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Survey Paper

# From PID to swarms: A decade of advancements in drone control and path planning - A systematic review (2013–2023)

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ABSTRACT

This systematic literature review synthesizes and evaluates existing research on drone control and path planning, encompassing the principles of swarm intelligence and nature-inspired algorithms. However, it is not limited to these; it also explores other algorithms to provide a comprehensive overview of the state-of-the-art in this rapidly evolving field. The review identifies and analyzes key trends, challenges, and advancements in drone control and path planning. It investigates the evolution of control strategies, ranging from classical proportional-integral-derivative (PID) controllers to modern swarm algorithms and reinforcement learning-based techniques. Additionally, it explores path planning methodologies, including traditional optimization algorithms and heuristic-based approaches, and specifically, swarm algorithms within the context of drone swarms. The emphasis on nature-inspired intelligent computation extends to the exploration of swarm intelligence and cooperative planning as integral components of drone path planning. By synthesizing and critically analyzing the literature, this systematic review not only presents a comprehensive understanding of the current landscape of drone control and path planning, but it also acknowledges the role of various nature-inspired algorithms, including but not limited to swarm intelligence, and identifies avenues for future research in this evolving field.

## 1. Introduction

While the development of Unmanned Aerial Vehicles/Unmanned aerial systems (UAVs/UASs) traces its origins back to the early 1900s [1], research in this field began to gain momentum around 2012–2013 [2] (see Fig. 1). In recent years, the integration of UAVs into various industries has seen remarkable growth and transformation. As of October 2023, there were 863,728 drones registered in the United States by the federal aviation administration (FAA) [3]. This number is expected to be around 955,000 by 2027 [4]. From precision agriculture [5,6] and environmental monitoring [7] to surveillance and disaster response [8,9], these versatile aerial platforms have transformed the way tasks are executed. Their ability to navigate complex environments and execute challenging missions depends on how they are controlled, and how paths are planned.

The connection between drone control and path planning is like a fundamental building block in the world of UAS. They are so tightly linked that thinking about one without the other is almost impossible. Drones have diverse uses as mentioned above, and their success relies on how well control and path planning work together. In a world where drones are increasingly vital, understanding how these two elements are interdependent is key, as they form the foundation for the safe and effective use of drones.

Drone control and path planning encompass the algorithms, strategies, and methodologies that empower these autonomous or semi-autonomous vehicles to operate efficiently, safely, and effectively. Drone control focuses on the dynamic management of UAVs during flight, ensuring stability and responsive maneuvering. Path planning, on the other hand, involves the intellectual coordination of selecting optimal routes for drones as they traverse intricate terrains, negotiate obstacles, and achieve mission objectives. Effective control and path planning are pivotal to the success and safety of drone missions [10]. Whether a drone is conducting a search and rescue operation in a disaster-stricken area, inspecting critical infrastructure, or delivering packages to doorstep destinations, the quality of control and path planning directly influences mission outcomes. Moreover, drone control and path planning rely on a wide range of techniques and technologies. Control algorithms stabilize UAVs, enabling precise flight and responsiveness. Path planning algorithms analyze environmental data, employ obstacle detection systems, and facilitate real-time decision-making.

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Machine learning and artificial intelligence are increasingly used to enhance both control and path planning [11–13], allowing drones to learn from experience and adapt to changing conditions.

With the increase in drone usage, drone swarms are becoming more popular. The coordination of multiple drones in swarms, facilitated by advanced control and path planning algorithms [14], revolutionizes aerial operations. These swarms enhance capabilities across various domains, such as search and rescue, environmental monitoring, and more. By working collaboratively, swarms cover larger areas, respond faster, and achieve mission objectives with unprecedented efficiency, making them a game-changing innovation in the world of drone technology. Furthermore, advancements in autonomous navigation systems empower drones to execute missions independently, diminishing the requirement for continuous human supervision [15]. These sophisticated systems enable drones to navigate complex environments, adapt to dynamic conditions, and complete tasks with a heightened degree of autonomy, marking a significant step forward in enhancing the efficiency and versatility of drone operations. In addition, ongoing refinement of optimization techniques aims to reduce energy consumption during extended drone missions, thereby extending both flight durations and operational ranges [16]. By focusing on energy efficiency, these developments enhance the sustainability and endurance of drone operations, paving the way for longer and more resource-effective flights.

### 1.1. Related surveys

In the literature, there are some surveys that cover different aspects of UAV/UAS/drone/swarm control systems and path planning algorithms. For instance, [17–21] focused on control strategies and architectures, covering strategies from basic to advanced. [17] focuses on the novel concept of quadrotors with tilting propellers, highlighting the need for hybrid control schemes to achieve optimal performance. [18] compares linear and nonlinear control strategies, emphasizing the trade-offs between stability, robustness, and complexity. Additionally, they discuss experimental implementation setups and future directions, such as integrating UAVs into traffic policing systems. [19] underscores the prevalence of PID control in quadrotor systems and explores variations and enhancements, including adaptive capabilities and stability analyses. They identify opportunities for further research, particularly in analyzing the stability of PID-based control schemes and addressing challenges related to disturbances and parameter uncertainty. [20] provides a concise overview of quadrotor UAV control algorithms, focusing on linear, nonlinear, and intelligent control methods. They emphasize the challenges posed by the quadrotor's underactuated nature, including robust stability, nonholonomic constraints, parameter optimization, and accurate dynamic modeling. [21] offers a comprehensive survey of control methods tailored for multi-rotor systems, particularly quadrotors, aiming to reveal future capability requirements. They cover linear controllers like PID, LQ, and H-infinity, which were initially sufficient for stable flight. They then explore nonlinear control techniques, necessary due to the inherent nonlinear under-actuated nature of quadrotors, including feedback linearization, backstepping, and sliding mode control. Intelligent control strategies, such as model predictive, fuzzy logic, and neural network controllers, are also reviewed for their adaptability to wider uncertainty ranges.

While these recent surveys focus on control strategies and architectures with a detailed exploration of basic and advanced techniques, our survey goes further to examine various aspects of drone control. It explores not only the traditional control strategies but also delves into human-robot interaction, safety and security, machine learning integration, communication frameworks, surveillance and area coverage, formation control, and applications in entertainment. This approach adds depth to the analysis of control systems, considering their broader application and integration in different contexts.

Moreover, [22–26] focused on path planning algorithms. [22] provides an extensive analysis of UAV path planning approaches, highlighting the prevalence of classical techniques, heuristic algorithms, meta-heuristics, and machine learning methods. The discussion underscores the trade-offs between simplicity, computational efficiency, and optimality across static and dynamic environments. [23] presents a comprehensive analysis of UAV path planning research focusing on computational intelligence (CI) algorithms. They identify trends in CI-based path planning and categorize studies based on time domain (offline and online) and space domain (2D and 3D). [24] explores the emerging field of UAV swarm path planning, emphasizing the role of artificial intelligence techniques in enhancing coordination and efficiency. [25] offers a thorough examination of 3D path planning algorithms for UAVs. They categorize methods into sampling-based, node-based, mathematical model-based, bio-inspired, and multi-fusion algorithms, comparing their characteristics and applicability. [26] provides a thorough examination of path planning techniques for UAVs. They categorize the techniques into representative, cooperative, and non-cooperative methods, and delve into their applicability, coverage, and connectivity within UAV communication networks. Furthermore, they identify key research directions, including the need for more efficient path planning, enhanced energy efficiency through green energy adoption, and the development of secure communication protocols to mitigate potential security threats.

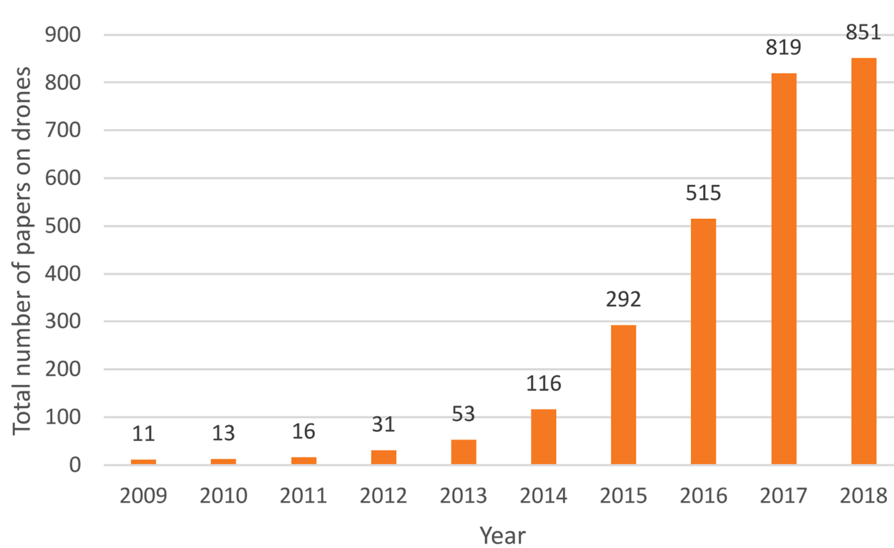


**Fig. 1.** Evolution of papers published on drones per year between 2009 and 2018.

The recent surveys focused on specific path planning algorithms, offering extensive insights into classical techniques, computational intelligence, and emerging fields. Our survey builds on this foundation by incorporating a wider range of methodologies, including genetic algorithms, particle swarm optimization, artificial intelligence, ant colony optimization, nature-inspired techniques, and multi-agent coordination. Moreover, our review discusses the real-world challenges and limitations, bridging the gap between theoretical path planning and practical applications.

In addition, our review brings a unique perspective on swarm control systems and swarm intelligence, an area with growing importance. While the existing surveys mention multi-rotor systems and control schemes, our paper explores advanced control strategies such as multi-region distributed control and consensus-based formation control, providing a comprehensive view of how UAV swarms can operate collaboratively. This detailed examination of swarm control systems adds a layer of insight that the existing surveys do not cover extensively.

Despite these valuable contributions, there exists a gap in the literature—a lack of a comprehensive survey that synthesizes insights from various domains within UAV/UAS/drone/swarm control systems and path planning algorithms. This gap motivates our proposal for a more exhaustive survey, aiming to consolidate existing knowledge and offer new insights. By addressing this void, our survey seeks to provide a holistic understanding of UAV/UAS/drone/swarm control systems and path planning algorithms, with a focus on control strategies, path planning, swarm control systems, and swarm intelligence. Through rigorous analysis and synthesis of existing literature, we aim to create a resource that not only describes the current state of the field but also anticipates future developments and challenges in UAV/UAS/drone/swarm systems.

The rest of the paper is organized as follows. In Section 2, we outline our objectives and research questions. Section 3 provides an explanation of the systematic methodology employed to discover, synthesize, and critically analyze the existing body of knowledge. Section 4 presents the research outcome and findings of the review. We discuss the results, evaluate their limitations and challenges, and peer into the future of these transformative technologies in Section 5. Finally, Section 6 concludes our paper.

## 2. Aims and scope

This systematic literature review aims to comprehensively investigate the state-of-the-art control systems and path planning techniques employed in UAV/UAS/drone/swarm systems, while concurrently examining the associated limitations and challenges. The research questions guiding this review are as follows:

*Identification of State-of-the-Art Control Systems and Path Planning Techniques:* This review seeks to answer the question, "What are the current state-of-the-art control systems and path planning techniques used in UAV/UAS/drone/swarm systems?" Through an exhaustive analysis of the literature, this objective aims to provide a comprehensive overview of the cutting-edge methods and technologies in the field.

*Assessment of Challenges and Limitations:* In addressing the question, "What are the key challenges and limitations in the existing UAV/UAS/drone/swarm control systems and path planning?" this review will critically evaluate the obstacles and constraints faced by researchers and practitioners in the design and implementation of these systems.

*Future Research Directions:* Lastly, in exploring "What are the future research directions and potential areas for improvement in UAV/UAS/drone/swarm control systems and path planning?" this review will provide insights into the emerging trends and opportunities for advancing the field, thereby guiding future research endeavors.

## 3. Methods

In this section, we outline the systematic methodology employed to identify, select, and analyze the relevant literature for our comprehensive review of UAV/UAS/drone/swarm control systems and path planning. To ensure methodological rigor and transparency, we adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2009 guidelines [27] for article screening and selection. This systematic approach allowed us to systematically retrieve and evaluate a broad spectrum of scholarly works, providing a foundation for an evidence-based synthesis of the state-of-the-art UAV/UAS/drone/swarm control systems and path planning techniques within the defined time frame of 2013 to 2023. The following subsections detail our search strategy, search criteria, and the outcomes of the screening process, highlighting our commitment to a comprehensive and structured review process.

### 3.1. Search strategy

To conduct a systematic and comprehensive review of the literature on UAV/UAS/drone/swarm control systems and path planning, a rigorous search strategy was developed. The search strategy was designed to identify relevant studies to address the specified research questions in Section 2. The primary search was performed across prominent academic databases, including IEEE Xplore, ACM Digital Library, and ScienceDirect, and the query used was as follows: ("UAV" OR "UAS" OR "drone") AND ("autonomous control algorithms" OR "swarm" OR "flight control" OR "mission planning" OR "path planning algorithms").

