajectories demonstrated improved sensing coverage. HMSS [42] similarly targets fine-grained city-scale outdoor air pollution maps.

High-Resolution Imaging System. UAV planning is critical for high-resolution imaging, enhancing applications from scene reconstruction to semantic segmentation. For UAVs with Synthetic Aperture Radar (SAR) systems, [194] analyzed factors affecting image quality in specific sensors and environments, formulating them into a constrained multi-objective optimization problem (CMOP). This approach considers both navigation [216] and imaging performance during path planning. For image-based reconstruction, planar segmentation defines, identifies, and divides surface segments to sample representative points. Recent advances include surface geometric primitive-guided UAV path planning (SGP-G) [222], four geometric classes for segmentation [110], statistical downscaling of planar segments (SDSM) [223], and high-resolution semantic segmentation [164], all validated in practical experiments and particularly effective for cultural heritage modeling. For high-resolution semantic segmentation under dynamic conditions, [164] proposed an adaptive online path planning algorithm, enabling UAVs to optimize data collection by targeting areas with fine details. The method incorporates a deep-learning-based precision model linking UAV altitude and segmentation accuracy.

Discussion. Recent work explores adaptive sensing strategies that dynamically adjust sampling density to balance imaging resolution and coverage efficiency. The Whole-Field Reinforcement Learning framework enables UAVs to focus sampling on high-information regions while avoiding redundant coverage in low-value areas [217]. Meanwhile, UAV-based agricultural monitoring systems combining deep learning and edge computing support real-time crop condition detection during flight [202]. In such deployments, path planning maintains sufficient observational redundancy while limiting excessive image overlap that would increase communication and processing overhead.

Spatial Coverage. Maximizing spatial coverage is a key objective in sensing scheduling, spanning mobile crowdsensing, robotic exploration, and active SLAM. Various approaches aim to achieve large and balanced coverage at low cost [40, 41, 195]. For autonomous exploration, attention-based models with reinforcement learning enable real-time path planning by predicting spatial gains and balancing exploitation with exploration [26]. In active SLAM, mobile robots incrementally map unknown environments while avoiding obstacles and revisiting landmarks to enhance accuracy [172]. In UAV sensing, incomplete coverage often arises from obstructed or hard-to-reach areas and the difficulty of identifying target features in complex scenes. Beyond simulation- and methodology-driven analyses, pioneering real-world deployment studies by Boubin's group [22, 139] demonstrate coordinated UAV swarms operating in operational agricultural settings, revealing practical challenges such as environmental variability, communication reliability, and coordination under GPS-degraded field conditions. These empirical findings provide valuable real-world validation for the spatial sensing objectives and system configuration strategies discussed in Section 5.2.

Incomplete Coverage due to Obstructed Areas. In close-range sensing, UAVs often navigate complex environments with dense obstacles, constraining flight trajectories and creating blind spots. To address this, a hybrid multi-algorithm framework combining GLocal and FUEL [27] merges sampling-based and boundary-based approaches, generating smooth paths in cluttered indoor spaces. Another UAV path planning algorithm [68] computes both waypoints and vehicle orientation for indoor and outdoor navigation [36], achieving full coverage in monitoring tasks. Visibility-Based Path Planning (VPP) [156] identifies hidden blind spots to maximize visual coverage, as demonstrated in simulations for Malaga and Nevado Mountain Natural Park. Considering 3D object surfaces and self-occlusions, a multi-rotor UAV 3D path planning method [215] plans imaging locations using an initial rough scene model and photogrammetric constraints, ensuring comprehensive image capture for accurate 3D reconstruction. This approach is applicable beyond building modeling, supporting large-scale photogrammetric tasks.

Inability to Identify Target Features within Complex Images. Complex urban and agricultural terrains illustrate the challenge of identifying irregular features from camera images. Zheng and Botteghi studied these environments respectively [20, 220]. Zheng optimized city map modeling using a deep learning framework guided by reinforcement signals [220], while Botteghi evaluated path-planning algorithms across European farms, showing that several popular methods are sensitive to complex topologies [20].

Coverage Overlap. Considering the impact of image overlap on sensing efficiency, recent studies have explored adaptive strategies that dynamically balance observation density and coverage efficiency. For example, the Whole-Field Reinforcement Learning framework enables UAVs to selectively sample high-information regions within large agricultural fields while avoiding redundant coverage in low-value areas [217]. By learning spatial information gain across the field, the system maintains sufficient observation density where needed while reducing unnecessary overlap. Complementary to adaptive sampling, Yang et al. [202] investigated the trade-off between observational redundancy and real-time recognition in high-resolution agricultural monitoring by integrating deep learning with edge computing for in-flight crop condition detection. In such deployments, flight planning must provide adequate visual redundancy for reliable detection while limiting excessive overlap that increases communication and processing overhead.

5.1.2 Temporal objectives. Two primary factors contribute to the enhanced efficiency of UAV swarm tasks: the reduction in path length and the minimization of sensing costs.

Path Length. Shorter paths improve the interconnection of points of interest (PoI) and simplify obstacle avoidance. The Teaching-Learning-Based Optimization (TLBO) algorithm [205] generates fast-converging paths by optimizing search angles and distances through teacher–learner interactions, while the R-dfs algorithm [168] reduces traversal time by optimizing visit sequences and minimizing turns, addressing limitations of traditional coverage path planning (CPP) in concave regions. Application-driven systems further formulate trajectory optimization problems under task constraints. For example, DDL [37, 38] models delivery-based sensing as a mixed-integer nonlinear programming (MINLP) problem to jointly optimize sensing utility and delivery time, while monitoring systems such as ARMS [203] and OA-MinTime [173] optimize visit order and trajectories for applications including real-time AQI mapping and surveillance under operational constraints. Informative planning further improves exploration efficiency by prioritizing regions that reduce environmental uncertainty, benefiting tasks such as active SLAM, target localization, and environmental monitoring. Representative approaches include biased sampling [88], reinforcement learning combined with tree search [152], and dynamic exploration planners (DEP) [199], which incrementally update node utilities to avoid redundant computation while efficiently generating obstacle-avoiding trajectories.

Sensing Cost. The efficiency of data collection also plays a vital role in the efficiency of multi-UAV planning for sensing. This can be achieved by optimizing UAV hovering or observation time, optimizing data acquisition quality, or optimizing UAV observation angles.

Optimizing UAV Hovering (Observation) Time. One innovative approach [34] involved formulating UAV network path planning as a Vehicle Routing Problem (VRP). This methodology optimized task assignment by minimizing the observation time of the UAV network, consequently enhancing the efficiency of data collection, therefore ensuring optimized path planning and preventing route intersections. [115] investigated the Fine-grained Trajectory Plan (FTP) problem for multi-UAVs, in which UAVs gather data from Wireless Sensor Networks (WSNs), leveraging their mobility and flexibility. The FTP problem requires not only to find the flight paths of multiple UAVs but also to design the detailed hovering and traveling plans along their paths. This work proposes a constant-factor approximation algorithm for approximating the optimal solution of the FTP problem.

Optimizing Data Acquisition Quality. [160] introduced another 3D coverage path planning method, co-optimizing paths efficiency, image quality, and computational complexity. Utilizing a highly parallelized algorithm based on the Particle Swarm Optimization (PSO) framework, the proposed method achieved more effective paths, enhancing both the quality of useful image data while maintaining efficiency.

Optimizing UAV Observation Angles. Chen, H., et al. [32] tried the application of machine learning to improve the FoV of UAV swarm path planning: the Opposition-Based Learning Artificial Bee Colony (OABC) algorithm. Considering observational angle constraints under conditions of obstacle existence around the target, an observation angle-based target information entropy ratio model was introduced. To efficiently find the optimal observation angles, the OABC algorithm generated bit points with a swarm consisting of lower-quality individuals. The algorithm searched for better individuals near current positions during the generation of new solutions. Additionally, to prevent individuals from observing targets from similar angles, the concept of individual abandonment probability was introduced.

5.2 System Configuration

5.2.1 Spatial System Configuration. UAV swarm scheduling can be broadly categorized into 2D and 3D sensing planning. For 2D spaces, representative studies include autonomous indoor exploration [26], UAV-enabled surveillance [173], coverage path planning [168], path routing optimization for robotic swarms in agricultural fields [20], and urban sensing with vehicle-mounted sensors [59]. For 3D sensing, 3DM [63] proposes a multi-UAV crowdsensing framework that jointly optimizes UAV matching and data transmission while maintaining cost-efficient trajectories. Other work includes 3D air quality mapping [203] and UAV-based 3D imaging and photogrammetric reconstruction [215, 223].

5.2.2 Dynamic System Conditions. Dynamic conditions of environments pose a challenge for planning for sensing. For instance, in the task of persistent surveillance, the target area is expected to be continuously surveyed. Hence, one-time coverage does not allow a direct application of exploration techniques to the problem. Besides, UAVs acting cooperatively to accomplish tasks may need to respond to dynamic tasks. This section summarizes related works under dynamic environment or dynamic task.

Dynamic Environment. Persistent sensing tasks prioritize continuous monitoring rather than shortest-path coverage. Xu et al. [199] introduced a Dynamic Exploration Planner (DEP) based on incremental sampling and Probabilistic Roadmaps (PRM) to optimize viewpoints, avoid dynamic obstacles, and reduce exploration time. Application-oriented systems such as SmartSpr [119] and SOScheduler [39] support real-time pollution detection and large-scale wildfire monitoring through coordinated ground–air or multi-UAV scheduling. Under UAV endurance constraints, minimizing revisit intervals is critical, and the Age-of-Information (AoI) metric is widely used to quantify data freshness. For instance, DRL-UCS [181] employs decentralized multi-agent deep reinforcement learning to maintain AoI thresholds via spatial cooperation, while Zhan et al. [213] jointly optimize UAV trajectories and base station associations to balance AoI and operational time. Additional approaches incorporate UAV dynamics and network coordination using control strategies and reinforcement learning [128, 154]. For real-time applications, Peak AoI (PAoI) is also important: MUSIC [85] minimizes PAoI via target sequencing, whereas QUEST [101] improves sensing coverage and reliability using the ASQ metric. Deep learning methods—including deep reinforcement learning, graph-based RL, and Double Deep Q-Learning (DDQN) [51, 134]—have shown strong performance in AoI-aware trajectory optimization. Boubin et al. [22] further demonstrate how environmental conditions influence sensing overlap strategies using real-world data. Their adaptive deployment strategy for soybean fields dynamically adjusts coverage patterns according to factors such as wind and illumination, improving sensing reliability while reducing energy consumption.

Dynamic Task. Many sensing applications—such as traffic monitoring and pollution detection—are time-sensitive, requiring mechanisms that support concurrent task assignments to satisfy multiple mission requirements. UMA [65] addresses UAV-assisted mobile crowd sensing by jointly optimizing task allocation and trajectory scheduling to improve sensing coverage and data quality. Liu et al. [108] proposed a coordinated dynamic task allocation (CDTA) strategy for heterogeneous UAVs based on a multi-agent reinforcement learning (MARL) framework, where a Q-network estimates expected returns to determine task responders. For dynamic missions such as autonomous exploration, target detection, and search-and-rescue, Sampedro et al. [155] developed a mission planning architecture that supervises high-level objectives while allocating subtasks to individual UAVs. Another temporally sensitive application is precision agriculture. Boubin's group has extensively studied UAV-based crop monitoring from both data collection and system deployment perspectives. Their work demonstrates that adaptive UAV scouting strategies can balance coverage efficiency and sensing accuracy in large-scale fields, while subsequent data-driven deployment approaches further improve system efficiency by reducing the energy consumption of collaborative UAV operations [22, 217].

6 Scheduling and Planning for Communication

6.1 UAV Communication Network

UAVs have emerged as a critical component in modern communication networks, enabling a wide range of applications such as disaster response, remote sensing, and aerial surveillance. Effective communication among UAVs and between UAVs and ground stations is essential for mission success, necessitating robust scheduling strategies. This section, visualized by Fig. 9, provides an overview of UAV communication systems and technologies, focusing on their classification, network topologies, and associated challenges.

