IAES International Journal of Robotics and Automation (IJRA)
Vol. 15, No. 3, September 2026, pp. 621∼638
ISSN: 2722-2586, DOI: 10.11591/ijra.v15i3.pp621-638

Consensus-based path planning for UAV swarms under multiple constraints: A review

Yana Lu, Lianpeng Li, Hui Zhao, Xu Zhao
School of Automation, Beijing Information Science and Technology University, Beijing, China

Article Info

Article history:

Received Feb 9, 2026
Revised Apr 27, 2026
Accepted May 22, 2026

Keywords:

Classical path search
Consistency constraints
Deep reinforcement learning
Intelligent optimization algorithms
Path planning
Unmanned aerial vehicle swarm

ABSTRACT

Unmanned aerial vehicle (UAV) swarms are essential for emergency response, logistics, reconnaissance, and environmental monitoring, yet achieving safe and scalable path planning under dynamic conditions and complex constraints remains challenging. Unlike existing surveys that categorize algorithms by theoretical foundations, this paper systematically reviews UAV swarm path planning through the lens of spatial, temporal, and task-level consistency constraints. We classify recent advances into classical path search, intelligent optimization, and deep reinforcement learning, emphasizing how each addresses geometric continuity, behavioral coordination, and full-chain perception–decision–planning consistency under multi-constraint coupling. We further identify critical limitations in scalability, dynamic adaptability, and heterogeneous swarm cooperation, and outline future directions, including distributed control, multi-source perception fusion, cross-platform collaboration, and robust autonomous decision-making. This review provides a unique, application-centric taxonomy based on consensus constraints, offering actionable insights for developing consistency-aware UAV swarm path planning technologies.

Corresponding Author:

Li Lianpeng
School of Automation, Beijing Information Science and Technology University
Beijing, China
Email: llp@bistu.edu.cn

1. INTRODUCTION

With the rapid evolution of autonomous intelligent systems, Unmanned aerial vehicle (UAV) swarms — composed of multiple UAVs with autonomous perception, distributed decision-making, and cooperative interaction capabilities — have shown transformative potential in emergency rescue, logistics, monitoring, and military reconnaissance [1], [2]. Recent breakthroughs in deep learning and swarm intelligence have further enhanced their situational awareness and cooperative control [3]. As the foundation of swarm cooperation, path planning directly determines mission safety and has become a key indicator of system intelligence. However, research on UAV swarm path planning under multiple consensus constraints remains in its early stages, with only a few studies having just begun to explore this challenging area [4].

UAV swarm path planning aims to generate a set of feasible trajectories for the entire swarm in complex environments while satisfying mission requirements. It must simultaneously ensure trajectory continuity, temporal synchronization, and task-level decision consistency, thereby enabling coordinated mission execution [5] and avoiding energy inefficiency or even obstacle avoidance failures. When performing complex missions in dynamic and uncertain environments, UAV swarms are required to satisfy consensus constraints across multiple dimensions, including spatial, temporal, and cooperative task aspects.

Specifically, spatial constraints [6] require planned paths to be continuously executable [7], safe, and capable of effective obstacle avoidance; temporal constraints [8] emphasize mission synchronization, formation maintenance [9], and consistency in action timing [10]; and cooperative task constraints [11] are reflected in information exchange [12], behavior coordination, and strategy unification among agents. With the increasing environmental dynamics, the strengthening coupling among heterogeneous constraints, and the continuous growth of swarm scale [13], path planning under multiple constraints has progressively evolved into a highly complex problem characterized by high dimensionality, nonlinearity, strong coupling, and multi-objective optimization. Consequently, the applicability of traditional path planning methods in such scenarios has become increasingly limited.

To address the above challenges, research efforts have focused on problem modeling, constraint integration and solution strategies [14]. In classical path search, improved heuristic functions, dynamic cost update mechanisms, and local conflict resolution enhance the ability to handle dynamic obstacles, spatiotemporal conflicts, and limited cooperative behaviors. Intelligent optimization algorithms, leveraging strong global search and adaptability, enable swarm-level cooperative optimization under complex constraints, moving path planning beyond geometric feasibility toward multi consensus constraint handling. Meanwhile, deep reinforcement learning and multi-agent learning allow UAV swarms to achieve continual learning and distributed cooperation in dynamic, uncertain environments, offering more adaptive solutions for multi-constraint path planning.

Despite significant progress in existing research, maintaining consensus among UAV swarms in dynamic environments remains a primary challenge for path planning. Factors such as environmental dynamics, multi-source perception inconsistencies, and platform heterogeneity often lead to degraded cooperative performance [15]. Therefore, it is necessary to conduct a systematic review from the perspective of consensus constraints, with the aim of providing important theoretical support and technical references for the development of highly autonomous UAV swarm systems. Unlike existing surveys that categorize algorithms by theoretical foundations [16], this paper provides a novel application-centric taxonomy based on spatial-temporal-cooperative task consensus constraints. It systematically analyzes how classical search, intelligent optimization, and deep reinforcement learning methods maintain consensus under multiple conflicting constraints, critically evaluating their scalability, real-time performance, and suitability for heterogeneous swarms.

To improve the structural clarity of the reviewed methodologies, the overall path planning process for UAV swarms can generally be summarized into several interconnected stages, including environment perception, constraint modeling, cooperative task allocation, global path generation, local dynamic replanning, and consistency maintenance. Different planning approaches reviewed in this paper mainly differ in their implementation strategies for these stages, particularly in balancing global optimality, real-time adaptability, and cooperative consistency under multi-constraint environments, shown in Figure 1. Furthermore, it discusses planning challenges under multi-constraint coupling, including scalability, real-time performance, and heterogeneous swarm cooperation, and concludes with major challenges, future research directions, and application prospects.

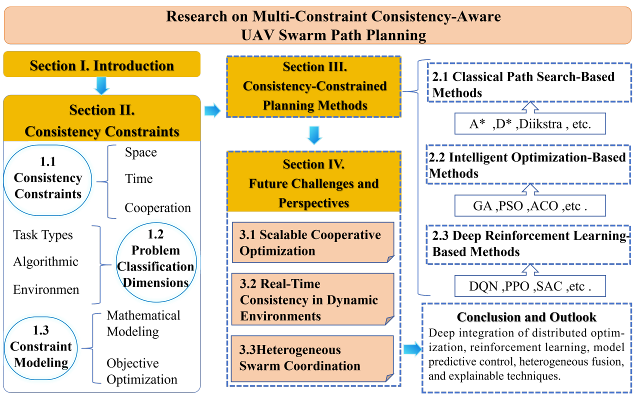

Figure 1. Overall framework of the proposed consistency-aware path planning methodology for UAV swarms

The structures of the paper are as follows. Section 1 describes models spatial, temporal, and cooperative constraints. Section 2 reviews classical search, intelligent optimization, and DRL methods. Section

3 highlights scalability, real-time consistency, and heterogeneous cooperation as future challenges. Finally, the conclusion summarizes the paper.

2. SPATIAL-TEMPORAL-COOPERATIVE TASK CONSENSUS CONSTRAINTS

2.1. Spatial, temporal, and cooperative task constraints in path planning

UAV swarm path planning must satisfy three critical constraint types. Spatial constraints ensure that the swarm operates continuously, feasibly, and without collisions within geometric and environmental limits [17]. Temporal constraints maintain stability and coordination in both path execution and decision-making. Cooperative task constraints require that the swarm's behaviors do not conflict and collectively achieve globally optimal performance [18]. Together, these three constraints constitute a consensus constraint framework for UAV swarm path planning.

In terms of spatial constraints, UAV swarms must operate within a predefined three-dimensional airspace, avoiding no-fly zones and preventing collisions with obstacles [19] to ensure safe and efficient mission execution. Static obstacles require that planned paths effectively avoid them at the initial planning stage028, whereas dynamic obstacles demand real-time perception [20] and adaptive trajectory adjustment [21]. Consequently, path planning algorithms must possess high-level predictive capabilities and efficient update mechanisms to handle such challenges effectively.

Regarding temporal constraints, UAV swarms missions must be executed in a sequential manner to prevent congestion or collisions caused by premature or delayed actions of individual UAV swarm. This is particularly critical in scenarios such as emergency response, disaster monitoring, and rapid inspection, where mission execution must be temporally continuous and coherent. Such requirements place high demands on the real-time performance and computational efficiency of path planning algorithms [22]. Temporal constraints additionally require rapid replanning capability under limited computational resources.

Cooperative task constraints represent a distinctive feature of UAV swarm path planning. Individual UAV swarm within the swarm are required to maintain appropriate spatial distribution and safety separation during mission execution to avoid collisions due to excessive proximity. Different UAV swarms must achieve complementarity and coordination in task allocation [23].

Furthermore, the swarm needs to maintain network connectivity through wireless communication to enable real-time information sharing and decision-making consistency. Consequently, path planning must consider not only geometric and temporal feasibility but also communication range constraints and topological robustness, ensuring that the swarm can cooperate stably in dynamic environments.

2.2. Problem classification dimensions

The cooperative collision avoidance problem for UAV swarms exhibits diverse mission objectives, algorithmic implementations, and operational environment characteristics. To systematically address the aforementioned multi-constraint path planning problem, existing research typically classifies the approaches along the following dimensions. In Figure 2, a three-dimensional classification is conducted from the perspectives of task types, algorithmic characteristics, and environment (Env). The algorithmic category includes deterministic algorithms (DEA), randomized algorithms (RA), centralized algorithms (CA), and distributed algorithms (DA).