### 3.2. Search criteria

We carefully selected studies for inclusion in this systematic review based on a set of specific criteria that ensured the relevance and quality of the selected literature. To be considered for inclusion, studies were required to meet the following criteria:

Firstly, studies were considered eligible if they directly addressed the subject matter of UAV/UAS/drone/swarm control systems and path planning. Moreover, we prioritized studies that offered substantial and detailed information on various aspects of the field, including methods, techniques, applications, challenges, and advancements. This stringent criterion served as the foundation for our review, ensuring that the selected studies were closely aligned with the central focus of our investigation. By adhering to this criterion, we were able to extract meaningful insights and information that pertained directly to this domain. In addition to relevance, we established a temporal boundary by including studies published between 2013 and 2023. This allowed us to capture the most recent developments, providing a comprehensive overview of the state-of-the-art practices.

Furthermore, our review incorporated various types of scholarly works, including book chapters, peer-reviewed journal articles, and conference papers. This broad inclusion criterion ensured that the selected studies had undergone rigorous peer review processes and met well-established academic standards, contributing to the robustness and credibility of our findings. On the other hand, we excluded certain types of publications that did not meet the academic standards mandated for inclusion in our review. Specifically, editorials, letters, opinions, and non-peer-reviewed sources were omitted from our analysis, emphasizing the importance of peer-reviewed scholarship to uphold the scholarly integrity of our work. Lastly, to maintain a consistent and comprehensive assessment of the literature, studies published in the English language were exclusively included. Proficiency in English was deemed essential for the effective evaluation and synthesis of the selected works.

### 3.3. Study selection and data collection

In the process of study selection and data collection, we followed a structured methodology. Initially, we screened the titles and abstracts of the identified articles to determine whether they aligned with our inclusion criteria. Subsequently, we conducted a thorough examination of the full texts of the selected articles to further assess their relevance to our study. To ensure a systematic and comprehensive data-gathering process, we devised a standardized data extraction form. This form was instrumental in capturing key information from each chosen article, including research questions, contributions, methodology, findings, limitations, and potential areas for future research. This approach allowed us to methodically collect and organize the essential details from the literature under consideration.

## 4. Results

In this section, we present the comprehensive results obtained from the systematic search and analysis conducted on the topic of drone control systems and path planning techniques. We delve into the outcomes of our search process, summarize the key findings from the collected studies, and identify state-of-the-art control systems and path planning techniques.

### 4.1. Search outcome

The initial search across prominent academic databases, including IEEE Xplore, ACM Digital Library, and ScienceDirect, resulted in a total of 7750 papers. Subsequently, after the screening of titles and abstracts following PRISMA guidelines, 770 papers were deemed potentially relevant for further review. Following a thorough examination of the full texts, study quality assessment, and removal of duplicates, 60 publications were included in the final review, contributing to the synthesis of the literature in this review paper (see Fig. 2).

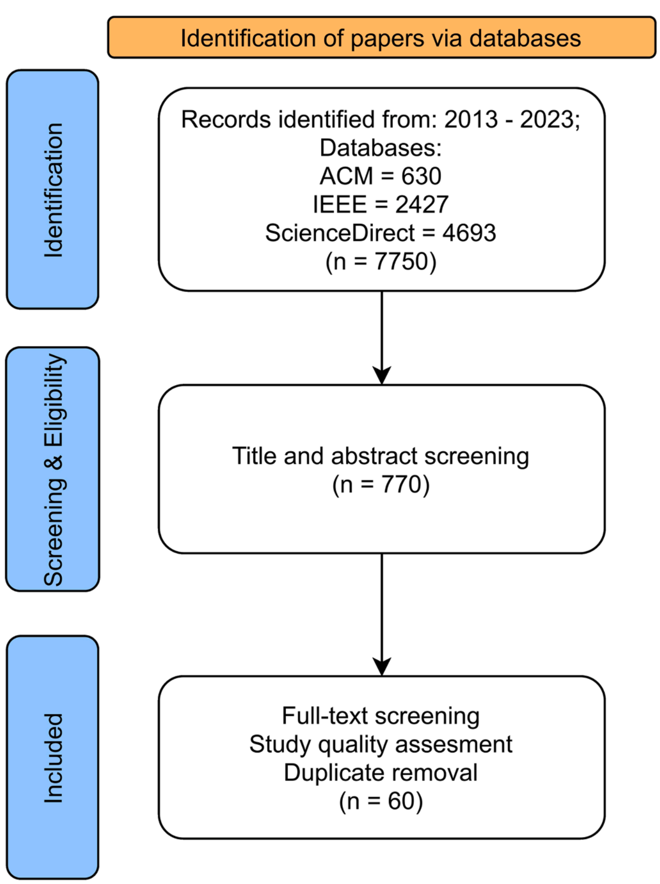


**Fig. 2.** An overview of the filtering process used in this paper.

### 4.2. Study summaries

In this section, we provide concise summaries of the studies included in our systematic literature review, each contributing valuable insights to the broader understanding of drone control and path planning. These studies encompass a diverse range of topics, methodologies, and applications, collectively helping us to understand the multifaceted landscape of drone technology. From gaze-based control systems to adaptive multi-UAV path planning, each investigation offers a unique perspective, contributing to the collective body of knowledge in these dynamic fields. Furthermore, we discuss the findings, challenges, and limitations of these studies, and future research directions extensively in Section 5.

#### 4.2.1. Drone control

This section of the systematic review focuses on drone control systems, drawing insights from thirty selected articles. These articles collectively contribute to a nuanced understanding of the advancements in drone control over the past decade. The subsequent subsections dissect various aspects of this domain, including human-robot interaction (Section 4.2.1.1), surveillance and area coverage (Section 4.2.1.2), attitude control systems (Section 4.2.1.3), safety and security considerations (Section 4.2.1.4), formation control (Section 4.2.1.5), machine learning integration (Section 4.2.1.6), communication and control frameworks (Section 4.2.1.7), and drone control in entertainment (Section 4.2.1.8).

*4.2.1.1. Human-Robot interaction in drone control systems.* Drones can be controlled in various ways, with the most common and traditional method being the use of a remote control. However, recent research has explored alternative methods to enhance the effectiveness and efficiency of control. These methods include utilizing electroencephalogram (EEG) signals [28,29], eye tracking [30], speech and gestures [31], among others. Hansen et al. [30] explored the innovative application of gaze-tracking technology in controlling drones. The investigation encompassed the examination of four distinct control modes, each combining gaze-directed movement and manual (keyboard) input to govern different aspects of drone flight, such as speed (pitch), altitude, rotation (yaw), and roll (drafting). The study involved ten participants who engaged in a basic drone flying task. Various metrics were collected, including task completion time, while also assessing the user experience in terms of complexity, dependability, and enjoyment. Among the key findings, the study reported that participants achieved similar task completion times across all four tested control modes. However, one specific combination of gaze-based and manual controls (Rotation and speed by gaze; translation and altitude by keyboard) was identified as significantly more dependable than the others. They believed that the reason was since all subjects were experienced gamers, the control mode closely resembles the one commonly employed by gamers in three-dimensional (3D) games, where the mouse is frequently utilized to adjust the viewing perspective. This study offers valuable insights into the utilization of gaze-based control modes for UAVs. Furthermore, Liu et al. [32] introduced a novel approach to enhance human-robot collaboration in controlling UAVs for beyond visual line of sight (BVLOS) applications. The framework combines manual control through hand gestures, recognized using the Mediapipe system [33], with autonomous task execution capabilities. These capabilities are achieved through the integration of ORB-SLAM2 [34] for 3D mapping and Detectron2 [35] for object detection and semantic segmentation. The control architecture is hierarchical, with commands categorized into three levels based on complexity. Level 1 encompasses basic flight control commands, Level 2 focuses on instructional and target selection commands, and Level 3 manages complex flight behaviors. Experimental results highlight the effectiveness and stability of this semi-automatic teleoperation approach, particularly in tasks requiring precise navigation, offering an intuitive and user-friendly alternative to traditional joystick-based UAV control.

*4.2.1.2. Drone control systems in surveillance and area coverage.* One of the most common application areas of drones is surveillance. Schleich et al. [36] explored the coordination of UAV fleets to fulfill collaborative missions with a focus on surveillance tasks. The study utilized a decentralized and localized algorithm designed for UAV mobility control, particularly in scenarios where network connectivity constraints are paramount, such as security-sensitive missions. This algorithm aimed to ensure that UAVs could maintain connectivity while operating autonomously. The study introduced the concept of the connected coverage mobility model, which relies on a tree-based overlay network anchored at the base station. This model not only ensures network connectivity but also leverages Ant Colony Optimization (ACO) [37] techniques to guide UAVs efficiently. Through a rigorous evaluation process involving extensive simulations, the researchers demonstrated the model's effectiveness. In comparison to other contributions in the field, this study stands out for its emphasis on connectivity in autonomous UAV fleets. While some trade-offs were observed, the paper's approach showed significantly better connectivity performance.

Rosalie et al. [38] tackled the complex challenge of area coverage using a swarm of UAVs within a military context. Their primary aim was to devise a mobility management system for a single autonomous UAV swarm tasked with information collection in military scenarios. This mission demanded addressing several crucial constraints, including the necessity for unpredictable UAV mobility, the capability for operator path prediction, mission autonomy to ensure continuous operation in hostile environments and fault tolerance. To achieve these goals, the researchers introduced the Chaotic Ant Colony Optimization to Coverage (CACOC) algorithm, a novel approach that blends ACO with chaotic dynamics. CACOC was designed to provide a deterministic yet unpredictable UAV mobility system, improving upon traditional random processes in ACO. The paper elaborates on how chaotic dynamics from the Rossler system [39] were incorporated into the UAV mobility model, utilizing tools like the logistics map and the Rossler system to generate chaos. Extensive experiments were conducted, accompanied by statistical comparisons among different models. The results reveal that CACOC exhibited impressive performance in terms of coverage, initialization phase, recent coverage, fairness, and network organization, with Model 5, combining chaos and pheromones, consistently outperforming other models.

The significance of UAVs in modern military technology is increasing due to their cost-effective advantages and the ability to integrate observation and combat functionalities. However, single UAVs face limitations in terms of endurance, coverage, and fault tolerance, particularly in complex mission environments. To overcome these limitations, researchers have turned their attention to multi-UAV coordinated missions, emphasizing mission planning as a core challenge. Various methods for area decomposition and assignment have been explored, including decomposition into cells and scan line-based distribution. In this context, Qiangwei et al. [40] addressed the problem of coordinated area coverage reconnaissance using multi-UAVs, taking into account the size of the mission area. The paper introduces two distinct mission modes based on the mission area's size, offering flexibility in deployment strategies. Their results show the potential of multi-UAV systems to enhance mission performance, reliability, and adaptability in evolving battlefield scenarios, envisioning a future where multiple UAVs collaborate with diverse mission payloads, employ multi-angle coverage for enhanced information reliability, and autonomously plan and execute missions.

Li and Duan [41] presented a novel game-theoretic approach for cooperative search and surveillance using multiple UAVs. They divided the problem into three phases: coordinated motion, sensor observation, and information fusion. Coordinated motion is formulated as a potential game, employing binary log-linear learning for optimal coverage. A consensus-based fusion algorithm constructs a probability map to guide subsequent motion. The modular framework allows the customization of utility functions and learning algorithms for diverse objectives and constraints. Their experiment results show the effectiveness and efficiency of their proposed approach.

*4.2.1.3. Attitude control systems.* One notable development in the realm of UAVs is the exploration of intelligent attitude control systems. While traditional Proportional-Integral-Derivative (PID) control systems have been effective in stable environments, researchers have increasingly turned to reinforcement learning (RL) algorithms to enhance flight control precision and adaptability. Koch et al. [42] investigated the performance of RL-based controllers in the "inner loop" responsible for aircraft stability and control, specifically focusing on attitude control. Using a high-fidelity simulation environment called GymFC, an OpenAI environment [43], the authors trained flight controllers for quadrotor UAVs with RL algorithms, including deep deterministic policy gradient (DDPG), trust region policy optimization (TRPO), and proximal policy optimization (PPO). The results indicated that controllers trained with PPO demonstrated superior performance, surpassing traditional PID control in multiple performance metrics. This research contributes valuable insights into the potential of RL to improve UAV attitude control, particularly in challenging and dynamic environments, signifying advancements in the field of flight control systems for UAVs.

Wang et al. [44] focused on creating a self-contained flight control system for small UAVs. They developed control laws for lateral and longitudinal flight management. Lateral control includes roll and yaw controllers, pivotal for trajectory tracking and overall stability. The roll controller minimizes errors in sideways movement, ensuring the UAV remains on its intended path. The yaw controller is especially significant during automatic takeoff and landing. Controlling altitude and airspeed is challenging due to their interconnected nature, especially during landing. To address this, the authors introduced the concept of the total energy control system (TECS) [45]. This approach synchronizes throttle and pitch angle to optimize altitude and airspeed control. Multiple flight tests were conducted to validate the system's stability and dependability. Trajectory control proved to be accurate within approximately 1.5 m, while altitude errors did not exceed 0.5 m.

