REVIEW ARTICLE

A Review of Fixed-Wing Unmanned Aerial Vehicle Formation Research

Wei Li[1], Jinbiao Zhu[2,*], Tiejun Liu[1], Fan Ni[2], Yiheng Liu[3] and Guoliang Liu[3]

[1] Honeycomb Aerospace Technologies (Beijing) Co., Ltd., Beijing 100071, China
[2] Aerospace Information Research Institute, Chinese Acaemy of Sciences, Beijing 100097, China
[3] Huzhou Institute of Zhejiang University, Huzhou 313098, China

Abstract

Fixed-wing unmanned aerial vehicle (UAV) formation technology, as a crucial research direction in multi-agent system cooperative control, while facing constraints in multiple areas, has demonstrated broad application prospects in military reconnaissance, disaster monitoring, agricultural plant protection and other fields in recent years. This paper systematically reviews the key technological systems of fixed-wing UAV formation control, including formation configuration design, communication topology, cooperative control algorithms, navigation positioning and obstacle avoidance strategies. By analyzing the latest research progress, the performance differences between centralized and distributed control architectures were summarized, and the applicable scenarios of mainstream formation control strategies such as behavior method, virtual structure method, and navigation-follow method were compared. The research results show that hybrid control architectures combining model predictive control and reinforcement learning algorithms exhibit superior performance in complex environments. Meanwhile, this paper discusses the technical challenges faced by formation systems in terms of communication reliability, dynamic obstacle avoidance, and energy optimization. This paper highlights the critical transition from traditional control to AI-enabled autonomous cooperation. By identifying the limitations of current communication protocols and energy management strategies, it provides a roadmap for the theoretical research and engineering application of large-scale fixed-wing UAV formations.

Keywords: fixed-wing UAV, formation control, obstacle avoidance strategy, autonomous decision-making.

1 Introduction

As a vital branch of multi-agent cooperative control, UAV swarm (formation) technology has developed rapidly from theoretical exploration to engineering applications since the early 21st century. In particular, fixed-wing UAV formation systems—thanks to their long endurance, high cruise speed, and large payload capacity—have shown unique advantages in both military and civilian domains. The global drone

Submitted: 30 November 2025
Accepted: 23 December 2025
Published: 24 January 2026

Vol. 1, **No.** 1, 2026.
10.62762/AEC.2025.339037

***Corresponding author:**
Jinbiao Zhu
zhujb@aircas.ac.cn

Citation
Li, W., Zhu, J., Liu, T., Ni, F., Liu, Y., & Liu, G. (2026). A Review of Fixed-Wing Unmanned Aerial Vehicle Formation Research. *Aerospace Engineering Communications*, 1(1), 3–27.

market size is estimated at USD 73.06 billion in 2024 and is projected to reach USD 163.60 billion by 2030, growing at a CAGR of 14.3% from 2025 to 2030 [1], reflecting vast industrialization prospects.

1.1 Research Background and Significance

In terms of theory, Reynolds' 1987 Boids model [2] first captured flocking behavior of birds and fish with simple rules, thereby laying the foundation for swarm intelligence research. This work inspired subsequent developments in distributed coordination, where Jadbabaie et al. [3] provided the first rigorous proof that simple nearest-neighbor rules could achieve asymptotic convergence in heading alignment. With advances in computing and control theory, UAV formation research accelerated significantly around 2007. Olfati-Saber et al. [4] systematically organized the consensus control framework for multi-agent systems, providing rigorous proofs that combine algebraic graph theory and Lyapunov theory, and supplying scalable, portable mathematical tools for distributed formation algorithms. Fax et al. [5] further developed information flow analysis methods for vehicle formations, establishing fundamental limits on achievable formation performance based on communication topology. The theoretical framework was further enriched by subsequent studies. Ren et al. [6] demonstrated how consensus protocols could be adapted to formation maintenance tasks, while Cao et al. [7] provided a comprehensive overview of distributed coordination paradigms. Murray [8] synthesized these developments, highlighting the transition from centralized to distributed architectures as formation scales increased.

From a graph-theoretic perspective, the algebraic properties of communication networks play a crucial role in formation stability and convergence rates. Mesbahi et al. [10] established that the second-smallest eigenvalue of the graph Laplacian (algebraic connectivity) directly determines consensus convergence speed, while Bullo et al. [9] developed comprehensive frameworks for analyzing coordination under switching topologies. The seminal work by Fiedler [11] on algebraic connectivity provided the mathematical foundation for understanding how network structure affects coordination performance. Chinese scholars have likewise made significant contributions: the 2021 survey by Do et al. [12] offered a panoramic review and performance comparison of leader–follower, virtual structure, behavior-based, consensus, and learning-based methods, giving a clear roadmap for engineering implementation and technical selection.

Coordinated turns in fixed-wing aircraft are governed by a tight relationship between speed, bank angle, and turning radius: higher speeds or shallower banks lead to wider turns, while lower speeds and steeper banks allow tighter maneuvers. This relationship directly constrains how formations can maneuver around obstacles or follow curved paths. At the same time, stall margins shrink during turns because the effective load on the wings increases with bank angle, meaning that the minimum safe airspeed rises as turns become steeper. Controllers must therefore ensure that bank commands are moderated when aircraft are operating near stall conditions or under gusty winds. In addition, fixed-wing airframes impose hard limits on bank angle, g-loading, and roll rate, all of which cap how sharply an aircraft can turn and how quickly it can roll into or out of a maneuver. These limits translate into upper bounds on formation agility and reconfiguration speed. Energy management adds another layer of coupling: climbing requires additional power, while banking increases drag and demands higher throttle settings to sustain altitude and speed. Formation members must therefore continuously balance throttle, drag, and altitude changes to maintain their relative geometry. Finally, safety spacing is not arbitrary but is shaped by the time required for sensing, communication, and control responses, plus additional margins for wind and modeling uncertainties. At typical small-UAV cruise speeds, even modest delays can translate into required separations of several to tens of meters. Together these aerodynamic, structural, and energy constraints define the feasible limits of how close fixed-wing aircraft can fly, how sharply they can maneuver, and how quickly they can reshape formations. Later sections of this review highlight how these limits are encoded in controllers, coordination logic, and evaluation metrics.

1.2 Technological Development Timeline

Fixed-wing UAV formation technology has generally experienced three stages:

1.2.1 *Stage I: Centralized control and basic formation keeping (2000–2010)*

Research centered on centralized architectures, where a ground station or a master UAV exerted global control. Early formation flights often relied on preset waypoints or simple feedback control. For example, in 2003 the U.S. Naval Research Laboratory

Table 1. Performance comparison of two typical control methods.

Control Method	Communication Complexity	Applicable Scale	Typical Application
Leader–Follower	O(N)	5–15 aircraft	Agricultural spraying swarms
Behavior-Based	O(N log N)	10–30 aircraft	Cooperative disaster search

(NRL) "Multi-UAV Cooperative Control Project" (MICA) achieved straight-line formation flight of four fixed-wing UAVs with ±5 m positioning accuracy [13]. The dominant controllers included PID and LQR. Communications during this stage required high-bandwidth data links, and formation sizes typically did not exceed six aircraft. Limitations included: 1) high single-point-of-failure risk at the central node; 2) communication load grew quadratically with the formation size; and 3) insufficient adaptability to dynamic environments.

1.2.2 *Stage II: Distributed control and dynamic reconfiguration (2011–2018)*

With the maturing of distributed control theory, researchers shifted their focus to local-interaction approaches. In 2014, MIT's Distributed Robotics Lab implemented consensus algorithms to maintain a stable 10-UAV diamond formation using only neighbor information, reducing communication load by 80% [14]. Key breakthroughs included: 1) practical engineering applications of the virtual-structure method (e.g., NASA Mars UAV program); 2) dynamic topology optimization for online formation reconfiguration; and 3) event-triggered communications that significantly reduce energy consumption. The performance comparison between these typical control methods is summarized in Table 1.

1.2.3 *Stage III: Intelligent autonomous cooperation (2019–present)*

AI is pushing formation control toward greater autonomy and environmental adaptability. Deep Reinforcement Learning (DRL) and Federated Learning have become hot topics. For example, Europe's "SESAR 2020" project [16] used multi-agent RL to enable obstacle avoidance for 50 UAVs in urban environments with decision latencies below 100 ms. Emerging technologies such as 5G/6G communications and quantum navigation are being integrated, further expanding the boundaries. Current features include: 1) hybrid architectures combining centralized mission planning with distributed execution; 2) bio-inspired clustering algorithms (e.g., pigeon-flock optimization) to enhance large-scale robustness; and 3) cross-domain teaming, extending to manned–unmanned formations. Representative achievements include DARPA's "Gremlins" aerial recovery demonstration [17] (2020) and the Hungarian Academy of Sciences' Guinness-record 1,024-UAV swarm flight (2023).

1.3 Current Technical Challenges

Despite significant progress, fixed-wing UAV formations still face key bottlenecks that arise from the platform's aerodynamics and flight mechanics, which limit performance and hinder reliable deployment in complex environments.

1.3.1 *Communication reliability*

In complex electromagnetic environments, multipath effects and spectrum congestion can severely degrade link quality [18]. In urban canyons or mountainous terrain, signal attenuation can exceed 20 dB. Research has shown that under strong interference, packet loss over conventional radio links can exceed 40% [19], threatening formation stability. New approaches such as terahertz communications and quantum encryption, are being explored but remain at the lab stage. The key parameters of various communication technologies suitable for formation applications are compared in Table 2.

Table 2. Communication technologies for formation applications.

Technology	Bandwidth (MHz)	Latency (ms)	Anti-Interference	Max Nodes
Conventional RF	20	50–100	Weak	10–15
5G NR	100	1–5	Medium	50–100
Terahertz	1000+	1	Strong	200+

1.3.2 *Dynamic obstacle avoidance and real-time decision-making*

There is a significant contradiction between the computational complexity and real-time performance of the existing algorithms: although optimal control-based method achieve high accuracy, the time consumption for a single planning may exceed 500 ms, while lightweight algorithms such as the artificial potential field method struggle to handle complex obstacle scenarios. A 2023 MIT study shows that at 30 m/s, traditional avoidance methods achieve only 68% success, whereas deep-learning solutions with edge computing raise it to 92% [20].

1.3.3 *Collaboration of heterogeneous systems*

With increasing task complexity, the lack of a general framework for cooperative control of heterogeneous UAV formations limits the system scalability [21]. Differences in configurations and payloads lead to incompatible control parameters and protocols. In its 2021 white paper, the European Telecommunications Standards Institute (ETSI) clearly pointed out that the drone market is flooded with a large number of incompatible private solutions, which has led to a closed ecosystem and seriously hindered the collaborative working ability of equipment from different manufacturers as well as the deployment of large-scale drone applications. This leads to a significant reduction in the efficiency of formation deployment in scenarios that require rapid networking, such as emergency disaster relief.

1.3.4 *Energy and endurance bottlenecks*

Energy management is a key factor restricting the long-endurance performance of UAV formations. The endurance of high performance fixed-wing UAVs degrades dramatically when performing high overload maneuvers. This fundamental trade-off between mobility and endurance is the main bottleneck currently faced by lithium battery-based electric propulsion systems and has also become the core challenge in mission planning and energy management algorithm design [23]. Hydrogen fuel cells are promising but their current energy density is insufficient for large-scale, long-duration formations.

1.3.5 *Lack of safety and standards*

The lack of security measures and standard frameworks is becoming the main obstacle to technological development. The 2019 incident involving Iran's drone formation being spoofed and intercepted via GPS indicates that there are obvious deficiencies in the anti-interference capability of the existing system [24]. Meanwhile, statistics from the International Civil Aviation Organization (ICAO) show that as of 2023, only 12 countries worldwide have established specific regulations for drone formation operations, and the standard system lags far behind technological development.

This paper aims to provide a systematically review of the research status of fixed-wing UAV formation technology. It focuses on analyzing the technological breakthroughs in control architecture, algorithm design, navigation and obstacle avoidance, etc. Over the past five years, objectively evaluates the advantages and disadvantages of various methods, and discusses the future development trends. By integrating the latest research achievements at home and abroad, it provides comprehensive technical references for researchers to promote technological innovation and application expansion in this field. The overall research framework and organization of this review are illustrated in Figure 1.