6.1.1 UAV Communication System Classification. UAV communication systems can be broadly classified into single-UAV and multi-UAV systems, each with distinct network architectures and operational constraints. In a single-UAV communication system, the UAV communicates directly with ground nodes, typically used in real-time data transmission

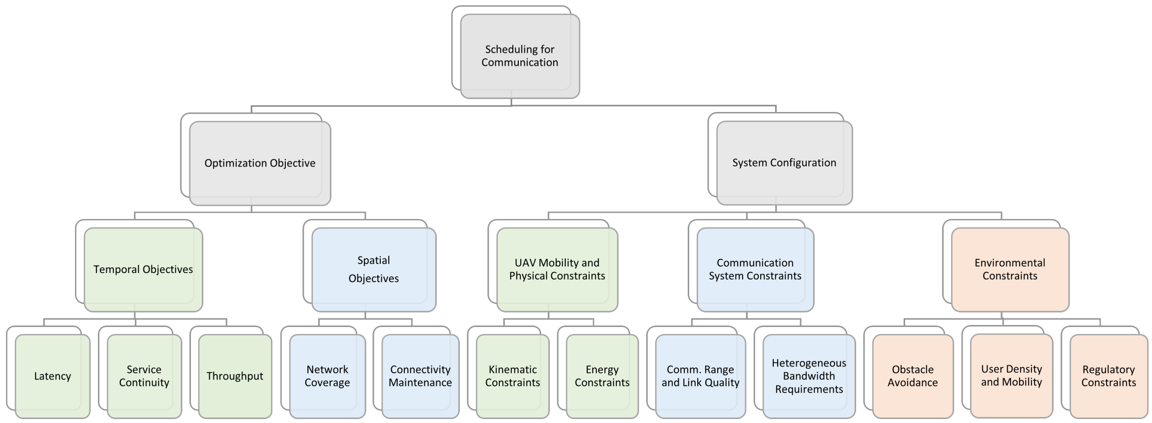

Fig. 9. Structure of Section 6. Scheduling for communication.

scenarios like aerial monitoring [60] and precision agriculture [89]. However, these systems are vulnerable to outages, as failure of the UAV or its communication link results in complete connectivity loss [118]. To enhance robustness and expand coverage, multi-UAV communication systems deploy multiple UAVs in a cooperative manner. Different network topologies can be adopted depending on the mission requirements:

- **Star Network:** Each UAV connects to a central node (e.g., a ground control station) that manages communication and data exchange, simplifying coordination but introducing a single point of failure.
- **Multi-Star Network:** A more resilient variant of the star network, where multiple clusters of UAVs form independent star networks, with one UAV in each cluster acting as a relay to a ground station.
- **Grid Network:** UAVs form a mesh-like structure, enabling direct inter-UAV communication without relying on a centralized node. This topology enhances fault tolerance but increases complexity in network management.
- **Hierarchical Grid Network:** A hybrid approach that combines grid and multi-star networks, ensuring network reconfiguration in case of UAV failures [75].

Multi-UAV networks offer significant advantages, including redundancy, resilience to node failures, and enhanced coverage [82, 212]. However, they also introduce challenges such as maintaining stable communication links, managing interference, and designing efficient scheduling algorithms to optimize network performance [118, 197, 198]. Recent advances have enabled multi-layer UAV networks, where UAVs operate alongside communication infrastructures such as the Internet of Things (IoT) [52], Wireless Sensor Networks (WSN), cloud computing, and Mobile Edge Computing (MEC) [192]. These integrated architectures support low-latency processing, extended communication range, and improved network resilience, but also introduce challenges in resource allocation and interoperability across heterogeneous network components.

6.1.2 UAV Communication Technologies. UAV communication relies on multiple technologies, each with distinct advantages and limitations depending on operational environments and mission requirements. Direct communication between UAVs and ground nodes enables low-latency transmission but is strongly constrained by line-of-sight (LoS) conditions, limiting its effectiveness in urban or obstacle-rich environments [187]. In addition, its communication range is typically limited, often requiring relay mechanisms for long-distance transmission. Satellite-based communication provides global coverage and supports beyond-visual-line-of-sight (BVLOS) operations. However, it suffers from high latency, greater propagation loss, and significant operational costs, restricting its suitability for real-time applications [99]. Flight Ad Hoc Networks (FANETs), a specialized form of Mobile Ad Hoc Networks (MANETs) and Vehicular Ad Hoc Networks (VANETs), enable UAV-to-UAV communication in highly dynamic environments [9]. Compared with conventional ad hoc networks, FANETs exhibit several distinctive characteristics:

- **Self-Organizing Topology:** UAVs dynamically establish and maintain communication links without relying on a fixed infrastructure.
- **High Mobility:** Unlike traditional MANETs, UAVs in FANETs move at high speeds, leading to frequent topology changes and link disruptions.
- **Connectivity Challenges:** Ensuring stable inter-UAV connectivity is a key research challenge, as frequent link breakages can degrade network performance.

Research efforts in FANETs focus on optimizing routing protocols, enhancing connectivity, and improving energy efficiency through adaptive scheduling strategies [18]. The integration of UAVs with existing cellular networks has gained increasing attention due to the widespread availability of cellular infrastructure [124]. UAV-based cellular communication can be categorized into:

- **UAV-Assisted Cellular Communication:** UAVs act as aerial base stations or relays to enhance coverage and network capacity, particularly in disaster-stricken or rural areas.
- **Cellular-Assisted UAV Communication:** UAVs leverage terrestrial cellular networks for connectivity, enabling reliable Beyond-Line-of-Sight (BLoS) operations.
- **UAV-to-UAV (U2U) Communication:** UAVs communicate directly using cellular spectrum, necessitating interference management and spectrum-sharing strategies.

With the advent of 5G and Beyond-5G (B5G) networks, UAV communication is expected to benefit from ultra-low latency, high reliability, and advanced network slicing capabilities. However, challenges such as interference management, handover optimization, and regulatory constraints remain areas of ongoing research [62, 192].

6.2 Distinctive Challenges: Communication vs. Sensing

UAV swarms support diverse missions, particularly sensing and communication [188]. Although both require efficient scheduling and coordination, they differ substantially in objectives and constraints. This section outlines the main distinctions between UAV-based sensing and communication tasks, with emphasis on the challenges of UAV communication networks.

6.2.1 Differences in Objectives and Constraints. UAV-based sensing primarily aims to maximize spatial coverage and data collection quality. Applications such as environmental monitoring, precision agriculture, and disaster assessment require extensive coverage and high-resolution sensing [59]. Key constraints include flight endurance, sensor accuracy, and periodic data transmission. In contrast, UAV-based communication focuses on maintaining network connectivity, latency, and throughput. UAVs serving as relays, aerial base stations, or backhaul nodes must sustain reliable links in dynamic environments [82]. Compared with sensing tasks, communication requires real-time data exchange under strict latency constraints while managing spectrum availability, interference, and dynamic network topology [9].

6.2.2 Network Dynamics and Stability. UAV mobility introduces significant stability challenges, particularly in communication networks. In sensing tasks, preplanned trajectories generally tolerate minor deviations without substantial performance loss. In contrast, communication networks are highly sensitive to positional changes that may disrupt links or degrade signal quality [140]. Maintaining stable connectivity is especially difficult in multi-UAV networks with dynamically changing topologies. Frequent topology updates complicate routing, handovers, and network reconfiguration compared with terrestrial systems [43]. These challenges become more pronounced in high-mobility scenarios such as disaster response or military operations [200].

6.2.3 Interference and Spectrum Management. Interference management is a major challenge in UAV communication networks due to mobility and shared spectrum resources [62]. Unlike sensing tasks, which often involve loosely coordinated UAVs, communication systems require effective spectrum-sharing mechanisms to mitigate interference among UAVs and with terrestrial networks. UAV movement leads to fluctuating signal strength and interference patterns, complicating spectrum allocation and frequency reuse. High-altitude UAVs may also interfere with ground networks, especially in cellular-connected UAV systems sharing spectrum with terrestrial users [118]. Although interference-aware scheduling and dynamic spectrum access approaches have been proposed [28, 74, 91, 121, 176, 177], efficient spectrum utilization while maintaining reliable communication remains an open challenge.

6.2.4 Energy Consumption Trade-offs. Energy efficiency is a key concern in UAV operations, with distinct trade-offs between sensing and communication. In sensing tasks, energy consumption is mainly driven by flight time and sensor operation, while data transmission typically incurs limited overhead [86]. Accordingly, energy-aware scheduling often focuses on trajectory optimization to extend mission duration while maintaining coverage. Communication tasks, however, require continuous data transmission, resulting in significantly higher energy consumption, particularly in long-range or high-throughput scenarios [86]. Maintaining communication links, relaying data, and mitigating interference further reduce operational time, especially when UAVs act as relays or aerial base stations that must hover for extended periods. Energy-efficient communication strategies—including adaptive power control, cooperative relaying, and trajectory optimization—have been proposed to reduce energy expenditure while preserving connectivity [61, 201]. Nevertheless, balancing communication performance and energy efficiency remains an open challenge.

6.3 Optimization Objectives in UAV Communication Scheduling

The dynamic nature of UAV communication networks introduces significant challenges in maintaining efficiency, stability, and reliability. To address these issues, various optimization objectives have been investigated to enhance communication performance under constraints such as mobility, energy consumption, and interference. These objectives can be broadly categorized into temporal and spatial aspects, corresponding to network responsiveness and structural robustness in UAV communication scheduling.

6.3.1 Temporal Objectives. Temporal optimization focuses on improving the responsiveness and efficiency of UAV communication networks by reducing delay, maintaining service continuity, and increasing data throughput. These objectives are particularly important in time-critical scenarios such as disaster response, military surveillance, and emergency communication.

Minimizing Latency. Latency minimization is essential for delay-sensitive UAV communication services. Network delays arise from propagation, queuing, and processing effects [13, 113], and are further influenced by UAV mobility and dynamic network topology. Several approaches have been proposed to reduce end-to-end delay. Predictive mobility models allocate communication resources based on anticipated UAV trajectories to reduce handover latency [113]. Multi-agent deep reinforcement learning methods, such as MAQMIX, dynamically optimize multi-hop routing, spectrum allocation, and UAV trajectories to alleviate congestion and improve delay performance [54]. In addition, edge–cloud collaborative architectures distribute computational workloads across UAV edge clusters and cloud infrastructure to reduce processing delays [12].

Maximizing Service Continuity. Service continuity is critical because UAV mobility frequently causes link disruptions. Adaptive scheduling strategies that dynamically adjust UAV positions and communication parameters can help maintain stable connectivity. Trajectory optimization is commonly used to mitigate network partitioning by guiding UAV movement to preserve communication links [60, 138]. UAVs can also operate as relay nodes to bridge connectivity gaps, while cooperative relay strategies improve link reliability. For instance, Q-learning–based adaptive positioning enables UAVs to reposition autonomously to maintain communication coverage [133]. Hierarchical aerial computing frameworks that integrate UAVs with high-altitude platforms (HAPs) further enhance service continuity through joint resource allocation and task offloading [87].

Maximizing Throughput. Maximizing throughput is another major objective in UAV communication networks. Joint optimization of UAV trajectories, communication scheduling, and transmit power has been widely studied to increase system throughput in UAV-assisted networks [78]. Adaptive bandwidth allocation methods, including frequency band-division-duplex (FDD) and time-fraction (TF) schemes, further improve spectrum utilization and reduce interference [80]. Cooperative scheduling approaches that integrate trajectory planning with transmission power control can also enhance network-wide throughput while maintaining energy efficiency and communication reliability [111].

6.3.2 Spatial Objectives. Spatial optimization focuses on the structural performance of UAV communication networks, particularly network coverage and connectivity maintenance. These objectives are critical when UAVs operate as aerial base stations, relays, or backbone nodes.

Maximizing Network Coverage. Coverage optimization aims to extend service areas and minimize communication blind spots through UAV placement and trajectory planning [208]. Dynamic repositioning strategies, such as the weighted targets sweep coverage (WTSC) algorithm, optimize UAV patrol paths to maximize coverage efficiency [97]. Machine learning–based approaches further improve coverage by predicting user mobility patterns and adjusting UAV deployment accordingly [145]. Reinforcement learning methods such as the UAV-enhanced coverage (QUEC) algorithm dynamically adapt UAV trajectories to balance coverage performance and energy efficiency [98].

Maximizing Connectivity Maintenance. Maintaining inter-UAV connectivity is essential for ensuring network robustness. Coordination mechanisms dynamically adjust UAV positions to prevent network fragmentation and maintain stable links. In flying ad hoc networks (FANETs), formation control methods such as the CMUFC algorithm maintain connectivity under interference while reconstructing broken links using artificial potential fields [226]. Graph-based coalition formation approaches also support adaptive network reconfiguration. For example, the SPT-GCF algorithm allows UAVs to autonomously form coalitions to restore connectivity and improve clustering efficiency in dynamic environments [79]. In addition, distributed cooperative control methods based on reinforcement learning and consensus mechanisms enable UAV swarms to maintain robust connectivity while navigating complex environments [206].

6.4 System Configuration Constraints in UAV Communication Scheduling

The performance of UAV communication networks is heavily impacted by various system constraints, which must be considered in scheduling algorithm design. These constraints fall into three main categories: UAV mobility and physical limitations, communication system constraints, and environmental factors. Addressing these challenges is essential for ensuring stable, efficient, and reliable UAV-based communication.

6.4.1 UAV Mobility and Physical Constraints. UAV mobility plays a critical role in communication scheduling, as it directly impacts link stability, network topology, and overall system performance. Two primary physical constraints that affect UAV operations are kinematic limitations and energy constraints.

Kinematic Constraints. UAVs face kinematic constraints, including flight speed, altitude, and maneuverability, which impact their ability to maintain stable communication links while adjusting positions for optimal network performance [118]. Unlike ground-based systems, UAV networks undergo frequent topology changes due to mobility, requiring advanced motion planning to balance communication efficiency and flight stability. Optimizing UAV trajectories under these constraints is challenging. High-speed UAVs, for instance, may struggle with consistent link quality due to rapid position shifts, causing frequent handovers and potential disruptions [70]. To mitigate these issues, motion-aware scheduling strategies that combine real-time mobility predictions with communication optimization are explored [196], alongside reinforcement learning methods for autonomous flight path adjustments to ensure stable connectivity [145].