Santana et al. [46] provided a comprehensive exploration of applying a low-cost quadrotor testbed to real outdoor flights. They proposed a design of a flight control system that addresses critical aspects such as managing out-of-sequence sensor measurements [47], aircraft modeling, and high-level flight controller development. To validate the effectiveness of this system, a series of practical flights were performed, specifically focusing on tasks related to positioning and trajectory tracking. The paper also highlights the importance of reliable sensor data in achieving optimal control performance and emphasizes the significance of fusing data from different sensors for outdoor navigation. The paper presents experimental results from various flight scenarios, demonstrating the system's capability to overcome disturbances caused by wind and positioning interference. It concludes that this system offers a robust and efficient control scheme, even in the face of significant wind gusts, making it suitable for real-time experimentation and outdoor applications.

Sato et al. [48] discussed the design of a flight controller for an unmanned airplane developed for radiation monitoring. The system relies on a traditional control structure due to limited onboard computing power. This structure incorporates Stability/Control Augmentation Systems (S/CAS) to bolster stability and utilizes PID controllers for guidance loops responsible for regulating speed, track angle, and three-dimensional position. The key challenge in designing the flight controller is to ensure its robustness against modeling errors and changing operating conditions. To address this, the "multiple model approach" is adopted, which incorporates several linearized aircraft motion models to account for various flight conditions, such as maximum and minimum weight and airspeed. The flight controller's performance is evaluated through flight tests, including tests conducted in both calm and windy conditions.

Fujimori et al. [49] introduced an autonomous flight control system designed for quadrotors relying on its internal sensors for precise navigation. The primary aim is to enable the quadrotor to operate autonomously, free from external positioning systems like GPS. The paper presents a systematic approach, encompassing the creation of four velocity models, each associated with specific control commands. These models account for various factors, including motion dynamics, communication delays, and control command nonlinearities. The autonomous flight control system itself combines fundamental control laws for diverse flight missions, incorporating tracking control for velocity profiles and positioning control for designated locations. Notably, the system addresses the physical characteristics of the quadrotor, such as control command saturation and dead zones. Furthermore, the paper outlines a practical method using waypoints to facilitate complex autonomous control. In an experiment involving a mobile robot with an ArUco marker [50], the system showcases its effectiveness, marking a promising development in autonomous flight technology.

Wang and Liu [51] presented an innovative method for enabling a quadrotor to accurately follow 3D spatial trajectories using a combination of saturated control and a specialized optimization algorithm called heterogeneous comprehensive learning particle swarm optimization (HCLPSO). The quadrotor model is first divided into a cascaded control structure with inner attitude and outer position control loops. Saturated control is employed to confine the thrust force, making it more manageable. The HCLPSO algorithm is then applied to optimize control parameters, reducing the complexity of manual tuning. The study focuses on adjusting three types of control parameters and demonstrates that the HCLPSO method is superior in achieving optimization precision and computational efficiency when compared to other techniques such as particle swarm optimization (PSO), comprehensive learning particle swarm optimization (CLPSO), genetic algorithm (GA), and differential evolution (DE), as observed in the simulation results. While the method shows promise in enhancing quadrotor control and optimization, it faces challenges in selecting the most suitable subpopulation combinations and addressing uncertainties and disturbances in control.

*4.2.1.4. Safety and security in drone control systems.* The precision and reliability of UAV control systems determine their ability to navigate complex environments and execute mission-critical tasks. At the same time, the increasing connectivity and complexity of UAV platforms have raised concerns about cybersecurity threats and safety vulnerabilities. These challenges have prompted researchers to develop innovative solutions that not only enhance control mechanisms but also fortify UAV systems against cyberattacks. In this context, Yoon et al. [52] addressed the escalating security challenges faced by modern UAS due to their increasing complexity and connectivity. The VirtualDrone Framework, introduced in this research, serves as a pioneering solution, safeguarding critical system resources by leveraging virtualization techniques on a multicore processor. This framework ingeniously divides the UAS control environment into two distinct realms: the normal control environment, where advanced but potentially untrusted applications operate, and the secure control environment, which offers a minimal set of capabilities to ensure safe control and minimize the attack surface. By implementing a security and safety monitoring module within the secure control environment, the framework continuously monitors the UAS's physical and logical states, swiftly detecting safety and security violations. Upon identification of such violations, the secure control environment takes charge, limiting unreliable functionalities. The study showcases the framework's robustness through comprehensive case studies and experimental validations, demonstrating its effectiveness in defending against various cyber threats. While the framework excels in addressing cyber threats, it does not handle physical sensor manipulations, known as sensor attacks, emphasizing the need for additional control-theoretic approaches. Additionally, the study underscores the negligible impact of the VirtualDrone Framework on power consumption, making it a promising solution for real-world implementation. This research contributes significantly to the understanding of UAS security challenges, offering a practical and resilient framework that bridges the gap between advanced functionalities and cybersecurity, thereby enhancing the safety and reliability of modern UAS operations.

With the widespread adoption of drones, incidents and misuse have increased. This has raised safety concerns. To address these challenges, Okutake et al. [53] introduced a collaborative safety flight control system for multiple drones. This system relies on pattern recognition from drone camera images, coordinated control among multiple drones, and emergency procedures for uncontrollable situations. The research also explores various drone formation types tailored for different purposes, including photography and safety-focused configurations. Preliminary experiments demonstrated the feasibility of these safety control methods.

Caliskan and Hajiyev [54] introduced a system designed to ensure the reliability and safety of UAVs by addressing the challenges of sensor and actuator failures. In the event of sensor malfunctions, the system employs a sophisticated approach: it isolates the problematic sensor and implements a reconfigurable Optimum Kalman filter (OKF) that effectively disregards the input from this sensor. It performs the isolation and identification of specific actuator faults, such as partial loss and stuck faults, using a two-stage Kalman filter. Subsequently, the feedback controller's parameters are recalibrated through a control reconfiguration process to maintain effective flight control even in the presence of actuator failures. To validate the effectiveness of their approach, the authors conducted simulations over a 100-second duration, with a sampling interval of 0.1 s. These simulations were performed considering scenarios where continuous measurement bias was introduced as a form of measurement malfunction. Additionally, the paper delves into the intricacies of tuning Proportional-Integral (PI) controllers, with a particular focus on their role in rejecting step disturbances. The goal is to optimize the system's disturbance rejection capabilities while acknowledging the inherent trade-off that may affect reference tracking performance. This innovative approach presents a valuable solution for achieving both effective reference tracking and disturbance rejection in a single PI controller. The results clearly illustrate that the conventional OKF provides inaccurate estimates, primarily during specific intervals when a sensor fault occurs. In contrast, the reconfigured OKF consistently produces significantly improved estimation results for various UAV state variables, even in the presence of sensor faults.

Wang et al. [55] explored the practical application of Model-Based Design (MBD) for designing flight control systems in UAVs. MBD is described as an organized approach that utilizes models to enhance communication, reduce manual work, and improve the efficiency of system design. A comparison between traditional and MBD methods is presented to illustrate the advantages of MBD, particularly in terms of code generation and algorithm updates. They used MATLAB/Simulink to categorize the models into control and UAV models. The control model enables flight path and attitude control, as well as mission-specific objectives. The results indicate that the flight control system effectively manages the flight path and orientation for planned missions. Following thorough testing and validation, including the conclusive Hardware-in-the-Loop (HIL) assessments, the flight control system is deemed prepared for actual flights.

Haitao and Yan [56] addressed the issue of parameter adjustment in nonlinear system controllers, primarily in the context of UAVs. The paper highlights the limitations of conventional PID controllers in handling nonlinear systems and introduces an enhanced PSO algorithm for fine-tuning controller parameters. It proposes a nonlinear dynamic inertia weight method that considers the distance between particles and the global optimum. They used the classic PID controller to design the pitch angle control law for nonlinear UAV models, and the PSO algorithm to optimize the parameters, considering both fuel efficiency and tracking performance.

Chee and Zhong [57] focused on an unmanned quadrotor aerial vehicle equipped with advanced control systems, including a nonlinear complementary filter and proportional-integral rate controllers for precise attitude estimation and stabilization. The vehicle boasts critical mission capabilities, including altitude holding and collision avoidance, and features an autonomous navigation system for user-defined waypoints. Two collision avoidance schemes are employed. The first, a reactive quad-directional approach, uses strategically positioned infra-red sensors to swiftly respond to nearby obstacles, guiding the vehicle to avoid collisions. The second scheme is integrated with the navigation algorithm, enabling obstacle-free path generation by moving backward and sideward when an obstacle is detected. This maneuver continues until the obstacle is out of range. Control systems operate through two loops. The first loop manages fundamental platform operations and attitude stabilization, while the second loop governs altitude control, navigation, and collision avoidance using data from various sensors. The study's findings are supported by practical experiments.

*4.2.1.5. Formation control in drone control systems.* With the increasing utilization of UAVs in various applications, employing multiple UAVs in formation control offers distinct advantages, including enhanced operational efficiency and robustness. Jia et al. [58] introduced a novel multi-region distributed control scheme for multi-UAV formation. The proposed control strategy adopts a hierarchical approach and divides the operational area into regions. Each region operates as a first-level follower that tracks a predefined trajectory, simplifying communication by limiting interactions to neighboring regions. Simultaneously, individual UAVs within a region function as second-level followers, aligning their paths with the first-level followers. Notably, this method allows UAVs to autonomously determine their positions, making it well-suited for dynamic environments. Stability is guaranteed through Lyapunov theory, and simulations validate the approach's effectiveness. In a scenario involving fifteen UAVs across five regions, the system successfully achieves formation flight while maintaining safe inter-UAV distances. This innovative approach shows promise for complex multi-UAV missions, providing autonomous and safe formation control.

Lwowski et al. [59] introduced a novel formation control algorithm inspired by bird flocking, designed for coordinating a swarm of UAVs with the primary goal of ensuring camera image overlap. This algorithm leverages stereo cameras, global positioning systems (GPS), and inertial measurement units (IMUs) while circumventing the need for feature or pattern matching. By calculating virtual tracking points through stereo cameras, the primary formation control objective becomes the convergence of these tracking points, ensuring consistent camera field-of-view overlap. The paper evaluates five distinct control algorithms, including direct control, PID, bang-bang control, short window model predictive control, and long window model predictive control, through extensive simulation testing to ascertain the robustness and efficacy of the proposed formation controller. The study outlines the five major approaches: leader-follower, behavioral, consensus-based, virtual leader-based, and the less common flocking formation control algorithm. The paper addresses the challenge of camera-based formation control using feature matching, citing drawbacks such as common feature loss and difficulty in complex environments. It then introduces the proposed stereo camera-based approach, emphasizing the achievement of camera image overlap without relying on feature matching.

Yasin et al. [60] addressed the complex challenge of coordinating a swarm of drones in terms of both maintaining a desired formation and avoiding collisions with obstacles. To tackle this, the authors proposed a multi-priority control strategy implemented in each drone node. This approach dynamically optimizes the trade-offs between collision avoidance and formation control, considering system constraints like energy and response time. The algorithm is founded on three key observations: maintaining formation relative to neighboring nodes, detecting obstacles via local sensors, and adapting to critical collision situations by measuring obstacle proximity. Through comprehensive experimental results, the proposed approach demonstrates its ability to effectively maintain swarm formation while navigating around various obstacles. Moreover, Wu et al. [61] introduced an innovative control law for maintaining close formation flight based on Lyapunov theory. It establishes a comprehensive mathematical model, analyzes the dynamic characteristics of the formation, and develops a robust control strategy. Simulation results confirm the system's ability to establish a stable triangular close formation swiftly and consistently with remarkable precision and resilience against external interference.

Luo et al. [62] focused on addressing the challenge of formation transformation UAV swarms. Formation transformation becomes necessary due to various factors, including environmental changes, modifications to mission objectives, and UAVs leaving the formation. The primary objective during these transformations is to ensure the safety of the UAVs, preventing collisions while completing the transformation within a specific time frame. The authors started by emphasizing the importance of maintaining formation among UAVs, highlighting the advantages of using multiple UAVs in a formation. This approach allows for better coverage, more effective surveillance, and enhanced capabilities in various tasks, such as search missions or strike operations. They adopted a distributed structure control model for formation keeping, designating one UAV as the Leader UAV (LU) responsible for tracking a reference path, while the others function as Follower UAVs (FUs). Each FU tracks the nearest UAV in the formation, creating a structured formation constituted by sub-queues of twin UAVs. Various situations necessitate formation changes, including the need to navigate obstacles, adapt to new battlefield conditions, or respond to emergencies. The central concern during these transformations is to maintain the safety of the UAVs and prevent collisions. To address these challenges, the authors employed a transformation method based on a 1–1 model to control the distances between UAVs during the transformation process. This method ensures that UAVs do not collide while transitioning from one formation to another. The results demonstrate the effectiveness of the design, suggesting that the developed control and transformation strategies can be successfully applied to UAV formation flight.