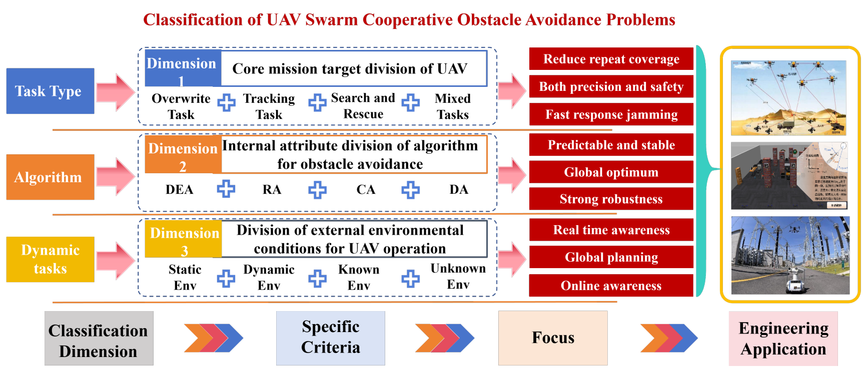

Figure 2. Cluster problem classification dimension

2.2.1. Task types

In tracking missions, UAV swarms are required to collaboratively track moving targets [24]. These tasks are commonly encountered in security patrols [25] and traffic flow monitoring [26], [27]. Collision avoidance strategies need to balance target-tracking accuracy with swarm safety separation, particularly when both targets and obstacles are in motion, imposing high real-time requirements on path planning.

In search and rescue missions [28], such as disaster relief or maritime search operations, UAV swarms must rapidly locate targets in complex and dynamic environments [29]. Collision avoidance strategies in these tasks must not only handle static obstacles but also adapt to dynamic disturbances such as debris, smoke, and moving rescue equipment, while completing mission coverage in minimal time.

In many practical applications, missions may simultaneously involve coverage, tracking, and search-and-rescue objectives. For example, post-disaster aerial inspection requires area coverage, real-time tracking of key targets, and searching for potential trapped individuals. Collision avoidance strategies for such complex missions must possess high flexibility and the capability to switch task priorities dynamically.

2.2.2. Algorithmic features

From the perspective of algorithmic features, UAV swarm path planning methods can be primarily classified along two dimensions: deterministic versus stochastic and centralized versus distributed. Deterministic algorithms [30] produce consistent outputs under identical initial conditions [31], offering high predictability and stability. They are well suited for scenarios with well-defined environmental models and clear mission objectives [32]. In contrast, stochastic algorithms [33] introduce probabilistic elements into the decision-making process, enabling more diverse solutions in highly uncertain environments or large search spaces. These algorithms are commonly employed for global search, avoidance of local optima, and adaptation to dynamically changing mission conditions.

Regarding decision-making architectures, centralized algorithms [34] rely on one or a few central nodes to aggregate information and make global decisions. They can maintain full awareness of system states and achieve globally optimal solutions; however, they impose high requirements on communication links and computational resources, and failure of central nodes may result in mission interruption. Distributed algorithms [35], on the other hand, allow individual UAV swarm to make autonomous decisions based solely on local information exchange [36], offering higher robustness and scalability, and are suitable for large-scale swarms and communication-constrained scenarios [37]. Nevertheless, distributed algorithms may exhibit limitations in global optimization and convergence speed [38], which can be mitigated by designing appropriate local rules and information-sharing mechanisms.

2.2.3. Environmental characteristics

Classification based on environmental characteristics primarily depends on environmental stability, which can be divided into static and dynamic environments. In static environments, the positions of targets and obstacles are fixed, as in inspection and mapping tasks, allowing for pre-planned trajectories and relatively simple algorithms. In dynamic environments, targets, obstacles, or conditions change over time, as in maritime search and rescue or traffic monitoring, requiring real-time perception and trajectory adjustment, making path planning more challenging.

Additionally, environments can be categorized according to the availability of environmental information into known and unknown environments [39]. In known environments, information such as maps of the mission area, obstacle locations, and target characteristics is available before mission execution, facilitating the use of global planning strategies [40]. In unknown environments, such information is not fully accessible prior to task execution, necessitating the use of UAV sensors [41] and cooperative perception capabilities [42] to progressively build an environmental model. Online decision-making and local path planning techniques are then employed to respond to unexpected changes [43]. Different environmental characteristics directly affect the complexity of mission planning, perception systems, and control strategies, making this classification an essential dimension in UAV swarms task design.

2.3. Constraint modeling

In the mathematical modeling of path planning, the proper formulation of constraints directly determines the feasibility and optimality of the planned trajectories. Based on mission execution characteristics and swarm coordination requirements, spatial, temporal, and cooperative task constraints need to be mathematically modeled to accurately describe the states of UAV swarms, including position, velocity, and heading. Path planning solutions are then obtained through objective optimization, enabling the swarm to efficiently coordinate [44], avoid obstacles [45], and accomplish task allocation and execution [46] during mission operations.

2.3.1. Mathematical modeling

The mission space is modeled as a three-dimensional Euclidean space, consisting of a feasible flight region and an obstacle set that do not overlap. The UAV swarm contains a total of N unmanned aerial vehicles. At any time, the state of each UAV includes its position vector, its velocity, and its heading angle.

In terms of spatial modeling, study [47] introduces a hybrid approach that combines discrete and continuous states to describe UAV swarms. By linking discrete swarm events with continuous state variables, this approach captures the dynamic motion and interaction of UAVs in three-dimensional space. The mission objective is commonly defined by a path cost function J, which considers multiple performance metrics, including flight distance, energy consumption, mission duration, and risk. Accordingly, the overall objective can be formulated as:

$$\min_{\mathcal{P}} \boldsymbol{J} = \sum_{i=1}^{N} (\boldsymbol{\alpha}_1 \boldsymbol{L}_i + \boldsymbol{\alpha}_2 \boldsymbol{E}_i + \boldsymbol{\alpha}_3 \boldsymbol{T}_i + \boldsymbol{\alpha}_4 \boldsymbol{R}_i) \tag{1}$$

Where P denotes the set of trajectories of all UAV swarms, L_i represents the total path length, $\boldsymbol{E}_i$ denotes the energy consumption, T_i is the mission execution time, and $\boldsymbol{R}_i$ corresponds to the risk cost. a_k denotes the weighting coefficients, which are assigned according to task priorities. The weighting coefficients α_k in (1) allow for mission-specific trade-offs, e.g., prioritizing energy (α_2) over path length (α_1) for long-endurance missions.

To ensure the feasibility of planned trajectories, dynamic constraints are introduced at the modeling stage to reflect the kinematic characteristics and platform performance limitations of UAV swarm [48]. Typically, the velocity, acceleration, and rate of change of heading angle of each UAV are required to satisfy:

$$\begin{aligned} &\nu_{\min} \leq \parallel \nu_i(t) \parallel \leq \nu_{\max}, \\ &\parallel \dot{\nu}_i(t) \parallel \leq a_{\max}, \\ &\mid \dot{\psi}_i(t) \mid \leq \psi_{\max} \end{aligned} \tag{2}$$

In (2), $\boldsymbol{v}_{\min}$,$\boldsymbol{v}_{\max}$, $a_{\max}$, and $\boldsymbol{\psi}_{\max}$ represent the platform's limits on speed, acceleration, and turning rate, respectively. These dynamic constraints ensure kinematic feasibility.

Spatial constraints are introduced to ensure the safe flight of UAV swarm within the mission space. Specifically, spatial safety constraints require that the flight trajectories do not intersect with obstacle sets while maintaining a prescribed minimum safety distance $d_{\min}$.

$$\parallel p_i(t) - p_j(t) \parallel \geq d_{\min}, p_i(t) \notin \Omega_o \tag{3}$$

This constraint ensures that UAVs follow planned trajectories within admissible attitude and velocity limits. It prevents aggressive maneuvers that may cause excessive energy consumption, flight instability, or control failure, thereby guaranteeing the physical feasibility and safety of the trajectories.

Temporal constraints describe time coordination among UAVs during mission execution. They ensure mission completion within a given time window while maintaining synchronization and cooperative behavior. In UAV swarm planning, time affects task efficiency, coordination accuracy, and system stability.

In UAV swarm cooperative missions [49], temporal constraints involve more than individual timing. They also capture task sequencing and synchronization within the swarm. For tasks requiring coordination, such as collaborative reconnaissance, formation flight, distributed monitoring, or multi-point strikes, the following constraints must be satisfied:

$$\begin{aligned} &t_i^{arrive} \leq t_j^{arrive} \\ &\mid t_i^{arrive} - t_j^{arrive} \mid \leq \Delta t_{sync} \end{aligned} \tag{4}$$

Here, Δt_{sync} represents the allowable time synchronization deviation. The former applies to scenarios with sequential task requirements; the latter applies to scenarios requiring simultaneous arrival or synchronized execution, ensuring that all UAV swarms perform actions within the permissible time deviation, thereby maintaining overall mission coordination.

Cooperative task modeling. Cooperative task constraints are introduced to ensure that UAV swarm systems achieve information sharing, motion coordination, and decision consistency during mission execution, serving as key elements for realizing efficient collective intelligence behavior [50].

Formation-keeping constraints are introduced to ensure that UAV swarm maintain a prescribed spatial geometric relationship during formation or cooperative missions [51]. Let r_i^* denote the relative position of UAV i with respect to the formation center in the ideal formation. During actual flight, the following condition must be satisfied:

$$\| (p_i(t) - p_c(t)) - r_i^* \| \leq \varepsilon_f \tag{5}$$

where $\boldsymbol{p}_c(t)$ represents the position of the formation center and ε_f denotes the allowable formation tolerance. This constraint enables the UAV swarm to maintain overall shape during maneuvers, obstacle avoidance, or target tracking, preventing excessive dispersion or structural disorder of the formation.