Energy Constraints. Energy limitations are a major challenge in UAV-based communication networks, as UAVs rely on battery power with limited flight duration. To sustain long-term communication, energy-efficient scheduling strategies are essential to optimize both flight and transmission power consumption [61]. Boubin et al. [23] establish early principles of energy-aware multi-agent coordination and power consumption optimization in UAV swarms, providing critical theoretical grounding for scheduling strategies. One approach to mitigating energy constraints is trajectory optimization, where UAVs adjust their movement patterns to reduce energy use while maintaining communication coverage [16]. Another strategy is adaptive power control, where UAVs dynamically adjust transmission power based on link conditions to extend operational time [167]. Additionally, cooperative communication models, in which multiple UAVs share communication loads and relay data efficiently, have been explored to enhance network longevity [109]. Related work on Micro MAV platforms [225] further emphasizes the severity of energy constraints in miniaturized aerial systems, highlighting the importance of joint flight–communication optimization for long-duration missions. Despite these advancements, achieving an optimal balance between communication performance and energy efficiency remains a critical research challenge [201].

6.4.2 Communication System Constraints. Beyond mobility and energy limitations, UAV communication networks must also address constraints related to communication range, link quality, and bandwidth allocation.

Communication Range and Link Quality. Communication performance depends heavily on transmission range and link quality, which are affected by distance, obstacles, and interference [82]. In dynamic UAV networks, maintaining stable links is challenging due to mobility and environmental variability. Relay-based communication, where UAVs serve as intermediate nodes in multi-hop transmission, has been widely adopted to extend coverage and improve link reliability [73]. While such strategies enhance connectivity and reduce transmission power requirements, they introduce additional challenges in relay selection and interference management [47]. Beamforming and directional antenna techniques have also been explored to mitigate path loss and improve communication quality [193].

Heterogeneous Bandwidth Requirements. UAV communication networks often involve heterogeneous nodes with diverse bandwidth demands. For example, relay or edge-computing UAVs typically require higher bandwidth, whereas sensing or data collection UAVs may have lower throughput requirements [166]. Ensuring quality of service (QoS) therefore requires adaptive resource allocation mechanisms. Dynamic spectrum management techniques allow UAVs to adjust frequency usage according to network conditions and traffic demands [2]. Machine learning approaches have also been applied to predict bandwidth requirements and improve resource allocation efficiency [96]. Nevertheless, achieving reliable real-time adaptation in highly dynamic environments remains challenging.

6.4.3 Environmental Constraints. In addition to system-level limitations, UAV communication scheduling must also account for environmental constraints, including obstacles, user density variations, and regulatory restrictions.

Obstacle Avoidance. UAVs operating in complex environments must avoid obstacles such as buildings, terrain, and other physical barriers that can disrupt communication links. Communication-aware trajectory planning is therefore essential for safe navigation while preserving connectivity. Recent studies have explored obstacle-aware path planning methods that dynamically adjust UAV trajectories while maintaining communication performance [221]. Techniques such as simultaneous localization and mapping (SLAM) and vision-based obstacle detection have been integrated to enhance situational awareness [45]. However, real-time obstacle avoidance remains computationally demanding, especially in dense urban environments.

User Density and Mobility. UAV communication systems must also adapt to dynamic user distributions and mobility patterns. In dense urban areas, UAVs need strategic placement to balance traffic loads, whereas in rural or disaster scenarios the priority is expanding coverage [131]. Adaptive deployment strategies dynamically reposition UAVs based on real-time user distributions [56]. Clustering-based approaches group users according to spatial and temporal characteristics to improve coverage efficiency [31]. Despite these advances, accurately predicting user mobility remains challenging and often requires advanced data analytics and AI-based models [1].

No-Fly Zones and Regulatory Constraints. Regulatory restrictions—including no-fly zones, altitude limits, and airspace regulations—introduce additional constraints for UAV communication scheduling and trajectory planning [9]. To address these issues, regulation-aware scheduling frameworks incorporate geofencing mechanisms and automatic trajectory adjustment to ensure compliance [14]. Collaborative control between UAVs and ground stations has also been explored to enable real-time responses to regulatory updates [30]. Nevertheless, integrating regulatory constraints into fully autonomous multi-UAV scheduling systems, particularly across different jurisdictions, remains a research challenge [9].

7 Challenges and Future Directions

This section highlights *open research problems* in large-scale UAV swarm scheduling and coordination. The discussion follows the survey's analytical frameworks: the spatiotemporal taxonomy (Fig. 3), optimization objectives (Tab. 3), and algorithmic taxonomy (Section 4.3), identifying key computational challenges and remaining theoretical gaps.

7.1 Open Problems in Spatiotemporal Coordination

UAV swarm coordination problems can be characterized along two dimensions: temporal requirements (low vs. high timeliness) and spatial resolution (fine vs. coarse granularity). The HT–FG (High-Timeliness, Fine-Granularity) regime requires real-time per-UAV decision making under strict latency constraints, such as collision avoidance in dense or dynamic environments, which can be formulated as

$$\min_{\mathbf{u}_i(t)} \sum_i \mathcal{L}_i(\mathbf{x}_i(t), \mathbf{u}_i(t)) \quad \text{s.t. } \tau_{\text{decision}} \leq \tau_{\max},\ C_{\text{safety}}. \tag{1}$$

Here, decision latency must satisfy system deadlines while ensuring safety constraints. Learning-based approaches demonstrate promising performance in decentralized coordination [21] and related tasks such as communication [106], routing [148], path planning [170], and target pursuit [44], but rarely provide worst-case latency guarantees required in time-critical missions [83]. In contrast, the LT–CG (Low-Timeliness, Coarse-Granularity) regime focuses on long-horizon planning and global task allocation, where many formulations reduce to NP-hard variants of multi-robot task assignment or coverage planning, limiting scalability of centralized methods. Key open questions include identifying polynomial-time approximable subclasses and understanding how global optimality degrades under decentralized execution. Multi-resolution planning that combines coarse global planning with fine local adaptation offers a promising direction [77], although existing simulators such as CoppeliaSim [147] and ARGoS [135] still struggle to jointly model individual UAV control and swarm-level coordination. Hybrid regimes, where subsets of UAVs operate under different spatiotemporal requirements, remain largely unformalized, and developing unified models that enable dynamic switching across resolutions without sacrificing stability or efficiency remains an open challenge.

7.2 Unresolved Multi-Objective Optimization Conflicts

Diverse and often competing objectives arise in UAV swarm coordination, including coverage, fairness, energy efficiency, entropy, and Age of Information (AoI). A representative formulation is

$$\min\left(-\mathcal{C},\ \mathcal{E},\ \mathrm{AoI},\ \mathcal{F}\right), \tag{2}$$

where $\mathcal{C}$ denotes coverage, $\mathcal{E}$ energy consumption, and $\mathcal{F}$ fairness. Although multi-objective optimization has been explored, fundamental trade-offs remain. Pareto-based methods often struggle in high-dimensional objective spaces and under online constraints. For instance, increasing coverage typically raises energy consumption due to longer flight paths, while improving information freshness requires more frequent sensing and communication updates [77]. Similarly, enforcing fairness among UAVs may conflict with minimizing overall mission time [83]. These trade-offs become more challenging under environmental uncertainty, where dynamic weather, communication variability, and unexpected events further affect optimization outcomes. Open problems therefore include identifying *structurally incompatible objective pairs* under decentralized control, designing adaptive objective-prioritization mechanisms across mission phases, and establishing approximation guarantees for multi-objective optimization under partial observability [83].

7.3 Algorithmic Gaps and Fundamental Limitations

Following the taxonomy in Section 4.3, several limitations persist across algorithmic paradigms. Sampling-based methods offer flexibility but suffer from exponential growth in sample complexity as swarm size increases [143, 199]. Maintaining probabilistic completeness therefore requires extensive sampling, limiting real-time applicability, while convergence guarantees in dynamic environments remain largely unexplored [199]. Graph-based approaches efficiently encode coordination but typically assume relatively stable communication topologies [93, 158, 207], whereas real UAV networks experience frequent topology changes due to mobility and intermittent communication, often requiring repeated re-planning [93]. Optimization-based formulations face scalability limits: centralized methods [158, 183] become intractable at large scales, while decentralized optimization [32, 46] improves scalability but may sacrifice global optimality guarantees [46]. Learning-based methods show strong empirical performance but still face challenges in stability, generalization, and interpretability [44, 106, 148, 170]. Although early reinforcement learning studies [21] demonstrate the potential of decentralized learning for scalable coordination, whether such approaches can provide certifiable performance guarantees comparable to optimization-based methods remains an open question.

7.4 Cross-Cutting Challenges: Security, Privacy, and Real-World Validation

Security and privacy constraints introduce additional complexity to UAV swarm coordination, often transforming tractable optimization problems into adversarial or stochastic decision processes. UAV swarms operating in real environments are vulnerable to signal interference, malicious attacks, and hardware failures that may disrupt missions [185]. Robust scheduling under adversarial jamming and partial trust therefore remains a key challenge, requiring resilient coordination strategies and distributed fault-recovery mechanisms. Privacy preservation introduces further constraints, as UAV swarms frequently collect sensitive data such as aerial imagery and location traces that may expose critical infrastructure or private information without proper safeguards [7, 71]. Lightweight encryption and secure communication protocols suitable for resource-constrained UAV platforms are essential, while decentralized coordination should minimize information leakage during decision making. Another open challenge lies in evaluation: algorithms validated in simulation often fail to transfer effectively to real deployments due to sensing errors, environmental variability, and hardware limitations [129]. Improving simulation fidelity and developing standardized benchmarking frameworks that integrate sensing, communication, and security constraints remain important directions [64, 135, 147].

8 Conclusion

This survey reviews scheduling and planning algorithms for large-scale UAV swarms under diverse spatiotemporal constraints. Representative approaches—including sampling-, graph-, optimization-, and learning-based methods—are summarized, with emphasis on their strengths, limitations, and implications for sensing and communication applications. Key challenges include unresolved spatiotemporal coordination regimes, conflicting optimization objectives, scalability limits, and security and reliability concerns. Addressing these issues requires unified coordination models, principled multi-objective optimization, and scalable algorithms with stronger theoretical guarantees and real-world validation. Overall, this survey highlights the role of spatiotemporal constraints in UAV swarm coordination and provides a reference for developing scalable and reliable solutions for real-world deployments.

References

[1] Hasini Viranga Abeywickrama, Ying He, Eryk Dutkiewicz, and Beeshanga Abewardana Jayawickrama. 2019. An Adaptive UAV Network for Increased User Coverage and Spectral Efficiency. *2019 IEEE Wireless Communications and Networking Conference (WCNC)* (2019), 1–6.

[2] Md. Abu Baker Siddiki Abir et al. 2023. Software-Defined UAV Networks for 6G Systems: Requirements, Opportunities, Emerging Techniques, Challenges, and Research Directions. *IEEE Open Journal of the Communications Society* 4 (2023), 2487–2547. https://api.semanticscholar.org/CorpusID:263841469

[3] Nour Ayman Abujabal, Raouf Fareh, Saif Sinan, Mohammed Baziyad, and Maamar Bettayeb. 2023. A comprehensive review of the latest path planning developments for multi-robot formation systems. *Robotica* 41 (2023), 2079 – 2104.

[4] Nour Ayman Abujabal, Tamer F. Rabie, and Ibrahim Kamel. 2023. Path Planning Techniques for Multi-robot Systems: A Systematic Review. *2023 15th International Conference on Innovations in Information Technology (IIT)* (2023), 1–6.

[5] Muhammad Naeem Adil, Mian Ahmad Jan, Yongxin Liu, Hussein Abulkasim, Ahmed Farouk, and Houbing Herbert Song. 2023. A Systematic Survey: Security Threats to UAV-Aided IoT Applications, Taxonomy, Current Challenges and Requirements With Future Research Directions. *IEEE Transactions on Intelligent Transportation Systems* 24 (2023), 1437–1455.

[6] Shubhani Aggarwal and Neeraj Kumar. 2020. Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges. 149 (2020), 270–299. doi:10.1016/j.comcom.2019.10.014

[7] Nehaluddin Ahmad, Saurabh Chaturvedi, and Ahmad Masum. 2021. Unregulated drones and an emerging threat to right to privacy: A critical overview. *Journal of Data Protection & Privacy* 4, 2 (2021), 124–145.

[8] Gamil Ahmed, Tarek Sheltami, Ashraf Mahmoud, and Ansar Yasar. 2023. Energy-Efficient UAVs Coverage Path Planning Approach. 136, 3 (2023), 3239–3263. doi:10.32604/cmes.2023.022860 Publisher: Tech Science Press.

[9] Sara Al-Emadi and Aisha Al-Mohannadi. 2020. Towards enhancement of network communication architectures and routing protocols for FANETs: A survey. In *2020 3rd international conference on advanced communication technologies and networking (CommNet)*. IEEE, 1–10.