Zhao et al. [63] focused on a novel consensus-based formation control technique for second-order nonlinear multi-agent systems, aiming to minimize resource usage and enhance adaptability. They introduced an improved constrained adaptive chaotic pigeon-inspired optimization algorithm (ACPIO) for parameter tuning, simplifying controller design, and reducing manual workload. Additionally, a pinning control method combined with a hierarchical leadership model from pigeon flocks is introduced, enhancing adaptability while reducing computational complexity. The paper establishes conditions for achieving desired formation patterns based on Lyapunov stability theory and matrix theory. Numerical simulations confirmed the effectiveness of this approach. Key contributions include proposing a consensus-based formation control method, deriving conditions for pinning control, and introducing an adaptable pinning control method with a leadership hierarchy. The method is shown to be fault-tolerant in scenarios where agents fail, making it a promising approach for multi-agent systems.

Wubben et al. [64] tackled the complexities associated with deploying and managing swarms of UAVs. They primarily focused on resolving two pivotal issues: swarm layout reconfiguration and handling lost swarm members. Furthermore, the paper introduces methods for addressing swarm fragmentation due to communication issues. The main contributions comprise an extended protocol for enhanced resilience, accommodating any failing swarm element, and a reconfiguration scheme to enable safe mid-flight formation adjustments. This work distinguishes itself by concentrating on the loss of swarm elements and real-time reconfiguration into new formations, offering practical implementations, and exploring swarm split-up scenarios not extensively addressed in prior research. The authors conducted extensive experiments to validate their proposed solutions. The results demonstrate a notable reduction in collision risks during swarm reconfiguration and seamless management of UAV losses, with minimal delays.

Chen et al. [65] focused on enhancing the design of a distributed leader-following formation control system for discrete multi-agent setups, particularly when the leader maintains a constant speed. The authors introduced a distributed control protocol that incorporates an integral term to enable followers to track the leader while preserving the desired formation, even when the data is obtained through periodic sampling. The main contributions include establishing the conditions for achieving leader-following formation asymptotically using the Jury criterion and providing explicit formulas for optimal control gains and convergence rates. The study's findings are validated through numerical simulations, confirming the effectiveness of the proposed method. In contrast to prior research primarily addressing continuous systems, this paper addresses the specific challenges of discrete systems and their sampling intervals, making leader-following formation control more practical for real-world applications.

*4.2.1.6. Machine learning in drone control systems.* Achieving effective coordination among UAVs within a swarm can be challenging, especially in scenarios marked by unreliable communication channels and operational heterogeneity. Yang et al. [66] addressed this coordination challenge by employing generative adversarial imitation learning (GAIL), a machine learning technique that enables drones to coordinate their actions by imitating the behaviors demonstrated by their peers. Unlike traditional RL methods, GAIL does not rely on predefined reward feedback, making it particularly suitable for scenarios where reward feedback is challenging to specify accurately. One noteworthy aspect of this research is its focus on partially observable environments, where drones have access to incomplete observations due to communication constraints or limited sensing capabilities. To bridge this gap and enable drones to make informed decisions, the authors proposed the use of belief representations. These belief representations are derived from historical observation-action trajectories and are trained alongside imitation policies. By leveraging belief representations, drones can better understand their environment, anticipate future states, and optimize their imitation policies for more accurate coordination. The results of the evaluation demonstrate the algorithm's superiority in several key aspects. Firstly, it excels in imitation accuracy, enabling slave UAVs to adapt their flight trajectories based on demonstrations from a master UAV. Secondly, it significantly reduces teamwork execution time, enhancing the efficiency of collaborative formations. Lastly, it exhibits superior energy efficiency compared to alternative methods, making it well-suited for scenarios with constrained energy resources.

*4.2.1.7. Communication and control frameworks in drone control systems.* Diller et al. [67] introduced ICCSwarm, a comprehensive framework that significantly advances the integration of communication and control in UAV swarms. ICCSwarm comprises two primary phases. The planning phase integrates communication constraints into UAV mission design, emphasizing communication-aware path planning. Researchers focused on factors such as limited communication range and bandwidth limitations. Simulations demonstrated significant data collection efficiency improvements with multi-hop routing protocols over single-hop approaches. The deployment phase validated planned missions on physical UAVs, providing a real-world assessment. The architecture featured a mission computer, autopilot, network routing, and network monitoring components. Autopilots managed UAV movements and data collection, while network routing enabled multi-hop data transmission, integrating communication and control. Their work emphasizes the critical role of considering communication constraints during mission planning and highlights the substantial benefits associated with multi-hop routing protocols.

Zacarias et al. [68] introduced an innovative solution to address the demand for managing multiple UAVs. The paper extends the capabilities of the DroidPlanner application [69], designed for single UAV control, by modifying the communication infrastructure and user interface. The system employs the MAVLink protocol for communication. The architecture adopted for controlling multiple UAVs adheres to the model-view-controller (MVC) pattern. In this context, the model component represents the virtualization of physical UAVs, the view component serves as the user interface for interacting with these UAVs, and the controller manages message handling and communication with the UAVs. They performed experiments with two, three, and four UAVs being controlled at the same time. Their results show the impact of controlling more UAVs on the user interface and application performance due to message overload, underscoring the need for enhanced communication channels.

*4.2.1.8. Drone control systems in entertainment.* Nowadays, UAVs have emerged as invaluable tools in the movie industry. These versatile aerial platforms have revolutionized the art of cinematography, offering filmmakers the ability to capture stunning aerial shots and complex camera movements with precision and creativity. However, there are several challenges associated with manual drone control. Fleureau et al. [70] addressed some of these challenges and introduced a global control architecture based on a generic API for UAVs, integrating a compound model for rotary-wing drones and a full-state feedback strategy. The authors also proposed an automatic camera path planning approach tailored for cinema scene capture and validated their system through a series of experiments. They proposed a new control architecture based on Linear Quadratic Gaussian [71] regulators. The controller relies on three key components: position, orientation, and speed. These components can be generated manually through third-party software or automatically derived from high-level specifications. They use the prose storyboard language (PSL) [72] to extract camera configurations. In addition to the controller, they computed a path and used steering behaviors, gradually guiding the camera toward its optimal position, and generating a smooth motion along the path. Although with some limitations such as supporting a single drone, this research represents an initial step toward the development of autonomous tools for the cinema industry.

*4.2.2. Path planning*

Thirty of the articles reviewed in this systematic review focused on path planning. In this section, we explore specific methodologies and strategies employed in path planning, including Genetic Algorithms (Section 4.2.2.1), particle swarm optimization (PSO) techniques (Section 4.2.2.2), Rapidly-exploring Random Tree (RRT) approaches (Section 4.2.2.3), the integration of artificial intelligence (AI) (Section 4.2.2.4), ant colony optimization (ACO) methodologies (Section 4.2.2.5), nature-inspired techniques (Section 4.2.2.6), emerging strategies (Section 4.2.2.7), and considerations for target tracking (Section 4.2.2.8).

*4.2.2.1. Genetic algorithms in path planning.* In the context of autonomous vehicle path planning, with a specific focus on UAVs operating within complex non-convex environments replete with no-fly zones, Arantes et al. [73] introduced an innovative hybrid approach. Their method strategically combines a multi-population genetic algorithm with visibility graphs to address the intricate challenge of planning secure flight paths, all the while considering the inherent uncertainties intrinsic to real-world operations. The comprehensive evaluation spans an extensive array of fifty diverse maps, systematically pitting this novel hybrid method against its exact and heuristic counterparts. The outcomes of this rigorous assessment underscore the efficiency and robustness of the hybrid genetic algorithm (HGA). Remarkably, HGA consistently procures solutions within an exceptionally brief time frame, typically well under 10 s, while adhering to a carefully conservative risk allocation strategy.

Bolourian and Hammad [74] introduced a 3D path planning method for UAVs equipped with LiDAR scanners, specifically designed for bridge inspection. The proposed method combines a GA and the A* algorithm to address the traveling salesman problem (TSP) in the context of bridge inspection, considering potential locations of surface defects, such as cracks. The primary objective is to minimize flight time while maximizing visibility. The approach identifies areas with potential damage based on structural analysis and assigns Importance Values (IVs) corresponding to the level of criticality (low, medium, high). virtual points of interest (VPIs) are then determined, guiding the UAV's path for data collection. The key to an optimal path lies in two main steps. Firstly, a path length matrix is calculated using the A* algorithm, ensuring a collision-free route between pairs of VPIs separated by obstacles. Secondly, a GA is employed to solve the TSP, taking all VPIs into account, to minimize path length while maintaining acceptable visibility. Notably, the proposed method prioritizes perpendicular views and overlapping perspectives, which enhance data collection accuracy and efficiency, particularly for high-risk zones.

*4.2.2.2. Particle swarm optimization (PSO) based path planning techniques.* PSO [75] is a well-known swarm intelligence algorithm. While PSO is effective for optimizing simple problems, it can struggle with complex, multimodal challenges and become trapped in local optima. In response to these limitations, comprehensive learning PSO (CLPSO) was introduced by Liang et al. [76], emphasizing a more efficient learning strategy. Cao et al. [77] introduced traditional local search (LS) methods into CLPSO and proposed a new CLPSO with an adaptive LS starting strategy (CLPSOLS). To further enhance global and local search capabilities, Liu et al. [78] introduced a novel algorithm, the comprehensive learning particle swarm optimization with limited local search (CLPSOLLS), which combines PSO with local search (LS) methods, specifically the broyden-fletcher-goldfarb-shanno (BFGS) approach, aiming to improve local convergence. The CLPSOLLS algorithm is designed to enhance the accuracy of path planning with significantly reduced computational costs in scenarios with limited degrees of freedom. Experimental results showcase CLPSOLLS' performance in five distinct path planning cases, compared to PSO, CLPSO, randomly occurring distributedly delayed PSO (RODDPSO) [79], and CLPSOLS. The experiments highlight the algorithm's ability to find lower-cost paths, particularly in cases with challenging environments, demonstrating its robustness. Furthermore, CLPSOLLS successfully achieves the desired path in all tested cases, emphasizing its superior performance compared to other algorithms. Additionally, it effectively reduces computational time compared to CLPSOLS while improving search accuracy.

Furthermore, Xiao et al. [80] introduced an enhanced PSO algorithm, termed Heterogeneous Adaptive Comprehensive Learning and Dynamic Multi-Swarm Particle Swarm Optimizer (HACLDMS-PSO). The HACLDMS-PSO builds upon the Heterogeneous Comprehensive Learning and Dynamic Multi-Swarm Particle Swarm Optimizer (HCLDMS-PSO)[81], which dynamically manages two subpopulations to adapt to changing conditions. One subpopulation focuses on exploration, while the other emphasizes exploitation. This approach also introduces a dynamic multi-swarm structure with evolving subgroups, thereby preventing the algorithm from getting trapped in local optima. The paper incorporates the concept of Levy flight, a stochastic search technique, to expand the search range, and Cauchy mutation to assist particles in swiftly escaping local extrema. In essence, the paper formulates a refined particle swarm optimizer equipped with population dynamics, perturbation mechanisms, and adaptive learning probabilities to enhance the optimization process. Simulation results confirm the algorithm's ability to discover feasible paths in various environmental models. Comparative assessments against alternative algorithms, such as DE [82], PSO, CLPSO, heterogeneous comprehensive learning particle swarm optimization (HCLPSO) [83], and HCLDMS-PSO, underscore the superior convergence speed and stability of the proposed HACLDMS algorithm.

Roberge et al. [84] addressed the crucial aspect of autonomous path planning for UAVs in complex 3D environments. They employed GAs and PSO algorithms to tackle the intricate problem of computing feasible and quasi-optimal trajectories for fixed-wing UAVs. The authors introduced a comprehensive cost function that encompasses optimization and feasibility criteria, allowing the utilization of generic optimization algorithms, such as GA and PSO, to search for paths that minimize this cost function. The cost function was designed to consider various path characteristics, including distance, average altitude, avoidance of danger zones, and adherence to UAV performance constraints. To expedite the solutions, the authors employed parallel programming and achieved near-linear speedup. Through extensive experiments, they demonstrated the feasibility of real-time path planning for UAVs, particularly emphasizing the utility of their parallel implementation. Additionally, the paper provides a rigorous comparison between GA and PSO in the context of UAV path planning, revealing that the GA consistently outperforms the PSO with statistical significance in a variety of scenarios.

Huang et al. [85] introduced a novel approach for planning optimal trajectories of solar-powered UAVs (SUAVs) to monitor stationary targets to maximize net energy gains while adhering to constraints such as aircraft dynamics and synchronized arrival at the destination. The problem is initially formulated to address energy optimization, encompassing aspects like energy harvesting, consumption, sensor coverage, and spatial constraints. It subsequently transformed into a nonlinear optimization problem with constraints, which is further converted into an unconstrained optimization problem using a penalty function method. To tackle the computational complexity, the study employed PSO with a penalty function. The proposed method is evaluated through simulation and compared to traditional approaches, demonstrating its feasibility and effectiveness in solving the energy-optimal path planning problem for SUAVs.