Cooperative task constraints capture functional division and complementarity among UAVs at the task level. For multi-objective missions, task allocation must be both unique and complete, enabling global optimization under swarm cooperation. These constraints help the swarm maintain structural stability, coordinated behavior, and information consistency in complex, dynamic environments, thereby improving operational efficiency and robustness. Together with spatial and temporal constraints, they form the foundational modeling framework for UAV swarm path planning.

The planning of the path of the UAV swarm must accommodate various application scenarios and strike missions, each imposing different requirements on coverage efficiency, target prioritization, formation maintenance, as well as path optimality and threat avoidance [52]. For heterogeneous swarms, differences in platform endurance, payload capacity, and sensing capabilities must also be considered [53]. Consequently, this problem is inherently a multi-objective constrained optimization task, whose complexity arises from high-dimensional state spaces, dynamic environments, and swarm coupling. In practice, a balance must be struck between modeling accuracy and computational feasibility to ensure mission effectiveness while maintaining real-time performance.

2.3.2. Objective optimization

In UAV swarm cooperative path planning and scheduling, the proper formulation of optimization objectives directly determines system performance and mission efficiency [54]. These objectives typically encompass multiple dimensions, including path length, energy consumption, time efficiency, safety, and task coverage. Owing to varying mission requirements, these objectives often conflict with one another, necessitating the use of multi-objective optimization methods to achieve effective trade-offs [55].

At the path planning level, minimizing flight distance or mission completion time is a key objective for improving operational efficiency, particularly in time-sensitive tasks such as emergency response and inspection. This problem is typically formulated as a shortest-path or optimal scheduling problem and is solved using enhanced methods such as A*, ant colony optimization, or particle swarm optimization, balancing computational efficiency with path feasibility.

At the mission level, swarm planning aims to maximize task completion and area coverage efficiently under time and energy limits. This is critical for area search, environmental monitoring, and agricultural inspection, typically achieved via region partitioning or information-gain-based coverage models.

From the perspective of energy utilization, minimizing energy consumption is a critical objective in UAV path planning [56], [57]. Energy expenditure is influenced by factors such as path length, flight speed, vehicle dynamics, and environmental disturbances. By incorporating flight dynamics models and optimizing speed profiles and trajectory design, energy efficiency can be significantly improved, which is particularly important in scenarios with limited endurance.

The aforementioned optimization objectives in practical missions are often coupled and involve trade-offs among multiple criteria. Consequently, multi-objective optimization frameworks are typically employed in modeling and solution processes [58], using weighting coefficients to achieve a balanced compromise [59]. Such optimization strategies enable coordination among different performance metrics, allowing the UAV swarm to achieve overall mission effectiveness in complex environments.

3. CONSISTENCY-CONSTRAINED PLANNING METHODS

Research on UAV swarm path planning involves various methods that differ in computational complexity, adaptability, global optimality, and real-time performance, as summarized in Table 1. These methods can be broadly classified into classical path search, intelligent optimization, machine learning and deep reinforcement learning, as well as hybrid and multi-objective approaches that combine multiple techniques.

Table 1. Overview of typical path planning techniques and their characteristics

Technology category	Main methods	Advantages	Limitations
Environment modeling	Grid-based [60], Topological graph [61], Continuous modeling [62], Semantic Map [63]	Clear information representation, adaptable to multiple scenarios	Trade-off between modeling accuracy and real-time performance
Classical search	Dijkstra [64], A* [65], D* [66], Theta* [67]	High interpretability, guaranteed optimality under certain conditions	High computational cost in high-dimensional scenarios
Sampling-based methods	RRT [68], RRT* [69], PRM [70]	Suitable for high-dimensional continuous spaces, capable of handling non-convex environments	Requires post-optimization, global optimality is difficult to guarantee
Intelligent optimization	Genetic algorithm [71], Particle swarm optimization [72], Ant colony optimization [73]	Strong global search capability, suitable for multi-objective optimization tasks	Slow convergence and sensitivity to parameter settings
Deep reinforcement learning	DQN [74], PPO [75], SAC [76], End-to-end navigation networks [77]	High adaptability and scalability, suitable for dynamic environments	High training cost and limited generalization capability

3.1. Classical path search-based methods

In path planning, graph search methods have long been central due to their clear structure, interpretability, and good convergence, as shown in Figure 3. With advances in unmanned systems and more complex scenarios, traditional frameworks have been extended to improve integrated optimization under temporal, spatial, and dynamic consistency constraints. These enhancements allow planning results to better match real missions and environmental dynamics.

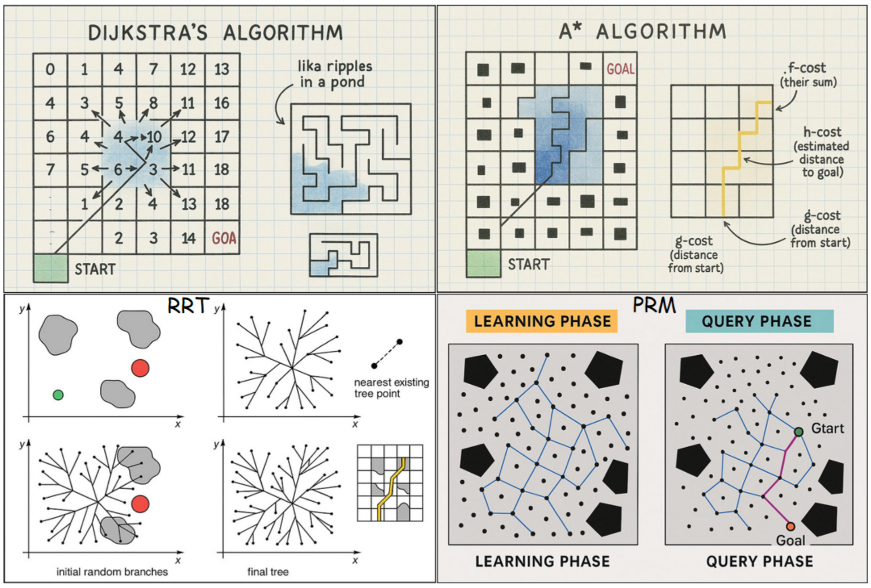

Figure 3. Logic diagram of classical algorithm, including Dijkstra, A*, RRT, and PRM, and compares their respective characteristics in global search, heuristic guidance, and sampling-based planning

The development of classical path search algorithms under consistency constraints has progressed from static optimization to dynamic consistency maintenance and then to multi-objective coordination. Early methods, based on the traditional Dijkstra algorithm [78], focused on finding optimal paths in static graphs. As tasks expanded to complex environments with varying attributes, In 2021 [79], proposed the reverse-label Dijkstra algorithm, which separates road travel time from intersection waiting time and dynamically updates costs using a reverse-label mechanism, ensuring path timing aligns with environmental attributes. In 2023, consistency constraints were further applied to state-space search and sensor calibration path planning [80]. The improved Dijkstra method uses observability as the path cost and employs dynamic error estimation with multi-path iteration to align error convergence with observability evaluation, enabling optimal path search in high-dimensional error space and improving the stability and accuracy of system-level calibration.

As application demands shift toward higher dynamic responsiveness and continuity, path smoothness and dynamic feasibility have become key extensions of classical search algorithms. To address the A* algorithm's limitations in efficiency and smoothness, study [81] proposed the self-adaptive neighborhood search A* (SANSA) algorithm. SANSA improves efficiency by adjusting the search neighborhood and obstacle handling, and applies path smoothing after generation. This ensures trajectories maintain geometric and kinematic continuity, enabling coordinated preservation of consistency and feasibility, marking a shift from discrete paths to continuous trajectories.

With the rise of UAV swarm planning, classical search algorithms have been integrated with cooperative mechanisms to support global consistency and multi-agent coordination. In [82] proposed a 3D jump point search (3D-JPS) cooperative algorithm, using incremental conflict resolution, dual-objective cost functions, and consistency constraints to maintain conflict-free trajectories. In [83] introduced a hybrid genetic algorithm-D* (GA-D*) method, combining genetic algorithms' global search with D*'s dynamic replanning. Probabilistic constraints and incremental consistency mechanisms enable coordinated task allocation and path planning.

In summary, while classical search algorithms like A* and Dijkstra offer theoretical optimality and high interpretability under static conditions , their extensions to dynamic environments often suffer from exponentially increasing computational costs. As summarized in Table 2, their primary limitation lies in maintaining real-time trajectory continuity and scalability for large swarms, a gap that intelligent optimization algorithms attempt to fill, albeit with their own convergence challenges.

Table 2. Classic path search algorithms and their consistency characteristics

Algorithm	Core mechanism	Manifestation of consistency constraint
Dijkstra [78]	Systematically traverses all reachable nodes in the graph to guarantee the optimal path	Static optimality consistency
Reverse-Label Dijkstra [79]	Separates static path cost from dynamic temporal cost to improve adaptability in time-varying environments	Cost consistency
Improved Dijkstra [80]	Performs optimal path search in high-dimensional state spaces, such as error or augmented state spaces	State consistency
SANSA [81]	Conducts heuristic search followed by path smoothing optimization to enhance trajectory feasibility	Motion consistency
3D-JPS [82]	Resolves path conflicts among multiple agents in an incremental and prioritized manner	Multi-agent cooperative consistency
GA-D* [83]	Combines the global search capability of genetic algorithms with the dynamic replanning of heuristic methods	Dynamic cooperative consistency

3.2. Intelligent optimization-based methods

Intelligent optimization algorithms, grounded in swarm intelligence and evolutionary mechanisms, exhibit robust global search capabilities and adaptability, rendering them well-suited for multi-constraint path planning in UAV swarms.