[10] Oluwatosin Ahmed Amodu, Rosdiadee Nordin, Chedia Jarray, Umar Ali Bukar, Raja Azlina Raja Mahmood, and Mohamed Othman. 2023. A Survey on the Design Aspects and Opportunities in Age-Aware UAV-Aided Data Collection for Sensor Networks and Internet of Things Applications. *Drones* (2023). https://api.semanticscholar.org/CorpusID:258115890

[11] Luke Antonyshyn, Jefferson Silveira, Sidney Givigi, and Joshua Marshall. 2023. Multiple Mobile Robot Task and Motion Planning: A Survey. 55, 10 (2023), 1–35. doi:10.1145/3564696 Number: 10.

[12] Zhuoyi Bai, Yifan Lin, Yang Cao, and Wei Wang. 2024. Delay-Aware Cooperative Task Offloading for Multi-UAV Enabled Edge-Cloud Computing. *IEEE Transactions on Mobile Computing* 23 (2024), 1034–1049.

[13] Anuradha Banerjee, Abu Sufian, Krishna Keshob Paul, and Sachin Kumar Gupta. 2022. EDTP: Energy and Delay Optimized Trajectory Planning for UAV-IoT Environment. *Comput. Netw.* 202, C (Jan. 2022), 17 pages. doi:10.1016/j.comnet.2021.108623

[14] Elgiz Baskaya, Guido Manfredi, Murat Bronz, and Daniel Delahaye. 2016. Flexible open architecture for UASs integration into the airspace: Paparazzi autopilot system. *2016 IEEE/AIAA 35th Digital Avionics Systems Conference (DASC)* (2016), 1–7.

[15] Norhan Bayomi and John E. Fernandez. 2023. Eyes in the Sky: Drones Applications in the Built Environment under Climate Change Challenges. *Drones* 7, 10 (2023). doi:10.3390/drones7100637

[16] Aliia Beishenalieva and Sang-Jo Yoo. 2023. Multiobjective 3-D UAV Movement Planning in Wireless Sensor Networks Using Bioinspired Swarm Intelligence. *IEEE Internet of Things Journal* 10 (2023), 8096–8110.

[17] Francesco Betti Sorbelli. 2024. UAV-based delivery systems: A systematic review, current trends, and research challenges. *Journal on Autonomous Transportation Systems* 1, 3 (2024), 1–40.

[18] Tarandeep Kaur Bhatia, Sona Tyagi, Aayushman Gusain, et al. 2022. A study on the flying ad-hoc networks: related challenges, routing protocols and mobility models. In *2022 11th International Conference on System Modeling & Advancement in Research Trends (SMART)*. IEEE, 438–444.

[19] Sayed Pedram Haeri Boroujeni, Abolfazl Razi, Sahand Khoshdel, Fatemeh Afghah, Janice L. Coen, Leo ONeill, P. Fulé, Adam Watts, Nick-Marios T. Kokolakis, and Kyriakos G. Vamvoudakis. 2024. A comprehensive survey of research towards AI-enabled unmanned aerial systems in pre-, active-, and post-wildfire management. *ArXiv* abs/2401.02456 (2024).

[20] N. Botteghi, A. Kamilaris, L. Sinai, and B. Sirmacek. 2020. Multi-Agent Path Planning of Robotic Swarms in Agricultural Fields. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 5, 1 (2020), 361–368. doi:10.5194/isprs-annals-V-1-2020-361-2020

[21] Jayson Boubin, Codi Burley, Peida Han, Bowen Li, Barry Porter, and Christopher Stewart. 2022. Marble: Multi-agent reinforcement learning at the edge for digital agriculture. In *2022 IEEE/ACM 7th symposium on edge computing (SEC)*. IEEE, 68–81.

[22] Jayson Boubin, Zichen Zhang, John Chumley, and Christopher Stewart. 2022. Adaptive deployment for autonomous agricultural UAV swarms. In *Proceedings of the 20th ACM Conference on Embedded Networked Sensor Systems*. 1089–1095.

[23] Jayson G Boubin, Naveen TR Babu, Christopher Stewart, John Chumley, and Shiqi Zhang. 2019. Managing edge resources for fully autonomous aerial systems. In *Proceedings of the 4th ACM/IEEE Symposium on Edge Computing*. 74–87.

[24] Eugen Valentin Butilă and Răzvan Gabriel Boboc. 2022. Urban Traffic Monitoring and Analysis Using Unmanned Aerial Vehicles (UAVs): A Systematic Literature Review. *Remote. Sens.* 14 (2022), 620.

[25] Pan Cao, Lei Lei, Shengsuo Cai, Gaoqing Shen, Xiaojiao Liu, Xinyi Wang, Lijuan Zhang, Liang Zhou, and Mohsen Guizani. 2024. Computational intelligence algorithms for UAV swarm networking and collaboration: A comprehensive survey and future directions. *IEEE Communications Surveys & Tutorials* (2024).

[26] Yuhong Cao, Tianxiang Hou, Yizhuo Wang, Xian Yi, and Guillaume Sartoretti. 2023. Ariadne: A reinforcement learning approach using attention-based deep networks for exploration. In *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 10219–10225.

[27] Marco Cella, Francesco d'Apolito, Phillipp Fanta-Jende, and Christoph Sulzbachner. 2023. FUELING GLOCAL: OPTIMIZATION-BASED PATH PLANNING FOR INDOOR UAVS IN AN AUTONOMOUS EXPLORATION FRAMEWORK, Vol. 48. Copernicus GmbH, 85–91. doi:10.5194/isprs-archives-XLVIII-1-W1-2023-85-2023

[28] Ursula Challita, Walid Saad, and Christian Bettstetter. 2019. Interference management for cellular-connected UAVs: A deep reinforcement learning approach. *IEEE Transactions on Wireless Communications* 18, 4 (2019), 2125–2140.

[29] Indu Chandran and Kizheppatt Vipin. 2024. Multi-UAV networks for disaster monitoring: challenges and opportunities from a network perspective. *Drone Systems and Applications* 12 (2024), 1–28.

[30] Serge Chaumette, Rémi Laplace, Christophe Mazel, Raphaël Mirault, A. Dunand, et al. 2011. CARUS, an operational retasking application for a swarm of autonomous UAVs: First return on experience. *2011 - MILCOM 2011 Military Communications Conference* (2011), 2003–2010.

[31] Vrajesh Kumar Chawra and Govind P. Gupta. 2020. Multiple UAV Path-Planning for Data Collection in Cluster-based Wireless Sensor Network. *2020 First International Conference on Power, Control and Computing Technologies (ICPC2T)* (2020), 194–198.

[32] Hao Chen, Yuheng Liang, and Xing Meng. 2023. A UAV Path Planning Method for Building Surface Information Acquisition Utilizing Opposition-Based Learning Artificial Bee Colony Algorithm. *Remote sensing (Basel, Switzerland)* 15, 17 (2023), 4312. doi:10.3390/rs15174312

[33] Wu Chen, Jiajia Liu, and Hongzhi Guo. 2020. Achieving Robust and Efficient Consensus for Large-Scale Drone Swarm. *IEEE Transactions on Vehicular Technology* 69, 12 (2020), 15867–15879. doi:10.1109/TVT.2020.3036833

[34] Xiaotong Chen, Qin Li, Ronghao Li, Xiangyuan Cai, Jiangnan Wei, and Hongying Zhao. 2023. UAV Network Path Planning and Optimization Using a Vehicle Routing Model. *Remote sensing (Basel, Switzerland)* 15, 9 (2023), 2227. doi:10.3390/rs15092227

[35] Xinlei Chen, Aveek Purohit, Carlos Ruiz Dominguez, Stefano Carpin, and Pei Zhang. 2015. Drunkwalk: Collaborative and adaptive planning for navigation of micro-aerial sensor swarms. In *Proceedings of the 13th ACM Conference on Embedded Networked Sensor Systems*. 295–308.

[36] Xinlei Chen, Carlos Ruiz, Sihan Zeng, Liyao Gao, Aveek Purohit, Stefano Carpin, and Pei Zhang. 2020. H-DrunkWalk: Collaborative and adaptive navigation for heterogeneous MAV swarm. *ACM Transactions on Sensor Networks (TOSN)* 16, 2 (2020), 1–27.

[37] Xuecheng Chen, Haoyang Wang, Yuhan Cheng, Haohao Fu, Yuxuan Liu, Fan Dang, Yunhao Liu, Jinqiang Cui, and Xinlei Chen. 2024. Ddl: Empowering delivery drones with large-scale urban sensing capability. *IEEE Journal of Selected Topics in Signal Processing* (2024).

[38] Xuecheng Chen, Haoyang Wang, Zuxin Li, Wenbo Ding, Fan Dang, Chengye Wu, and Xinlei Chen. 2022. Deliversense: Efficient delivery drone scheduling for crowdsensing with deep reinforcement learning. In *Adjunct proceedings of the 2022 ACM international joint conference on pervasive and ubiquitous computing and the 2022 ACM international symposium on wearable computers*. 403–408.

[39] Xuecheng Chen, Zijian Xiao, Yuhan Cheng, ChenChun Hsia, Haoyang Wang, Jingao Xu, Susu Xu, Fan Dang, Xiao-Ping Zhang, et al. 2024. Soscheduler: Toward proactive and adaptive wildfire suppression via multi-UAV collaborative scheduling. *IEEE Internet of Things Journal* (2024).

[40] Xinlei Chen, Susu Xu, Haohao Fu, Carlee Joe-Wong, Lin Zhang, Hae Young Noh, and Pei Zhang. 2019. ASC: Actuation system for city-wide crowdsensing with ride-sharing vehicular platform. In *Proceedings of the Fourth Workshop on International Science of Smart City Operations and Platforms Engineering*. 19–24.

[41] Xinlei Chen, Susu Xu, Jun Han, Haohao Fu, Xidong Pi, Carlee Joe-Wong, Yong Li, Lin Zhang, Hae Young Noh, et al. 2020. PAS: Prediction-Based Actuation System for City-Scale Ridesharing Vehicular Mobile Crowdsensing. 7, 5 (2020), 3719–3734. doi:10.1109/JIOT.2020.2968375 Number: 5.

[42] Xinlei Chen, Susu Xu, Xinyu Liu, Xiangxiang Xu, Hae Young Noh, Lin Zhang, and Pei Zhang. 2020. Adaptive hybrid model-enabled sensing system (HMSS) for mobile fine-grained air pollution estimation. *IEEE Transactions on Mobile Computing* 21, 6 (2020), 1927–1944.

[43] Ziyan Chen, Nan Cheng, Zhisheng Yin, Jingchao He, and Ning Lu. 2022. Service-oriented topology reconfiguration of UAV networks with deep reinforcement learning. In *2022 14th International Conference on Wireless Communications and Signal Processing (WCSP)*. IEEE, 753–758.

[44] Yuhan Cheng, Jirong Zha, Renjue Yang, Zhi Sun, Susu Xu, and Xinlei Chen. 2024. Multi-Agent Target Pursuit Using Perception Uncertainty-Aware Reinforcement Learning. In *Proceedings of the 30th Annual International Conference on Mobile Computing and Networking*. 1992–1997.

[45] Yeon Ji Choi, I Nyoman, Apraz Ramatryana, and Soo Young Shin. 2021. Cellular Communication-Based Autonomous UAV Navigation with Obstacle Avoidance for Unknown Indoor Environments. *International Journal of Intelligent Engineering and Systems* (2021).

[46] Hongyue Chu, Junkai Yi, and Fei Yang. 2022. Chaos Particle Swarm Optimization Enhancement Algorithm for UAV Safe Path Planning. 12, 18 (2022), 8977. doi:10.3390/app12188977

[47] Thi My Chinh Chu and Hans-Jürgen Zepernick. 2024. Hybrid Orthogonal-Nonorthogonal Multiple Access for CR-Assisted Cooperative UAV Systems. *2024 Tenth International Conference on Communications and Electronics (ICCE)* (2024), 54–59.

[48] Leighton Collins, Payam Ghassemi, Ehsan T. Esfahani, David Doermann, Karthik Dantu, and Souma Chowdhury. 2021. Scalable Coverage Path Planning of Multi-Robot Teams for Monitoring Non-Convex Areas. In *2021 IEEE International Conference on Robotics and Automation (ICRA)* (2021-05). 7393–7399. doi:10.1109/ICRA48506.2021.9561550 ISSN: 2577-087X.

[49] Matthew Coombes, Wen-Hua Chen, and Cunjia Liu. 2019. Flight Testing Boustrophedon Coverage Path Planning for Fixed Wing UAVs in Wind. In *2019 International Conference on Robotics and Automation (ICRA)* (Montreal, QC, Canada, 2019-05). IEEE, 711–717. doi:10.1109/ICRA.2019.8793943

[50] Xingxia Dai, Zhu Xiao, Hongbo Jiang, and John C.S. Lui. 2024. UAV-Assisted Task Offloading in Vehicular Edge Computing Networks. *IEEE Transactions on Mobile Computing* 23 (2024), 2520–2534.