Wang et al. [86] introduced a novel approach to 3D path planning for UAVs by employing a concentric spherical coordinate-based encoding scheme and an enhanced PSO algorithm. The study addresses the complexities of UAV path planning, considering fuel consumption, threat avoidance, and flight altitude optimization. Various constraints, such as minimum step size, maximum yaw and pitch angles, minimum and maximum flight heights, and maximum range, are taken into account during the UAV's penetration process. To streamline the optimization process, the authors introduced an encoding method based on concentric spherical coordinates, offering several advantages over conventional 3D coordinate encodings, such as reduced search space, improved handling of angle constraints, and fixed azimuth and altitude angles for specific mission conditions. The enhanced PSO algorithm is designed to optimize UAV paths efficiently and considers factors like matrix particle encoding, angle restrictions, and asynchronous learning factors. The research demonstrates the proposed method's feasibility and effectiveness through MATLAB-based simulations. The results indicate that the improved algorithm successfully generates UAV paths that meet diverse constraint conditions and terrain following/threat avoidance (TF/TA2) requirements while making efficient use of terrain cover for radar evasion. A comparison between the enhanced method and basic PSO with 3D encoding further confirms the superiority of the proposed approach in terms of computational speed and planning effectiveness.

Xiao et al. [87] presented a novel approach to tackle the path planning problem for UAVs by harnessing the power of large-scale swarm optimizers. Diverging from previous research employing low-dimensional optimizers, the authors advocated for using a variation encoding scheme that encapsulates relative movements of UAVs along the three Cartesian coordinate axes, significantly simplifying the search space. This encoding method facilitates optimizing numerous anchor points while mitigating issues of repetition in the resultant paths. The authors integrated this innovative encoding scheme into four established large-scale swarm optimizers: stochastic dominant learning swarm optimizer (SDLSO), level-based learning swarm optimizer (LLSO), competitive swarm optimizer (CSO), and social learning particle swarm optimizer (SL-PSO) and tested them across various scenarios. Their experiments, spanning sixteen scenes with varying levels of complexity, demonstrate the effectiveness of the proposed encoding scheme, with SDLSO emerging as the most proficient optimizer in producing refined and smoother paths for UAVs.

Liu et al. [88] introduced an innovative 3D path planning algorithm for UAVs, using an adaptive sensitivity decision operator integrated with PSO. The proposed method addresses limitations such as local optima and slow convergence commonly associated with PSO. It does so by creating an adaptive sensitivity decision area that identifies potential particle locations with high probabilities while eliminating fewer promising candidates to enhance computational efficiency. The algorithm also restricts the search space of particles within specified boundaries to avoid premature convergence. Furthermore, it improves search accuracy by considering relative particle directivity from the current location and redesigns the objective function to account for distance to the destination and UAV self-constraints. The authors discussed the problem domain, including terrain and threat modeling, which incorporates terrain constraint and deterministic threat modeling. Path representation is defined as a series of waypoints, and the objective function is formulated to consider the impact of threats, minimum path length, minimum flight altitude, distance to the destination, and constrained searching space. The proposed algorithm leverages adaptive sensitivity decision operators and incorporates global path planning techniques for UAVs, demonstrating its efficiency and effectiveness through experimentation. Comparative evaluations with other optimization algorithms, such as GA [84] and firefly algorithm (FA) [89], show the proposed method's superiority in finding high-quality paths in various scenarios.

Wang et al. [90] presented a cutting-edge approach to UAV path planning known as the Particle Swarm Optimization and Enhanced Sparrow Search Algorithm (PESSA). PESSA is designed to optimize UAV routes in complex environments, combining PSO with an enhanced sparrow search algorithm (SSA). ESSA, in particular, undergoes significant modifications. The basic ESSA's random positional jumps are replaced with a systematic, step-by-step movement process. Additionally, a standard normal distribution random number is incorporated into the algorithm. PESSA stands out through its parallel operation of PSO and ESSA, selecting the best result after each iteration. To enhance global search capabilities and escape local optima, PESSA introduces a reverse search strategy. To validate the algorithm's performance, a comprehensive set of experiments is conducted. The paper evaluates PESSA using ten benchmark functions, comparing it against twelve different algorithms. These functions include both unimodal and multimodal cases. The results are statistically significant, showing that PESSA consistently achieves optimal or near-optimal solutions across these benchmark functions. Furthermore, the paper extends the evaluation to real-world scenarios by applying PESSA in 2D and 3D environments. In the 2D case, PESSA is pitted against PSO and SSA. The results reveal that PESSA consistently produces smoother and more efficient paths, surpassing the other algorithms. In the 3D experiments, where the complexity is heightened, PESSA still outperforms. The paths generated by PESSA exhibit the desired characteristics and outperform those generated by PSO and SSA in both the quality and efficiency of the routes.

Blasi et al. [91] presented an algorithm for optimizing flight trajectories of UAVs while adhering to stringent environmental constraints. These constraints encompass obstacles, fixed waypoints, and chosen destinations, with the primary objective being the minimization of path length. The proposed path planning strategy is built upon a unique trajectory modeling approach combined with a PSO method. Flight paths, which extend from specified starting points to selected destinations, are divided into segments, represented as sequences of binary-coded basic maneuvers. This approach allows for efficient handling of discrete variables by leveraging the PSO's capabilities. Moreover, the inclusion of mixed-type variables provides flexibility in the decision-making processes and scenario definitions. The authors also detailed the implementation of geometric-based linear obstacle avoidance models, supplemented with suitable penalty functions. These models ensure that every path adheres to environmental constraints, expediting the identification of feasible trajectories and reducing the need for extensive iterations and particles. Furthermore, the paper tentatively assesses the algorithm's applicability to vehicles equipped with Vertical Take-Off and Landing (VTOL) and hovering capabilities. The algorithm demonstrates notable efficiency in terms of computational resources while maintaining the reliability of results.

Ou et al. [92] presented an enhanced PSO algorithm designed for UAV path planning, emphasizing the improvement of real-time path quality and the mitigation of local optima concerns. The primary focus of this study is to address the issue of PSO's proclivity to converge toward local optima. To achieve this, the research introduced a Chaos strategy into the PSO framework, aiming to prevent particle entrapment in local optima. Furthermore, the path quality is enhanced through the incorporation of the Dijkstra algorithm [93]. The study conducts experimental comparisons between paths generated by the traditional PSO algorithm and the enhanced PSO approach to validate the efficacy of the improvement strategy. The research additionally adopts a deterministic risk model for modeling the threat environment, defining obstacles as regions where UAVs may encounter mission failure. Additionally, the research performs real-time analysis of various path planning algorithms, including PSO, Rapidly-exploring Random Tree (RRT) [94], and bilevel programming (BLP) [95], offering insights into the respective advantages and disadvantages of the PSO-based path planning approach.

*4.2.2.3. Rapidly-exploring random tree (RRT) based path planning techniques.* Dai et al. [96] addressed the fundamental need for obstacle avoidance path planning in small UAVs to ensure their safe navigation. While sampling-based obstacle avoidance path planning algorithms have gained popularity, RRT* stands out due to its probability completeness and asymptotic optimality. However, the incorporation of optimization procedures in RRT* adversely affects its convergence rate. To mitigate this, the paper introduces an enhanced RRT* algorithm based on biased sampling. This approach improves convergence speed by concentrating sampling around the goal point and path point, thus expediting obstacle avoidance path planning. To evaluate the performance of the enhanced RRT* algorithm for 2D UAV obstacle avoidance path planning, the paper conducts simulation experiments comparing RRT, traditional RRT*, and the improved RRT* algorithm. Results revealed that the improved RRT* algorithm outperforms the traditional RRT algorithm and RRT* by planning shorter obstacle avoidance paths in less time. According to the authors, lower thresholds reduce planning time but may not yield the shortest path, while higher thresholds lead to suboptimal planning due to overly concentrated sampling.

Hu and Xie [97] introduced an innovative approach to enhance UAV path planning, aiming to overcome limitations in real-time performance. They extended the widely utilized RRT algorithm by incorporating a priori information, with a specific focus on UAV dynamics constraints, and introducing a dedicated cost function. Through these enhancements, the convergence of the path planning process is significantly accelerated. The paper discussed critical challenges associated with path planning, including the complexities introduced by considerations such as threats and special mission requirements. Additionally, it provides a comprehensive mathematical model to address these constraints and underlines the importance of discretizing planning spaces to optimize path feasibility. The simulation results offer compelling evidence of the algorithm's exceptional performance, highlighting its operational efficiency, rapid convergence, and robust planning capabilities.

*4.2.2.4. Artificial intelligence in path planning.* One of the other well-known swarm intelligence algorithms is ACO which is based on the foraging behavior of some ant species. Pehlivanoglu and Pehlivanoglu [98] addressed the challenge of autonomous UAV path planning for target coverage. However, as the number of checkpoints and constraints in the mission increases, it becomes increasingly difficult and time-consuming to find a viable solution. To tackle this issue, the authors presented an approach that leverages artificial intelligence methods, including GA, ACO, Voronoi diagrams, and clustering techniques. The primary contribution of this study is the enhancement of the initial population generation in GA, which plays a pivotal role in speeding up the convergence process. Traditionally, the initial population is crucial in guiding the optimization algorithm towards either a local or global optimal solution. The authors introduced three unique strategies to improve this initial population: employing Voronoi vertices, cluster centers, and collision points as additional waypoints. These strategies were designed to address the critical concern of terrain collisions, ensuring safe UAV path planning. To evaluate the effectiveness of their proposed methods, the authors conducted experiments in various three-dimensional environments, encompassing rural, urban, and spatial terrain models. The results from these experiments reveal that the problem of collisions with the terrain surface is localized. Their approach of using collision-based cluster centers proves to be the most efficient, leading to a substantial reduction of at least 70 % in the number of required objective function evaluations.

*4.2.2.5. Ant colony optimization (ACO) based path planning techniques.* Guan et al. [99] focused on the crucial role of path planning for UAVs, outlining how it enables autonomous route computation from start to finish while adhering to specific control points or mission-specific constraints like obstacle avoidance and fuel consumption. While ACO has garnered considerable attention for its capacity to leverage cooperative behavior for optimal path discovery, it exhibits sluggish convergence, particularly in expansive problem domains. In response, this research introduced a novel approach grounded in a double-ant colony paradigm. Specifically, a GA is integrated in the initial stages to expedite convergence. The study employs the double-ant colony algorithm (DB-ACO) and the improved double ant colony algorithm (GA+DB-ACO) to validate their effectiveness through simulations. The study's numerical results validate the approach's effectiveness, offering a promising solution for UAV path planning.

Cekmez et al. [100] presented a path planning algorithm for UAVs using a Multi-Colony ACO approach. The paper highlights that while single colony ACO can yield reasonable solutions, it is susceptible to premature convergence, which can lead to suboptimal solutions. To mitigate this, the Multi-Colony ACO approach was introduced, where multiple ant colonies work collaboratively to optimize path planning for UAVs. The proposed algorithm involves multiple colonies working on the same problem set, each maintaining its own pheromone table. At specified time intervals, colonies share their information with one another. The proposed approach is experimentally tested, focusing on solving the TSP efficiently and adapting it for UAV path planning by introducing obstacles represented by radars. The experimental results demonstrate the advantages of the Multi-Colony ACO approach over the classical ACO. The single colony ACO is shown to sometimes get stuck in suboptimal solutions due to premature convergence, while the multi-colony approach maintains a diverse exploration of paths and has a higher chance of finding better solutions.

Wan et al. [101] introduced an Accurate UAV 3-D Path Planning Method using an Enhanced Multiobjective Swarm Intelligence Algorithm (APPMS). The key elements of the APPMS approach include multiobjective modeling of flight distance and terrain threat, accurate constraint-based modeling, and a sophisticated global and local search strategy. To optimize UAV flight paths effectively in complex, multimodal objective spaces, the APPMS method employs an improved ACO algorithm, which enhances global and local search capabilities. The search mechanism maintains a uniform distribution and diversity in the Pareto solution set. The paper demonstrates the effectiveness of the APPMS approach through simulated experiments and a real-data scenario. Results from three sets of simulated terrain with varying degrees of threat, along with a real digital elevation model (DEM) dataset for an emergency response task, are compared with traditional methods such as A* [102] and other multiobjective optimization techniques (the nondominated sorting GA II (NSGA-II) [103], the multiobjective evolutionary algorithm based on decomposition (MOEA/D) [104], and the nondominated sorting GA III (NSGA-III) [105]). In these experiments, APPMS consistently outperforms other methods, offering smoother and shorter flight paths with reduced collision risk.