2 System Architectures for Fixed-Wing UAV Formation Control

2.1 Comparison of centralized and distributed control architectures

The architecture of fixed-wing UAV formation control systems can be broadly classified into two categories: centralized and distributed. Each architecture has its specific applicable scenarios and technical characteristics. Centralized architectures use a star topology: all UAVs send state information to a ground station or master node, which computes and issues commands [25]. A typical representative of this architecture is the "Cooperative Operations" system of Northrop Grumman. Its advantages lie in the visibility of global information, which facilitates the achievement of optimal control, and the relatively simple algorithm design [26]. However, as formation size grows, communication bandwidth and computation balloon. Theoretical analysis shows that the communication complexity of the centralized control system for N unmanned aerial vehicles is $O(N^2)$, and when $N > 10$, the system performance degrades significantly [27]. Farooq et al. [27] demonstrated that centralized coordination of nonholonomic mobile robots suffers from computational intractability as the number of agents increases beyond a critical threshold. In addition, the single-point failure risk of the central node also limits the system reliability, which is

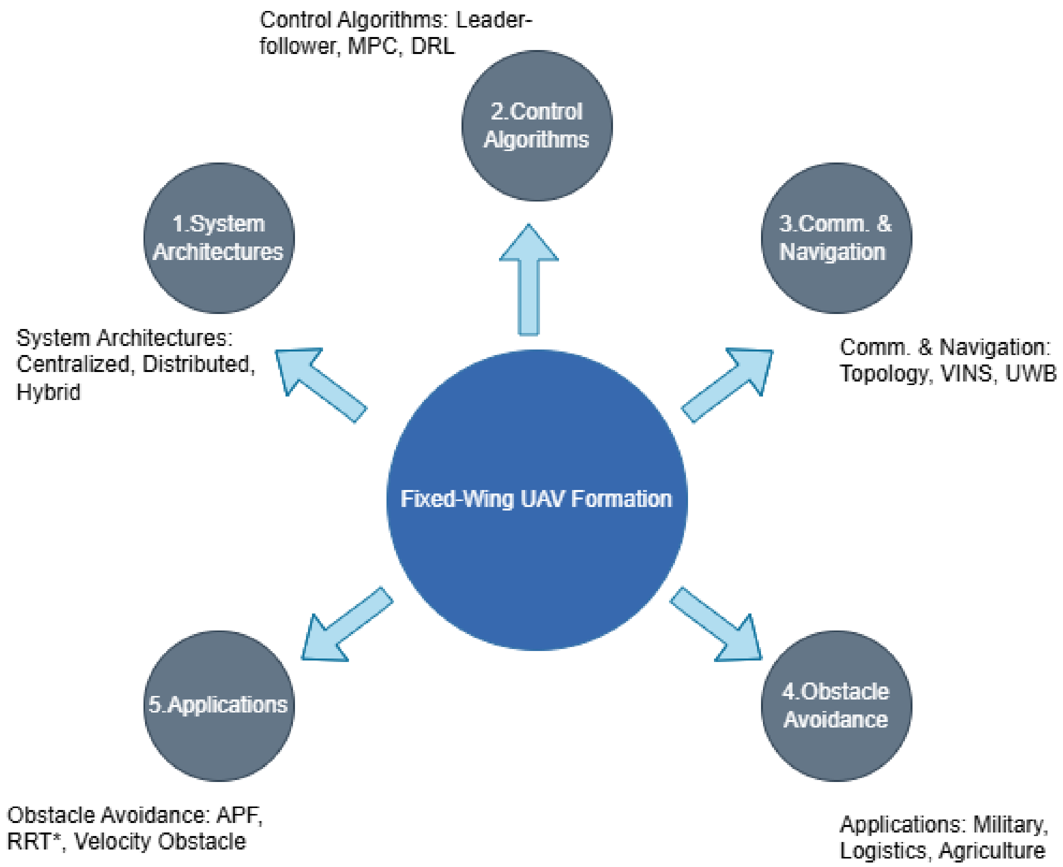

Figure 1. Overall research framework and organization of the review.

Table 3. Centralized vs. distributed architectures.

Dimension	Centralized Architecture	Distributed Architecture
Control Structure	Star topology; central decision-maker	Mesh topology; autonomous node decisions
Communication Cost	$O(N^2)$, grows sharply with scale	$O(N)$, scalable
Typical Latency	100–500 ms (depends on backhaul)	10–50 ms (local)
Single-Point Failure	High risk of system collapse	Affects only local portions
Computation Load	Concentrated at central node	Balanced across nodes
Suitable Scale	$\leq$10 aircraft	10–100 aircraft
Typical Scenarios	Precise formation shows, short-range ISR	Wide-area monitoring, dynamic missions

particularly prominent in military confrontation environments [28].

The distributed control architecture achieves global coordination through local information interaction [32]. Each UAV only exchanges data with neighboring members, significantly reducing the communication burden. The consensus-based framework developed by Hrabia et al. [29] and Dimarogonas et al. [30] established stability guarantees even under communication delays and packet losses, addressing key practical concerns in aerial networks. The distributed model predictive control framework proposed by the research team from MIT [31] in 2017 has achieved stable formation flight of 20 fixed-wing UAV, with a communication complexity of only $O(N)$. Building on earlier work by Keviczky et al. [66] and Dunbar [68], these approaches decompose the global optimization problem into coupled local problems that can be solved iteratively. Richards et al. [67] further enhanced robustness by incorporating uncertainty bounds directly into the distributed MPC framework. Advantages include scalability, robustness to node failure, and adaptability to dynamic topology [33], though it poses greater coordination challenges, and global performance may be suboptimal, especially for heterogeneous formations [35].

The theoretical foundations for analyzing distributed

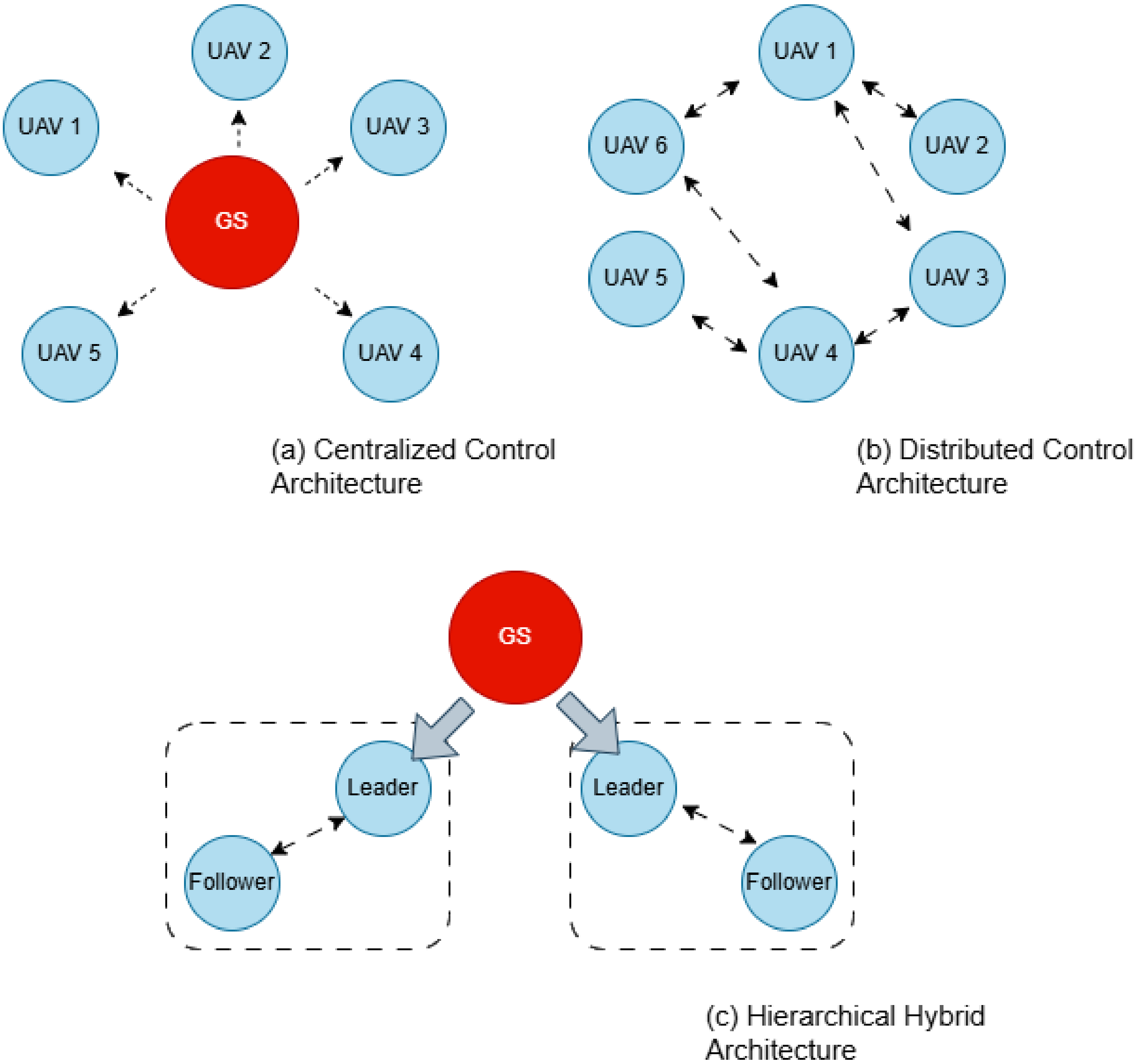

Figure 2. Comparison of three typical formation control topologies.

architectures were established by Anderson et al. [38], who characterized formation rigidity using graph theory, and Lin et al. [39], who derived necessary and sufficient graphical conditions for maintaining desired geometric configurations. Tanner et al. [40] extended these results to switching networks, proving that connectivity preservation is sufficient for flocking under broad conditions. The typical topologies associated with these architectures are illustrated in Figure 2, and a comprehensive comparison of their key characteristics is presented in Table 3.

In practical applications, a hierarchical hybrid architecture is often adopted: high-level task planning is centralized, while low-level execution is distributed. This combination can not only ensure the overall coordination of the task but also enhance the robustness of the system. Tests conducted by Beihang University in 2021 showed that the hybrid architecture demonstrated the best cost-effectiveness in formations of 15 to 30 aircraft.

2.2 Innovations in Hybrid Architectures

Hybrid architectures combine centralized high-level mission planning with distributed low-level execution. Layered designs can improve coordination while preserving robustness. Event-triggered communication—transmitting only when deviations exceed thresholds—can significantly reduce network load while maintaining stability. The typical features and operational characteristics of such hybrid architectures are detailed in Table 4.

In recent years, many researchers have proposed various Hybrid Control frames. The HAC (Hybrid Adaptive Control) system developed by Stanford

Table 4. Typical features of hybrid architectures.

Feature	Centralized Layer	Distributed Layer	Coordination Mechanism
Role	Global mission planning	Local control execution	Event-triggered communications
Response Time	100–300 ms	10–50 ms	Adaptive dynamics
Typical Algorithms	Model Predictive Control (MPC)	Consensus algorithms	Adaptive triggering
Fault Tolerance	Larger impact of single fault	Local tolerance to node faults	Layered backup
Scale	10–50	10–50	Task-dependent

Table 5. Comparison of optimization methods.

Method	Core Idea	Strengths	Limitations	Scenarios
Minimum Spanning Tree	Connectivity with minimal edges	Minimal communications overhead	Poor dynamic adaptability	Static/low-speed formations
Algebraic Graph	Optimize Laplacian eigenstructure	Fast convergence	High computational cost	Medium/ large formations
Dynamic Topology	Real-time link quality adaptation	Strong environmental fit	Extra sensing required	High-speed maneuvers

University adopts a hierarchical design: the upper layer is guided by the global trajectory provided by the task planning node, and the lower layer is distributed controlled by each unmanned aerial vehicle based on local information. The test results show that this architecture improves the coordination of task execution while maintaining distributed robustness [39]. Another innovative idea is the event-triggering mechanism, where drones only communicate when the state change exceeds a threshold, which effectively reducing the network load [40]. The adaptive triggering strategy proposed by the team from Beihang University in 2021 reduced the communication volume by over 60% while ensuring the stability of the formation [41].

2.3 Communication Topology Optimization Technology

Communication topology structure directly affects the formation control performance. Researchers have proposed a variety of optimization methods grounded in algebraic graph theory [42, 43]. The minimum spanning tree algorithm can construct the most economical topology with guaranteed connectivity, drawing on classical results from combinatorial optimization. Mesbahi et al. [10] demonstrated that optimizing the eigenstructure of the Laplacian matrix can further improve the convergence speed of formation consensus algorithms, with the algebraic connectivity (second-smallest eigenvalue) serving as a key performance metric. Mozaffari et al. [43] provided comprehensive mathematical foundations for understanding how graph properties influence dynamic coordination, while Horn et al. [34] established the spectral analysis tools necessary for stability assessment.

In view of the high-speed movement characteristics of fixed-wing UAV, dynamic topology optimization algorithms adjust the communication link in real time to balance communication quality and control performance [45, 48, 49]. Cortés et al. [36] developed proximity-based topology reconfiguration strategies that maintain formation cohesion while adapting to environmental obstacles and communication constraints. Belta et al. [37] formalized abstraction methods that enable hierarchical reasoning about formation topology changes, facilitating real-time reconfiguration decisions.

Recent advances in UAV communication networking have opened new possibilities for formation coordination. Hayat et al. [42] surveyed communication challenges specific to UAV networks, highlighting issues of mobility-induced topology changes and line-of-sight requirements. Mozaffari et al. [43] provided a comprehensive tutorial on UAV wireless communications, covering channel modeling, interference management, and network optimization. Gharibi et al. [44] introduced the "Internet of Drones" concept, proposing layered architectures that integrate UAV formations into broader cyber-physical systems. For mobile ad-hoc networks formed by UAVs, Sahingoz [45] and Bekmezci et al. [46] analyzed routing protocols specifically designed for Flying Ad-Hoc Networks (FANETs), which must cope with rapid topology changes and frequent link breaks. Asadpour et al. [47] conducted experimental analyses revealing that conventional ground-based ad-hoc protocols often fail in aerial environments due to three-dimensional mobility patterns and altitude-dependent connectivity. A comparison of these topology optimization methods is summarized in Table 5.

It is worth noting that 5G network slicing technology provides a new solution for formation communication [50]. In the 2022 trial, China Mobile achieved formation control with a latency of 1ms and a reliability of 99.999%. Sharma et al. [51] demonstrated

Table 6. Key metrics across architectures.