Early genetic algorithm-based path planning focused on path geometry and feasibility consistency. In 2024 [84], proposed a hybrid genetic algorithm-rapidly exploring random tree (GA-RRT) method, using RRT to build the initial population and applying redundant node elimination and path backtracking to improve path smoothness, obstacle-avoidance continuity, and executability, turning consistency constraints into explicit operations. As UAV swarm applications demand partial information, high dynamics, and strong coupling, consistency extends to strategy and task coordination. In [85] used multi-agent proximal policy optimization (MAPPO) with a centralized value network to ensure behavioral and strategy consistency among agents, while dynamic cluster particle swarm optimization (DCPSO) applied dynamic clustering, potential field constraints, and receding-horizon replanning to align search direction, velocity, and path convergence. These approaches enhance system-level consistency, improve stability in multi-agent scenarios, and reduce issues of local optima and behavioral oscillations.

In dynamic, real-time tasks, intelligent optimization algorithms extend consistency to full-chain synchronization across information, decisions, and planning. Methods like online multi-iteration ant colony with receding-horizon [86] update environmental perception, resource states, and local costs at each step, keeping planned paths consistent with the changing environment.

In [87] proposed a modified ant colony optimization (MACO) within a two-step framework. ant colony optimization (ACO) plans feasible paths for ground vehicles, and a genetic algorithm optimizes UAV flight strategies. By enforcing consistency constraints on takeoff/landing order, endurance, and path coupling, it achieves global coordination for heterogeneous systems under road network limits. This reflects the evolution of intelligent optimization algorithms from single-step to full-process consistency.

In summary,intelligent optimization algorithms excel at global search and multi-objective optimization, making them suitable for complex multi-constraint path planning. As summarized in Table 3, they have evolved from ensuring geometric path continuity to achieving full-chain information–decision–planning consistency. However, their slow convergence, parameter sensitivity, and high computational overhead limit their use in highly dynamic or real-time scenarios. For large-scale swarms or rapidly changing environments, intelligent optimization alone is insufficient, often requiring hybrid or learning-based integration.

Table 3. Intelligent optimization algorithms and their consistency characteristics

Algorithm	Core mechanism	Manifestation of consistency constraints
GA-RRT [84]	Global optimization search using heuristic methods	Path geometric consistency
MAPPO [85]	Centralized learning during training and distributed decision-making during execution	Multi-agent strategy consistency
DCPSO [85]	Adaptive optimization of particle swarm in dynamic environments	Search process consistency
Online Multi-iteration ant colony strategy [86]	Online planning strategy based on a receding-horizon window	Information-decision consistency
MACO [87]	Cooperative use of multiple algorithms to solve complex planning problems	Full-chain consistency

To provide a clear and intuitive comparison across the three methodological streams, Table 4 summarizes their key characteristics in terms of real-time performance, adaptability to dynamics, multi-constraint handling, scalability, and computational cost.

Table 4. Comparative summary of path planning methods for UAV swarms

Algorithm class	Real-time performance	Adaptability to dynamics	Multi-constraint handling	Scalability	Computational cost
Classical search	High	Low to medium	High	Low	Medium to high
Intelligent optimization	Low	Medium	High	Medium	High
Deep reinforcement learning	High	High	Medium	High	Low

Beyond the qualitative comparison in Table 4, existing studies indicate that classical search algorithms generally achieve faster deterministic convergence in low-dimensional static environments, whereas intelligent optimization methods provide superior global exploration capability under coupled constraints. Deep reinforcement learning approaches demonstrate stronger adaptability and scalability in highly dynamic environments, although their training complexity and simulation-to-reality transfer remain significant challenges. Therefore, different planning methods exhibit distinct trade-offs in computational efficiency, adaptability, and cooperative consistency maintenance.

3.3. Deep reinforcement learning-based methods

Deep reinforcement learning (DRL) has become a key approach for UAV path planning in unknown and dynamic environments due to its adaptability and ability to handle high-dimensional continuous states. To address dynamic, multi-modal, and communication-constrained scenarios, researchers enhance DRL with improved reward functions, exploration strategies, and environment-coupled models, improving path continuity, decision stability, and environmental consistency.

Early DRL studies introduced consistency constraints using hybrid approaches. In [88] proposed firefly algorithm-enhanced deep Q-network (FADQN), which incorporated firefly-inspired guidance into the DRL framework. By simulating firefly attraction, it provided directional action preferences to the Q-network, producing smoother and more continuous paths during initial training, marking a shift from free exploration to geometric consistency. As research moved from geometric features to dynamic environmental consistency, study [89] proposed instructed reinforcement Q-learning algorithm (IR-QLA), embedding environmental signal strength into the reward. This instructed reinforcement allows UAV swarms to adjust paths in real time, maintaining dynamic compliance with temporal and environmental changes, evolving from static state consistency to real-time environmental consistency.

To address DRL limitations like slow training and local optima, study [90] introduced a cumulative reward model and region segmentation mechanism. The cumulative reward decomposes path progress and environmental sparsity into continuous rewards, improving temporal consistency and controllability, while region segmentation imposes soft global constraints to prevent local loops and enhance policy stability. In [91] proposed the constrained-interfered fluid dynamical system (C-IFDS) algorithm, integrating UAV kinematics and constraints into a DRL-based reactive disturbance planning framework, producing high-quality, low-conflict trajectories with maintained trackability and consistency. This stage reflects DRL's evolution from rapid convergence to global consistency, enhancing robustness in complex environments.

With the integration of unmanned systems and communication networks, consistency constraints have evolved toward real-world modeling. In [92] combined dueling double DQN (D3QN) with simultaneous navigation and radio mapping (SNARM) to build an online 3D radio map, using urban communication channels as physical consistency constraints. This allows UAV swarms to coordinate obstacle avoidance, signal quality, and flight time.

As illustrated in Figure 4, existing UAV swarm path planning approaches can be broadly classified into three categories: classical path search–based methods, intelligent optimization–based methods, and machine learning and deep reinforcement learning (DRL)–based methods. DRL methods offer high adaptability and scalability for dynamic environments, handling high-dimensional state spaces and decentralized execution in Table 5. However, they suffer from high training costs, poor sample efficiency, simulation-to-reality gaps, and lack of safety/consistency guarantees. To address these limitations, hybrid frameworks combining classical search, intelligent optimization, and DRL have emerged leveraging interpretability, global search, and adaptability. While a systematic hybrid solution remains an open challenge, it is a promising direction for balancing real-time performance, optimality, and multi-constraint consistency.

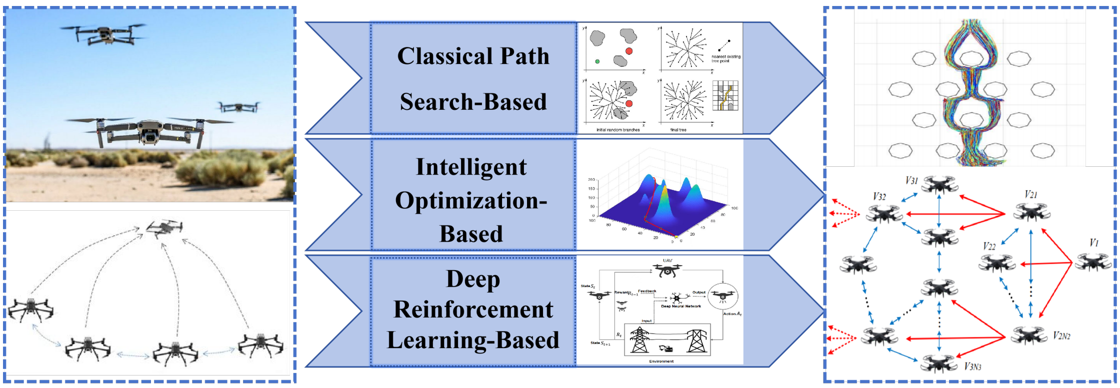

Figure 4. Consistency constraint method

Table 5. Deep reinforcement learning methods and their consistency characteristics

Algorithm	Core mechanism	Manifestation of consistency constraint
FADQN [88]	Guides the reinforcement learning process using heuristic information	Geometric consistency
IR-QLA [89]	Designs reward functions based on real-time environmental feedback	Environmental dynamic consistency
Cumulative reward model and Region segmentation [90]	Enhances learning efficiency through structured reward design	Training stability and global consistency
C-IFDS [91]	Real-time planning under kinematic model constraints	Kinematic model consistency
D3QN-SNARM [92]	Deeply integrates physical-world models into the learning framework	Physical-real-world consistency

4. FUTURE CHALLENGES AND SOLUTIONS

Future UAV swarm path planning will focus on autonomous coordination under multi-dimensional consistency. Robust, verifiable end-to-end mechanisms are required. Representative solutions for scalability, real-time consistency, and heterogeneous swarm cooperation are reviewed to highlight strengths, limitations, and guide future research.

4.1. Scalable cooperative optimization

As highlighted in section 3.1 and 3.2, classical and intelligent optimization methods struggle with scalability due to their inherent computational complexity or slow convergence. As UAV swarm scales grow, limited communication and asynchronous node updates make global consistency challenging. Centralized planning is often infeasible for large swarms due to high computation and latency. In such systems, state, trajectory, and behavioral consistency are easily disrupted by dynamic topologies and variable communication, threatening stable operation.

To improve scalability, distributed cooperative optimization strategies have been proposed. In [93] introduced an asynchronous alternating direction method of multipliers (ADMM)-based framework, enabling collaborative state updates under limited communication and reducing computation and communication load, validated for swarms of hundreds of UAVs, though it struggles with dynamic topologies and extreme communication failures. As shown in section 3.2, most intelligent optimization algorithms scale polynomially with swarm size and become impractical beyond 50 agents, whereas distributed frameworks like ADMM achieve sub-quadratic scaling by sacrificing global optimality. However, the asynchronous ADMM framework, which scales linearly to 500 agents in simulation, loses global optimality when the communication loss rate exceeds 30 percent. Meanwhile, study [94] proposed a multi-agent reinforcement learning (MARL) framework with global value consistency, aligning individual policies with global objectives and using a flexible consensus mechanism to support dynamic agent changes, enhancing policy stability in large-scale swarms.