He and Zhao [106] conducted a comparative analysis of four distinct 3D path planning algorithms based on geometry searches for UAVs. The algorithms under investigation were Dijkstra, Floyd, A*, and ACO. The authors uniformly implemented a grid map method across these algorithms to model the working environments. This method partitions the terrain into uniform grids, distinguishing between 'free' grids and 'obstructed' ones, providing the foundational framework for the subsequent path planning. The authors introduced a novel element in this study, namely the 'perpendicular approach.' This innovative approach facilitates the selection of key path nodes based on obstacles encountered during the path planning process, notably enhancing the efficiency and performance of the Dijkstra and Floyd algorithms. The authors offered an in-depth exploration of each of the four algorithms, articulating their fundamental principles and functions. A notable contribution of this study is the integration of a 'terrain following' technique to adapt 3D path plans, a concept proposed by the authors. This approach involves making adjustments to paths that were initially determined by the four algorithms to account for the nuanced variations in topography. The authors conducted an extensive series of simulations to assess the real-time path planning capabilities of the four algorithms across a range of conditions. These conditions include scenarios with both fixed and sudden threats. The authors affirmed that while all four algorithms demonstrate adept online real-time path planning capabilities, the Dijkstra algorithm stands out as the most efficient choice. It is followed by the Floyd, A*, and ACO when considering criteria such as runtime, complexity, and path length. Furthermore, the authors emphasized the positive impact of terrain following 3D path planning, particularly highlighting its enhancing effect on the A* algorithm's performance.

*4.2.2.6. Nature-Inspired path planning techniques.* Zhou et al. [107] introduced an innovative algorithm known as the Improved Bat Algorithm (IBA), which combines the principles of the bat algorithm (BA) [108] with those of the artificial bee colony algorithm (ABC) [109]. The core motivation behind IBA is to enhance the BA's somewhat limited local search capabilities, ultimately enabling the generation of shorter, safer, and collision-free flight paths for UAVs. The IBA algorithm integrates the characteristics of BA and ABC, where BA plays a key role in the initial generation of path points. To bolster local search capabilities, the algorithm introduces a mutation factor, which is pivotal in avoiding local optima. ABC, on the other hand, steps in to further refine the path solutions generated by BA, creating an iterative process that combines the strengths of both algorithms. The results indicate that the IBA significantly outperforms the traditional BA, achieving optimal solutions about 50 % faster while simultaneously improving the quality of these solutions by approximately 14 % compared to ABC. Notably, the comparative analyses demonstrated that the IBA excels when pitted against traditional and enhanced swarm intelligence path planning algorithms. It consistently produced flight paths that are faster, shorter, and safer for UAVs, highlighting the IBA's potential for path planning optimization in dynamic environments.

Han et al. [110] introduced a novel path planning strategy for unmanned autonomous helicopters (UAH) facing multiple constraints. The proposed approach leverages the multi-strategy evolutionary learning artificial bee colony (MSEL-ABC) algorithm. To enhance the traditional ABC algorithm, an evolutionary learning framework inspired by human cognitive mechanisms is established, thus infusing the bee colony with higher levels of autonomy and intelligence. A pivotal component of this method is the creation of a multi-strategy evolutionary database, which replaces the conventional evolutionary approach of the ABC algorithm. This database enables different nectar sources to employ varying evolutionary strategies, dynamically adapting through an integrated feedback mechanism. The authors addressed the problem formulation of UAH path planning, taking into account various constraints such as radar and missile threats, within a framework that integrates multi-strategy evolutionary learning. This framework consists of two key components: the Algorithm Enhancement Module, which introduces the MSEL-ABC algorithm based on cognitive principles, and the Flight Path Solution Module, which calculates the flight path considering mission, threat, and UAH performance constraints. The UAH environment is modeled to ensure a safe and feasible flight path, accounting for mission requirements and performance constraints. Path costs and constraints were calculated, considering factors such as threat cost, fuel cost, and collision cost. A series of systematic simulations were conducted to validate the effectiveness of the MSEL-ABC algorithm in UAH path planning. Comparisons are made with other algorithms, including PSO, BA, wolf pack algorithm (WPA), ABC, BAS-ABC [111], and IL-ABC [112]. Through experiments, the MSEL-ABC algorithm demonstrates its capability to identify safe and feasible flight paths, especially in complex flight environments.

The grey wolf optimization (GWO) [113], another swarm intelligent optimization algorithm, constructs a hierarchical grey wolf population and mimics wolf hunting behaviors, with alpha, beta, delta, and omega wolves corresponding to different levels of solutions. In the algorithm, wolves update their positions based on the locations of alpha, beta, and delta individuals. To overcome challenges like premature convergence and local optima, Zhang et al. [114] presented an Improved adaptive grey wolf optimization algorithm (AGWO) for 3D path planning of UAVs in complex environments, particularly in earthquake-stricken areas. The primary contributions of this method are twofold. First, it introduced an adaptive convergence factor adjustment strategy and an adaptive weight factor to update individual positions, enhancing the algorithm's convergence. Second, it applied the improved AGWO to UAV path planning, utilizing an environmental map model. The environmental model considers elevation data and terrain threat in its path planning. The digital elevation information forms a 3D map, with a minimum allowable flight altitude. Threats, represented mainly by mountainous terrain, are modeled using cone shapes. The algorithm employs a cost function, taking into account fuel consumption and threat costs, to evaluate flight trajectories. Furthermore, the paper conducted a simulation experiment for UAV route planning in complex 3D terrain, comparing AGWO with other algorithms. AGWO demonstrates its ability to avoid threats and produce efficient flight paths, outperforming other methods in terms of both performance and computation time.

The navigation of UAVs in such environments poses substantial challenges due to obstacles of varying sizes and unpredictable movements. Goel et al. [115] introduced an algorithm that utilizes Glow-worm Swarm Optimization (GSO) [116] for path planning, demonstrating enhanced convergence rates and accuracy when compared to alternative meta-heuristic optimization techniques. The authors outlined the cost function, designed to minimize the cost associated with UAV movement by considering factors such as path length and altitude. The algorithm's primary objective was to determine the most cost-effective path, with each agent computing the cost of reaching the goal. This information guided the swarm toward the agent with the lowest cost. The effectiveness of the algorithm was validated through results, showcasing how metrics such as the number of expanded nodes, path cost, and time are influenced by the complexity of the environment.

Li et al. [117] addressed the challenging problem of path planning for multiple UAVs operating in a dynamic 3D environment, with a specific focus on UAV-based oilfield inspection. This challenging task encompasses finding optimal flight paths that account for various constraints and adapt to changing tasks in real time. The authors made notable contributions in this domain, introducing a comprehensive approach that offers significant advancements in terms of computational efficiency, precision, and stability. One key aspect of their work is the development of a method for generating optimal initial flight paths for multiple UAVs in a complex 3D environment. These initial paths lay the groundwork for subsequent path planning efforts, improving overall computational efficiency. Furthermore, the research introduced a task assignment approach that considers task priorities and dynamically changing tasks, a novel contribution to the field. This method allows for the determination of the optimal number of UAVs and solves task assignment problems when new tasks are introduced. Real-time adaptation to evolving mission requirements is a crucial aspect of their approach. Simulation experiments validate the effectiveness of the proposed approach, comparing it against six other swarm intelligence optimization algorithms. The results demonstrated that the proposed improved fruit fly optimization algorithm (ORPFOA) excels in various aspects, including fast-solving ability, high precision, and optimization stability.

Hu et al. [118] introduced SaCHBA_PDN, a modified Honey Badger Algorithm (HBA) [119] designed to enhance optimization performance in the context of UAV path planning. This improved algorithm combines innovative strategies, including the integration of the Bernoulli shift map during initialization, the introduction of a piecewise optimal decreasing neighborhood strategy (PODNS), and the application of horizontal crossing with strategy adaptation. These strategies addressed the limitations of the basic HBA algorithm and improved its efficiency in balancing exploration and exploitation. The authors evaluated SaCHBA_PDN extensively, comparing its performance to various other optimization algorithms using benchmark functions. The results showcase SaCHBA_PDN's exceptional ability to find optimal solutions, particularly excelling in unimodal and multimodal optimization problems. Furthermore, the paper applies SaCHBA_PDN to UAV path planning, assessing its performance in diverse scenarios, including those with circular and irregular obstacles, as well as 2D grid maps. The algorithm consistently delivers optimal paths while successfully avoiding obstacles in these scenarios.

*4.2.2.7. Emerging path planning strategies.* Mondal et al. [120] focused on enhancing the dynamic path planning of small-scale UAVs in the context of post-disaster scenarios. These scenarios demand efficient data collection and dissemination for tasks such as damage assessment and search and rescue operations. The research introduced two novel dynamic path planning algorithms: MIN_ROUTE and ROUTE_PRIORITY. These algorithms aim to optimize the coverage of shelter points within limited flight durations, accounting for variables like wind speed and wind direction. To evaluate the effectiveness of these algorithms, extensive simulations were conducted. The results revealed that both MIN_ROUTE and ROUTE_PRIORITY outperformed a baseline algorithm in terms of flight duration and battery consumption. In fact, these dynamic path planning techniques exhibited notable advantages, consuming approximately 20 % less time and 19 % less battery power. Moving beyond simulations, the research conducted field experiments using a micro-jet UAV prototype. The findings from these real-world tests demonstrated close alignment with the simulation results, indicating the practical feasibility of the proposed path planning methods.

Bhattacharya et al. [121] introduced an autonomous and onboard image-based agricultural land demarcation and path-planning system, named IDeA, employing UAVs within an advanced UAV-based aerial Internet of Things (IoT) framework. The primary innovation of this system lies in its capacity for autonomous path planning during stand-alone UAV operations, without prior GPS markers for waypoints. The UAV visually identifies untagged agricultural plots and determines their boundaries, subsequently generating GPS waypoints for comprehensive yet non-overlapping coverage. The proposed system achieves an area coverage efficiency of 95.39 % and pixel-to-GPS coordinate conversion accuracy of 90.35 %. This technology bears significant potential in precision agriculture applications, including crop health assessment and pesticide/herbicide spraying. It offers broad utility for tasks necessitating aerial detection, demarcation, geographical tagging, and area coverage. The system is resilient to intermittent IoT network connectivity and can withstand the loss of base station connection during operations, addressing issues associated with constrained IoT networks. It overcomes errors attributed to GPS repositioning through marker-based detection and enhances path planning through the conversion of complex field boundaries to convex hulls.

Yang and Gang [122] addressed the challenge of Multi-UAV Cooperative Trajectory Planning (MUCTP) for navigating multiple UAVs safely and efficiently from their respective starting points to designated target points within environments of varying knowledge levels. The proposed approach emphasizes considering UAV constraints and synergy constraints to enhance the efficiency of collaborative path planning. It introduces a path planning algorithm founded on key path points, which involves defining individual population gene location representation, creating a 3D feasible domain, and establishing an objective function by integrating constraint conditions. Experimental results demonstrate the algorithm's effectiveness in terms of rapid convergence and robust synergy in multi-UAV cooperative path planning, leading to more rational planned trajectories. The paper further discussed population partitioning, dynamic hybrid evolution strategies, modeling cooperative target assignment relationships, and methods to set feasible domains for path points. It formulated a comprehensive objective function for flight path planning, encompassing UAV trajectory distance, altitude control, and constraint violation. Two sets of simulation experiments validate the improved algorithm's effectiveness and feasibility in different scenarios. The collaborative target allocation algorithm proves capable of addressing multi-UAV cooperative target allocation problems, and the trajectory planning algorithm generates practical and compliant flight paths.

*4.2.2.8. Path planning techniques for target tracking.* When multiple UAVs need to attack a target simultaneously in complex combat environments, path planning becomes an intricate challenge. To address this, Xiong et al. [123] developed a path planning algorithm based on a GA framework, ensuring that multiple UAVs arrive at the target simultaneously while adhering to environmental and UAV motion constraints. The algorithm employs a regionalization method for path initialization, introduces a well-considered fitness function, and incorporates an adaptive disturbance operator for path planning. The paths' length disparities are utilized as path evaluation criteria, leading to the re-planning of some paths to achieve uniform path lengths for simultaneous UAV attacks. The experimental results, conducted in a MATLAB programming environment, validated the algorithm's effectiveness. The parameters and constraints for these experiments are carefully defined. The algorithm successfully navigates the complexities of 3D environments with terrain constraints and radar threats, resulting in nearly equal-length paths for multiple UAVs, enabling simultaneous multi-directional attacks. Comparisons between the algorithm with and without adaptive disturbance operators revealed the latter's superiority in preventing premature convergence and achieving optimal solutions, although with slightly slower convergence rates.

Yao et al. [124] introduced a novel 3D real-time path planning method for UAVs to tackle the challenges of tracking targets and avoiding obstacles in complex dynamic environments. The approach combines three key components: an enhanced Lyapunov Guidance Vector Field (LGVF) [125], the Interfered Fluid Dynamical System (IFDS) [126], and the strategy of varying receding-horizon optimization inspired by Model Predictive Control (MPC). To address the target tracking aspect in a 3D environment, the LGVF method was improved by incorporating flight height into the traditional Lyapunov function. The IFDS method, inspired by fluid dynamics, was employed for collision-free path planning. It imitated fluid flow phenomena and was particularly efficient. The suboptimal route was achieved through real-time adjustments based on the varying receding-horizon optimization strategy. The proposed method takes into account UAV dynamic constraints and adapts the path based on predicted motions. The objective function incorporates sub-objective functions related to target tracking, obstacle avoidance, and path smoothness. The simulation results demonstrated the applicability of this hybrid method in various dynamic environments, emphasizing its potential for efficient target tracking and obstacle avoidance in real-time UAV applications.