Architecture	Comm. Complexity	Scalability	Robustness	Scale
Centralized	$O(N^2)$	Poor	Weak	10
Distributed	O(N)	Excellent	Strong	10–100
Hybrid	O(N)	Good	Medium	10–50

how intelligent UAV deployment in heterogeneous 5G networks can improve coverage and capacity, while addressing the unique challenges of aerial base stations. However, the integration of heterogeneous networks in cross-domain collaboration remains an unsolved problem, especially the issue of reliable navigation in GPS denial environments, which requires urgent breakthroughs [55]. For scenarios with intermittent connectivity, delay-tolerant networking approaches [56] and epidemic routing strategies [57, 58] offer alternative paradigms. Zhang et al. [35] specifically designed data-delivery protocols for UAV "flying courier" applications, where formation members opportunistically relay information in challenged communication environments. To provide a holistic view, the key performance metrics of the three main control architectures (centralized, distributed, and hybrid) discussed earlier are consolidated in Table 6.

3 Advances in Formation Control Algorithms

3.1 Classic Control Paradigm

After more than two decades of development in the field of fixed-wing UAV formation control, several classic control paradigms with distinct characteristics have emerged. These algorithms exhibit significant differences in theoretical basis, implementation methods and application scenarios, and together they constitute the core pillar of the formation control technology system.

3.1.1 Based on the emergent characteristics of behavioral methods

Behavior-based methods decompose complex control tasks into basic behaviors such as aggregation, collision avoidance, and target approaching, and adapt to different scenarios by adjusting behavior weights [60]. The AuRA system developed by Georgia Tech adopts this method to achieve formation reconstruction in a dynamic environment, but its global stability is difficult to be strictly proved [61].

3.1.2 Accurate control of virtual structure method

The virtual structure method regards the entire formation as a virtual rigid body, and each UAV tracks the corresponding point in the structure [53]. This approach, formalized by Lewis et al. [54], provides intuitive geometric control and simplifies trajectory planning by treating the formation as a single entity. Ren et al. [55] extended the virtual structure concept to spacecraft formations, demonstrating that carefully designed feedback laws can maintain precise relative positioning despite orbital perturbations. Beard et al. [56] developed coordination architectures that combine virtual structure control with decentralized collision avoidance, achieving both formation maintenance and safety guarantees.

NASA successfully applied this method in the Mars unmanned aerial vehicle project. By introducing the elastic deformation mechanism of the virtual structure, centimeter-level relative position control was achieved. Askari et al. [57] further refined this approach for fixed-wing UAVs, incorporating aerodynamic constraints and coordinated turn dynamics into the virtual structure framework. The latest research shows that combining model predictive control can further optimize the structural deformation trajectory. Kuriki et al. [58] developed a fourth-order flight dynamics model integrated with virtual structure control, enabling high-fidelity formation maneuvers that respect actuator limits and stall constraints. Ferrante et al. [19] introduced elasticity-based mechanisms that allow the virtual structure to deform adaptively in response to obstacles or environmental disturbances, combining the geometric simplicity of rigid formations with the flexibility needed for real-world deployment.

3.1.3 Engineering practicability of pilot-following method

The leader-following method has become the most widely used method in engineering due to its intuitive concept and simple implementation. In this paradigm, one or more leader UAVs follow predetermined trajectories while follower UAVs maintain desired relative positions. Consolini et al. [59] developed nonholonomic leader-follower controllers that explicitly handle input constraints such as minimum turning radius and maximum bank angle—critical for fixed-wing platforms. Dong et al. [60] extended these results to time-varying formations, enabling dynamic reconfiguration during flight missions.

The hierarchical architecture developed by Boeing in the "Loyal Wingman" project has increased energy efficiency by 30-40% compared to the distributed approach. Peng et al. [61] demonstrated adaptive dynamic surface control techniques that compensate for uncertain hydrodynamic parameters in marine vehicle formations; similar principles apply to atmospheric turbulence compensation in aerial formations. Arrichiello et al. [62] proposed null-space-based behavioral control that allows leader-follower coordination to be combined with secondary objectives such as obstacle avoidance or communication link maintenance. Wang et al. [63] formulated integrated optimal formation control problems that jointly optimize trajectory planning and formation geometry, achieving significant fuel savings in multi-UAV cooperative missions.

3.2 Innovations in Modern Control

The development of modern control theory has provided more precise and robust solutions for formation control of fixed-wing UAV. These algorithms have demonstrated significant advantages in handling system nonlinearities, environmental uncertainty, and real-time requirements.

3.2.1 Constraint handling ability of model predictive control

Model Predictive Control (MPC) has become the core method of formation control due to its ability to explicitly handle constraints [33, 80–84]. The distributed MPC framework proposed by ETH Zurich innovatively combines rolling time-domain optimization and distributed consensus algorithms [71]. While ensuring formation stability, it strictly satisfies state constraints (such as anti-collision) and control input constraints (such as rudder surface deflection limit). The experiment shows that its position tracking error is less than 0.3 meters.

The theoretical foundations were established by Dunbar et al. [65], who proved stability of distributed receding horizon control for multi-vehicle systems using appropriately designed terminal constraints. Keviczky et al. [66] demonstrated that decentralized MPC with sparse information exchange could approach centralized performance while maintaining computational tractability. Richards et al. [67] addressed robustness explicitly, incorporating bounded disturbances and model uncertainties into tube-based MPC formulations that guarantee constraint satisfaction despite uncertainties. Giselsson et al. [70] developed efficient distributed optimization algorithms with provable suboptimality bounds, enabling real-time implementation on embedded flight computers. Maestre et al. [69] compiled comprehensive methodologies for distributed MPC design, covering communication protocols, constraint tightening strategies, and stability certification.

For fixed-wing UAVs specifically, the coupling between longitudinal and lateral dynamics, along with aerodynamic nonlinearities near stall, necessitates careful MPC formulation. Venkat et al. [64] demonstrated successful applications to power system control with similar distributed structure, providing algorithmic templates adaptable to UAV formations. Recent advances incorporate learning-based models that refine aerodynamic predictions online, combining the safety guarantees of MPC with the adaptability of data-driven methods.

3.2.2 Anti-interference characteristics of sliding mode control

In terms of anti-interference control, sliding mode control demonstrates significant advantages due to its inherent robustness to matched uncertainties [74, 75]. The foundational theory established by Utkin et al. [73] provides comprehensive treatment of sliding mode design for electro-mechanical systems, directly applicable to UAV actuator control. The super-twisted sliding mode observer developed by Moscow Aviation Institute, through a second-order sliding mode surface design, effectively suppresses high-frequency chatters and reduces the head angle estimation error under 30m/s crosswind conditions from $\pm 5°$ to $\pm 1.5°$ [76].

Shtessel et al. [71] presented modern sliding mode control and observation techniques, including higher-order sliding modes that eliminate chattering while preserving robustness properties. Yu et al. [74] surveyed sliding mode control combined with soft computing approaches, demonstrating how fuzzy logic and neural networks can enhance adaptive gain tuning. Defoort et al. [75] specifically developed sliding-mode formation control for cooperative mobile robots, proving finite-time convergence to desired configurations despite external disturbances. Meanwhile, its integrated wind speed estimation module can compensate for wind disturbance in real time and balance response speed and stability via adaptive gain adjustment mechanism. For crosswind approaches, introduce a crab-angle estimator and schedule controller gains with airspeed to cap sideslip and preserve coordinated-turn assumptions. Alwi et al. [76] extended sliding mode techniques to fault detection and fault-tolerant control, enabling formations to maintain cohesion even when individual UAVs experience actuator failures or sensor faults.

3.2.3 Stability assurance of backstepping method

For strict feedback systems, the backstep method can ensure global stability by recursive construction of Lyapunov functions, and is particularly suitable for the dynamic models of fixed-wing UAV with nonlinear and coupled characteristics. Meanwhile, by considering the strong coupling characteristics of fixed-wing UAV, a decoupling control strategy is designed and an adaptive law is introduced to estimate the uncertain parameters online, further enhancing its stability.

3.2.4 Parameter robustness of adaptive control

Furthermore, the Model Reference Adaptive Control (MRAC) system developed by Lockheed Martin compensates for the uncertainty of aerodynamic parameters by adjusting the controller parameters online through a multi-model switching mechanism, an online parameter identification algorithm, and a stability monitoring module [80–83]. Lavretsky et al. [77] provided comprehensive treatment of robust adaptive control architectures suitable for aerospace applications, while Ioannou et al. [78] established the theoretical foundations for stability and convergence under parameter adaptation.

Cao et al. [79] developed the L1 adaptive control architecture, which guarantees transient performance bounds—a critical requirement for formation flight where temporary deviations can lead to collisions. This approach has been successfully applied to the “Sky Borg” unmanned aerial vehicle project, compensating for its $\pm 30\%$ aerodynamic parameter deviation. Krstic et al. [80] formalized backstepping-based adaptive control design, enabling systematic handling of nonlinear systems in strict feedback form. The related technology has also been granted a US patent. For formation applications, Rashid et al. [82] integrated adaptive control with optimal trajectory generation, allowing formations to maintain coordination while individual members adapt to changing flight conditions.

3.2.5 Innovation trend of algorithm integration

The integrated innovation of modern control algorithms in the future will become a research hotspot: the combination of MPC and sliding mode control will further take into account both constraint processing and anti-interference capabilities.The adaptive backstepping framework was used to enhance the robustness of parameters.Through distributed adaptive MPC, the performance of large-scale formation is improved. These advancements have significantly enhanced the control performance of UAV formations in complex environments, laying the foundation for future autonomous and collaborative tasks.

3.3 Breakthroughs in Intelligent Control

Recent advances in multi-agent reinforcement learning (MARL) have significantly enhanced UAV swarm capabilities, offering solutions to coordination challenges that are intractable with classical control methods [84–88]. The fundamental challenge in MARL is credit assignment: determining which agent’s actions contributed to team success in cooperative tasks. Foerster et al. [81] introduced counterfactual multi-agent policy gradients (COMA), which decompose team rewards using counterfactual reasoning to provide individual feedback signals. Rashid et al. [82] developed QMIX, a value factorization method that learns a monotonic mixing function to combine individual agent values into a team value, enabling centralized training with decentralized execution. Sunehag et al. [83] proposed value-decomposition networks (VDN) that linearly combine individual value functions, while Yu et al. [84] demonstrated that Proximal Policy Optimization (PPO) achieves surprisingly strong performance in cooperative multi-agent games, often outperforming more complex algorithms. Lowe et al. [85] developed multi-agent actor-critic frameworks for mixed cooperative-competitive environments, enabling formations to coordinate internally while competing against adversarial agents. For fixed-wing platforms specifically, PPO-based methods have demonstrated stable formation keeping under aerodynamic constraints [15].

DARPA and the USAF reported the first in-flight AI-controlled within-visual-range dogfight on the X-62A VISTA in 2024, demonstrating rapid decision-making in air-combat maneuvers [89]. This milestone validated that deep reinforcement learning can handle the time-critical, safety-critical decisions required in high-speed aerial engagements. For UAV-specific control tasks, Koch et al. [91] applied RL to attitude control, demonstrating superior disturbance rejection compared to classical

Table 7. Performance of control algorithms.

Algorithm Type	Computational Load	Disturbance Rejection	Explainability	Suitable Scenarios
Behavior-based	Low	Medium	High	Simple environments
Virtual Structure	Medium	High	High	Precise formations
MPC	High	High	Medium	Constrained settings
DRL	Very High	Very High	Low	Complex environments

PID controllers. Hwangbo et al. [92] trained quadrotor controllers entirely in simulation using domain randomization, achieving robust real-world performance. Liaq et al. [93] developed autonomous UAV navigation using RL in GPS-denied environments, while Rodriguez-Ramos et al. [94] solved the challenging problem of autonomous landing on moving platforms using deep Q-learning.

For sim-to-real transfer—a critical bottleneck in deploying learned policies on physical UAVs—Stanford's DroneTransfer framework combines meta-learning with domain randomization, enabling effective strategy deployment after just 15 minutes of real-world adaptation [94, 95]. The foundational work by Tobin et al. [87] demonstrated that randomizing visual textures, lighting, and dynamics parameters during training produces policies robust to real-world variations. Peng et al. [88] extended this to dynamics randomization, enabling simulated training to transfer to robots with significantly different physical properties. Chebotar et al. [89] closed the sim-to-real loop by incorporating real-world experience to refine simulation distributions, iteratively improving transfer performance. Muratore et al. [90] developed transferability assessment metrics that predict sim-to-real success before deployment, reducing costly real-world failures. Loquercio et al. [95] specifically addressed high-speed flight in natural environments, combining learning-based perception with classical control to achieve agile maneuvers through forests at speeds up to 10 m/s.

Large-scale coordination has been achieved through bio-inspired approaches, as exemplified by the Flocking 3.0 system's Guinness-record 1024-UAV formation with $\pm$0.25m precision [95]. This system synthesizes Reynolds' original flocking rules [2, 96] with modern sensing and communication technologies. Duan et al. [99] developed pigeon-inspired optimization algorithms that mimic the navigation strategies of homing pigeons, achieving superior performance in UAV path planning compared to particle swarm optimization. Ho et al. [100] applied swarm-based fuzzy logic control to mobile sensor networks for hazardous contaminant localization, demonstrating the versatility of bio-inspired coordination beyond aerial platforms.

Security concerns in distributed learning are addressed by Huawei's FedFly framework, which employs federated learning with differential privacy to reduce communication overhead by 67% during collaborative training [103]. This approach enables multiple UAVs to jointly improve flight policies without sharing raw flight data, preserving operational security. The federated learning paradigm is particularly valuable for military and commercial applications where data privacy is paramount.