Although such methods demonstrate notable advantages in learning efficiency and generalization, they remain highly sensitive to reward function design, and policy performance may degrade in highly dynamic task environments. Future research could further integrate the strengths of distributed optimization and learning approaches to construct cooperative decision-making frameworks with high scalability and strong disturbance resilience, enabling real-time path planning for ultra-large UAV swarms.

4.2. Real-time consistency in dynamic environments

In dynamic environments, sudden obstacles and local collision-avoidance reactions can disrupt swarm formation, causing trajectory oscillations or conflicts. Inconsistent perception updates across nodes can create spatiotemporal gaps, undermining temporal consistency in obstacle avoidance, tracking, and formation maintenance. To address this, integrating model predictive control (MPC) with reinforcement learning has become a key research focus.

In [95] incorporated multiple consistency constraints into the rolling optimization of a distributed MPC framework, maintaining trajectory smoothness, collision avoidance, and formation keeping during local replanning, which mitigates path oscillations from dynamic obstacles. However, it requires high computational real-time performance, limiting its use in high-speed scenarios. In [96] proposed a multi-source collaborative localization for micro-UAV swarms, integrating distributed graph optimization with delay-augmented Kalman filtering to achieve spatiotemporal perception consistency under limited computation. While it reduces environmental awareness discrepancies, global consistency and dynamic adaptability remain limited in restricted visual or low-communication scenarios.

Future research should prioritize intelligent collaborative decision-making algorithms that enable UAV swarms to rapidly adapt to dynamic environments with minimal communication reliance. These algorithms must be predictive, anticipating neighboring swarm behaviors to maintain coordination, while simplifying information exchange to critical situational data only. By integrating efficient local perception with collaborative decision-making, UAV swarms can achieve flexible, stable, and autonomous cooperative flight in dynamic scenarios.Currently, no reviewed method provides a formal quantitative bound on multi-constraint consistency under real-time uncertainties and dynamic environmental perturbations; this remains a critical open problem for future research.

4.3. Heterogeneous swarm coordination

Heterogeneous UAV swarms include platforms with different dynamics, sensors, and energy limits, making homogeneous consistency models inadequate. Differences in speed, maneuverability, and task capability can cause inconsistent trajectories, mismatched perception, and desynchronized tasks, reducing overall system stability in multi-level coordination.

For the collaborative control of heterogeneous UAV swarms, researchers have proposed hierarchical coordination architectures and cross-platform calibration strategies. In [97], a three-layer coordination framework for heterogeneous unmanned systems was designed. At the task layer, a distributed auction mechanism is used for role assignment, while at the control layer, an adaptive consensus protocol ensures that the dynamic constraints of different platforms are satisfied, effectively enhancing system stability in collaborative search and rescue missions.

In terms of heterogeneous perception fusion, in [98] achieves consistent transformation and integration of perception data and state information among heterogeneous UAV swarms by performing online calibration and mapping of different sensor parameters and dynamic characteristics.

As summarized in Table 6, future challenges can be systematically addressed by deeply integrating distributed optimization, reinforcement learning, model predictive control, heterogeneous fusion, and explainability technologies, with a focus on scalability, dynamic environment adaptability, and heterogeneous platform cooperation. Future UAV swarm path planning will leverage large language models for high-level task comprehension and instruction decomposition, enabling intelligent transformation from natural language commands to precise waypoints. Additionally, the integration of neural radiance fields (NeRF) for environment perception and planning will facilitate real-time construction of high-fidelity 3D scenes, supporting precise obstacle avoidance and cooperative maneuvers in complex urban canyons for dense swarms.

Table 6. Comparison of challenges and solutions

Challenge category	Potential solutions	Key techniques
Scalable cooperative optimization	Develop scalable distributed solution frameworks; incorporate multi-agent reinforcement learning models; design robust consistency maintenance mechanisms	Distributed optimization, global value consistency, dynamic agent management
Dynamic environment real-time consistency	Embed MPC; construct consistency-aware deep reinforcement learning models; leverage perception consistency techniques	Multi-constraint DRL models, distributed filtering and graph optimization
Heterogeneous swarm coordination	Establish unified reference models; adopt hierarchical consistency architectures; develop heterogeneous information fusion methods	Parameter mapping and unified modeling, hierarchical constraints, consistency fusion algorithms

4.4. Simulation-to-reality

Despite promising simulation results, deep reinforcement learning and other advanced methods are rarely deployed on real UAV swarm platforms. Most studies reviewed in sections 3.1–3.3 are validated only in simulation environments such as Gazebo, AirSim, and MATLAB/Simulink. The Simulation-to-Reality gap manifests in four dimensions: dynamic discrepancies including aerodynamics, sensor noise, actuator delays, and wind; perception inconsistencies such as lighting, occlusions, and reflections; communication constraints like packet loss, bandwidth, and latency; and platform heterogeneity, i.e., distinct dynamics and sensor characteristics across UAV types.

Most DRL-based works are evaluated exclusively in simulation. Only a few incorporate kinematic constraints but still lack hardware validation. To bridge this gap, promising directions include domain randomization, hybrid DRL-classical control architectures for instance with MPC, hardware-in-the-loop simulation, and standardized real-world benchmarks. Future research must prioritize real-world validation to ensure practical utility.

4.5. Case study: Post-disaster UAV swarm search and rescue

To further illustrate the practical significance of consistency-constrained path planning, a representative post-disaster search-and-rescue scenario is analyzed. In such missions, multiple UAVs are required to collaboratively perform area coverage, dynamic target tracking, and obstacle avoidance in partially damaged urban environments.

Spatial consistency constraints ensure collision-free trajectories among buildings, debris, and dynamic obstacles. Temporal consistency constraints maintain synchronized arrival and cooperative monitoring of critical regions, while cooperative task consistency enables distributed task allocation and information sharing among heterogeneous UAVs.

In practical implementations, classical search algorithms such as A* and D* are often adopted for rapid local replanning in structured regions, whereas intelligent optimization algorithms are utilized for global coverage optimization. Deep reinforcement learning methods further improve adaptability in unknown environments by enabling online policy updates under dynamic disturbances.

This case study demonstrates that consistency-aware hybrid planning frameworks are more suitable for complex real-world UAV swarm missions than single-method approaches, particularly in dynamic and communication-constrained environments.

5. CONCLUSION

This paper provides a systematic review of UAV swarm path planning from an original perspective centered on spatial, temporal, and cooperative task consistency constraints. The mathematical modeling framework under multiple constraints is established, and the quantitative requirements for path continuity, spatiotemporal synchronization, and task coordination are clearly specified. The existing methods are classified into three categories: classical path search, intelligent optimization algorithms, and deep reinforcement learning. Their respective advantages and limitations in handling multi-constraint coupling are analyzed. Classical search methods offer theoretical optimality and high interpretability under static environments, but they cannot adequately meet the real-time demands of large-scale swarms in dynamic scenarios. Intelligent optimization algorithms provide strong global search capabilities suitable for complex multi-constraint optimization problems, yet they are hindered by slow convergence and sensitivity to parameter settings. Deep reinforcement learning methods exhibit high adaptability and scalability in dynamic unknown environments, while training costs and the simulation-to-reality gap remain significant challenges.

The analysis also identifies three major future challenges for UAV swarm path planning: scalable cooperative optimization, real-time consistency maintenance in dynamic environments, and coordination of heterogeneous swarms. Potential solutions to these challenges include distributed optimization frameworks, multi-agent reinforcement learning, model predictive control, and heterogeneous fusion strategies. Moreover, the transition from simulation validation to real-world deployment is essential for the practical utility of advanced planning methods. Emerging technologies such as large language models for high-level task comprehension and neural radiance fields for real-time 3D scene reconstruction offer promising directions to enhance the swarm's capability for complex mission understanding and environment perception. The consistency-constraint taxonomy presented in this review is expected to provide a theoretical reference and practical guidance for the development of highly autonomous and strongly cooperative UAV swarm path planning technologies.

FUNDING INFORMATION

This work was supported by the Beijing Natural Science Foundation (Grant No. 4242036), the Youth Fund of the National Natural Science Foundation of China (Grant No. 62406032), and the 2025 Open Fund of the State Key Laboratory of Space Intelligent Control Technology (Grant No. HTKJ2025KL502016).

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Yana Lu	✓	✓	✓	✓	✓	✓		✓	✓	✓				
Lianpeng Li		✓				✓		✓	✓	✓	✓	✓	✓	✓
Hui Zhao	✓		✓	✓		✓			✓		✓		✓	
Xu Zhao					✓		✓			✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal Analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject Administration
Fu : **Fu**nding Acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

Not applicable.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, L. L., upon reasonable request.

REFERENCES

[1] R. Wang *et al.*, "Global path planning of climbing robot for weld quality inspection in large-scale storage tanks," *International Journal of Robotics and Automation*, vol. 40, no. 3, pp. 242–253, 2025, doi: 10.2316/J.2024.206-1164.

[2] H. Liu, Y. P. Tsang, C. K. M. Lee, C. H. Wu, and K. L. Yung, "Optimizing UAV flocks for emergency response in post-disaster industrial zones," *IEEE Transactions on Industrial Informatics*, vol. 22, no. 1, pp. 37–48, 2026, doi: 10.1109/TII.2025.3608299.

[3] C. Tang, L. Pan, J. Chen, Y. Liu, and J. Lai, "A game theory-reinforcement learning approach to cooperation for UAVs," *IEEE Transactions on Vehicular Technology*, vol. 74, no. 6, pp. 9864–9869, 2025, doi: 10.1109/TVT.2025.3539382.