### *4.3. Identification of state-of-the-art control systems and path planning techniques*

A summary of the discussed approaches to UAV/UAS/drone/swarm control systems and path planning techniques is provided in Table 1 and Table 2 to conclude the outstanding findings of the given literature.

## 5. Discussion

One of the aims of this review is to address the question, "What are the current state-of-the-art control systems and path planning techniques used in UAV/UAS/drone/swarm systems?" Our comprehensive analysis of the existing literature showed that the current state-of-the-art encompasses a diverse range of control algorithms and path planning techniques (see Table 1 and Table 2).

The last decade has witnessed a notable surge in research focusing on improving human-robot interfaces for UAV control. This increased attention has allowed for more intuitive and efficient interaction between human operators and drones, resulting in more user-friendly and adaptable systems. As we move forward, it is crucial to refine these interfaces even further, ensuring that they cater to a broad range of users and tasks. Moreover, research in surveillance and area coverage has emphasized the potential of UAVs in applications related to security and monitoring. Innovations in this domain have introduced advanced algorithms and models to optimize the coverage and efficiency of UAV fleets. The significance of these contributions lies in enhancing the capabilities of drones to perform surveillance tasks while addressing challenges such as connectivity, mobility, and resource constraints.

The exploration of intelligent control systems especially using machine learning algorithms [127,128] has marked a significant advancement in UAV technology. Such developments have opened up possibilities for enhanced flight control precision and adaptability, particularly in challenging and dynamic environments. Moreover, with the growing complexity and connectivity of UAVs, addressing cybersecurity threats and safety vulnerabilities has become imperative. Recent research contributions, such as the VirtualDrone Framework [52], have laid the foundation for safeguarding UAV systems against cyberattacks. These solutions are vital for securing critical resources and ensuring the safety and reliability of UAV operations in the face of evolving threats.

Coordinating multiple UAVs within a formation is a challenging yet promising area of research. Advanced control schemes, such as the multi-region distributed control strategy [60] and the consensus-based formation control techniques [41,59,63], offer more efficient and adaptive ways for UAV swarms to work collaboratively. These innovations improve operational efficiency, robustness, and adaptability,

**Table 1**
Summary of the discussed approaches to UAV/UAS/drone/swarm control systems.

| Technique/Algorithm/Method | Reference | Highlights |
|---|---|---|
| Gaze-tracking combined with manual input | [30] | They explored gaze-tracking technology combined with manual keyboard input for drone control. The study found that participants achieved similar task completion times across all four control modes, but one specific mode (Rotation and speed by gaze; translation and altitude by keyboard) was significantly more dependable, potentially due to its resemblance to control modes in 3D games commonly used by experienced gamers. |
| Hand gestures recognition | [32] | They introduced a novel approach for enhancing human-robot collaboration in UAV control for BVLOS applications, combining hand gesture control with autonomous task execution. They integrated ORB-SLAM2 and Detectron2 for 3D mapping, object detection, and semantic segmentation. |
| Connected Coverage Mobility Model | [36] | They explored UAV fleet coordination for collaborative surveillance missions. They introduced the connected coverage mobility model, which ensures network connectivity through a tree-based overlay network and utilizes ACO techniques for efficient UAV guidance. This approach showed significantly improved connectivity performance compared to other contributions in the field. |
| Chaotic Ant Colony Optimization to Coverage (CACOC) | [38] | They introduced the CACOC algorithm, blending ACO with chaotic dynamics for deterministic yet unpredictable UAV mobility. Their experiments demonstrated CACOC's remarkable performance in terms of coverage, fairness, and network organization. |
| Coordinated area coverage based on the mission's size | [40] | They introduced two mission modes based on the mission area's size for flexible deployment strategies. They demonstrated the potential of multi-UAV systems to enhance mission performance, reliability, and adaptability in evolving battlefield scenarios. |
| Game-theoretic approach | [41] | They introduced a game-theoretic approach for cooperative search and surveillance using multiple UAVs. Their modular framework allows the customization of utility functions and learning algorithms to accommodate diverse objectives and constraints. |
| Proximal Policy Optimization (PPO) | [42] | They investigated the performance of RL-based controllers. Controllers trained with PPO outperformed traditional PID control, showcasing the potential of RL for enhancing UAV attitude control, especially in dynamic environments. |
| Self-contained flight control system | [44] | The authors developed lateral control laws, including roll and yaw controllers for trajectory tracking and stability. They introduced the TECS to synchronize throttle and pitch angle for effective altitude and airspeed control. Flight tests confirmed accurate trajectory control within about 1.5 m and altitude errors under 0.5 m. |
| Low-cost quadrotor flight control system for outdoor flights | [46] | They presented a flight control system addressing sensor data sequencing, aircraft modeling, and high-level control. Practical outdoor flights demonstrated the system's effectiveness in positioning, trajectory tracking, and handling wind disturbances. |
| PID Controller | [48] | They presented a flight controller for radiation monitoring, utilizing PID controllers and S/CAS within a traditional control structure. They adopted a "multiple model approach" to ensure robustness against modeling errors and changing conditions. Flight tests, including windy conditions, validated the controller's performance, making it suitable for radiation monitoring applications. |
| Autonomous flight control system using internal sensors | [49] | They introduced an autonomous flight control system that operates without external positioning systems, emphasizing internal sensor-based navigation. Practical waypoint-based control is presented, showcasing effectiveness in experiments with mobile robots. |
| Heterogeneous Comprehensive Learning Particle Swarm Optimization (HCLPSO) | [51] | They introduced a novel method for precise 3D spatial trajectory followed by quadrotors, combining saturated control and HCLPSO optimization. It utilizes cascaded control loops and restricts thrust force with saturated control. The HCLPSO algorithm optimizes control parameters, outperforming other techniques in precision and computational efficiency. |
| VirtualDrone Framework | [52] | They introduced the VirtualDrone Framework, a novel approach to address the growing security challenges of complex UAS. It divides the control environment into normal and secure realms, allowing advanced applications while ensuring safe control. While excelling in addressing cyber threats and minimizing power consumption, it doesn't cover physical sensor manipulations. |
| Collaborative safety flight control system for multiple drones | [53] | They introduced a collaborative safety flight control system for multiple drones, utilizing pattern recognition, coordinated control, and emergency procedures to enhance safety. The study explored various drone formation types, including those for photography and safety purposes. Preliminary experiments demonstrated the feasibility and potential of these safety control methods, offering a promising |

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**Table 1** (*continued*)

| Technique/Algorithm/Method | Reference | Highlights |
|---|---|---|
| | | solution to mitigate drone-related safety challenges. |
| Reconfigurable Optimum Kalman filter (OKF) and Proportional-Integral (PI) controllers | [54] | They addressed sensor and actuator failures. They employed reconfigurable Kalman filters for sensor and actuator fault isolation, along with a control reconfiguration process to maintain effective flight control in the presence of actuator failures. Simulations validated the system's effectiveness, showcasing improved estimation results for various UAV state variables, even during sensor faults. |
| Model-Based Design (MBD) | [55] | They explored the practical application of Model-Based Design (MBD). Using MATLAB/Simulink, control and UAV models are categorized to enable flight path, attitude control, and mission-specific objectives. The results demonstrated effective management of flight path and orientation for planned missions, and rigorous testing, including Hardware-in-the-Loop (HIL) assessments, confirms the flight control system's readiness for real flights. |
| Enhanced Particle Swarm Optimization (PSO) | [56] | They addressed the challenge of parameter adjustment in nonlinear system controllers, focusing on UAVs. They identified the limitations of conventional PID controllers for handling nonlinear systems. They introduced an enhanced PSO algorithm with a nonlinear dynamic inertia weight method that considers particle distances and global optima. |
| Nonlinear complementary filter and proportional-integral rate controllers | [57] | They improved quadrotor capabilities, including attitude control, stabilization, altitude holding, and collision avoidance. They employed two collision avoidance schemes. The control systems consist of two loops for platform operations and obstacle-free navigation, with practical experiments confirming their effectiveness. |
| Hierarchical approach | [58] | They presented a hierarchical control strategy, dividing operational areas into regions, simplifying communication, and enabling UAVs to autonomously determine positions. Stability was ensured through Lyapunov theory, and simulations with fifteen UAVs validated the approach's effectiveness, making it suitable for complex multi-UAV missions. |
| Bird flocking-like formation control algorithm | [59] | They introduced a novel formation control algorithm inspired by bird flocking for UAV swarm coordination, with a primary focus on ensuring camera image overlap. It leveraged stereo cameras, GPS, and IMUs, eliminating the need for feature matching. They evaluated five control algorithms through extensive simulations and emphasized achieving camera image overlap without relying on feature matching, addressing common feature loss and complexity challenges. |
| Multi-priority control strategy | [60] | They presented a dynamic control strategy for drones that optimizes collision avoidance and formation maintenance, considering energy and response time constraints. Experimental results demonstrated its effectiveness in navigating obstacles while maintaining formation. |
| Control law based on Lyapunov theory for close formation flight | [61] | They introduced a robust control strategy for establishing and maintaining a stable triangular close formation using the Lyapunov theory. Simulation results confirmed precise and resilient formation control against external interference. |
| Transformation method for UAV swarm formation changes | [62] | They addressed the critical challenge of ensuring safety during formation transformations in UAV swarms. By using a distributed structure control model, they successfully developed a transformation method that controls the distances between UAVs during changes, preventing collisions and ensuring safe transitions between formations. |
| Adaptive chaotic pigeon-inspired optimization algorithm (ACPIO) | [63] | They introduced a novel formation control technique for multi-agent systems, which utilizes an improved adaptive optimization algorithm and a pinning control method inspired by pigeon flocks. The approach simplifies controller design and reduces manual workload while enhancing adaptability. |
| Swarm layout reconfiguration | [64] | They introduced an extended protocol for enhanced resilience, allowing for any failing swarm element, and a reconfiguration scheme for safe mid-flight formation adjustments. This work distinguishes itself by addressing the loss of swarm elements and real-time reconfiguration into new formations, offering practical implementations, and exploring swarm split-up scenarios. |
| Distributed leader-following formation control | [65] | They introduced a distributed control protocol that incorporates an integral term, allowing followers to track the leader while preserving the desired formation, even with periodic data sampling. They established conditions for achieving leader-following formation asymptotically, provided explicit formulas for optimal control gains and convergence rates, and validated their findings through numerical simulations. |
| Generative adversarial imitation learning (GAIL) | [66] | They introduced GAIL, which is used for drones to imitate peer behaviors, enhancing coordination. They focused on partially observable environments, addressing limited observations. They introduced belief representations, enhancing |

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**Table 1** (*continued*)

| Technique/Algorithm/Method | Reference | Highlights |
|---|---|---|
| | | understanding and decision-making. Results demonstrated superior imitation accuracy, reduced teamwork execution time, and improved energy efficiency. |
| ICCSwarm Framework | [67] | They introduced ICCSwarm, which integrates communication constraints into UAV mission design, emphasizing communication-aware path planning and multi-hop routing protocols. The framework enhances data collection efficiency and features mission computer, autopilot, network routing, and network monitoring components for real-world assessments. |
| DroidPlanner Application Extension | [68] | They extended the DroidPlanner application, originally designed for single UAV control, to manage multiple UAVs through modifications in communication infrastructure and user interface. They employed the MAVLink protocol and adhered to the MVC pattern. |
| Linear Quadratic Gaussian (LQG) regulators | [70] | They proposed a control architecture based on LQG regulators for position, orientation, and speed. They presented an automatic camera path planning method for cinema scene capture using the PSL. They validated the system's feasibility in experiments, marking an initial step toward cinema industry automation. |

opening doors for the deployment of UAV fleets in diverse mission scenarios. UAV swarm communication and control have evolved to tackle issues related to reliability, coordination, and efficiency. The integration of communication constraints into mission planning and the utilization of novel communication protocols have significantly improved swarm management. These advancements are essential for enhancing the effectiveness of large-scale UAV missions, where communication plays a critical role.

As mentioned earlier, path planning is a fundamental aspect of UAV control, influencing their operational efficiency and effectiveness in various applications. Over the past decade, researchers have explored a diverse array of path planning techniques to address the complex challenges faced by UAVs in different scenarios. These techniques aim to optimize routes, minimize energy consumption, and adapt to dynamic environments.