Imitation learning offers an alternative to pure RL by leveraging expert demonstrations. Ho et al. [100] developed Generative Adversarial Imitation Learning (GAIL), which trains policies to produce behavior indistinguishable from expert trajectories. Bojarski et al. [101] famously applied end-to-end imitation learning to autonomous driving, mapping raw camera images directly to steering commands. Wang et al. [102] adapted these techniques to UAV navigation in large-scale complex environments, achieving robust obstacle avoidance through learned perception-action mappings. Meta-learning frameworks [107, 108] enable "learning to learn," where agents acquire the ability to rapidly adapt to new tasks. Ferreira et al. [107] developed Model-Agnostic Meta-Learning (MAML), which trains model parameters such that a few gradient steps on new tasks yield effective policies. Duan et al. [103] proposed RL^2, a meta-learning framework where the recurrent policy itself encodes the learning algorithm, enabling extremely rapid adaptation to new environments.

Together, these developments suggest promising directions for fixed-wing formation research, while also underscoring the need to adapt algorithms to aerodynamic constraints and long-range mission profiles. The high speeds, large turning radii, and stall constraints of fixed-wing platforms necessitate control policies that respect flight envelope limits, unlike the more forgiving flight dynamics of quadrotors used in most existing RL research. The performance characteristics of various control algorithms discussed throughout this section, including classical, modern, and intelligent methods, are systematically compared in Table 7.

3.4 Real-Time Command and Cooperative Operations

The efficient task execution of fixed-wing UAV formation requires real-time command and control technology. The current development of technology is mainly reflected in the following three dimensions:

3.4.1 *Intelligent task segmentation management*

Modern formation systems utilize an adaptive five-phase mission segmentation strategy: During take-off, reinforcement learning-enabled cluster coordination achieves ±0.5m vertical synchronization accuracy. The cruise phase employs model predictive control for optimal formation-keeping and energy management, boosting endurance by 15-20%. Standby operations benefit from enhanced phase synchronization (spatiotemporal error of less than 0.1s) [109], while the operational phase dynamically selects terrain-optimized coverage patterns (square/bow-shaped) via intelligent trajectory planning, improving efficiency by 22-25% [110]. Finally, the landing phase ensures multi-UAV touchdown synchronization within 0.3s through distributed autonomous decision-making.

3.4.2 *Collaborative control system architecture*

The collaborative operation control system is developed based on the QGC open-source architecture. The communication layer realizes multi-machine link management (supporting concurrent connection of 20 UAVs), protocol parsing and self-recovery after disconnection. The interaction layer integrates a 3D digital twin map and a dynamic formation editor, supporting visual planning of 8 standard formations.

3.4.3 *Hardware platform innovation*

At the hardware level, a dual-screen ground station device has been developed, equipped with an i7-12800H processor and an SDR communication module (with a transmission distance of 50km), capable of simultaneously controlling 12 unmanned aerial vehicles and connecting to third-party payload control software. The CPU load rate is maintained below 65%. These technological advancements have significantly enhanced the operational efficiency of the formation system in scenarios such as emergency rescue and precision agriculture. Recent SDR-based systems demonstrate end-to-end RF architectures suitable for UAV control and counter-UAS, including GPS spoofing/jamming and reconfigurable radio pipelines [111]. The 2023 report of the United States Department of Agriculture shows that the formation operation efficiency of agricultural drones using this technology has reached 5.8 times that of individual drones.

4 Navigation and Obstacle Avoidance for Formations

4.1 Advances in Cooperative Navigation

Cooperative navigation system for the fixed-wing unmanned aerial vehicle (UAV) formation significantly enhances positioning accuracy and reliability through multi-source data fusion technology [112, 113]. The main technical routes currently adopted include:

4.1.1 *Visual inertia fusion navigation system*

The VINS-Fusion system (ETH Zurich) integrates monocular vision (2MP) and IMU data (1000Hz) in a tightly coupled graph-optimization framework, achieving ±3cm relative positioning accuracy and $<0.1°$ angular error in GPS-denied environments [114]. By incorporating deep learning-assisted feature extraction, it attains a 92% feature-matching success rate under challenging conditions. The theoretical foundations were established by Mourikis et al. [114], who developed the Multi-State Constraint Kalman Filter (MSCKF) that marginalizes old camera poses while retaining feature observations, enabling computationally efficient visual-inertial odometry. Leutenegger et al. [110] developed keyframe-based visual-inertial SLAM using nonlinear optimization, balancing accuracy and computational efficiency through selective keyframe retention. Bloesch et al. [111] proposed direct EKF-based visual-inertial odometry that operates on image intensities rather than extracted features, improving robustness in texture-poor environments. Mur-Artal et al. [109] created ORB-SLAM2, an open-source system supporting monocular, stereo, and RGB-D cameras with real-time loop closure detection and relocalization capabilities.

4.1.2 *Ultra-wideband ranging technology*

For missions where satellite navigation is unavailable or unreliable, alternative positioning methods become critical. Groves [112] provided comprehensive treatment of GNSS, inertial, and multisensor integrated navigation principles, establishing the theoretical framework for fault-tolerant navigation systems. Sabatini et al. [113] assessed avionics-based GNSS integrity augmentation systems specifically for UAS sense-and-avoid applications, addressing the unique safety requirements of autonomous flight. Vetrella et al. [116] demonstrated differential GNSS combined with vision-based tracking to improve navigation performance in cooperative multi-UAV systems, achieving positioning accuracies suitable for close-formation flight even with partial GPS outages.

4.1.3 *Distributed integrated navigation architecture*

The fundamental advantage of formation flight is the ability to share information among members. Roumeliotis et al. [115] pioneered distributed multirobot localization, proving that relative position measurements between robots can significantly improve individual localization accuracy compared to independent operation. Nerurkar et al. [117] developed distributed maximum a posteriori estimation algorithms that fuse proprioceptive sensing with relative observations, achieving near-optimal performance without requiring a central estimator. Howard et al. [118] applied maximum likelihood estimation to mobile robot team localization, demonstrating how intermittent communication can still yield significant localization improvements.

4.1.4 *Breakthrough in quantum inertial navigation*

The Qualcomm QTM8295 chipset has achieved a significant breakthrough in drone formation ranging [119, 120]. It adopts the 6.5GHz frequency band and a time-of-flight (TOF) algorithm, achieving a ranging accuracy of 10cm [121] and a maximum ranging of 800m. It also supports self-organizing networks with over 100 nodes, with a time slot allocation efficiency reaching 95% [122]. UWB technology offers advantages over GPS for relative positioning: immunity to multipath fading, high precision at short to medium ranges, and low latency suitable for real-time control.

4.1.5 *Distributed Integrated Navigation Architecture*

The distributed Kalman filtering framework developed by DARPA's CODE project, by integrating data from multiple sensors, can maintain a formation positioning error of less than 5 meters in GPS rejection environments and data integrity of 99.99% under electromagnetic interference conditions, demonstrating an anti-interference capability [123]. Its dynamic reconfiguration mechanism supports the system's degraded operation in the event of 50% node failure. Herbert et al. [124] developed a general optimization-based framework for local odometry estimation with multiple sensors (VINS-Fusion), enabling UAVs to fuse heterogeneous sensing modalities adaptively based on availability and quality.

4.1.6 *Breakthrough in Quantum Inertial Navigation*

The quantum inertial navigation prototype tested by the UK Ministry of Defence uses the cold atom interference principle (that is, based on the 87Rb atomic interferometer and using Raman laser to achieve acceleration measurement) to control the positioning drift rate within 1.5m/h, demonstrating the potential to solve the problem of cumulative errors in long-duration navigation [125, 126]. While still in early development, quantum navigation promises orders-of-magnitude improvement over conventional IMUs for strategic missions requiring multi-hour autonomy without external position references.

4.2 Breakthroughs in Dynamic Obstacle Avoidance

Recent advancements in dynamic obstacle avoidance for fixed-wing UAV formations have led to significant progress in algorithmic innovation, computational efficiency, and environmental adaptability.

4.2.1 *Improved Artificial Potential Field Method*

The conventional artificial potential field method employs virtual attractive and repulsive fields for obstacle avoidance, achieving computational times below 10 ms per planning cycle [127]. However, it suffers from inherent limitations such as local minima and target inaccessibility, first identified by Khatib [128] in robotic manipulator control. Ge et al. [129] addressed local minima through dynamic goal switching and virtual obstacle techniques. Park et al. [130] combined potential fields with simulated annealing to escape local optima in complex environments. Through dynamic situational field reconstruction, the success rate of obstacle avoidance has been increased to 92%, while the average response time in dense dynamic environments has been reduced to 15 ms[130].

4.2.2 *Sampling-Based Algorithm Optimization*

The rapidly-exploring random tree (RRT) algorithm, introduced by LaValle [125], provides probabilistic completeness for motion planning in high-dimensional spaces. Karaman et al. [126] developed RRT*, which asymptotically converges to optimal paths through incremental rewiring of the search tree. Gammell et al. [127] introduced Informed RRT*, which focuses sampling within informed subsets of the configuration space using admissible heuristics, dramatically reducing planning time in cluttered environments.

The improved RRT* algorithm proposed by Beijing Institute of Technology reduces the path planning time from the traditional 2-3 seconds to 0.4-0.6 seconds by introducing adaptive sampling area division, GPU parallel accelerated computing architecture and incremental update strategy, which is particularly suitable for application in complex urban environments [133]. The computational efficiency gains are critical for fixed-wing UAVs, where high cruise speeds demand rapid replanning to maintain safety margins.

4.2.3 *Velocity Obstacle Methods*

For dynamic obstacle avoidance, the velocity obstacle (VO) paradigm introduced by Fiorini et al. [131] enables collision-free navigation among moving obstacles by reasoning in velocity space rather than configuration space. Van den Berg et al. [132] extended this to reciprocal velocity obstacles (RVO), which assume that all agents cooperatively avoid collisions, enabling scalable multi-agent collision avoidance without explicit communication. These methods are particularly suitable for formation flight, where each UAV must avoid not only external obstacles but also neighboring formation members during maneuvers.

4.2.4 *Optimal Control-Based Implementation*

The Fastrack framework, developed by MIT, formulates obstacle avoidance as a constrained optimization problem [137]. By incorporating safety corridor construction, distributed optimization algorithms, and real-time performance guarantees, it maintains a safety margin exceeding 5 meters even at high speeds of 30 m/s [126]. Herbert et al. [124] demonstrated modular integration of FaSTrack with existing trajectory planners, providing certifiable safety guarantees without requiring complete controller redesign. This approach has been successfully deployed in Amazon's logistics drone fleet, achieving a mission completion rate of 98.7%.

4.2.5 *Deep Learning of Obstacle Avoidance*

NVIDIA's FlightNet system utilizes an end-to-end convolutional neural network architecture, attaining an obstacle avoidance success rate of 92% under adverse weather conditions such as heavy rain and dense fog, compared to 65% with traditional methods [137]. Liu et al. [72] developed neural networks for high-speed flight in cluttered environments using efficiently updatable architectures that adapt online to changing obstacle distributions. Feng et al. [134] designed persistent full-area coverage strategies with dynamic priorities, enabling formations to adapt coverage patterns based on real-time obstacle detection.

4.2.6 *Collaborative Group Avoidance*

The distributed obstacle avoidance strategy developed by the European SESAR project coordinates the obstacle avoidance actions of the entire formation through V2V communication, establishing a complete collaborative obstacle avoidance framework including 5G-V2X communication protocol, three-level decision-making architecture, and commercial operation [138, 139]. This hierarchical approach assigns tactical obstacle avoidance to individual UAVs while ensuring formation-level path feasibility through higher-level coordination. Meanwhile, this system has been commercially applied in the civil aviation unmanned aerial vehicle (UAV) traffic management system, capable of handling over 1,000 UAV flights per day [138].

These technological breakthroughs greatly enhance the autonomous obstacle avoidance capability of UAV formations in complex dynamic settings, facilitating the large-scale commercial application of drone operations. A schematic illustrating typical formation reconfiguration maneuvers during dynamic obstacle avoidance is shown in Figure 3.

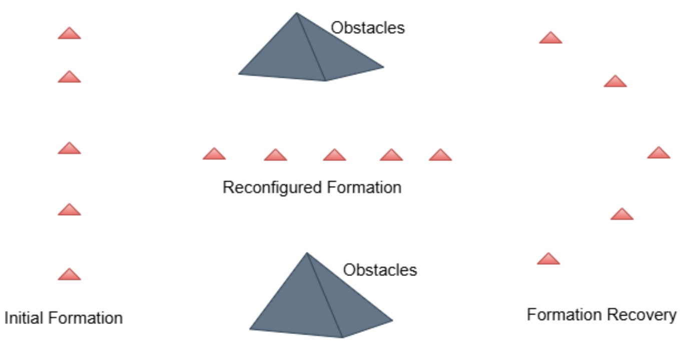

Figure 3. Schematic of formation reconfiguration during dynamic obstacle avoidance.

5 Application Challenges and Trends

5.1 Unique Value and Status of Fixed-Wing Formations

With its unique aerodynamic characteristics and flight performance, fixed-wing UAV formation technology is showing revolutionary application potential in several key fields. Compared with multi-rotor platforms, fixed-wing UAVs have significant advantages in terms of endurance, flight speed and load capacity, which make them an irreplaceable technical solution in specific application scenarios.

5.1.1 *Breakthroughs in large-scale surveillance*

In the fields of meteorological monitoring and environmental observation, the "Swift" project led by NASA, which uses a formation system composed of five medium-sized fixed-wing UAV, has set a record of 72 consecutive hours of hurricane monitoring.The formation configuration is adjusted in real time according to meteorological conditions to ensure the best monitoring coverage.