[4] J. Yang, X. You, G. Wu, M. M. Hassan, A. Almogren, and J. Guna, "Application of reinforcement learning in UAV cluster task scheduling," *Future generation computer systems*, vol. 95, pp. 140–148, 2019, doi: 10.1016/j.future.2018.11.014.

[5] S. Javed *et al.*, "State-of-the-art and future research challenges in UAV swarms," *IEEE Internet of Things Journal*, vol. 11, no. 11, pp. 19 023–19 045, 2024, doi:10.1109/JIOT.2024.3364230.

[6] Z. Mao, M. Hou, H. Li, Y. Yang, and W. Song, "Multi-UAV cooperative motion planning under global spatio-temporal path inspiration in constraint-rich dynamic environments," *IEEE Transactions on Intelligent Vehicles*, 2024, doi:10.1109/TIV.2024.3422172.

[7] S. Feng, L. Zeng, J. Liu, Y. Yang, and W. Song, "Multi-UAVs collaborative path planning in the cramped environment," *IEEE/CAA Journal of Automatica Sinica*, vol. 11, no. 2, pp. 529–538, 2024, doi: 10.1109/JAS.2023.123945.

[8] T. Wang, W. Du, C. Jiang, Y. Li, and H. Zhang, "Safety constrained trajectory optimization for completion time minimization for UAV communications," *IEEE Internet of Things Journal*, vol. 11, no. 21, 2024, doi: 10.1109/JIOT.2024.3355906.

[9] J. Zheng, S. Zhao, X. Wang, J. Tang, and Z. Zuo, "Prescribed-time maneuvering target closing for multiple fixed-wing UAVs," *IEEE Transactions on Vehicular Technology*, vol. 73, no. 9, pp. 12 614–12 624, 2024, doi: 10.1109/TVT.2024.3394003.

[10] C. Zammit and E.-J. van Kampen, "Real-time 3D UAV path planning in dynamic environments with uncertainty," *Unmanned Systems*, vol. 11, no. 03, pp. 203–219, 2023, doi: 10.1142/S2301385023500073.

[11] M. Yang, B. Zhang, Z. Shi, and J. Li, "A hybrid task allocation approach for multi-UAV systems with complex constraints: A market-based bidding strategy and improved NSGA-III optimization," *The Journal of Super Computing*, vol. 81, no. 4, pp. 1–33, 2025, doi: 10.1007/s1122702507027x.

[12] P. Cao *et al.*, "Computational intelligence algorithms for UAV swarm networking and collaboration: A comprehensive survey and future directions," *IEEE Communications Surveys and Tutorials*, vol. 26, no. 4, pp. 2684–2728, 2024, doi: 10.1109/COMST.2024.3395358.

[13] P. Zhu *et al.*, "Multiple UAV swarms collaborative firefighting strategy considering forest fire spread and resource constraints," *Drones*, vol. 9, no. 1, pp. 1–17, 2024, doi: 10.3390/drones9010017.

[14] J. Tang, H. Duan, and S. Lao, "Swarm intelligence algorithms for multiple unmanned aerial vehicles collaboration: A comprehensive review," *Artificial Intelligence Review*, vol. 56, no. 5, pp. 4295–4327, 2023, doi: 10.1007/s10462022102817.

[15] C. Tao, R. Zhang, Z. Song, B. Wang, and Y. Jin, "Multi-UAV formation control in complex conditions based on improved consistency algorithm," *Drones*, vol. 7, no. 3, p. 185, 2023, doi: 10.3390/drones7030185.

[16] P. Kumar, K. Pal, and M. C. Govil, "Comprehensive review of path planning techniques for unmanned aerial vehicles (UAVs)," *ACM Computing Surveys*, vol. 58, no. 3, pp. 1–44, 2025, doi: 10.1145/3737280.

[17] H. Zhao, M. Gu, S. Qiu, A. Zhao, and W. Deng, "Dynamic path planning for space-time optimization cooperative tasks of multiple unmanned aerial vehicles in uncertain environment," *IEEE Transactions on Consumer Electronics*, vol. 71, no. 3, pp. 7673–7682, 2025, doi: 10.1109/TCE.2025.3593383.

[18] F. Yan, J. Chu, J. Hu, and X. Zhu, "Cooperative task allocation with simultaneous arrival and resource constraint for multi-UAV using a genetic algorithm," *Expert Systems with Applications*, vol. 245, p. 123023, 2024, doi: 10.1016/j.eswa.2023.123023.

[19] K. Meng, D. Li, X. He, and M. Liu, "Space pruning based time minimization in delay constrained multi-task UAV-based sensing," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 3, pp. 2836–2849, 2021, doi: 10.1109/TVT.2021.3061243.

[20] M. Z. Butt, N. Nasir, and R. B. A. Rashid, "A review of perception sensors, techniques, and hardware architectures for autonomous low-altitude UAVs in non-cooperative local obstacle avoidance," *Robotics and Autonomous Systems*, vol. 173, p. 104629, 2024, doi: 10.1016/j.robot.2024.104629.

[21] Y. Niu, X. Yan, Y. Wang, and Y. Niu, "3D real-time dynamic path planning for UAV based on improved interfered fluid dynamical system and artificial neural network," *Advanced Engineering Informatics*, vol. 59, p. 102306, 2024, doi: 10.1016/j.aei.2023.102306.

[22] K. Liu and J. Zheng, "UAV trajectory optimization for time-constrained data collection in UAV-enabled environmental monitoring systems," *IEEE Internet of Things Journal*, vol. 9, no. 23, pp. 24 300–24 314, 2022, doi: 10.1109/JIOT.2022.3189214.

[23] Y. Jiang, Q. Wu, W. Chen, and K. Meng, "UAV-enabled integrated sensing and communication: Tracking design and optimization," *IEEE Communications Letters*, vol. 28, no. 5, pp. 1024–1028, 2024, doi: 10.1109/LCOMM.2024.3379504.

[24] D. Wang, M. Zhang, and Z. Huang, "A path-planning method recommended for multi-UAV police patrols based on the wolf pack optimization algorithm using CDRS and DRSS," *Symmetry*, vol. 17, no. 2, pp. 1–208, 2025, doi: 10.3390/sym17020208.

[25] X. Lei, X. Hu, G. Wang, and H. Luo, "A multi-UAV deployment method for border patrolling based on Stackelberg game," *Journal of Systems Engineering and Electronics*, vol. 34, no. 1, pp. 99–116, 2023, doi: 10.23919/JSEE.2023.000022.

[26] S. Upadhye, S. Neelakandan, K. Thangaraj, D. V. Babu, N. Arulkumar, and K. Qureshi, "Modeling of real time traffic flow monitoring system using deep learning and unmanned aerial vehicles," *Journal of mobile multimedia*, vol. 19, no. 2, pp. 477–496, 2023, doi: 10.13052/jmm1550-4646.1926.

[27] W. Ma, Z. Chu, H. Chen, and M. Li, "Spatio-temporal envolutional graph neural network for traffic flow prediction in UAV-based urban traffic monitoring system," *Scientific Reports*, vol. 14, no. 1, p. 26800, 2024, doi: 10.1038/s41598-024-78335-0.

[28] Q. Diao, J. Zhang, M. Liu, and J. Yang, "A disaster relief UAV path planning based on APF-IRRT* fusion algorithm," *Drones*, vol. 7, no. 5, p. 323, 2023, doi: 10.3390/drones7050323.

[29] Y. Wang, Z. Su, Q. Xu, R. Li, T. H. Luan, and P. Wang, "A secure and intelligent data sharing scheme for UAV-assisted disaster rescue," *IEEE/ACM Transactions on Networking*, vol. 31, no. 6, pp. 2422–2438, 2023, doi: 10.1109/TNET.2022.3226458.

[30] Q. Jiang *et al.*, "Autonomous task planning of intelligent unmanned aerial vehicle swarm based on deep deterministic policy gradient," *Drones*, vol. 9, no. 4, p. 272, 2025, doi: 10.3390/drones9040272.

[31] D. Zhang, Z. Xuan, Y. Zhang, J. Yao, X. Li, and X. Li, "Path planning of unmanned aerial vehicle in complex environments based on state-detection twin delayed deep deterministic policy gradient," *Machines*, vol. 11, no. 1, p. 108, 2023, doi: 10.3390/machines11010108.

[32] R. Azzam, I. Boiko, and Y. Zweiri, "Swarm cooperative navigation using centralized training and decentralized execution," *Drones*, vol. 7, no. 3, p. 193, 2023, doi: 10.3390/drones7030193.

[33] J. M. Kelner, W. Burzynski, and W. Stecz, "Modeling UAV swarm flight trajectories using rapidly-exploring random tree algorithm," *Journal of King Saud University-Computer and Information Sciences*, vol. 36, no. 1, p. 101909, 2024, doi: 10.1016/j.jksuci.2023.101909.

[34] B. D. Nwilag, A. E. Eyoh, and C. E. Ndehedehe, "Digital topographic mapping and modelling using low altitude unmanned aerial vehicle," *Modeling Earth Systems and Environment*, vol. 9, no. 2, pp. 1463–1476, 2023, doi: 10.1007/s40808-022-01677-z.

[35] Y. Ding, Z. Yang, Q.-V. Pham, Y. Hu, Z. Zhang, and M. Shikh-Bahaei, "Distributed machine learning for UAV swarms: Computing, sensing, and semantics," *IEEE Internet of Things Journal*, vol. 11, no. 5, pp. 7447–7473, 2023, doi: 10.1109/JIOT.2023.3341307.

[36] J. Zheng, M. Ding, L. Sun, and H. Liu, "Distributed stochastic algorithm based on enhanced genetic algorithm for path planning of multi-UAV cooperative area search," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 8, pp. 8290–8303, 2023, doi: 10.1109/TITS.2023.3258482.