[51] Zipeng Dai, Chi Harold Liu, Yuxiao Ye, Rui Han, Ye Yuan, Guoren Wang, and Jian Tang. 2022. AoI-minimal UAV Crowdsensing by Model-based Graph Convolutional Reinforcement Learning. In *IEEE INFOCOM 2022 - IEEE Conference on Computer Communications* (London, United Kingdom, 2022-05-02). IEEE, 1029–1038. doi:10.1109/INFOCOM48880.2022.9796732

[52] Rodrigo S De Moraes and Edison P de Freitas. 2018. Distributed control for groups of unmanned aerial vehicles performing surveillance missions and providing relay communication network services. *Journal of Intelligent & Robotic Systems* 92, 3 (2018), 645–656.

[53] Carmelo Di Franco and Giorgio Buttazzo. 2015. Energy-aware Coverage Path Planning of UAVs. doi:10.1109/ICARSC.2015.17

[54] Ruijin Ding, Jiawei Chen, Wen Wu, Jun Liu, Feifei Gao, and Xuemin (Sherman) Shen. 2022. Packet Routing in Dynamic Multi-Hop UAV Relay Network: A Multi-Agent Learning Approach. *IEEE Transactions on Vehicular Technology* 71 (2022), 10059–10072.

[55] Rong Du, Paolo Santi, Ming Xiao, Athanasios V. Vasilakos, and Carlo Fischione. 2019. The Sensable City: A Survey on the Deployment and Management for Smart City Monitoring. 21, 2 (2019), 1533–1560. doi:10.1109/COMST.2018.2881008 Number: 2.

[56] Rahul Dubey and Sushil J. Louis. 2023. Genetic Algorithms Optimized Adaptive Wireless Network Deployment. *Applied Sciences* (2023).

[57] Chiara Ercolani, Lixuan Tang, Ankita Arun Humne, and Alcherio Martinoli. 2022. Clustering and Informative Path Planning for 3D Gas Distribution Mapping: Algorithms and Performance Evaluation. 7, 2 (2022), 5310–5317. doi:10.1109/LRA.2022.3154026 Number: 2.

[58] Roghieh Eskandari, Masoud Mahdianpari, Fariba Mohammadimanesh, Bahram Salehi, Brian Brisco, and Saeid Homayouni. 2020. Meta-analysis of Unmanned Aerial Vehicle (UAV) Imagery for Agro-environmental Monitoring Using Machine Learning and Statistical Models. *Remote Sensing* 12, 21 (2020). doi:10.3390/rs12213511

[59] Guiyun Fan, Yiran Zhao, Zilang Guo, Haiming Jin, Xiaoying Gan, and Xinbing Wang. 2021. Towards fine-grained spatio-temporal coverage for vehicular urban sensing systems. In *IEEE INFOCOM 2021-IEEE conference on computer communications*. IEEE, 1–10.

[60] Alessio Fascista. 2022. Toward Integrated Large-Scale Environmental Monitoring Using WSN/UAV/Crowdsensing: A Review of Applications, Signal Processing, and Future Perspectives. *Sensors* 22, 5 (2022). doi:10.3390/s22051824

[61] Georgios Fevgas, Thomas D. Lagkas, Vasileios Argyriou, and Panagiotis G. Sarigiannidis. 2022. Coverage Path Planning Methods Focusing on Energy Efficient and Cooperative Strategies for Unmanned Aerial Vehicles. *Sensors (Basel, Switzerland)* 22 (2022).

[62] Azade Fotouhi, Haoran Qiang, Ming Ding, Mahbub Hassan, Lorenzo Galati Giordano, Adrián García-Rodríguez, and Jinhong Yuan. 2018. Survey on UAV Cellular Communications: Practical Aspects, Standardization Advancements, Regulation, and Security Challenges. *IEEE Communications Surveys & Tutorials* 21 (2018), 3417–3442.

[63] Luwei Fu, Zhiwei Zhao, Geyong Min, Wang Miao, Liang Zhao, and Wenjie Huang. 2022. Energy-Efficient 3-D Data Collection forMulti-UAV Assisted Mobile Crowdsensing. *IEEE Trans. Comput.* 72, 7 (2022), 2025–2038.

[64] Chen Gao, Baining Zhao, Weichen Zhang, Jinzhu Mao, Jun Zhang, Zhiheng Zheng, Fanhang Man, Jianjie Fang, Zile Zhou, Jinqiang Cui, et al. 2024. EmbodiedCity: A Benchmark Platform for Embodied Agent in Real-world City Environment. *arXiv preprint arXiv:2410.09604* (2024).

[65] Hui Gao, Jianhao Feng, Yu Xiao, Bo Zhang, and Wendong Wang. 2022. A UAV-assisted multi-task allocation method for mobile crowd sensing. *IEEE Transactions on Mobile Computing* 22, 7 (2022), 3790–3804.

[66] Hakim Ghazzai, Hamid Menouar, Abdullah Kadri, and Yehia Massoud. 2019. Future UAV-Based ITS: A Comprehensive Scheduling Framework. *IEEE Access* 7 (2019), 75678–75695. https://api.semanticscholar.org/CorpusID:195222532

[67] Shimin Gong, Meng Wang, Bo Gu, Wenjie Zhang, Dinh Thai Hoang, and Dusit Niyato. 2023. Bayesian Optimization Enhanced Deep Reinforcement Learning for Trajectory Planning and Network Formation in Multi-UAV Networks. (2023), 1–16. doi:10.1109/TVT.2023.3262778

[68] L. M. González-Desantos, J. Martínez-Sánchez, H. González-Jorge, and P. Arias. 2020. Path planning for indoor contact inspection tasks with UAVS, Vol. 43. Copernicus GmbH, 345–351. doi:10.5194/isprs-archives-XLIII-B4-2020-345-2020

[69] Qiuyi Gu, Zhaocheng Ye, Jincheng Yu, Jiahao Tang, Tinghao Yi, Yuhan Dong, Jian Wang, Jinqiang Cui, Xinlei Chen, et al. 2025. MR-COGraphs: Communication-efficient multi-robot open-vocabulary mapping system via 3D scene graphs. *IEEE Robotics and Automation Letters* (2025).

[70] Xinglong Gu, Guifen Chen, and Yiming Sun. 2023. UAV Cluster Obstacle Avoidance Method Based on Improved Artificial Potential Field Method. *2023 3rd International Conference on Electrical Engineering and Control Science (IC2ECS)* (2023), 568–572.

[71] Hassan Jalil Hadi, Yue Cao, Khaleeq Un Nisa, Abdul Majid Jamil, and Qiang Ni. 2023. A comprehensive survey on security, privacy issues and emerging defence technologies for UAVs. *Journal of Network and Computer Applications* 213 (2023), 103607.

[72] Aicha Hafid, Riadh Hocine, and Lahcene Guezouli. 2024. Analyzing Swarm Robotics Approaches in Natural Disaster Scenarios: A Comparative Study. *2024 1st International Conference on Innovative and Intelligent Information Technologies (IC3IT)* (2024), 1–6.

[73] Mohammed R. Hayal, Ebrahim E. Elsayed, Dhiman Kakati, Mehtab Singh, Abdelrahman Elfikky, Ayman I. Boghdady, Amit Grover, Shilpa Mehta, et al. 2023. Modeling and investigation on the performance enhancement of hovering UAV-based FSO relay optical wireless communication systems under pointing errors and atmospheric turbulence effects. *Optical and Quantum Electronics* 55 (2023), 1–23.

[74] Samira Hayat, Evşen Yanmaz, and Raheeb Muzaffar. 2016. Survey on unmanned aerial vehicle networks for civil applications: A communications viewpoint. *IEEE communications surveys & tutorials* 18, 4 (2016), 2624–2661.

[75] Aicha Idriss Hentati and Lamia Chaari Fourati. 2020. Comprehensive survey of UAVs communication networks. *Computer Standards & Interfaces* 72 (2020), 103451.

[76] Hanno Hildmann and Ernö Kovacs. 2019. Review: Using Unmanned Aerial Vehicles (UAVs) as Mobile Sensing Platforms (MSPs) for Disaster Response, Civil Security and Public Safety. *Drones* 3, 3 (2019). doi:10.3390/drones3030059

[77] Justin Hu, Ariana Bruno, Brian Ritchken, Brendon Jackson, Mateo Espinosa, Aditya Shah, and Christina Delimitrou. 2020. Hivemind: A scalable and serverless coordination control platform for uav swarms. *arXiv preprint arXiv:2002.01419* (2020).

[78] Meng Hua, Luxi Yang, Qingqing Wu, and A. L. Swindlehurst. 2020. 3D UAV Trajectory and Communication Design for Simultaneous Uplink and Downlink Transmission. *IEEE Transactions on Communications* 68 (2020), 5908–5923.

[79] Yeting Huang, Nan Qi, Zanqi Huang, Luliang Jia, Qihui Wu, Rugui Yao, and Wenjing Wang. 2023. Connectivity Guarantee Within UAV Cluster: A Graph Coalition Formation Game Approach. *IEEE Open Journal of the Communications Society* 4 (2023), 79–90.

[80] Zhiyu Huang, Shuzhen Liu, Zhichao Sheng, Hongwen Yu, and Antonino Masaracchia. 2023. Optimization for UAV-assisted simultaneous transmission and reception communications in the existence of malicious jammers. *Secur. Saf.* 3 (2023), 2023031.

[81] Amber Israr, Zain Anwar Ali, Eman H. Alkhammash, and Jari Juhani Jussila. 2022. Optimization Methods Applied to Motion Planning of Unmanned Aerial Vehicles: A Review. *Drones* (2022).

[82] Shumaila Javaid, Nasir Saeed, Zakria Qadir, Hamza Fahim, Bin He, Houbing Song, and Muhammad Bilal. 2023. Communication and control in collaborative UAVs: Recent advances and future trends. *IEEE Transactions on Intelligent Transportation Systems* 24, 6 (2023), 5719–5739.

[83] Sadaf Javed, Ali Hassan, Rizwan Ahmad, Waqas Ahmed, Rehan Ahmed, Ahsan Saadat, and Mohsen Guizani. 2024. State-of-the-art and future research challenges in uav swarms. *IEEE Internet of Things Journal* 11, 11 (2024), 19023–19045.

[84] Imad Jawhar, Nader Mohamed, Jameela Al-Jaroodi, Dharma P. Agrawal, and Sheng Zhang. 2017. Communication and networking of UAV-based systems: Classification and associated architectures. *Journal of Network and Computer Applications* 84 (2017), 93–108. doi:10.1016/j.jnca.2017.02.008

[85] Wenwen Jiang, Bo Ai, Chao Shen, Mushu Li, and Xuemin Shen. 2023. Age-of-Information Minimization for UAV-Based Multi-View Sensing and Communication. *IEEE Transactions on Vehicular Technology* (2023).

[86] Huilong Jin, Xiaozi Jin, Yucong Zhou, Pingkang Guo, J. Ren, Jian Yao, and Shuang Zhang. 2023. A survey of energy efficient methods for UAV communication. *Veh. Commun.* 41 (2023), 100594. https://api.semanticscholar.org/CorpusID:257335988

[87] Hongyue Kang, Xiaolin Chang, Jelena V. Misic, Vojislav B. Mišić, Junchao Fan, and Yating Liu. 2023. Cooperative UAV Resource Allocation and Task Offloading in Hierarchical Aerial Computing Systems: A MAPPO-Based Approach. *IEEE Internet of Things Journal* 10 (2023), 10497–10509.

[88] Yiannis Kantaros, Brent Schlotfeldt, Nikolay Atanasov, and George J Pappas. 2021. Sampling-based planning for non-myopic multi-robot information gathering. *Autonomous Robots* 45, 7 (2021), 1029–1046.