5.1.2 *Economic innovation in logistics and transportation*

The latest research report of Amazon Prime Air [135] shows that for transportation distance of 100-300 kilometers, the fixed-wing formation system demonstrates significant speed advantages, ultra-high load capacity and low energy consumption. These advantages make fixed-wing formations particularly valuable in the following logistics scenarios: emergency transportation of medical supplies, complex island supply logistics, and biological agents delivery.

The economic viability of drone delivery depends critically on energy efficiency and operational range. Dorling et al. [136] formulated vehicle routing problems specifically for drone delivery, demonstrating that formation flight can reduce per-package energy consumption by 25-35% through aerodynamic drafting effects at scale. Stolaroff et al. [141] conducted comprehensive life-cycle analysis of drone delivery systems, finding that fixed-wing formations offer superior greenhouse gas emissions profiles compared to ground transportation for medium-range deliveries (50-200 km) in low-density areas. Di Franco et al. [137] developed energy-aware coverage path planning algorithms that optimize battery usage while ensuring delivery deadlines, critical for commercial viability.

5.1.3 *Tactical advantages in military security*

The border patrol system deployed by the Israel Defense Forces adopts an innovative "swarm" tactic, enabling continuous monitoring capabilities for 24-hour non-stop patrols through a formation rotation mechanism of eight drones. Its maximum tracking speed can reach 200km/h, effectively dealing with fast-moving targets. In addition, in mountainous environments with an altitude difference of over 1,000 meters, it can still maintain a positioning accuracy of $\pm$1.5 meters [22, 52].

5.1.4 *Technological innovation in the Agricultural plant protection*

In the field of precision agriculture, fixed-wing formation technology is driving the transformation of plant protection operations. Test data from DJI agriculture [143] in 2023 shows that a 10-UAV formation can cover an area of up to 133 hectares ($\approx$2,000 mu) in a single day, increase the uniformity of pesticide application by 40%, reduce comprehensive operating costs by 35%, and decrease pesticide usage by 25%. Fixed-wing UAV formations automatically optimize their flight trajectories based on terrain and crop distribution, and precisely control the dosage of pesticides through multi-aircraft collaboration. All these demonstrate technological innovation breakthroughs in agricultural environments [144].

5.2 Energy Management and Endurance Optimization

Energy management is a key factor restricting the long-endurance performance of UAV formations. The endurance of high performance fixed-wing UAVs degrades dramatically when performing high overload maneuvers. This fundamental trade-off between mobility and endurance is the main bottleneck currently faced by lithium battery-based electric propulsion systems and has also become the core challenge in mission planning and energy management algorithm design [23, 140, 141].

Zhang et al. [145] developed energy-efficient UAV communication strategies with trajectory optimization, jointly optimizing flight path and transmission power to maximize network lifetime. Their results show that cooperative trajectory planning in formations can extend mission duration by 40-60% compared to independent operation. Basescu et al. [151] proposed predictive model-based energy management for fixed-wing UAVs, using nonlinear MPC to optimize throttle settings while respecting battery discharge constraints and thermal limits. Nigam et al. [147] addressed energy-aware multi-drone coordination for target tracking, demonstrating that intelligent task allocation based on remaining battery capacity prevents premature mission termination due to individual UAV exhaustion.

The aerodynamic benefits of formation

flight—particularly V-formation configurations inspired by migrating birds—can yield significant energy savings. Theoretical analysis suggests that trailing aircraft in echelon formations experience reduced induced drag, potentially saving 10-30% of propulsive power depending on spacing and position. However, maintaining precise relative positioning requires continuous control effort, and turbulent wakes from leading aircraft impose additional disturbances on followers. The net energy benefit depends critically on formation geometry, wind conditions, and control efficiency.

Alternative propulsion technologies offer pathways to extended endurance. Hydrogen fuel cells provide 2-3× the energy density of lithium batteries, enabling multi-hour missions at the cost of increased system complexity and refueling infrastructure requirements. Solar-augmented propulsion has enabled demonstration flights exceeding 24 hours, though payload capacity and operational flexibility remain limited. Hybrid architectures combining batteries with internal combustion engines or fuel cells represent practical compromises for near-term applications.

5.3 Heterogeneous System Collaboration

With increasing task complexity, the lack of a general framework for cooperative control of heterogeneous UAV formations limits the system scalability [21, 148–152]. Differences in configurations and payloads lead to incompatible control parameters and protocols. In its 2021 white paper, the European Telecommunications Standards Institute (ETSI) clearly pointed out that the drone market is flooded with a large number of incompatible private solutions, which has led to a closed ecosystem and seriously hindered the collaborative working ability of equipment from different manufacturers as well as the deployment of large-scale drone applications. This leads to a significant reduction in the efficiency of formation deployment in scenarios that require rapid networking, such as emergency disaster relief.

Chung et al. [142] provided a comprehensive survey of aerial swarm robotics, identifying heterogeneity as a key challenge requiring research attention. Heterogeneous formations may combine fixed-wing UAVs for wide-area coverage with rotorcraft for precision hovering, ground vehicles for persistent presence, or even manned aircraft for supervisory control. Freeman et al. [149] developed hierarchical formation control architectures specifically for heterogeneous UAVs, decomposing the control problem into layers that handle differing dynamics. Yan et al. [146] analyzed coordination mechanisms across heterogeneous multi-robot systems, identifying communication protocol standardization and capability-aware task allocation as critical enablers.

Nigam et al. [147] demonstrated control of multiple UAVs for persistent surveillance using mixed fleets of fixed-wing and rotary-wing platforms, with flight test results validating the practical feasibility of heterogeneous coordination. Kuriki et al. [148] developed consensus-based cooperative formation control with collision avoidance for multi-UAV systems accommodating different flight dynamics. Their approach uses virtual forces that scale with platform capabilities, ensuring that faster fixed-wing aircraft maintain safe separation from slower rotorcraft during coordinated maneuvers.

The integration of manned and unmanned platforms represents an advanced form of heterogeneity with significant military and civilian applications. Human operators provide high-level reasoning, ethical decision-making, and adaptability to novel situations, while autonomous systems offer precision, tirelessness, and scalability. "Manned-unmanned teaming" (MUM-T) architectures must address trust, transparency, and workload allocation to enable effective human-machine collaboration.

5.4 Safety, Standards, and Regulatory Frameworks

The lack of security measures and standard frameworks is becoming the main obstacle to technological development. The 2019 incident involving Iran's drone formation being spoofed and intercepted via GPS indicates that there are obvious deficiencies in the anti-interference capability of the existing system [24]. Meanwhile, statistics from the International Civil Aviation Organization (ICAO) show that as of 2023, only 12 countries worldwide have established specific regulations for drone formation operations, and the standard system lags far behind technological development.

International regulatory bodies have begun addressing UAV integration into controlled airspace. ICAO's Manual on Remotely Piloted Aircraft Systems [153] establishes baseline operational procedures and safety standards, though formation-specific guidance remains limited. The U.S. Federal Aviation Administration's UAS Integration Roadmap [154] outlines a phased approach to enabling routine

UAV operations, with formation flight identified as a medium-term milestone requiring additional safety analysis. The European Union Aviation Safety Agency (EASA) has published Acceptable Means of Compliance for UAS operations [155], providing regulatory clarity for commercial applications while emphasizing risk-based approaches to certification.

In China, the "Interim Regulation on the Flight Management of Unmanned Aircraft," implemented on January 1, 2024, has established a comprehensive legal framework. It specifically regulates collaborative flight activities and airspace usage approvals, providing clear compliance standards for large-scale formation operations.

Clothier et al. [161] proposed a comprehensive airworthiness certification framework for civil UAS, adapting manned aircraft standards to autonomous systems. Their framework addresses unique UAS risks including communication link loss, autonomous decision errors, and cyber vulnerabilities. For formations, additional considerations include collision risk within the formation, coordinated emergency procedures, and fail-safe behaviors when individual members malfunction.

Cybersecurity emerges as a critical concern for networked UAV systems. GPS spoofing attacks [24], communication jamming, and malware injection threaten both individual platforms and coordinated formations. Ferreira et al. [107] demonstrated software-defined radio-based counter-UAS systems capable of jamming and spoofing UAV control links, highlighting vulnerabilities that formation systems must address through encryption, authentication, and anomaly detection.

5.5 Application Domains

5.5.1 Military and Security Applications

The border patrol system deployed by the Israel Defense Forces adopts an innovative “swarm” tactic, enabling continuous monitoring capabilities for 24-hour non-stop patrols through a formation rotation mechanism of eight drones. Its maximum tracking speed can reach 200km/h, effectively dealing with fast-moving targets. In addition, in mountainous environments with an altitude difference of over 1,000 meters, it can still maintain a positioning accuracy of $\pm$1.5 meters [157].

Park et al. [23] developed differential game-based air combat maneuver generation using scoring function matrices, applicable to coordinated offensive and defensive formations. Vásárhelyi et al. [24] demonstrated outdoor flocking and formation flight with autonomous aerial robots, validating collision avoidance and cohesion maintenance under real-world wind and GPS noise conditions. These capabilities extend to cooperative reconnaissance, electronic warfare, and suppression of enemy air defenses (SEAD), where formations can overwhelm defenses through saturation tactics or provide mutual support against threats.

5.5.2 Civilian and Commercial Applications

Fixed-wing UAV formations are widely used in civilian applications including large-area mapping, forest fire monitoring, and power-line inspection; and emergency scenarios like disaster assessment, communications relay, and material delivery [158].

Watts et al. [155] classified UAS applications in remote sensing and scientific research, identifying formation-enabled missions such as stereoscopic terrain mapping and distributed atmospheric sampling. Villa et al. [156] surveyed small UAVs for air quality measurements, noting that formation flights enable simultaneous multi-point sampling for understanding pollutant dispersion. Erdelj et al. [157] examined wireless sensor networks and multi-UAV systems for natural disaster management, highlighting formation coordination for rapid damage assessment and survivor localization.

In precision agriculture, fixed-wing formation technology is driving the transformation of plant protection operations. Test data from DJI Agriculture [152] in 2023 shows that a 10-UAV formation can cover an area of up to 133 hectares ($\approx$2,000 mu) in a single day, increase the uniformity of pesticide application by 40%, reduce comprehensive operating costs by 35%, and decrease pesticide usage by 25%.

Fixed-wing UAV formations automatically optimize their flight trajectories based on terrain and crop distribution, and precisely control the dosage of pesticides through multi-aircraft collaboration. Kim et al. [144] developed smart spraying systems for UAV swarms that adapt application rates based on vegetation indices measured during flight, demonstrating technological innovation breakthroughs in agricultural environments.

5.6 Future Research Directions

The future development of fixed-wing UAV formation technology is expected to advance along three major directions: intelligent autonomous cooperative control, novel communication and navigation systems, and cross-domain collaborative operations.Intelligent Autonomous Control: Deep reinforcement learning will be employed to achieve dynamic task allocation and autonomous decision-making [84–106]. Current RL successes in simulated environments must be extended to handle the full complexity of real-world flight, including aerodynamic uncertainties, sensor noise, and adversarial conditions. Sim-to-real transfer techniques [94, 96–99] will become increasingly sophisticated, incorporating physics-informed priors and online adaptation mechanisms. Meta-learning approaches [107, 108] promise rapid adaptation to novel mission profiles and environmental conditions with minimal real-world data. Communication and Navigation Breakthroughs: Terahertz communications offer 10-100× bandwidth improvements over current RF systems, enabling real-time sharing of high-resolution sensor data for cooperative perception [19]. Pulsar navigation and quantum inertial systems [125] will address positioning challenges in highly contested environments where GPS is denied or spoofed. Delay-tolerant networking protocols [56–59] will enable formation coordination with intermittent connectivity, critical for beyond-line-of-sight operations and urban environments with frequent link breaks. Cross-Domain Collaboration: The development of heterogeneous platform collaboration frameworks [148–152] will enable joint operations among UAVs, manned aircraft, and ground equipment. Standardized interfaces and protocols [22, 153–161] will facilitate interoperability across manufacturers and mission systems. Human-machine teaming architectures will leverage human judgment for high-level reasoning while delegating precision execution and tireless vigilance to autonomous systems [162]. Bio-Inspired and Quantum Technologies: Bio-inspired swarm algorithms [2, 100, 101] will significantly enhance system adaptability, drawing on millions of years of evolutionary optimization in natural flocking and schooling behaviors. Quantum technologies extend beyond navigation to include quantum communications for unhackable data links and quantum sensing for unprecedented measurement precision. Quantum encryption communication will enhance system security against sophisticated cyber threats.Sustainability and Energy Innovation: New energy technologies—including advanced batteries, hydrogen fuel cells, and solar augmentation—will substantially extend mission endurance [23, 140, 141, 163]. Aerodynamic formation optimization will exploit wake interactions to reduce overall drag [164], potentially enabling transoceanic flights and persistent area coverage. Energy-aware mission planning will jointly optimize paths, speeds, and formation geometry to maximize range and endurance.

Together, these developments will drive fixed-wing UAV formations toward greater intelligence, robustness, and persistence in complex mission environments, enabling applications that are currently infeasible with existing technology.

Data Availability Statement

Not applicable.

Funding

This work was supported by the National Key R&D Program of China under Grant 2022YFB3902602.