[37] H. Zhang, H. Ma, B. W. Mersha, X. Zhang, and Y. Jin, "Distributed cooperative search method for multi-UAV with unstable communications," *Applied Soft Computing*, vol. 148, p. 110592, 2023, doi: 10.1016/j.asoc.2023.110592.

[38] Z. Liu, Y. Li, and Y. Wu, "Multiple UAV formations delivery task planning based on a distributed adaptive algorithm," *Journal of the Franklin Institute*, vol. 360, no. 4, pp. 3047–3076, 2023, doi: 10.1016/j.jfranklin.2023.01.008.

[39] L. Lyu, H. Jiang, and F. Yang, "Improved dung beetle optimizer algorithm with multi-strategy for global optimization and UAV 3D path planning," *IEEE Access*, vol. 12, pp. 69 240–69 257, 2024, doi: 10.1109/ACCESS.2024.3401129.

[40] Y. Li, S. Li, Y. Zhang, W. Zhang, and H. Lu, "Dynamic route planning for a USV-UAV multi-robot system in the rendezvous task with obstacles," *Journal of Intelligent & Robotic Systems*, vol. 107, no. 4, p. 52, 2023, doi: 10.1007/s10846-023-01830-5.

[41] H. V. Dudukcu, M. Taskiran, and N. Kahraman, "UAV sensor data applications with deep neural networks: A comprehensive survey," *Engineering Applications of Artificial Intelligence*, vol. 123, p. 106476, 2023, doi: 10.1016/j.engappai.2023.106476.

[42] G. ZHANG, Z. GU, and M. CUI, "Joint trajectory and resource allocation optimization for air-ground collaborative integrated sensing and communication systems," *Journal of Electronics & Information Technology*, vol. 46, no. 6, pp. 2382–2390, 2024, doi: 10.11999/JEIT230716.

[43] K. Meng *et al.*, "UAV-enabled integrated sensing and communication: Opportunities and challenges," *IEEE Wireless Communica-*

tions, vol. 31, no. 2, pp. 97–104, 2023, doi: 10.1109/MWC.131.2200442.
[44] W. Sun and M. Hao, "A survey of cooperative path planning for multiple UAVs," in *International Conference on Autonomous Unmanned Systems*, 2021, pp. 189–196, doi: 10.1007/978-981-16-9492-9 20.
[45] Y. Zeng, R. Zhang, and T. J. Lim, "Wireless communications with unmanned aerial vehicles: Opportunities and challenges," *IEEE Communications magazine*, vol. 54, no. 5, pp. 36–42, 2016, doi: 10.1109/MCOM.2016.7470933.
[46] D. V. Lyridis, "An improved ant colony optimization algorithm for unmanned surface vehicle local path planning with multi-modality constraints," *Ocean Engineering*, vol. 241, p. 109890, 2021, doi: 10.1016/j.oceaneng.2021.109890.
[47] X. Wang, Y. Guo, N. Lu, and P. He, "UAV cluster behavior modeling based on spatial-temporal hybrid Petri net," *Applied Sciences*, vol. 13, no. 2, pp. 1–762, 2023, doi: 10.3390/app13020762.
[48] Z. Yu *et al.*, "Optimization of multi-target continuous dynamic trajectory for unmanned aerial vehicles," *Aerospace Science and Technology*, vol. 150, p. 108958, 2024, doi: 10.1016/j.ast.2024.108958.
[49] J. Wu, K. Bai, and H. Wu, "Advancing convergence speed of distributed consensus time synchronization algorithms in unmanned aerial vehicle ad hoc networks," *Drones*, vol. 8, no. 7, p. 285, 2024, doi: 10.3390/drones8070285.
[50] W. Yue, X. Zhang, and Z. Liu, "Distributed cooperative task allocation for heterogeneous UAV swarms under complex constraints," *Computer Communications*, vol. 231, p. 108043, 2025, doi: 10.1016/j.comcom.2024.108043.
[51] Y. Liu, Z. Liu, G. Wang, C. Yan, X. Wang, and Z. Huang, "Flexible multi-UAV formation control via integrating deep reinforcement learning and affine transformations," *Aerospace Science and Technology*, vol. 157, p. 109812, 2025, doi: 10.1016/j.ast.2024.109812.
[52] S. Agrawal, B. K. Patle, and S. Sanap, "A systematic review on metaheuristic approaches for autonomous path planning of unmanned aerial vehicles," *Drone Systems and Applications*, vol. 12, pp. 1–28, 2024, doi: 10.1139/dsa-2023-0093.
[53] B. Zhao, M. Huo, Z. Li, Z. Yu, and N. Qi, "Clustering-based hyper-heuristic algorithm for multi-region coverage path planning of heterogeneous UAVs," *Neurocomputing*, vol. 610, p. 128528, 2024, doi: 10.1016/j.neucom.2024.128528.
[54] J. Li, Y. Xiong, and J. She, "UAV path planning for target coverage task in dynamic environment," *IEEE Internet of Things Journal*, vol. 10, no. 20, pp. 17 734–17 745, 2023, doi: 10.1109/JIOT.2023.3277850.
[55] A. Zheng, B. Li, M. Zheng, and H. Zhong, "Multi-objective UAV trajectory planning in uncertain environment," *Symmetry*, vol. 13, no. 11, pp. 1–2160, 2021, doi: 10.3390/sym13112160.
[56] Z. Zhuo, S. Dong, H. Zheng, and Y. Zhang, "Method of minimizing energy consumption for RIS assisted UAV mobile edge computing system," *IEEE access*, vol. 12, pp. 39 678–39 688, 2024, doi: 10.1109/ACCESS.2024.3375345.
[57] X. Kong, C. Ni, G. Duan, G. Shen, Y. Yang, and S. K. Das, "Energy consumption optimization of UAV-assisted traffic monitoring scheme with tiny reinforcement learning," *IEEE Internet of Things Journal*, vol. 11, no. 12, 2024, doi: 10.1109/JIOT.2024.3365293.
[58] J. Li, G. Sun, L. Duan, and Q. Wu, "Multi-objective optimization for UAV swarm-assisted IoT with virtual antenna arrays," *IEEE Transactions on Mobile Computing*, vol. 23, no. 5, pp. 4890–4907, 2023, doi: 10.1109/TMC.2023.3298888.
[59] M. K. Singh, A. Choudhary, S. Gulia, and A. Verma, "Multi-objective NSGA-II optimization framework for UAV path planning in an UAV-assisted WSN: MK Singh et al." *The Journal of Supercomputing*, vol. 79, no. 1, pp. 832–866, 2023, doi: 10.1007/s11227-022-04701-2.
[60] Y. Sun *et al.*, "A multi-unmanned aerial vehicle fast path-planning method based on non-rigid hierarchical discrete grid voxel environment modeling," *International Journal of Applied Earth Observation and Geoinformation*, vol. 116, p. 103139, 2023, doi: 10.1016/j.jag.2022.103139.
[61] Q. Dong *et al.*, "Fast and communication-efficient multi-UAV exploration via Voronoi partition on dynamic topological graph," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2024, doi: 10.1109/IROS58592.2024.10801613.
[62] D. T. ¨Ozt¨urk and M. K¨oksalan, "Biobjective route planning of an unmanned air vehicle in continuous space," *Transportation Research Part B: Methodological*, vol. 168, pp. 151–169, 2023, doi: 10.1016/j.trb.2023.01.001.
[63] T. Sun, W. Sun, C. Sun, and R. He, "Path planning of UAV formations based on semantic maps," *Remote Sensing*, vol. 16, no. 16, pp. 3096–4009, 2024, doi: 10.3390/rs16163096.
[64] J. Zhang and J. Bai, "Dijkstra algorithm based cooperative caching strategy for UAV-assisted edge computing system," *Wireless Networks*, vol. 30, no. 3, pp. 1201–1219, 2024, doi: 10.1007/s11276-023-03551-x.
[65] Y.-D. Yoo and J.-H. Moon, "Study on a-star algorithm-based 3D path optimization method considering density of obstacles," *Aerospace*, vol. 12, no. 2, pp. 1–85, 2025, doi: 10.3390/aerospace12020085.
[66] P. Suanpang and P. Jamjuntr, "Optimizing autonomous UAV navigation with d* algorithm for sustainable development," *Sustainability*, vol. 16, no. 17, pp. 7867–7880, 2024, doi: 10.3390/su16177867.
[67] S. R. Bassolillo, G. Raspaolo, L. Blasi, E. D'Amato, and I. Notaro, "Path planning for fixed-wing unmanned aerial vehicles: An integrated approach with theta* and clothoids," *Drones*, vol. 8, no. 2, p. 62, 2024, doi: 10.3390/drones8020062.
[68] T. Huang, K. Fan, and W. Sun, "Density gradient-RRT: An improved rapidly exploring random tree algorithm for UAV path planning," *Expert Systems with Applications*, vol. 252, p. 124121, 2024, doi: 10.1016/j.eswa.2024.124121.
[69] S. J. Fusic and R. Sitharthan, "Improved RRT* algorithm-based path planning for unmanned aerial vehicle in a 3D metropolitan environment," *Unmanned Systems*, vol. 12, no. 05, pp. 859–875, 2024, doi: 10.1142/S2301385024500225.
[70] R. Jia, Y. Wei, D. Zhu, C. Zuo, W. Yuan, and F. Wang, "Overview of path planning algorithms for unmanned aerial vehicles," in *International Conference on Pattern Recognition and Image Analysis (PRIA 2024)*, vol. 13646, 2025, pp. 199–208, doi: 10.1117/12.3056218.
[71] D. Debnath, F. Vanegas, S. Boiteau, and F. Gonzalez, "An integrated geometric obstacle avoidance and genetic algorithm tsp model for UAV path planning," *Drones*, vol. 8, no. 7, p. 322, 2024, doi: 10.3390/drones8070302.
[72] C. Huang, H. Ma, X. Zhou, and W. Deng, "Cooperative path planning of multiple unmanned aerial vehicles using cylinder vector particle swarm optimization with gene targeting," *IEEE Sensors Journal*, 2025, doi: 10.1109/JSEN.2024.3516124.
[73] Y. Tian, J. Zhang, Q. Wang, S. Liu, Z. Guo, and H. Zhang, "Application of hybrid algorithm based on ant colony optimization and sparrow search in UAV path planning," *International Journal of Computational Intelligence Systems*, vol. 17, no. 1, p. 286, 2024, doi: 10.1007/s44196-024-00652-z.
[74] H. Zhao, G. Lu, Y. Liu, Z. Chang, L. Wang, and T. H¨am¨al¨ainen, "Safe DQN-based AoI-minimal task offloading for UAV-aided edge computing system," *IEEE Internet of Things Journal*, vol. 11, no. 19, 2024, doi: 10.1109/JIOT.2024.3422670.
[75] L. Li, W. Li, J. Wang, X. Chen, Q. Peng, and W. Huang, "UAV trajectory optimization for spectrum cartography: A PPO approach,"

IEEE Communications Letters, vol. 27, no. 6, pp. 1575–1579, 2023, doi: 10.1109/LCOMM.2023.3265214.