[89] Ioanna Karampelia, Thomas Kyriakidis, and Malamati Louta. 2023. UAV swarms & Task allocation: the way ahead in precision agriculture. In *2023 14th International Conference on Information, Intelligence, Systems & Applications (IISA)*. IEEE, 1–8.
[90] Amina Khan, Sumeet Gupta, and Sachin Kumar Gupta. 2022. Emerging UAV technology for disaster detection, mitigation, response, and preparedness. *Journal of Field Robotics* 39, 6 (2022), 905–955.
[91] Puneet Kumar, Sahil Garg, Amritpal Singh, Shalini Batra, Neeraj Kumar, and Ilsun You. 2018. MVO-based 2-D path planning scheme for providing quality of service in UAV environment. *IEEE Internet of Things Journal* 5, 3 (2018), 1698–1707.
[92] Vijay Kumar and Nathan Michael. 2012. Opportunities and challenges with autonomous micro aerial vehicles. *The International Journal of Robotics Research* 31, 11 (2012), 1279–1291.
[93] Tushar Kusnur, Dhruv Mauria Saxena, and Maxim Likhachev. 2021. Search-based Planning for Active Sensing in Goal-Directed Coverage Tasks. In *2021 IEEE International Conference on Robotics and Automation (ICRA)* (Xi'an, China, 2021-05-30). IEEE, 15–21. doi:10.1109/ICRA48506.2021.9561310
[94] Hian Lee Kwa, Jabez Leong Kit, and Roland Bouffanais. 2022. Balancing Collective Exploration and Exploitation in Multi-Agent and Multi-Robot Systems: A Review. *Frontiers in Robotics and AI* 8 (2022).
[95] Hian Lee Kwa, Jabez Leong Kit, Nikolaj Horsevad, Julien Philippot, Mohammadzaman Savari, and Roland Bouffanais. 2023. Adaptivity: a path towards general swarm intelligence? *Frontiers in Robotics and AI* 10 (2023).
[96] Victoria Lee. 2024. DEEP REINFORCEMENT LEARNING FOR DYNAMIC SHARDING IN UAV NETWORKS. *World Journal of Information Technology* (2024).
[97] Jing Li et al. 2020. A Path Planning Method for Sweep Coverage With Multiple UAVs. *IEEE Internet of Things Journal* 7 (2020), 8967–8978.
[98] Li Li and Hongbin Chen. 2022. UAV Enhanced Target-Barrier Coverage Algorithm for Wireless Sensor Networks Based on Reinforcement Learning. *Sensors (Basel, Switzerland)* 22 (2022).
[99] Xiangling Li, Wei Feng, Yunfei Chen, Cheng-Xiang Wang, and Ning Ge. 2020. Maritime coverage enhancement using UAVs coordinated with hybrid satellite-terrestrial networks. *IEEE Transactions on Communications* 68, 4 (2020), 2355–2369.
[100] Yi Li, Min Liu, and Dandan Jiang. 2022. Application of Unmanned Aerial Vehicles in Logistics: A Literature Review. *Sustainability* 14, 21 (2022). doi:10.3390/su142114473
[101] Zuxin Li, Fanhang Man, Xuecheng Chen, Susu Xu, Fan Dang, Xiao-Ping Zhang, and Xinlei Chen. 2024. QUEST: Quality-informed Multi-agent Dispatching System for Optimal Mobile Crowdsensing. In *IEEE INFOCOM 2024-IEEE Conference on Computer Communications*. IEEE, 1811–1820.
[102] Fei Lin, Yonglin Tian, Yunzhe Wang, Tengchao Zhang, et al. 2024. Airvista: Empowering uavs with 3d spatial reasoning abilities through a multimodal large language model agent. In *2024 IEEE 27th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 476–481.
[103] Huan Lin et al. 2024. Multi-hop Differential Topology based Algorithms for Resilient Network of UAV Swarm. *ArXiv* abs/2411.11342 (2024).
[104] Xiaoshan Lin, Yasin Yazcoglu, and Derya Aksaray. 2022. Robust Planning for Persistent Surveillance With Energy-Constrained UAVs and Mobile Charging Stations. 7, 2 (2022), 4157–4164. doi:10.1109/LRA.2022.3146938
[105] Chi Harold Liu, Zheyu Chen, Jian Tang, Jie Xu, and Chengzhe Piao. 2018. Energy-Efficient UAV Control for Effective and Fair Communication Coverage: A Deep Reinforcement Learning Approach. 36, 9 (2018), 2059–2070. doi:10.1109/JSAC.2018.2864373
[106] Chi Harold Liu, Zheyu Chen, Jian Tang, Jie Xu, and Chengzhe Piao. 2018. Energy-efficient UAV control for effective and fair communication coverage: A deep reinforcement learning approach. *IEEE Journal on Selected Areas in Communications* 36, 9 (2018), 2059–2070.
[107] Chi Harold Liu, Zheyu Chen, and Yufeng Zhan. 2019. Energy-Efficient Distributed Mobile Crowd Sensing: A Deep Learning Approach. 37, 6 (2019), 1262–1276. doi:10.1109/JSAC.2019.2904353 Number: 6.
[108] Da Liu, Liqian Dou, Ruilong Zhang, Xiuyun Zhang, and Qun Zong. 2022. Multi-agent reinforcement learning-based coordinated dynamic task allocation for heterogenous UAVs. *IEEE Transactions on Vehicular Technology* 72, 4 (2022), 4372–4383.
[109] Dianxiong Liu, Jinlong Wang, Kun Xu, Yuhua Xu, Yang Yang, Yitao Xu, Qi hui Wu, and Alagan Anpalagan. 2019. Task-Driven Relay Assignment in Distributed UAV Communication Networks. *IEEE Transactions on Vehicular Technology* 68 (2019), 11003–11017.
[110] X. Liu, Z. Ji, H. Zhou, Z. Zhang, P. Tao, K. Xi, L. Chen, and J. Marcato Junior. 2022. AN OBJECT-ORIENTED UAV 3D PATH PLANNING METHOD APPLIED IN CULTURAL HERITAGE DOCUMENTATION. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 5, 1 (2022), 33–40. doi:10.5194/isprs-annals-V-1-2022-33-2022
[111] Xin Liu, Biaojun Lai, Bin-Feng Lin, and Victor C. M. Leung. 2022. Joint Communication and Trajectory Optimization for Multi-UAV Enabled Mobile Internet of Vehicles. *IEEE Transactions on Intelligent Transportation Systems* 23 (2022), 15354–15366.
[112] Yongheng Liu and Shanmei Liu. 2022. Design and Implementation of Farmland Environment Monitoring System Based on Micro Quadrotor UAV. *Journal of Physics: Conference Series* 2281 (2022).
[113] Ying-Ying Liu, Junjie Yan, and Xiaohui Zhao. 2022. Deep Reinforcement Learning Based Latency Minimization for Mobile Edge Computing With Virtualization in Maritime UAV Communication Network. *IEEE Transactions on Vehicular Technology* 71 (2022), 4225–4236.
[114] Zhengzhi Lu, Yufeng Chen, Li Chen, Yanxiang Ling, and Fengyao Zhi. 2024. Operational Evaluation of UAV Swarm Precision Strikes with Agent Based Modeling and Simulation. *2024 10th International Conference on Big Data and Information Analytics (BigDIA)* (2024), 389–395.
[115] Chuanwen Luo, Meghana N Satpute, Deying Li, Yongcai Wang, Wenping Chen, and Weili Wu. 2020. Fine-grained trajectory optimization of multiple UAVs for efficient data gathering from WSNs. *IEEE/ACM Transactions on Networking* 29, 1 (2020), 162–175.
[116] Junhai Luo, Yuxin Tian, and Zhiyan Wang. 2024. Research on unmanned aerial vehicle path planning. *Drones* 8, 2 (2024), 51.
[117] Junhai Luo, Zhiyan Wang, Ming Xia, Linyong Wu, Yuxin Tian, and Yu Chen. 2022. Path Planning for UAV Communication Networks: Related Technologies, Solutions, and Opportunities. (2022), 3560261. doi:10.1145/3560261

[118] Junhai Luo, Zhiyan Wang, Ming Xia, Linyong Wu, Yuxin Tian, and Yu Chen. 2023. Path planning for UAV communication networks: Related technologies, solutions, and opportunities. *Comput. Surveys* 55, 9 (2023), 1–37.

[119] Ji Luo, Zijian Xiao, Zuxin Li, Xuecheng Chen, Chaopeng Hong, Xiao-Ping Zhang, and Xinlei Chen. 2025. Smartspr: A physics-informed mobile sprinkler scheduling system for reducing urban particulate matter pollution. *IEEE Transactions on Mobile Computing* (2025).

[120] Mingyang Lyu, Yibo Zhao, Chao Huang, and Hailong Huang. 2023. Unmanned Aerial Vehicles for Search and Rescue: A Survey. *Remote Sensing* 15, 13 (2023). doi:10.3390/rs15133266

[121] Zhonghao Lyu, Chenhao Ren, and Ling Qiu. 2020. Movement and communication co-design in multi-UAV enabled wireless systems via DRL. In *2020 IEEE 6th International Conference on Computer and Communications (ICCC)*. IEEE, 220–226.

[122] Ashish Mahalle, Sarika Khandelwal, Abhishek Dhore, Vishwajit Barbudhe, and Vivek Waghmare. 2024. Cyber attacks on UAV networks: A comprehensive survey. *Review of Computer Engineering Research* (2024).

[123] Aurelio G Melo, Milena F Pinto, Andre LM Marcato, Leonardo M Honório, and Fabrício O Coelho. 2021. Dynamic optimization and heuristics based online coverage path planning in 3D environment for UAVs. *Sensors* 21, 4 (2021), 1108.

[124] Debashisha Mishra and Enrico Natalizio. 2020. A survey on cellular-connected UAVs: Design challenges, enabling 5G/B5G innovations, and experimental advancements. *Computer Networks* 182 (2020), 107451.

[125] Aisyah Marliza Muhmad Kamarulzaman, Wan Shafrina Wan Mohd Jaafar, et al. 2023. UAV Implementations in Urban Planning and Related Sectors of Rapidly Developing Nations: A Review and Future Perspectives for Malaysia. *Remote Sensing* 15, 11 (2023). doi:10.3390/rs15112845

[126] Koppány Máthé and Lucian Buşoniu. 2015. Vision and Control for UAVs: A Survey of General Methods and of Inexpensive Platforms for Infrastructure Inspection. *Sensors* 15, 7 (2015), 14887–14916. doi:10.3390/s150714887

[127] Matthias Nieuwenhuisen and Sven Behnke. 2019. Search-based 3D Planning and Trajectory Optimization for Safe Micro Aerial Vehicle Flight Under Sensor Visibility Constraints. In *2019 International Conference on Robotics and Automation (ICRA)* (Montreal, QC, Canada, 2019-05). IEEE, 9123–9129. doi:10.1109/ICRA.2019.8794086

[128] N. Nigam, S. Bieniawski, I. Kroo, and J. Vian. 2012. Control of Multiple UAVs for Persistent Surveillance: Algorithm and Flight Test Results. 20, 5 (2012), 1236–1251. doi:10.1109/TCST.2011.2167331

[129] Mykola Nikolaiev et al. 2024. Comparative Review of Drone Simulators. *Information, Computing and Intelligent systems* 4 (2024), 79–99.

[130] Zieziyana Nordin and Anuar Mohd Salleh. 2022. Application of unmanned aerial vehicle (UAV) in terrain mapping: Systematic literature review. *International Journal of Sustainable Construction Engineering and Technology* 13, 4 (2022), 216–223.

[131] Babatunji Omoniwa, Boris Galkin, and Ivana Dusparic. 2023. Density-Aware Reinforcement Learning to Optimise Energy Efficiency in UAV-Assisted Networks. *2023 19th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)* (2023), 267–273.

[132] Gonzalo Pajares. 2015. Overview and current status of remote sensing applications based on unmanned aerial vehicles (UAVs). *Photogrammetric Engineering & Remote Sensing* 81, 4 (2015), 281–330.

[133] Kirtan Gopal Panda, Amulya Wilson, and Debarati Sen. 2022. Energy-Efficient Initial Deployment and ML-Based Postdeployment Strategy for UAV Network With Guaranteed QoS. *IEEE Trans. Aerospace Electron. Systems* 58 (2022), 5220–5239.

[134] Yingsheng Peng, Yong Liu, Dong Li, and Han Zhang. 2022. Deep Reinforcement Learning Based Freshness-Aware Path Planning for UAV-Assisted Edge Computing Networks with Device Mobility. *Remote sensing (Basel, Switzerland)* 14, 16 (2022), 4016. doi:10.3390/rs14164016

[135] Carlo Pinciroli, Vito Trianni, Rehan O'Grady, Giovanni Pini, Arne Brutschy, Manuele Brambilla, Nithin Mathews, Eliseo Ferrante, Gianni Di Caro, Frederick Ducatelle, et al. 2012. ARGoS: a modular, parallel, multi-engine simulator for multi-robot systems. *Swarm intelligence* 6 (2012), 271–295.

[136] Manish Prajapat, Matteo Turchetta, Melanie N. Zeilinger, and Andreas Krause. 2022. Near-Optimal Multi-Agent Learning for Safe Coverage Control. arXiv:2210.06380 [cs, math] http://arxiv.org/abs/2210.06380

[137] A. Puri, K. P. Valavanis, and M. Kontitsis. 2007. Statistical profile generation for traffic monitoring using real-time UAV based video data. *2007 Mediterranean Conference on Control & Automation* (2007), 1–6. doi:10.1109/MED.2007.4433658

[138] Zakria Qadir, Fahim Ullah, Hafiz Suliman Munawar, and Fadi M. Al-turjman. 2021. Addressing disasters in smart cities through UAVs path planning and 5G communications: A systematic review. *Comput. Commun.* 168 (2021), 114–135. https://api.semanticscholar.org/CorpusID:232051783

[139] Chengyi Qu, Jayson Boubin, Durbek Gafurov, Jianfeng Zhou, Noel Aloysius, Henry Nguyen, and Prasad Calyam. 2022. Uav swarms in smart agriculture: Experiences and opportunities. In *2022 IEEE 18th International Conference on e-Science (e-Science)*. IEEE, 148–158.