Conflicts of Interest

Wei Li and Tiejun Liu are affiliated with the Honeycomb Aerospace Technologies (Beijing) Co., Ltd., Beijing 100071, China. The authors declare that this affiliation had no influence on the study design, data collection, analysis, interpretation, or the decision to publish, and that no other competing interests exist.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

References

[1] Grand View Research. (2025). Drone market size, share & trends analysis report by component (hardware, software, services), by product, by technology, by payload capacity, by power source, by end use, by region, and segment forecasts, 2025–2030 [Market research report overview]. Retrieved November 11, 2025, from https://www.grandviewresearch.com/industry-analysis/drone-market-report

[2] Reynolds, C. W. (1987, August). Flocks, herds and schools: A distributed behavioral model. In *Proceedings of the 14th annual conference on*

Computer graphics and interactive techniques (pp. 25-34). [CrossRef]

[3] Jadbabaie, A., Lin, J., & Morse, A. S. (2003). Coordination of groups of mobile autonomous agents using nearest neighbor rules. *IEEE Transactions on Automatic Control, 48*(6), 988–1001. [CrossRef]

[4] Olfati-Saber, R., Fax, J. A., & Murray, R. M. (2007). Consensus and cooperation in networked multi-agent systems. *Proceedings of the IEEE, 95*(1), 215-233. [CrossRef]

[5] Fax, J. A., & Murray, R. M. (2004). Information flow and cooperative control of vehicle formations. *IEEE transactions on automatic control, 49*(9), 1465-1476. [CrossRef]

[6] Ren, W., Beard, R. W., & Atkins, E. M. (2007). Information consensus in multivehicle cooperative control. *IEEE Control Systems Magazine, 27*(2), 71–82. [CrossRef]

[7] Cao, Y., Yu, W., Ren, W., & Chen, G. (2012). An overview of recent progress in the study of distributed multi-agent coordination. *IEEE Transactions on Industrial informatics, 9*(1), 427-438. [CrossRef]

[8] Murray, R. M. (2007). Recent research in cooperative control of multivehicle systems. *Journal of Dynamic Systems, Measurement, and Control, 129*(5), 571–583. [CrossRef]

[9] Bullo, F., Cortés, J., & Martinez, S. (2009). *Distributed control of robotic networks: a mathematical approach to motion coordination algorithms*. Princeton University Press. [CrossRef]

[10] Mesbahi, M., & Egerstedt, M. (2010). *Graph theoretic methods in multiagent networks*. Princeton University Press. [CrossRef]

[11] Fiedler, M. (1973). Algebraic connectivity of graphs. *Czechoslovak Mathematical Journal, 23*(2), 298–305.

[12] Do, H. T., Hua, H. T., Nguyen, M. T., Nguyen, C. V., Nguyen, H. T., Nguyen, H. T., & Nguyen, N. T. (2021). Formation Control Algorithms for Multiple-UAVs: A Comprehensive Survey. *EAI Endorsed Trans. Ind. Networks Intell. Syst., 8*(27), e3. [CrossRef]

[13] McLain, T., & Beard, R. (2000, August). Trajectory planning for coordinated rendezvous of unmanned air vehicles. In *AIAA Guidance, navigation, and control conference and exhibit* (p. 4369). [CrossRef]

[14] Alonso-Mora, J., Montijano, E., Schwager, M., & Rus, D. (2016, May). Distributed multi-robot formation control among obstacles: A geometric and optimization approach with consensus. In *2016 IEEE international conference on robotics and automation (ICRA)* (pp. 5356-5363). IEEE. [CrossRef]

[15] Hu, T. Y., & Li, Z. Y. (2024). A multi-agent deep reinforcement learning approach for traffic signal coordination. *IET Intelligent Transport Systems, 18*(8), 1428-1444. [CrossRef]

[16] Oh, K. K., Park, M. C., & Ahn, H. S. (2015). A survey of multi-agent formation control. *Automatica, 53*, 424–440. [CrossRef]

[17] Khuwaja, A. A., Chen, Y., Zhao, N., Alouini, M. S., & Dobbins, P. (2018). A survey of channel modeling for UAV communications. *IEEE Communications Surveys & Tutorials, 20*(4), 2804-2821. [CrossRef]

[18] Loquercio, A., Kaufmann, E., Ranftl, R., Müller, M., Koltun, V., & Scaramuzza, D. (2021). Learning high-speed flight in the wild. *Science Robotics, 6*(59), eabg5810. [CrossRef]

[19] Ferrante, E., Turgut, A. E., Dorigo, M., & Huepe, C. (2013). Elasticity-based mechanism for the collective motion of self-propelled particles with springlike interactions: a model system for natural and artificial swarms. *Physical review letters, 111*. [CrossRef]

[20] Wuerll, R., Robert, J., & Heuberger, A. (2019, March). An overview of current and proposed communication standards for large deployment of Unmanned Aircraft Systems. In *2019 IEEE Aerospace Conference* (pp. 1-7). IEEE. [CrossRef]

[21] ZHANG, Y., Meiyan, D. I. N. G., Yao, Y. U. A. N., ZHANG, J., Qiming, Y. A. N. G., Guoqing, S. H. I., & JIANG, J. (2025). Large-scale UAV swarm path planning based on mean-field reinforcement learning. *Chinese Journal of Aeronautics*, 103484. [CrossRef]

[22] Cordesman, A. H. (2022). *Gulf and Iran's Capability for Asymmetric Warfare*. Center for Strategic and International Studies (CSIS).

[23] Park, H., Lee, B. Y., Tahk, M. J., & Yoo, D. W. (2016). Differential game based air combat maneuver generation using scoring function matrix. *International Journal of Aeronautical and Space Sciences, 17*(2), 204-213. [CrossRef]

[24] Vásárhelyi, G., Virágh, C., Somorjai, G., Tarcai, N., Szörényi, T., Nepusz, T., & Vicsek, T. (2014, September). Outdoor flocking and formation flight with autonomous aerial robots. In *2014 IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 3866-3873). IEEE. [CrossRef]

[25] Desai, J. P., Ostrowski, J. P., & Kumar, V. (2002). Modeling and control of formations of nonholonomic mobile robots. *IEEE transactions on Robotics and Automation, 17*(6), 905-908. [CrossRef]

[26] Zhang, J., Yan, J., Zhang, P., & Kong, X. (2018). Collision avoidance in fixed-wing UAV formation flight based on a consensus control algorithm. *IEEE access, 6*, 43672-43682. [CrossRef]

[27] Farooq, A., Xiang, Z., Chang, W. J., & Aslam, M. S. (2025). Recent Advancement in Formation Control of Multi-Agent Systems: A Review. Computers, *Materials & Continua, 83*(3). [CrossRef]

[28] Xu, Y., Xin, M., & Wang, J. (2011, August). Unmanned aerial vehicle formation flight via a hierarchical cooperative control approach. In *AIAA Guidance, Navigation, and Control Conference* (p. 6329). [CrossRef]

[29] Hrabia, C. E., Lützenberger, M., & Albayrak, S. (2018). Towards adaptive multi-robot systems: Self-organization and self-adaptation. *The Knowledge Engineering Review, 33*, e16. [CrossRef]

[30] Dimarogonas, D. V., & Johansson, K. H. (2009, December). Event-triggered control for multi-agent systems. In *Proceedings of the 48h IEEE Conference on Decision and Control (CDC) held jointly with 2009 28th Chinese Control Conference* (pp. 7131-7136). IEEE. [CrossRef]

[31] Pratama, R., Nugroho, D., Setiawan, F., & Islam, A. (2025). Event-Triggered Swarm Optimization of Formation Control Policies for Unmanned Aerial Vehicle Networks with Limited Bandwidth. *Archives of Interdisciplinary Science and Engineering Research, 15*(10), 1-14.

[32] Lewis, F. L., Zhang, H., Hengster-Movric, K., & Das, A. (2014). Algebraic graph theory and cooperative control consensus. In *Cooperative control of multi-agent systems: Optimal and adaptive design approaches* (pp. 23-71). London: Springer London. [CrossRef]

[33] Royle, G. F., & Godsil, C. (2001). *Algebraic graph theory* (Vol. 207). New York: Springer. [CrossRef]

[34] Horn, R. A., & Johnson, C. R. (2012). *Matrix analysis* (2nd ed.). Cambridge University Press. [CrossRef]

[35] Zhang, J., Wang, W., Zhang, Z., Luo, K., & Liu, J. (2019, July). Cooperative control of UAV cluster formation based on distributed consensus. In *2019 IEEE 15th International Conference on Control and Automation (ICCA)* (pp. 788-793). IEEE. [CrossRef]

[36] Cortés, J., Martínez, S., & Bullo, F. (2006). Robust rendezvous for mobile autonomous agents via proximity graphs in arbitrary dimensions. *IEEE Transactions on Automatic Control, 51*(8), 1289–1298. [CrossRef]

[37] Belta, C., & Kumar, V. (2004). Abstraction and control for groups of robots. *IEEE Transactions on Robotics, 20*(5), 865–875. [CrossRef]

[38] Anderson, B. D. O., Yu, C., Fidan, B., & Hendrickx, J. M. (2008). Rigid graph control architectures for autonomous formations. *IEEE Control Systems Magazine, 28*(6), 48–63. [CrossRef]

[39] Lin, Z., Francis, B., & Maggiore, M. (2005). Necessary and sufficient graphical conditions for formation control of unicycles. *IEEE Transactions on Automatic Control, 50*(1), 121–127. [CrossRef]

[40] Tanner, H. G., Jadbabaie, A., & Pappas, G. J. (2007). Flocking in fixed and switching networks. *IEEE Transactions on Automatic Control, 52*(5), 863–868. [CrossRef]

[41] Jarraya, I., Al-Batati, A., Kadri, M. B., Abdelkader, M., Ammar, A., Boulila, W., & Koubaa, A. (2025). Gnss-denied unmanned aerial vehicle navigation: analyzing computational complexity, sensor fusion, and localization methodologies. *Satellite Navigation, 6*(1), 9. [CrossRef]

[42] Hayat, S., Yanmaz, E., & Muzaffar, R. (2016). Survey on unmanned aerial vehicle networks for civil applications: A communications viewpoint. *IEEE Communications Surveys & Tutorials, 18*(4), 2624–2661. [CrossRef]

[43] Mozaffari, M., Saad, W., Bennis, M., Nam, Y. H., & Debbah, M. (2019). A tutorial on UAVs for wireless networks: Applications, challenges, and open problems. *IEEE Communications Surveys & Tutorials, 21*(3), 2334–2360. [CrossRef]

[44] Gharibi, M., Boutaba, R., & Waslander, S. L. (2016). Internet of drones. *IEEE Access, 4*, 1148–1162. [CrossRef]

[45] Sahingoz, O. K. (2014). Networking models in flying ad-hoc networks (FANETs): Concepts and challenges. *Journal of Intelligent & Robotic Systems, 74*(1), 513–527. [CrossRef]

[46] Bekmezci, İ., Sahingoz, O. K., & Temel, Ş. (2013). Flying ad-hoc networks (FANETs): A survey. *Ad Hoc Networks, 11*(3), 1254–1270. [CrossRef]

[47] Asadpour, M., Van den Bergh, B., Giustiniano, D., Hummel, K. A., Pollin, S., & Plattner, B. (2014). Micro aerial vehicle networks: An experimental analysis of challenges and opportunities. *IEEE Communications Magazine, 52*(7), 141-149. [CrossRef]

[48] Fall, K. (2003, August). A delay-tolerant network architecture for challenged internets. In *Proceedings of the 2003 conference on Applications, technologies, architectures, and protocols for computer communications* (pp. 27-34). [CrossRef]

[49] Spyropoulos, T., Psounis, K., & Raghavendra, C. S. (2005, August). Spray and wait: an efficient routing scheme for intermittently connected mobile networks. In *Proceedings of the 2005 ACM SIGCOMM workshop on Delay-tolerant networking* (pp. 252-259). [CrossRef]

[50] Goudarzi, S., Kama, N., Anisi, M. H., Zeadally, S., & Mumtaz, S. (2019). Data collection using unmanned aerial vehicles for Internet of Things platforms. *Computers & Electrical Engineering, 75*, 1-15. [CrossRef]

[51] Sharma, V., Srinivasan, K., Chao, H. C., Hua, K. L., & Cheng, W. H. (2017). Intelligent deployment of UAVs in 5G heterogeneous communication environment for improved coverage. *Journal of Network and Computer Applications, 85*, 94-105. [CrossRef]

[52] Balch, T., & Arkin, R. C. (1998). Behavior-based formation control for multirobot teams. *IEEE Transactions on Robotics and Automation, 14*(6), 926–939. [CrossRef]

[53] Raj, R., & Kos, A. (2022). A comprehensive study of mobile robot: history, developments, applications, and future research perspectives. *Applied Sciences, 12*(14), 6951. [CrossRef]

[54] Lewis, M. A., & Tan, K. H. (1997). High precision formation control of mobile robots using virtual structures. *Autonomous Robots, 4*(4), 387–403.