[76] X. Zhao, T. Zhao, F. Wang, Y. Wu, and M. Li, "SAC-based UAV mobile edge computing for energy minimization and secure data transmission," *Ad Hoc Networks*, vol. 157, p. 103435, 2024, doi: 10.1016/j.adhoc.2024.103435.

[77] N. Zhang, F. Nex, G. Vosselman, and N. Kerle, "End-to-end nano-drone obstacle avoidance for indoor exploration," *Drones*, vol. 8, no. 2, p. 33, 2024, doi: 10.3390/drones8020033.

[78] E. W. Dijkstra, "A note on two problems in connexion with graphs," in *Edsger Wybe Dijkstra: his life, work, and legacy*, 2022, pp. 287–290, doi: 10.1145/3544585.3544600.

[79] D.-D. Zhu and J.-Q. Sun, "A new algorithm based on Dijkstra for vehicle path planning considering intersection attribute," *IEEE access*, vol. 9, pp. 19 761–19 775, 2021, doi: 10.1109/ACCESS.2021.3053169.

[80] X. Bai, L. Wang, Y. Hu, P. Li, and Y. Zu, "Optimal path planning method for IMU system-level calibration based on improved Dijkstra's algorithm," *IEEE Access*, vol. 11, pp. 11 364–11 376, 2023, doi: 10.1109/ACCESS.2023.3240518.

[81] Q. Zhou and G. Liu, "UAV path planning based on the combination of a-star algorithm and RRT-star algorithm," in *2022 IEEE International Conference on Unmanned Systems (ICUS). IEEE*, 2022, pp. 146–151, doi: 10.1109/ICUS55513.2022.9986703.

[82] Y. Lu, D. Yan, Z. Wan, and C. Feng, "Conflict-free 3D path planning for multi-UAV based on jump point search and incremental update," *Drones*, vol. 9, no. 10, p. 700, 2025, doi: 10.3390/drones9100688.

[83] S. Hao-peng, T. Xiao-gang, G. Yuan, and W. Sun'an, "A comparative simulation study of multi- aircraft cooperative task planning based on artificial intelligence optimization algorithm," in *2021 2nd International Conference on Artificial Intelligence and Education (ICAIE). IEEE*, 2021, pp. 15–24, doi: 10.1109/ICAIE53562.2021.00011.

[84] B. Chen and J. Huang, "Research on shortest path planning for unmanned aerial vehicles based on genetic algorithm," in *2024 IEEE 6th International Conference on Civil Aviation Safety and Information Technology (ICCASIT). IEEE*, 2024, pp. 1239–1244, doi: 10.1109/ICCASIT62299.2024.10827886.

[85] W. Hu and X. Ma, "Optimization algorithm of UAVs task assignment and path planning based on dynamic cluster particle swarm optimization," *IEEE Transactions on Intelligent Transportation Systems*, 2025, doi: 10.1109/TITS.2025.3578464.

[86] J. Ma, X. Ma, and S. Zang, "Multi-destination path planning based on ant colony decision and rolling control," *IEEE Transactions on Aerospace and Electronic Systems*, 2024, doi: 10.1109/TAES.2024.3434777.

[87] C. Meng-Qing, C. Yang, C. Zhi-Huan, and Z. Xin-Gang, "Path planning for heterogeneous robot system with road network constraints," *Acta Automatica Sinica*, vol. 2023, no. 4, pp. 718–730, 2023, doi: 10.16383/j.aas.c200806.

[88] W. Sun, Q. Wang, J. Huan, H. Yu, and S. Gao, "FADQN: A heuristic reinforcement learning mechanism for UAV path planning in unknown environment," *IEEE Access*, 2025, doi: 10.1109/ACCESS.2025.3591457.

[89] M. Muzammul, M. Assam, Y. Y. Ghadi, N. Innab, M. Alajmi, and T. J. Alahmadi, "IR-QLA: Machine learning-based q-learning algorithm optimization for UAVs faster trajectory planning by instructed-reinforcement learning," *IEEE Access*, vol. 12, pp. 91 300–91 315, 2024, doi: 10.1109/ACCESS.2024.3420169.

[90] Z. Wang, S. X. Ng, and E.-H. Mohammed, "Deep reinforcement learning assisted UAV path planning relying on cumulative reward mode and region segmentation," *IEEE Open Journal of Vehicular Technology*, vol. 5, pp. 737–751, 2024, doi: 10.1109/OJVT.2024.3402129.

[91] W. Jian-Fa, W. Hong-Lun, W. Yan-Xiang, and L. Yi-Heng, "UAV reactive interfered fluid path planning," *Acta Automatica Sinica*, vol. 49, no. 2, pp. 272–287, 2023, doi: 10.16383/j.aas.c210231.

[92] X. Liu *et al.*, "Deep reinforcement learning-based 3D trajectory planning for cellular connected UAV," *Drones*, vol. 8, no. 5, p. 220, 2024, doi: 10.3390/drones8050199.

[93] A. I. Rikos, W. Jiang, T. Charalambous, and K. H. Johansson, "Asynchronous distributed optimization via ADMM with efficient communication," in *2023 62nd IEEE Conference on Decision and Control (CDC). IEEE*, 2023, pp. 7002–7008, doi: 10.1109/CDC49753.2023.10383681.

[94] T. Li *et al.*, "Applications of multi-agent reinforcement learning in future internet: A comprehensive survey," *IEEE Communications Surveys & Tutorials*, vol. 24, no. 2, pp. 1240–1279, 2022, doi: 10.1109/COMST.2022.3160697.

[95] Q. Chen, Y. Jin, T. Wang, Y. Wang, T. Yan, and Y. Long, "UAV formation control under communication constraints based on distributed model predictive control," *IEEE Access*, vol. 10, pp. 126 494–126 507, 2022, doi: 10.1109/ACCESS.2022.3225434.

[96] C. Xiong *et al.*, "Onboard cooperative relative positioning system for Micro-UAV swarm based on UWB/Vision/INS fusion through distributed graph optimization," *Measurement*, vol. 234, p. 114897, 2024, doi: 10.1016/j.measurement.2024.114897.

[97] P. Han, W. Zhang, T. Xie, S. Yang, and H. Chen, "A cooperative heterogeneous system design of unmanned aerial and surface vehicles," *IEEE Transactions on Instrumentation and Measurement*, 2024, doi: 10.1109/TIM.2024.3488155.

[98] Z. Bai *et al.*, "A survey and framework of cooperative perception: From heterogeneous singleton to hierarchical cooperation," *IEEE Transactions on Intelligent Transportation Systems*, 2024, doi: 10.1109/TITS.2024.3436012.

BIOGRAPHIES OF AUTHORS

Yana Lu received the B.S. degree in Automation from the College of Modern Science and Technology, Hebei Agricultural University, China, in 2023. She is currently pursuing the M.S. degree in Control Engineering at the School of Automation, Beijing Information Science and Technology University, Beijing, China. Her current research interests include cooperative control, path planning, and obstacle avoidance for unmanned aerial vehicle (UAV) swarm systems. She can be contacted at 15712519262@163.com.

Lianpeng Li received the Ph.D. degree in Computer and Communication Engineering from the University of Science and Technology Beijing, Beijing, China, in 2021. He is currently an Associate Professor with the Beijing Information Science and Technology University, Beijing, China. His current research interests include cyber–physical system (CPS) security, robot control, LiDAR sensing, and inertial navigation. He can be contacted at llp@bistu.edu.cn.

Hui Zhao received the B.S. degree in Intelligent Science and Technology and the M.S. degree in Navigation, Guidance, and Control from Beijing Information Science and Technology University, Beijing, China, in 2014 and 2017, respectively. He is currently pursuing the Ph.D. degree with the School of Automation, Beijing Institute of Technology, Beijing, China. His research interests include attitude estimation of high-spinning projectiles, integrated navigation, and personal inertial navigation. He can be contacted at zhhui@bistu.edu.cn.

Xu Zhao received the Ph.D. degree in Control Science and Engineering from the School of Automation, Beijing Institute of Technology, Beijing, China, in 2018. He is currently an Associate Researcher and Ph.D. Supervisor at Beijing Information Science and Technology University. From 2022 to 2023, he was a visiting scholar at the School of Aerospace Engineering, Tsinghua University. His research interests focus on high-dynamic navigation, guidance and control, inertial navigation, LiDAR-based perception, and intelligent robotic systems. He can be contacted at zhaoxu@bistu.edu.cn.