[140] Yuben Qu, Haipeng Dai, Zhuang Yan, Jiafa Chen, Chao Dong, Fan Wu, and Song Guo. 2021. Serverless Federated Learning for UAV Networks: Architecture, Challenges, and Opportunities. *ArXiv* abs/2104.07557 (2021).

[141] Ouyang Quan, Zhaoxiang Wu, Yuhua Cong, and Zhisheng Wang. 2022. Formation control of unmanned aerial vehicle swarms: A comprehensive review. *Asian Journal of Control* 25 (2022), 570 – 593.

[142] Mohammadreza Radmanesh, Manish Kumar, Paul H. Guentert, and Mohammad Sarim. 2018. Overview of Path-Planning and Obstacle Avoidance Algorithms for UAVs: A Comparative Study. *Unmanned Syst.* 6 (2018), 95–118.

[143] Sudha Ramasamy, Kristina M Eriksson, Fredrik Danielsson, and Mikael Ericsson. 2023. Sampling-Based Path Planning Algorithm for a Plug & Produce Environment. *Applied Sciences* 13, 22 (2023), 12114.

[144] Carmine Tommaso Recchiuto and Antonio Sgorbissa. 2018. Post-disaster assessment with unmanned aerial vehicles: A survey on practical implementations and research approaches. *Journal of Field Robotics* 35, 4 (2018), 459–490.

[145] Jiyuan Ren, Yanggang Xu, Zuxin Li, Chaopeng Hong, Xiao-Ping Zhang, and Xinlei Chen. 2023. Scheduling uav swarm with attention-based graph reinforcement learning for ground-to-air heterogeneous data communication. In *Adjunct Proceedings of the 2023 ACM International Joint Conference*

on Pervasive and Ubiquitous Computing & the 2023 ACM International Symposium on Wearable Computing. 670–675.
[146] Yara Rizk, Mariette Awad, and Edward W. Tunstel. 2020. Cooperative Heterogeneous Multi-Robot Systems: A Survey. 52, 2 (2020), 1–31. doi:10.1145/3303848 Number: 2.
[147] Eric Rohmer, Surya PN Singh, and Marc Freese. 2013. V-REP: A versatile and scalable robot simulation framework. *2013 IEEE/RSJ international conference on intelligent robots and systems* (2013), 1321–1326.
[148] Arnau Rovira-Sugranes, Abolfazl Razi, Fatemeh Afghah, and Jacob Chakareski. 2022. A review of AI-enabled routing protocols for UAV networks: Trends, challenges, and future outlook. *Ad Hoc Networks* 130 (2022), 102790.
[149] Julius Ruckin, Liren Jin, Federico Magistri, Cyrill Stachniss, and Marija Popovic. 2022. Informative Path Planning for Active Learning in Aerial Semantic Mapping. In *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (Kyoto, Japan, 2022-10-23). IEEE, 11932–11939. doi:10.1109/IROS47612.2022.9981738
[150] Carlos Ruiz, Shijia Pan, Adeola Bannis, Xinlei Chen, Carlee Joe-Wong, Hae Young Noh, and Pei Zhang. 2018. Idrone: Robust drone identification through motion actuation feedback. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 2 (2018), 1–22.
[151] Julius Rückin, Liren Jin, and Marija Popović. 2022. Adaptive Informative Path Planning Using Deep Reinforcement Learning for UAV-based Active Sensing. arXiv:2109.13570 [cs] doi:10.48550/arXiv.2109.13570
[152] Julius Rückin, Liren Jin, and Marija Popović. 2022. Adaptive Informative Path Planning Using Deep Reinforcement Learning for UAV-based Active Sensing. *arXiv.org* (2022). doi:10.48550/arxiv.2109.13570
[153] Amylia Ait Saadi, Assia Soukane, Yassine Meraihi, Asma Benmessaoud Gabis, Seyed Mohammad Mirjalili, and Amar Ramdane-Cherif. 2022. UAV Path Planning Using Optimization Approaches: A Survey. *Archives of Computational Methods in Engineering* 29 (2022), 4233 – 4284.
[154] Moataz Samir, Chadi Assi, Sanaa Sharafeddine, Dariush Ebrahimi, and Ali Ghrayeb. 2020. Age of information aware trajectory planning of UAVs in intelligent transportation systems: A deep learning approach. *IEEE Transactions on Vehicular Technology* 69, 11 (2020), 12382–12395.
[155] Carlos Sampedro, Hriday Bavle, Jose Luis Sanchez-Lopez, Ramon A Suárez Fernández, Alejandro Rodríguez-Ramos, Martin Molina, and Pascual Campoy. 2016. A flexible and dynamic mission planning architecture for uav swarm coordination. In *2016 International Conference on Unmanned Aircraft Systems (ICUAS)*. IEEE, 355–363.
[156] Andres J. Sanchez-Fernandez, Luis F. Romero, Gerardo Bandera, and Siham Tabik. 2022. VPP: Visibility-Based Path Planning Heuristic for Monitoring Large Regions of Complex Terrain Using a UAV Onboard Camera. 15 (2022), 944–955. doi:10.1109/JSTARS.2021.3134948
[157] Jose Luis Sanchez-Lopez, Ramón A Suárez Fernández, Hriday Bavle, Carlos Sampedro, Martin Molina, et al. 2016. Aerostack: An architecture and open-source software framework for aerial robotics. In *2016 International Conference on Unmanned Aircraft Systems (ICUAS)*. IEEE, 332–341.
[158] Brent Schlotfeldt, Dinesh Thakur, Nikolay Atanasov, Vijay Kumar, and George J. Pappas. 2018. Anytime Planning for Decentralized Multirobot Active Information Gathering. 3, 2 (2018), 1025–1032. doi:10.1109/LRA.2018.2794608
[159] Koteeswaran Seerangan, Malarvizhi Nandagopal, Tamilmani Govindaraju, Nalini Manogaran, Balamurugan Balusamy, and Shitharth Selvarajan. 2024. A novel energy-efficiency framework for UAV-assisted networks using adaptive deep reinforcement learning. *Scientific Reports* 14 (2024).
[160] Zhexiong Shang, Justin Bradley, and Zhigang Shen. 2020. A co-optimal coverage path planning method for aerial scanning of complex structures. *Expert systems with applications* 158 (2020), 113535. doi:10.1016/j.eswa.2020.113535
[161] Yunyi Shen, Jian Liu, et al. 2021. Review of Path Planning Algorithms for Unmanned Vehicles. In *2021 IEEE 2nd International Conference on Information Technology, Big Data and Artificial Intelligence (ICIBA)* (Chongqing, China, 2021-12-17). IEEE, 400–405. doi:10.1109/ICIBA52610.2021.9688064
[162] Baoye Song, Gaoru Qi, and Lin Xu. 2019. A Survey of Three-Dimensional Flight Path Planning for Unmanned Aerial Vehicle. In *2019 Chinese Control And Decision Conference (CCDC)* (Nanchang, China, 2019-06). IEEE, 5010–5015. doi:10.1109/CCDC.2019.8832890
[163] Zhengyu Song, Xintong Qin, Yuanyuan Hao, Tianwei Hou, Jun Wang, and Xin Sun. 2022. A comprehensive survey on aerial mobile edge computing: Challenges, state-of-the-art, and future directions. *Comput. Commun.* 191 (2022), 233–256.
[164] Felix Stache, Jonas Westheider, Federico Magistri, Cyrill Stachniss, and Marija Popović. 2023. Adaptive path planning for UAVs for multi-resolution semantic segmentation. *Robotics and autonomous systems* 159 (2023), 104288. doi:10.1016/j.robot.2022.104288
[165] Jinya Su, Xiaoyong Zhu, Shihua Li, and Wen-Hua Chen. 2023. AI meets UAVs: A survey on AI empowered UAV perception systems for precision agriculture. *Neurocomputing* 518 (2023), 242–270.
[166] B Suganya, R. Gopi, A. Ranjith Kumar, and Gavendra Singh. 2024. Dynamic task offloading edge-aware optimization framework for enhanced UAV operations on edge computing platform. *Scientific Reports* 14 (2024).
[167] Enchang Sun, Hanxing Qu, Yongyi Yuan, Meng Li, Zhuwei Wang, and Dawei Chen. 2021. A Joint Channel Allocation and Power Control Scheme for D2D Communication in UAV-based Networks. *2021 IEEE 21st International Conference on Communication Technology (ICCT)* (2021), 919–924.
[168] Gang Tang, Congqiang Tang, Hao Zhou, Christophe Claramunt, and Shaoyang Men. 2021. R-dfs: A coverage path planning approach based on region optimal decomposition. *Remote sensing (Basel, Switzerland)* 13, 8 (2021), 1525. doi:10.3390/rs13081525
[169] Jun Tang, Haibin Duan, and Songyang Lao. 2022. Swarm intelligence algorithms for multiple unmanned aerial vehicles collaboration: a comprehensive review. *Artif. Intell. Rev.* 56, 5 (Sept. 2022), 4295–4327.
[170] Mirco Theile, Harald Bayerlein, Richard Nai, David Gesbert, and Marco Caccamo. 2020. UAV coverage path planning under varying power constraints using deep reinforcement learning. *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (2020), 1444–1449.
[171] Amila Thibbotuwawa, Grzegorz Bocewicz, Grzegorz Radzki, Peter Nielsen, and Zbigniew Banaszak. 2020. UAV Mission Planning Resistant to Weather Uncertainty. *Sensors* 20, 2 (2020). doi:10.3390/s20020515

[172] Darko Trivun, Edin Šalaka, Dinko Osmanković, Jasmin Velagić, and Nedim Osmić. 2015. Active SLAM-based algorithm for autonomous exploration with mobile robot. In *2015 IEEE International Conference on Industrial Technology (ICIT)*. IEEE, 74–79.

[173] Hsiang-Chun Tsai, Y-W Peter Hong, and Jang-Ping Sheu. 2022. Completion time minimization for UAV-enabled surveillance over multiple restricted regions. *IEEE Transactions on Mobile Computing* 22, 12 (2022), 6907–6920.

[174] Nikolaos Tsiogkas and David M. Lane. 2018. An Evolutionary Algorithm for Online, Resource-Constrained, Multivehicle Sensing Mission Planning. 3, 2 (2018), 1199–1206. doi:10.1109/LRA.2018.2794578 Number: 2.

[175] Gheorghe Udeanu, Alexandra Dobrescu, et al. 2016. Unmanned aerial vehicle in military operations. *Sci. Res. Educ. Air Force* 18, 1 (2016), 199–206.

[176] Mojtaba Vaezi, Xingqin Lin, Hongliang Zhang, Walid Saad, and H Vincent Poor. 2023. Deep reinforcement learning for interference management in UAV-based 3D networks: Potentials and challenges. *IEEE Communications Magazine* 62, 2 (2023), 134–140.

[177] Bertold Van Der Bergh, Alessandro Chiumento, and Sofie Pollin. 2016. LTE in the sky: Trading off propagation benefits with interference costs for aerial nodes. *IEEE Communications Magazine* 54, 5 (2016), 44–50.

[178] Rodolfo Vera-Amaro, Mario Eduardo Rivero-Ángeles, and Alberto Luviano-Juárez. 2020. Data Collection Schemes for Animal Monitoring Using WSNs-Assisted by UAVs: WSNs-Oriented or UAV-Oriented. *Sensors* 20, 1 (2020). doi:10.3390/s20010262

[179] Chuqi Wang, Chao Yu, Xin Xu, Yuman Gao, Xinyi Yang, Wenhao Tang, Shu'ang Yu, Yinuo Chen, Feng Gao, ZhuoZhu Jian, et al. 2025. Multi-robot system for cooperative exploration in unknown environments: A survey. *arXiv preprint arXiv:2503.07278* (2025).

[180] Hao Wang. 2021. Energy-Efficient 3D Vehicular Crowdsourcing For Disaster Response by Distributed Deep Reinforcement Learning. (2021). doi:10.1145/3447548.3467070

[181] Hao Wang, Chi Harold Liu, Haoming Yang, Guoren Wang, and Kin K Leung. 2023. Ensuring threshold AoI for UAV-assisted mobile crowdsensing by multi-agent deep reinforcement learning with transformer. *IEEE/ACM Transactions on Networking* (2023).

[182] Haoyang Wang, Jingao Xu, Chenyu Zhao, Zihong Lu, Yuhan Cheng, Xuecheng Chen, Xiao-Ping Zhang, Yunhao Liu, and Xinlei Chen. 2024. Transformloc: Transforming mavs into mobile localization infrastructures in heterogeneous swarms. In *IEEE INFOCOM 2024-IEEE Conference on Computer Communications*. IEEE, 1101–1110.

[183] Qiuzhen Wang and Hai Zhang. 2021. A Self-Organizing Area Coverage Method for Swarm Robots Based on Gradient and Grouping. 13, 4 (2021), 680. doi:10.3390/sym13040680 Number: 4 Publisher: Multidisciplinary Digital Publishing Institute.

[184] Shuaijun Wang, Fan Jiang, Bin Zhang, Rui Ma, and Qi Hao. 2019. Development of UAV-based target tracking and recognition systems. *IEEE Transactions on Intelligent Transportation Systems* 21, 8 (2019), 3409–3422.