[CrossRef]

[55] Ren, W., & Beard, R. W. (2004). Formation feedback control for multiple spacecraft via virtual structures. *IEE Proceedings - Control Theory and Applications, 151*(3), 357–368. [CrossRef]

[56] Beard, R. W., Lawton, J., & Hadaegh, F. Y. (2001). A coordination architecture for spacecraft formation control. *IEEE Transactions on Control Systems Technology, 9*(6), 777–790. [CrossRef]

[57] Askari, A., Mortazavi, M., & Talebi, H. A. (2015). UAV formation control via the virtual structure approach. *Journal of Aerospace Engineering, 28*(1), 04014047. [CrossRef]

[58] Kuriki, Y., & Namerikawa, T. (2014). Formation control of UAVs with a fourth-order flight dynamics. *SICE Journal of Control, Measurement, and System Integration, 7*(2), 74-81. [CrossRef]

[59] Consolini, L., Morbidi, F., Prattichizzo, D., & Tosques, M. (2008). Leader–follower formation control of nonholonomic mobile robots with input constraints. *Automatica, 44*(5), 1343-1349. [CrossRef]

[60] Dong, X., Yu, B., Shi, Z., & Zhong, Y. (2014). Time-varying formation control for unmanned aerial vehicles: Theories and applications. *IEEE Transactions on Control Systems Technology, 23*(1), 340-348. [CrossRef]

[61] Peng, Z., Wang, D., Chen, Z., Hu, X., & Lan, W. (2013). Adaptive dynamic surface control for formations of autonomous surface vehicles with uncertain dynamics. *IEEE Transactions on Control Systems Technology, 21*(2), 513–520. [CrossRef]

[62] Arrichiello, F., Chiaverini, S., & Fossen, T. I. (2006, October). Formation control of underactuated surface vessels using the null-space-based behavioral control. In *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 5942-5947). IEEE. [CrossRef]

[63] Wang, J., & Xin, M. (2013). Integrated optimal formation control of multiple unmanned aerial vehicles. *IEEE Transactions on Control Systems Technology, 21*(5), 1731–1744. [CrossRef]

[64] Venkat, A. N., Hiskens, I. A., Rawlings, J. B., & Wright, S. J. (2008). Distributed MPC strategies with application to power system automatic generation control. *IEEE transactions on control systems technology, 16*(6), 1192-1206. [CrossRef]

[65] Dunbar, W. B., & Murray, R. M. (2006). Distributed receding horizon control for multi-vehicle formation stabilization. *Automatica, 42*(4), 549-558. [CrossRef]

[66] Keviczky, T., Borrelli, F., & Balas, G. J. (2006). Decentralized receding horizon control for large scale dynamically decoupled systems. *Automatica, 42*(12), 2105-2115. [CrossRef]

[67] Richards, A., & How, J. P. (2007). Robust distributed model predictive control. *International Journal of control, 80*(9), 1517-1531. [CrossRef]

[68] Dunbar, W. B. (2007). Distributed receding horizon control of dynamically coupled nonlinear systems. *IEEE Transactions on Automatic Control, 52*(7), 1249-1263. [CrossRef]

[69] Maestre, J. M., & Negenborn, R. R. (Eds.). (2014). *Distributed model predictive control made easy*. Springer. [CrossRef]

[70] Giselsson, P., & Rantzer, A. (2010, December). Distributed model predictive control with suboptimality and stability guarantees. In *49th IEEE Conference on Decision and Control (CDC)* (pp. 7272-7277). IEEE. [CrossRef]

[71] Shtessel, Y., Edwards, C., Fridman, L., & Levant, A. (2014). *Sliding mode control and observation* (Vol. 10). New York: Springer New York. [CrossRef]

[72] Liu, J., Sun, M., Chen, Z., & Sun, Q. (2020). Super-twisting sliding mode control for aircraft at high angle of attack based on finite-time extended state observer. *Nonlinear Dynamics, 99*(4), 2785-2799. [CrossRef]

[73] Utkin, V., Guldner, J., & Shi, J. (2009). *Sliding mode control in electro-mechanical systems* (2nd ed.). CRC Press. [CrossRef]

[74] Yu, X., & Kaynak, O. (2009). Sliding-mode control with soft computing: A survey. *IEEE transactions on industrial electronics, 56*(9), 3275-3285. [CrossRef]

[75] Defoort, M., Floquet, T., Kokosy, A., & Perruquetti, W. (2008). Sliding-mode formation control for cooperative autonomous mobile robots. *IEEE Transactions on Industrial Electronics, 55*(11), 3944–3953. [CrossRef]

[76] Alwi, H., Edwards, C., & Tan, C. P. (2011). *Fault detection and fault-tolerant control using sliding modes* (pp. 7-28). London: Springer. [CrossRef]

[77] Lavretsky, E., & Wise, K. A. (2024). Robust adaptive control. In *Robust and adaptive control: With aerospace applications* (pp. 469-506). Cham: Springer International Publishing. [CrossRef]

[78] Ioannou, P. A., & Sun, J. (1996). *Robust adaptive control*. Prentice-Hall.

[79] Cao, C., & Hovakimyan, N. (2008). Design and analysis of a novel L1 adaptive control architecture with guaranteed transient performance. *IEEE Transactions on Automatic Control, 53*(2), 586–591. [CrossRef]

[80] Krstic, M., Kanellakopoulos, I., & Kokotovic, P. V. (1995). *Nonlinear and adaptive control design*. Wiley.

[81] Foerster, J., Farquhar, G., Afouras, T., Nardelli, N., & Whiteson, S. (2018, April). Counterfactual multi-agent policy gradients. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 32, No. 1). [CrossRef]

[82] Rashid, T., Samvelyan, M., De Witt, C. S., Farquhar, G., Foerster, J., & Whiteson, S. (2020). Monotonic value function factorisation for deep multi-agent reinforcement learning. *Journal of Machine Learning*

Research, 21(178), 1-51.

[83] Sunehag, P., Lever, G., Gruslys, A., Czarnecki, W. M., Zambaldi, V., Jaderberg, M., ... & Graepel, T. (2018, July). Value-Decomposition Networks For Cooperative Multi-Agent Learning Based On Team Reward. In *Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems* (pp. 2085-2087).

[84] Yu, C., Velu, A., Vinitsky, E., Gao, J., Wang, Y., Bayen, A., & Wu, Y. (2022). The surprising effectiveness of ppo in cooperative multi-agent games. *Advances in neural information processing systems, 35*, 24611-24624.

[85] Lowe, R., Wu, Y. I., Tamar, A., Harb, J., Pieter Abbeel, O., & Mordatch, I. (2017). Multi-agent actor-critic for mixed cooperative-competitive environments. *Advances in neural information processing systems, 30*.

[86] U.S. Air Force Test Pilot School & DARPA. (2024). *Autonomous air combat operations flight test on X-62A VISTA (ACE program)*. Retrieved from https://www.darpa.mil

[87] Tobin, J., Fong, R., Ray, A., Schneider, J., Zaremba, W., & Abbeel, P. (2017, September). Domain randomization for transferring deep neural networks from simulation to the real world. In *2017 IEEE/RSJ international conference on intelligent robots and systems (IROS)* (pp. 23-30). IEEE. [CrossRef]

[88] Peng, X. B., Andrychowicz, M., Zaremba, W., & Abbeel, P. (2018, May). Sim-to-real transfer of robotic control with dynamics randomization. In *2018 IEEE international conference on robotics and automation (ICRA)* (pp. 3803-3810). IEEE. [CrossRef]

[89] Chebotar, Y., Handa, A., Makoviychuk, V., Macklin, M., Issac, J., Ratliff, N., & Fox, D. (2019, May). Closing the sim-to-real loop: Adapting simulation randomization with real world experience. In *2019 International Conference on Robotics and Automation (ICRA)* (pp. 8973-8979). IEEE. [CrossRef]

[90] Muratore, F., Treede, F., Gienger, M., & Peters, J. (2018, October). Domain randomization for simulation-based policy optimization with transferability assessment. In *Conference on Robot Learning* (pp. 700-713). PMLR.

[91] Koch, W., Mancuso, R., West, R., & Bestavros, A. (2019). Reinforcement learning for UAV attitude control. *ACM Transactions on Cyber-Physical Systems, 3*(2), 1-21. [CrossRef]

[92] Hwangbo, J., Sa, I., Siegwart, R., & Hutter, M. (2017). Control of a quadrotor with reinforcement learning. *IEEE Robotics and Automation Letters, 2*(4), 2096-2103. [CrossRef]

[93] Liaq, M., & Byun, Y. (2019). Autonomous UAV Navigation Using Reinforcement Learning. *International Journal of Machine Learning and Computing, 9*(6). [CrossRef]

[94] Rodriguez-Ramos, A., Sampedro, C., Bavle, H., De La Puente, P., & Campoy, P. (2019). A deep reinforcement learning strategy for UAV autonomous landing on a moving platform. *Journal of Intelligent & Robotic Systems, 93*(1), 351-366. [CrossRef]

[95] Loquercio, A., Kaufmann, E., Ranftl, R., Müller, M., Koltun, V., & Scaramuzza, D. (2021). Learning high-speed flight in the wild. *Science Robotics, 6*(59), eabg5810. [CrossRef]

[96] Bauersfeld, L., & Scaramuzza, D. Accurate Dynamics Models for Agile Drone Flight: Zero-Shot Sim2Real-Transfer of Neural Controllers.

[97] Dey, S., & Xu, H. (2024). Distributed adaptive flocking control for large-scale multiagent systems. *IEEE Transactions on Neural Networks and Learning Systems, 36*(2), 3126-3135. [CrossRef]

[98] Lin, W., & Mak, M. W. (2023). Model-agnostic meta-learning for fast text-dependent speaker embedding adaptation. *IEEE/ACM Transactions on Audio, Speech, and Language Processing, 31*, 1866-1876. [CrossRef]

[99] Duan, Y., Schulman, J., Chen, X., Bartlett, P. L., Sutskever, I., & Abbeel, P. (2016). Rl \$^ 2\$: Fast reinforcement learning via slow reinforcement learning. *arXiv preprint arXiv:1611.02779*.

[100] Ho, J., & Ermon, S. (2016). Generative adversarial imitation learning. *Advances in neural information processing systems, 29*.

[101] Bojarski, M., Del Testa, D., Dworakowski, D., Firner, B., Flepp, B., Goyal, P., ... & Zieba, K. (2016). End to end learning for self-driving cars. *arXiv preprint arXiv:1604.07316*.

[102] Wang, C., Wang, J., Shen, Y., & Zhang, X. (2019). Autonomous navigation of UAVs in large-scale complex environments: A deep reinforcement learning approach. *IEEE Transactions on Vehicular Technology, 68*(3), 2124–2136. [CrossRef]

[103] Duan, H., & Qiao, P. (2014). Pigeon-inspired optimization: A new swarm intelligence optimizer for air robot path planning. *International Journal of Intelligent Computing and Cybernetics, 7*(1), 24–37. [CrossRef]

[104] Reynolds, C. W. (1999, March). Steering behaviors for autonomous characters. In *Game developers conference* (Vol. 1999, pp. 763-782).

[105] Jin, X., Ke, S., An, J., Wang, S., Pan, G., & Niyato, D. (2024). A novel consensus-based distributed time synchronization algorithm in high-dynamic multi-UAV networks. *IEEE Transactions on Wireless Communications*. [CrossRef]

[106] Yang, Y., Xiong, X., & Yan, Y. (2023). UAV formation trajectory planning algorithms: A review. *Drones, 7*(1), 62. [CrossRef]

[107] Ferreira, R., Gaspar, J., Sebastião, P., & Souto, N. (2022). A software defined radio based anti-UAV mobile system with jamming and spoofing capabilities. *Sensors, 22*(4), 1487. [CrossRef]

[108] ETH Zurich. (2020). *VINS-Fusion: A robust visual-inertial navigation system*. Retrieved from https://github.com/HKUST-Aerial-Robotics/VINS-Fusion

[109] Mur-Artal, R., & Tardós, J. D. (2017). Orb-slam2: An open-source slam system for monocular, stereo, and rgb-d cameras. *IEEE transactions on robotics, 33*(5), 1255-1262. [CrossRef]

[110] Leutenegger, S., Lynen, S., Bosse, M., Siegwart, R., & Furgale, P. (2015). Keyframe-based visual–inertial odometry using nonlinear optimization. *International Journal of Robotics Research, 34*(3), 314–334. [CrossRef]

[111] Bloesch, M., Omari, S., Hutter, M., & Siegwart, R. (2015, September). Robust visual inertial odometry using a direct EKF-based approach. In *2015 IEEE/RSJ international conference on intelligent robots and systems* (*IROS*) (pp. 298-304). IEEE. [CrossRef]

[112] Groves, P. D. (2013). *Principles of GNSS, inertial, and multisensor integrated navigation systems* (2nd ed.). Artech House.

[113] Sabatini, R., Moore, T., & Hill, C. (2016). Avionics-Based GNSS Integrity Augmentation for UAS mission planning and real-time trajectory optimisation. In *Proceedings of the 29th International Technical Meeting of the Satellite Division of The Institute of Navigation* (*ION GNSS+ 2016*) (pp. 1415-1431). [CrossRef]

[114] Mourikis, A. I., & Roumeliotis, S. I. (2007, April). A multi-state constraint Kalman filter for vision-aided inertial navigation. In *Proceedings 2007 IEEE international conference on robotics and automation* (pp. 3565-3572). IEEE. [CrossRef]

[115] Roumeliotis, S. I., & Bekey, G. A. (2002). Distributed multirobot localization. *IEEE transactions on robotics and automation, 18*(5), 781-795. [CrossRef]

[116] Vetrella, A. R., Fasano, G., Accardo, D., & Moccia, A. (2016). Differential GNSS and vision-based tracking to improve navigation performance in cooperative multi-UAV systems. *Sensors, 16*(12), 2164. [CrossRef]

[117] Nerurkar, E. D., Roumeliotis, S. I., & Martinelli, A. (2009, May). Distributed maximum a posteriori estimation for multi-robot cooperative localization. In *2009 IEEE International Conference on Robotics and Automation* (pp. 1402-1409). IEEE. [CrossRef]

[118] Howard, A., Matark, M. J., & Sukhatme, G. S. (2002, September). Localization for mobile robot teams using maximum likelihood estimation. In *IEEE/RSJ international conference on intelligent robots and systems* (Vol. 1, pp. 434-439). IEEE. [CrossRef]

[119] Qualcomm Technologies. (2024). *FastConnect 7900 mobile connectivity system* (*Wi-Fi 7 + Bluetooth + UWB*). Retrieved from https://www.qualcomm.com/products/technology/wi-fi/fastconnect/fastconnect-7900

[120] Wang, K., Cao, C., Ma, S., & Ren, F. (2021). An optimization-based multi-sensor fusion approach towards global drift-free motion estimation. *IEEE Sensors Journal, 21*(10), 12228-12235. [CrossRef]

[121] UK Ministry of Defence (Dstl). (2022). *Quantum inertial navigation systems: A defence evaluation*. Retrieved from https://www.gov.uk/government/organisations/defence-science-and-technology-laboratory

[122] Qualcomm Technologies, Inc. (n.d.). *UAV-to-UAV communication and relative positioning for V2X-based drone swarms*. Retrieved from https://www.qualcomm.com/content/dam/qcomm-martech/dm-assets/documents/uav-to-uav_communication_and_relative_positioning_for_v2x-based_drone_swarms.pdf

[123] Chen, X., Wang, Y., & Zhang, L. (2023). Dynamic obstacle avoidance for UAV swarms in complex environments. *Robotics and Autonomous Systems, 159*, 104321. [CrossRef]

[124] Herbert, S. L., Chen, M., Han, S., Bansal, S., Fisac, J. F., & Tomlin, C. J. (2017, December). FaSTrack: A modular framework for fast and guaranteed safe motion planning. In *2017 IEEE 56th Annual Conference on Decision and Control* (*CDC*) (pp. 1517-1522). IEEE. [CrossRef]

[125] LaValle, S. M. (1998). *Rapidly-exploring random trees: A new tool for path planning* (Technical Report No. 98-11). Iowa State University, Department of Computer Science.

[126] Karaman, S., & Frazzoli, E. (2011). Sampling-based algorithms for optimal motion planning. *The international journal of robotics research, 30*(7), 846-894. [CrossRef]

[127] Gammell, J. D., Srinivasa, S. S., & Barfoot, T. D. (2014, September). Informed RRT*: Optimal sampling-based path planning focused via direct sampling of an admissible ellipsoidal heuristic. In *2014 IEEE/RSJ international conference on intelligent robots and systems* (pp. 2997-3004). IEEE. [CrossRef]

[128] Khatib, O. (1986). Real-time obstacle avoidance for manipulators and mobile robots. *International Journal of Robotics Research, 5*(1), 90–98. [CrossRef]

[129] Ge, S. S., & Cui, Y. J. (2002). Dynamic motion planning for mobile robots using potential field method. *Autonomous Robots, 13*(3), 207–222. [CrossRef]

[130] Park, M. G., Jeon, J. H., & Lee, M. C. (2001, June). Obstacle avoidance for mobile robots using artificial potential field approach with simulated annealing. In *ISIE 2001. 2001 IEEE International Symposium on Industrial Electronics Proceedings* (*Cat. No. 01TH8570*) (Vol. 3, pp. 1530-1535). IEEE. [CrossRef]

[131] Fiorini, P., & Shiller, Z. (1998). Motion planning in dynamic environments using velocity obstacles. *International Journal of Robotics Research, 17*(7), 760–772. [CrossRef]

[132] Van den Berg, J., Lin, M., & Manocha, D. (2008, May). Reciprocal velocity obstacles for real-time multi-agent navigation. *2008 IEEE International Conference on Robotics and Automation*, Pasadena, CA, United States. 1928–1935. [CrossRef]

[133] Beijing Institute of Technology. (2022). Path planning algorithm for UAVs based on improved RRT. *Acta Automatica Sinica, 48*(3), 1–10.

[134] Feng, L., & Katupitiya, J. (2022). UAV-based persistent full area coverage with dynamic priorities. *Robotics and Autonomous Systems, 157*, 104244. [CrossRef]

[135] Amazon Science. (2022). *Prime Air's approach to efficient long-range delivery*. Retrieved from https://www.amazon.science/latest-news/prime-airs-approach-to-efficient-long-range-delivery

[136] Dorling, K., Heinrichs, J., Messier, G. G., & Magierowski, S. (2017). Vehicle routing problems for drone delivery. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 47*(1), 70–85. [CrossRef]

[137] Di Franco, C., & Buttazzo, G. (2015, April). Energy-aware coverage path planning of UAVs. *2015 IEEE International Conference on Autonomous Robot Systems and Competitions*, Vila Real, Portugal. 111–117. [CrossRef]

[138] Zeng, Y., & Zhang, R. (2017). Energy-efficient UAV communication with trajectory optimization. *IEEE Transactions on Wireless Communications, 16*(6), 3747–3760. [CrossRef]

[139] Safwat, E., Reda, M., & Kamel, A. M. (2025). Model-based simulation and validation of small fixed wing UAV. *Journal of Engineering Science and Military Technologies, 9*(1), 33-51.

[140] Qu, C., Sorbelli, F. B., Singh, R., Calyam, P., & Das, S. K. (2023). Environmentally-aware and energy-efficient multi-drone coordination and networking for disaster response. *IEEE transactions on network and service management, 20*(2), 1093-1109. [CrossRef]

[141] Stolaroff, J. K., Samaras, C., O'Neill, E. R., Lubers, A., Mitchell, A. S., & Ceperley, D. (2018). Energy use and life cycle greenhouse gas emissions of drones for commercial package delivery. *Nature Communications, 9*(1), 409. [CrossRef]

[142] Chung, S. J., Paranjape, A. A., Dames, P., Shen, S., & Kumar, V. (2018). A survey on aerial swarm robotics. *IEEE Transactions on Robotics, 34*(4), 837–855. [CrossRef]

[143] Otto, A., Agatz, N., Campbell, J., Golden, B., & Pesch, E. (2018). Optimization approaches for civil applications of unmanned aerial vehicles (UAVs) or aerial drones: A survey. *Networks, 72*(4), 411-458. [CrossRef]

[144] Kim, J., Kim, S., Ju, C., & Son, H. I. (2019). Unmanned aerial vehicles in agriculture: A review of perspective of platform, control, and applications. *IEEE Access, 7*, 105100-105115. [CrossRef]

[145] Zhang, T., Yu, D., Cheong, K. H., Liu, Y., & Wang, Z. (2025). Hierarchical Distributed Strategy for Autonomous UAV Swarm Formation Aggregation. *IEEE Transactions on Vehicular Technology*. [CrossRef]

[146] Yan, Z., Jouandeau, N., & Cherif, A. A. (2013). A survey and analysis of multi-robot coordination. *International Journal of Advanced Robotic Systems, 10*(12), 399. [CrossRef]

[147] Nigam, N., Bieniawski, S., Kroo, I., & Vian, J. (2011). Control of multiple UAVs for persistent surveillance: Algorithm and flight test results. *IEEE transactions on control systems technology, 20*(5), 1236-1251. [CrossRef]

[148] Kuriki, Y., & Namerikawa, T. (2014, June). Consensus-based cooperative formation control with collision avoidance for a multi-UAV system. *2014 American Control Conference*, Portland, OR, United States. 2077–2082. [CrossRef]

[149] Freeman, R. A., Yang, P., & Lynch, K. M. (2006, December). Stability and convergence properties of dynamic average consensus estimators. In *Proceedings of the 45th IEEE Conference on Decision and Control* (pp. 338-343). IEEE. [CrossRef]

[150] Seuret, A., Dimarogonas, D. V., & Johansson, K. H. (2008, December). Consensus under communication delays. *47th IEEE Conference on Decision and Control*, Cancun, Mexico. 4922–4927. [CrossRef]

[151] Basescu, M., Polevoy, A., Yeh, B., Scheuer, L., Sutton, E., & Moore, J. (2024). Agile fixed-wing UAVs for urban swarm operations. *IEEE Transactions on Field Robotics*. [CrossRef]

[152] DJI Agriculture. (2023). *Precision agriculture report 2023*. Retrieved from https://ag.dji.com

[153] Salam, A., Javaid, Q., & Ahmad, M. (2021). Bio-inspired cluster–based optimal target identification using multiple unmanned aerial vehicles in smart precision agriculture. *International Journal of Distributed Sensor Networks, 17*(7), 15501477211034071. [CrossRef]

[154] Ren, W., & Beard, R. W. (2008). *Distributed consensus in multi-vehicle cooperative control: theory and applications*. London: Springer London. [CrossRef]

[155] Watts, A. C., Ambrosia, V. G., & Hinkley, E. A. (2012). Unmanned aircraft systems in remote sensing and scientific research: Classification and considerations of use. *Remote sensing, 4*(6), 1671-1692. [CrossRef]

[156] Villa, T. F., Gonzalez, F., Miljievic, B., Ristovski, Z. D., & Morawska, L. (2016). An overview of small unmanned aerial vehicles for air quality measurements: Present applications and future prospectives. *Sensors, 16*(7), 1072. [CrossRef]

[157] Erdelj, M., Król, M., & Natalizio, E. (2017). Wireless sensor networks and multi-UAV systems for natural disaster management. *Computer Networks, 124*, 72–86. [CrossRef]

[158] International Civil Aviation Organization. (2015). *Manual on remotely piloted aircraft systems (RPAS)* (Doc 10019 AN/507).

[159] Federal Aviation Administration. (2018). *Integration of civil unmanned aircraft systems (UAS) in the National*

Airspace System (NAS) roadmap (2nd ed.).

[160] European Union Aviation Safety Agency. (2019). *Acceptable means of compliance (AMC) and guidance material (GM) to Commission Implementing Regulation (EU) 2019/947*.

[161] Clothier, R. A., Palmer, J. L., Walker, R. A., & Fulton, N. L. (2011). Definition of an airworthiness certification framework for civil unmanned aircraft systems. *Safety Science*, *49*(6), 871–885. [CrossRef]

[162] Stefan, N., & Axel, S. (2025, May). The Impact of HAT on Team Dynamics and Coordination: A Teaming-Oriented Study for MUM-T. In *2025 IEEE 5th International Conference on Human-Machine Systems (ICHMS)* (pp. 465-470). IEEE. [CrossRef]

[163] Chen, P., Shang, M., Liu, K., Zhu, L., Wang, S., Fu, Y., ... & Qing, Q. (2024, December). Application of Carbon Dioxide Energy Storage Technology Based on New Energy Atmospheric Pressure Flexible Gas Film Storage Bin: Take Xinjiang Region as a Case. In *2024 Boao New Power System International Forum-Power System and New Energy Technology Innovation Forum (NPSIF)* (pp. 228-231). IEEE. [CrossRef]

[164] Ma, L., Hu, C., Yu, J., Wen, S., & Wang, L. (2025). Distributed optimization-based fixed-time formation control with external disturbances: an event-based intermittent approach. *Nonlinear Dynamics*, 1-16. [CrossRef]

Wei Li Chairman of Honeycomb Aerospace Technologies (Beijing) Co., Ltd., Associate Professor, Doctor of Engineering. In the professional domain, he holds multiple important academic and industrial positions: Vice Chairman of the UAV Professional Committee of the Beihang University Alumni General Aviation Association, Member of the Unmanned System Professional Committee of the Chinese Association of Command and Control, and Executive Committee Member of the UAV Special Committee of the China Air Transport Association. These roles have enabled him to exert a significant influence in the industry.In terms of scientific research, he has achieved remarkable results. To date, he has secured over 100 authorized Chinese patents, making outstanding contributions to advancing technological innovation and development in the UAV industry. (Email: liwei@honeycombs.com)

Jinbiao Zhu Jinbiao Zhureceived the bachelor's degree from North China Electric Power University, BaoDing, China, in 2000 ,the Master's degree from Tsinghua University, BeiJing, China, in 2008, and the Ph.D. degree from Northwestern Polytechnical University, Xi'an, China, in 2025. He is currently a professor in Aerospace Information Research Institute, Chinese Academy of Sciences. He research interests include synthetic aperture radar, artificial intelligence, remote sensing image processing. (Email: zhujb@aircas.ac.cn)

Tiejun Liu He has successively held key management and technical positions in well-known aerospace and aviation institutions, including Director of the Special Aircraft Research Institute of Shenyang Aerospace Xinguang Group, Technical Deputy Director of the UAV Technology Research Institute of the Third Academy of China Aerospace Science and Industry Corporation, and Chief Engineer & Technical Director of Haiying Aviation General Equipment Co., Ltd. His professional focus lies in aircraft overall design and the integrated application of air-space-ground data. (Email: liutj@hcuav.com)

Fan Ni , employed at the Aerospace Information Research Institute of the Chinese Academy of Sciences, has participated in multiple national key research and development projects.

Yiheng Liu holds a Bachelor degree of Engineering in Mechatronics from Zhejiang University and a Master degree of Science in Electrical Engineering from Columbia University. His academic interests span robotics, autonomous systems, and applied machine learning. He is committed to rigorous analysis and strives to contribute clear, well-founded perspectives to the research community. (Email: yl5354@columbia.edu)

Guoliang Liu holds a Master's degree from Qilu University of Technology and works at the Huzhou Institute of Zhejiang University. His research focuses on embedded systems, robotics, and control theory, with a commitment to solving practical technical challenges in the industry. (Email: GLLiu0524@163.com)