[185] Xiaojie Wang, Zhonghui Zhao, Ling Yi, Zhaolong Ning, Lei Guo, F Richard Yu, and Song Guo. 2024. A Survey on Security of UAV Swarm Networks: Attacks and Countermeasures. *Comput. Surveys* 57, 3 (2024), 1–37.

[186] Yutong Wang, Mehul Damani, Pamela Wang, Yuhong Cao, and Guillaume Sartoretti. 2022. Distributed Reinforcement Learning for Robot Teams: a Review. *Current Robotics Reports* 3 (2022), 239 – 257.

[187] Zhe Wang, Lingjie Duan, and Rui Zhang. 2019. Adaptive Deployment for UAV-Aided Communication Networks. *IEEE Transactions on Wireless Communications* 18, 9 (2019), 4531–4543. doi:10.1109/TWC.2019.2926279

[188] Ziyuan Wang, Xiao-Ping Zhang, Wenbo Ding, Yuhan Dong, and Xinlei Chen. 2025. A Novel Integrated Sensing and Communication Scheme in UAVs-Enabled Vehicular Networks with MARL-Driven Adaptive Control. *IEEE Transactions on Mobile Computing* (2025).

[189] Yongyong Wei and Rong Zheng. 2020. Informative Path Planning for Mobile Sensing with Reinforcement Learning. In *IEEE INFOCOM 2020 - IEEE Conference on Computer Communications* (Toronto, ON, Canada, 2020-07). IEEE, 864–873. doi:10.1109/INFOCOM41043.2020.9155528

[190] Yongyong Wei and Rong Zheng. 2021. Multi-Robot Path Planning for Mobile Sensing through Deep Reinforcement Learning. In *IEEE INFOCOM 2021 - IEEE Conference on Computer Communications* (Vancouver, BC, Canada, 2021-05-10). IEEE, 1–10. doi:10.1109/INFOCOM42981.2021.9488669

[191] Zhiqing Wei, Mingyue Zhu, Ning Zhang, Lin Wang, Yingying Zou, Zeyang Meng, Huici Wu, and Zhiyong Feng. 2022. UAV-assisted data collection for Internet of Things: A survey. *IEEE Internet of Things Journal* 9, 17 (2022), 15460–15483.

[192] Qingqing Wu, Jie Xu, Yong Zeng, Derrick Wing Kwan Ng, et al. 2021. A comprehensive overview on 5G-and-beyond networks with UAVs: From communications to sensing and intelligence. *IEEE Journal on Selected Areas in Communications* 39, 10 (2021), 2912–2945.

[193] Lin Xiang, Fengcheng Pei, and Anja Klein. 2024. Joint Optimization of Beamforming and 3D Array Steering for Multi-Antenna UAV Communications. *2024 IEEE Wireless Communications and Networking Conference (WCNC)* (2024), 1–6.

[194] Fanyun Xu, Yongchao Zhang, Rufei Wang, Chenyang Mi, et al. 2021. Heuristic Path Planning Method for Multistatic UAV-Borne SAR Imaging System. *IEEE journal of selected topics in applied earth observations and remote sensing* 14 (2021), 8522–8536. doi:10.1109/JSTARS.2021.3106449

[195] Susu Xu, Xinlei Chen, Xidong Pi, Carlee Joe-Wong, Pei Zhang, and Hae Young Noh. 2020. iLOCuS: Incentivizing Vehicle Mobility to Optimize Sensing Distribution in Crowd Sensing. 19, 8 (2020), 1831–1847. doi:10.1109/TMC.2019.2915838 Number: 8.

[196] Weijian Xu, Zhongzhe Song, Zhibin Gao, Lianyou Lai, Yanglong Sun, and Wenqian Luo. 2024. Latency-Aware MIoT Service Strategy in UAV-Assisted Dynamic MMEC Environment. *IEEE Internet of Things Journal* 11 (2024), 22220–22231.

[197] Yanggang Xu, Weijie Hong, Jirong Zha, Geng Chen, Jianfeng Zheng, Chen-Chun Hsia, and Xinlei Chen. 2025. Scalable UAV Multi-Hop Networking via Multi-Agent Reinforcement Learning with Large Language Models. *arXiv preprint arXiv:2505.08448* (2025).

[198] Yanggang Xu, Jirong Zha, Jiyuan Ren, Xintao Jiang, et al. 2024. Scalable Multi-Agent Reinforcement Learning for Effective UAV Scheduling in Multi-Hop Emergency Networks. In *Proceedings of the 30th Annual International Conference on Mobile Computing and Networking*. 2028–2033.

[199] Zhefan Xu, Di Deng, and Kenji Shimada. 2021. Autonomous UAV Exploration of Dynamic Environments Via Incremental Sampling and Probabilistic Roadmap. 6, 2 (2021), 2729–2736. doi:10.1109/LRA.2021.3062008 Number: 2.

[200] Biao Yang, Xuanrui Xiong, He Liu, Yumei Jia, Yunli Gao, Amr Tolba, and Xingguo Zhang. 2023. Unmanned Aerial Vehicle Assisted Post-Disaster Communication Coverage Optimization Based on Internet of Things Big Data Analysis. *Sensors (Basel, Switzerland)* 23 (2023).

[201] Gang Yang, Rao Dai, and Ying-Chang Liang. 2020. Energy-efficient UAV backscatter communication with joint trajectory design and resource optimization. *IEEE Transactions on Wireless Communications* 20, 2 (2020), 926–941.

[202] Ming-Der Yang, Jayson Boubin, Hui Ping Tsai, et al. 2020. Adaptive autonomous UAV scouting for rice lodging assessment using edge computing with deep learning EDANet. *Computers and Electronics in Agriculture* 179 (10 2020). doi:10.1016/j.compag.2020.105817

[203] Yuzhe Yang, Zijie Zheng, Kaigui Bian, Lingyang Song, and Zhu Han. 2017. Real-time profiling of fine-grained air quality index distribution using UAV sensing. *IEEE Internet of Things Journal* 5, 1 (2017), 186–198.

[204] Junho Yeom, Youkyung Han, Anjin Chang, and Jinha Jung. 2019. Hurricane Building Damage Assessment using Post-Disaster UAV Data. *IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium* (2019), 9867–9870.

[205] Guolin Yu, Hui Song, and Jie Gao. 2022. Unmanned Aerial Vehicle Path Planning Based On Tlbo Algorithm. *International journal on smart sensing and intelligent systems* 7, 3 (2022), 1310–1325. doi:10.21307/ijssis-2017-707

[206] Hao Yu, Xiuxia Yang, Yi Zhang, and Zijie Jiang. 2024. Cooperative Target Fencing Control for Unmanned Aerial Vehicle Swarm with Collision, Obstacle Avoidance, and Connectivity Maintenance. *Drones* (2024).

[207] Kevin Yu, Jason M. O'Kane, and Pratap Tokekar. 2019. Coverage of an Environment Using Energy-Constrained Unmanned Aerial Vehicles. In *2019 International Conference on Robotics and Automation (ICRA)* (Montreal, QC, Canada, 2019-05). IEEE, 3259–3265. doi:10.1109/ICRA.2019.8794150

[208] Yong Zeng et al. 2019. Accessing From the Sky: A Tutorial on UAV Communications for 5G and Beyond. *Proc. IEEE* 107 (2019), 2327–2375.

[209] Jirong Zha, Yuxuan Fan, Kai Li, Han Li, Chen Gao, Xinlei Chen, and Yong Li. 2025. DIMM: Decoupled Multi-hierarchy Kalman Filter for 3D Object Tracking. *arXiv preprint arXiv:2505.12340* (2025).

[210] Jirong Zha, Yuxuan Fan, Xiao Yang, Chen Gao, and Xinlei Chen. 2025. How to enable llm with 3d capacity? a survey of spatial reasoning in llm. *arXiv preprint arXiv:2504.05786* (2025).

[211] Jirong Zha, Yuxuan Fan, Tianyu Zhang, Geng Chen, Yingfeng Chen, Chen Gao, and Xinlei Chen. 2025. Aircopbench: A benchmark for multi-drone collaborative embodied perception and reasoning. *arXiv preprint arXiv:2511.11025* (2025).

[212] Jirong Zha, Nan Zhou, Zhenyu Liu, Tao Sun, and Xinlei Chen. 2024. Diffusion-based filter for fast and accurate collaborative tracking with low data transmission. *Authorea Preprints* (2024).

[213] Cheng Zhan, Han Hu, Jing Wang, Zhi Liu, and Shiwen Mao. 2023. Tradeoff between age of information and operation time for uav sensing over multi-cell cellular networks. *IEEE Transactions on Mobile Computing* 23, 4 (2023), 2976–2991.

[214] Haidong Zhang, Lingqing Wang, Ting Tian, and Jianghai Yin. 2021. A review of unmanned aerial vehicle low-altitude remote sensing (UAV-LARS) use in agricultural monitoring in China. *Remote Sensing* 13, 6 (2021), 1221.

[215] S. Zhang, C. Liu, and N. Haala. 2020. Three-Dimensional Path Planning of Uavs Imaging for Complete Photogrammetric Reconstruction. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 5, 1 (2020), 325–331. doi:10.5194/isprs-annals-V-1-2020-325-2020

[216] Weichen Zhang, Chen Gao, Shiquan Yu, Ruiying Peng, Baining Zhao, Qian Zhang, Jinqiang Cui, Xinlei Chen, and Yong Li. 2025. CityNavAgent: Aerial Vision-and-Language Navigation with Hierarchical Semantic Planning and Global Memory. *arXiv preprint arXiv:2505.05622* (2025).

[217] Zichen Zhang, Jayson Boubin, Christopher Stewart, and Sami Khanal. 2020. Whole-Field Reinforcement Learning: A Fully Autonomous Aerial Scouting Method for Precision Agriculture. *Sensors* 20, 22 (2020). doi:10.3390/s20226585

[218] Baining Zhao, Jianjie Fang, Zichao Dai, Ziyou Wang, et al. 2025. Urbanvideo-bench: Benchmarking vision-language models on embodied intelligence with video data in urban spaces. *arXiv preprint arXiv:2503.06157* (2025).

[219] Baining Zhao, Ziyou Wang, Jianjie Fang, Chen Gao, Fanhang Man, Jinqiang Cui, Xin Wang, Xinlei Chen, et al. 2025. Embodied-R: Collaborative Framework for Activating Embodied Spatial Reasoning in Foundation Models via Reinforcement Learning. *arXiv preprint arXiv:2504.12680* (2025).

[220] Kexin Zheng, Xiaobo Liu, Jianfeng Yang, Zhihua Cai, Haoran Dai, Zhilang Zhou, Xiao Xiao, and Xin Gong. 2021. BRR-DQN: UAV path planning method for urban remote sensing images. IEEE, 6113–6117. doi:10.1109/CAC53003.2021.9728066

[221] Chen Zheyi and Xu Bing. 2021. AGV Path Planning Based on Improved Artificial Potential Field Method. *2021 IEEE International Conference on Power Electronics, Computer Applications (ICPECA)* (2021), 32–37.

[222] Hao Zhou, Zheng Ji, Xiangyu You, Yuchen Liu, Lingfeng Chen, Kun Zhao, Shan Lin, and Xiangxiang Huang. 2023. Geometric Primitive-Guided UAV Path Planning for High-Quality Image-Based Reconstruction. *Remote sensing (Basel, Switzerland)* 15, 10 (2023), 2632. doi:10.3390/rs15102632

[223] Hao Zhou, Yuchen Liu, and Zheng Ji. 2023. A UAV PHOTOGRAPHIC PATH PLANNING METHOD FOR HIGH-QUALITY RECONSTRUCTION OF CULTURAL HERITAGE, Vol. 48. Copernicus GmbH, 579–586. doi:10.5194/isprs-archives-XLVIII-1-W1-2023-579-2023

[224] Nan Zhou, Zuxin Li, Fanhang Man, Xuecheng Chen, Susu Xu, Fan Dang, Chaopeng Hong, Yunhao Liu, Xiao-Ping Zhang, and Xinlei Chen. 2026. QUIDS: Quality-informed Incentive-driven Multi-agent Dispatching System for Mobile Crowdsensing. *IEEE Internet of Things Journal* (2026).

[225] Xin Zhou, Xiangyong Wen, Zhepei Wang, Yuman Gao, Haojia Li, Qianhao Wang, Tiankai Yang, Haojian Lu, Yanjun Cao, Chao Xu, et al. 2022. Swarm of micro flying robots in the wild. *Science robotics* 7, 66 (2022), eabm5954.

[226] Liangbin Zhu, Cheng Ma, Jinglei Li, et al. 2023. Connectivity-Maintenance UAV Formation Control in Complex Environment. *Drones* (2023).

[227] Wenjing Zhu, Zhankang Feng, Shiyuan Dai, Pingping Zhang, and Xinhua Wei. 2022. Using UAV Multispectral Remote Sensing with Appropriate Spatial Resolution and Machine Learning to Monitor Wheat Scab. *Agriculture* (2022). https://api.semanticscholar.org/CorpusID:253220506