Genetic algorithms [73,74,98] have demonstrated their versatility in optimizing UAV path planning. By mimicking the principles of natural selection, genetic algorithms explore and evolve paths, allowing UAVs to adapt to changing conditions. This technique has been instrumental in devising efficient and adaptive routes for UAV missions. Moreover, particle swarm optimization (PSO), a nature-inspired optimization approach, has been leveraged in path planning to find optimal trajectories and meet mission objectives [84,85,90]. Its balance between exploration and exploitation makes it a valuable tool in generating paths that minimize costs or satisfy specific criteria.

Research also showcases the utilization of advanced optimization methods like the variation of comprehensive learning particle swarm optimization (CLPSO) [78,80], and Improved bat algorithm (IBA) [107]. These techniques offer enhanced capabilities in optimizing UAV routes and adapting them to evolving environmental factors. Furthermore, some studies combine multiple path planning techniques, such as the

**Table 2**
Summary of the discussed approaches to UAV/UAS/drone/swarm path planning techniques.

| Technique/Algorithm/Method | Reference | Highlights |
|---|---|---|
| Hybrid Genetic Algorithm (HGA) | [73] | They planned secure UAV flight paths in complex environments with no-fly zones. They employed a conservative risk allocation strategy to ensure path planning safety. Their approach consistently provides solutions in under 10 s, emphasizing safety with a brief response time. |
| Genetic Algorithm (GA) and A* Algorithm | [74] | They integrated GA and A* Algorithm for 3D path planning in UAVs, optimized for bridge inspection. Their method balances flight time and visibility, especially in high-risk areas, enhancing data collection accuracy. They prioritized perpendicular views and overlapping perspectives, further improving data collection accuracy. |
| Comprehensive Learning Particle Swarm Optimization with Limited Local Search (CLPSOLLS) | [78] | They introduced CLPSOLLS, a novel algorithm that combines PSO with BFGS Local Search to improve local convergence in path planning. CLPSOLLS enhances path planning accuracy with significantly reduced computational costs, particularly in limited degrees of freedom scenarios. Experimental results showed CLPSOLLS outperforms the other algorithms, finding lower-cost paths in challenging environments, and highlighting its robustness. |
| Heterogeneous Adaptive Comprehensive Learning and Dynamic Multi-Swarm Particle Swarm Optimizer (HACLDMS-PSO) | [80] | They introduced HACLDMS-PSO, an enhanced PSO algorithm, building upon HCLDMS-PSO. The algorithm incorporates Levy flight and Cauchy mutation for expanded search ranges and rapid escape from local extrema. Simulation results confirmed the algorithm's ability to discover feasible paths in various environmental models. |
| GAs and PSO | [84] | They employed GAs and PSO algorithms to address autonomous path planning for fixed-wing UAVs in complex 3D environments. They introduced a comprehensive cost function that considers various path characteristics, optimizing for distance, average altitude, danger zone avoidance, and adherence to UAV performance constraints. |
| PSO with Penalty Function | [85] | They introduced a novel approach for planning optimal trajectories of SUAVs to monitor stationary targets with a focus on maximizing net energy gains while adhering to various constraints. Their use of PSO with a penalty function addressed the computational complexity. |
| Concentric Spherical Coordinate-Based Encoding and Enhanced PSO | [86] | They introduced a novel 3D path planning method for UAVs using concentric spherical coordinates and an enhanced PSO algorithm. Their approach optimized fuel consumption, threat avoidance, |

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**Table 2** (*continued*)

| Technique/Algorithm/Method | Reference | Highlights |
|---|---|---|
| | | and flight altitude while considering various constraints. The concentric spherical encoding reduced the search space and handled angle constraints efficiently. |
| Large-Scale Swarm Optimizers with Variation Encoding | [87] | They presented a novel approach for UAV path planning using large-scale swarm optimizers. Their variation encoding scheme simplified the search space, optimizing UAV movements along three Cartesian axes and reducing path repetition. Experiments across various scenarios highlighted the effectiveness of the encoding scheme. |
| Adaptive Sensitivity Decision Operator with PSO | [88] | They introduced an innovative 3D path planning algorithm for UAVs that enhances PSO by addressing issues like local optima and slow convergence. The algorithm restricts the search space to prevent premature convergence and considers relative particle directivity and redesigned objective functions for improved search accuracy. It incorporates global path planning techniques, demonstrating its efficiency and effectiveness through experimentation. |
| Particle Swarm Optimization and Enhanced Sparrow Search Algorithm (PESSA) | [90] | They introduced PESSA, a cutting-edge UAV path planning approach that combines PSO with ESSA. Parallel operation of PSO and ESSA with a reverse search strategy enhanced global search capabilities and prevented local optima. Extensive experiments showed that PESSA consistently achieves optimal or near-optimal solutions across benchmark functions and outperforms other algorithms. |
| Trajectory Modeling with PSO | [91] | They introduced an algorithm for optimizing UAV flight trajectories while adhering to strict environmental constraints, including obstacles, waypoints, and destinations. The path planning strategy divides flight paths into segments, represented as binary-coded basic maneuvers, allowing efficient handling of discrete variables with PSO. |
| Enhanced PSO Algorithm with Chaos Strategy and Dijkstra Algorithm | [92] | They introduced an enhanced PSO algorithm for UAV path planning, specifically targeting the improvement of real-time path quality and the mitigation of local optima concerns. The Chaos strategy integrated into PSO aims to prevent particle entrapment in local optima. Path quality is enhanced through the incorporation of the Dijkstra algorithm. |
| Enhanced RRT* Algorithm with Biased Sampling | [96] | They introduced an enhanced RRT* algorithm for small UAV obstacle avoidance path planning, addressing the need for safe navigation. The enhanced RRT* algorithm, based on biased sampling, improved convergence speed by concentrating sampling around the goal and path points. |
| Enhanced RRT Algorithm with A Priori Information and Dedicated Cost Function | [97] | They introduced an enhanced RRT Algorithm. The RRT algorithm is extended by incorporating a priori information, particularly regarding UAV dynamics constraints, and introducing a dedicated cost function. The enhancements significantly accelerated the convergence of the path planning process. |
| GA, ACO, Voronoi diagrams, and clustering. | [98] | They employed AI methods, including GA, ACO, Voronoi diagrams, and clustering techniques. The primary contribution is the enhancement of the initial population generation in GA to speed up the convergence process. Three unique strategies are introduced to improve the initial population, using Voronoi vertices, cluster centers, and collision points as additional waypoints to address terrain collisions. |
| Double-Ant Colony Paradigm with GA (GA+DB-ACO) | [99] | They introduced a novel approach based on a double-ant colony paradigm, integrating GA in the initial stages to expedite convergence. DB-ACO and GA+DB-ACO are employed to validate their effectiveness through simulations. |
| Multi-Colony ACO | [100] | They presented a path planning algorithm for UAVs using a Multi-Colony ACO approach, addressing the susceptibility of single colony ACO to premature convergence. Multiple ant colonies worked collaboratively to optimize UAV path planning, with each colony maintaining its own pheromone table and sharing information at specified intervals. Experimental results demonstrated the advantages of the Multi-Colony ACO approach over classical ACO. |
| Accurate UAV 3-D Path Planning with Enhanced Multiobjective Swarm Intelligence (APPMS) | [101] | They introduced the APPMS method for UAV 3-D path planning, emphasizing multiobjective modeling, accurate constraint-based modeling, and advanced search strategies. The method employs an improved ACO algorithm to enhance global and local search capabilities, maintaining uniform distribution and diversity in the Pareto solution set. |
| Dijkstra, Floyd, A*, and ACO | [106] | They conducted a comparative analysis of four distinct 3D path planning algorithms for UAVs: Dijkstra, Floyd, A*, and ACO. A grid map method is uniformly implemented across these algorithms to model working environments, distinguishing 'free' and 'obstructed' grids. The 'perpendicular approach' is introduced, enhancing the efficiency and performance of Dijkstra and Floyd algorithms by selecting key path nodes based on encountered obstacles. |

(*continued on next page*)

**Table 2** (*continued*)

| Technique/Algorithm/Method | Reference | Highlights |
|---|---|---|
| Improved Bat Algorithm (IBA) | [107] | They introduced IBA. It integrates BA for initial path point generation and introduces a mutation factor to avoid local optima. ABC refines the path solutions generated by BA in an iterative process that combines the strengths of both algorithms. |
| Multi-Strategy Evolutionary Learning ABC (MSEL-ABC) | [110] | They introduced a path planning strategy for UAH facing multiple constraints, leveraging the MSEL-ABC algorithm. The creation of a multi-strategy evolutionary database replaces the conventional evolutionary approach of the ABC algorithm. They addressed the problem formulation of UAH path planning, considering constraints such as radar and missile threats, within a framework that integrates multi-strategy evolutionary learning. |
| Improved Adaptive Grey Wolf Optimization Algorithm (AGWO) | [114] | They presented AGWO for 3D path planning of UAVs in complex environments, with a focus on earthquake-stricken areas. AGWO introduced an adaptive convergence factor adjustment strategy and an adaptive weight factor to update individual positions, enhancing the algorithm's convergence. |
| Glow-worm Swarm Optimization (GSO) | [115] | They introduced an algorithm that utilizes GSO for the path planning of UAVs in complex environments with obstacles of varying sizes and unpredictable movements. The algorithm features a cost function designed to minimize the cost associated with UAV movement, considering factors such as path length and altitude. |
| Improved fruit fly optimization algorithm (ORPFOA) | [117] | They introduced a method for generating optimal initial flight paths for multiple UAVs in a complex 3D environment, improving computational efficiency. A novel task assignment approach is presented, considering task priorities and dynamically changing tasks, allowing for the optimal number of UAVs and solving task assignment problems when new tasks are introduced. |
| Dynamic path planning algorithms: MIN_ROUTE and ROUTE_PRIORITY | [120] | Two novel dynamic path planning algorithms, MIN_ROUTE and ROUTE_PRIORITY, are introduced to optimize shelter point coverage within limited flight durations, accounting for variables such as wind speed and wind direction. |
| IDeA | [121] | They introduced IDeA, an autonomous and onboard image-based agricultural land demarcation and path-planning system for UAVs within an advanced UAV-based aerial IoT framework. They developed a system that autonomously plans paths for UAVs without the need for prior GPS markers for waypoints. |
| Multi-UAV Cooperative Trajectory Planning (MUCTP) | [122] | They planned trajectories for multiple UAVs in various environments. They emphasized UAV constraints and synergy constraints. They used path planning with key path points for rapid convergence. |
| SaCHBA_PDN | [118] | They introduced an enhanced HBA for UAV path planning. They presented innovative strategies, including the Bernoulli shift map, PODNS, and horizontal crossing. |
| GA-based | [123] | They developed a GA-based path planning algorithm for multiple UAVs to arrive simultaneously at a target while considering environmental and UAV constraints. They utilized regionalization for path initialization, introduced a well-considered fitness function, and incorporated an adaptive disturbance operator for path planning. |
| Hybrid method | [124] | They introduced a hybrid method that combined the enhanced LGVF, IFDS, and a varying receding-horizon optimization strategy inspired by MPC. |

Chaos Strategy and Dijkstra Algorithm, to achieve more robust and adaptable path planning [92]. This approach harnesses the strengths of each method to improve path quality and mission success.

Ant colony optimization (ACO) techniques have been instrumental in solving complex path planning problems [99,101,106]. By simulating the foraging behavior of ants, ACO algorithms help UAVs discover efficient routes, especially in scenarios with multiple objectives and constraints. Some path planning strategies leverage multi-agent coordination principles, like the Multi-Colony ACO approach [100]. These methods aim to enhance coordination among multiple UAVs, making them collectively plan routes that optimize coverage and minimize duplication of efforts. Path planning inspired by swarm behaviors and hierarchical leadership models has shown potential in optimizing routes and ensuring effective communication and coordination among UAVs.

### 5.1. *Assessment of challenges and limitations*

The existing UAV/UAS/drone/swarm control systems and path planning techniques encounter a set of significant challenges and limitations. To answer the question, "What are the key challenges and limitations in the existing UAV/UAS/drone/swarm and swarm control systems and path planning?" this review assessed the obstacles and constraints faced by researchers and practitioners in the design and implementation of these systems.

It is essential to acknowledge certain limitations that may apply to various systems. One common limitation is the maintenance of connectivity, which can pose constraints in scenarios with a limited number of UAVs [36]. On the other hand, while some of the studies successfully maintained connectivity, it had a slight negative impact on coverage performance. This trade-off between connectivity and coverage is a crucial consideration for practitioners in the field of UAV coordination.

As system density increases, issues related to fairness and speed can arise due to concurrent decision-making and collaboration delays, potentially affecting system performance [68]. Furthermore, some investigations have shown the systems' capacity to manage only a single drone, restricting their applicability to scenarios demanding the utilization of multiple drones for intricate tasks. Moreover, given that UAVs typically rely on fuel or battery power, effective power consumption and management are recurrent challenges faced by researchers in this field.

In various machine learning and reinforcement learning (RL) studies, a set of key challenges and limitations confront researchers. One such challenge revolves around state space expansion, which is a common issue in scaling RL models to more complex environments [42]. Larger memory sizes have been shown to lead to reduced convergence and stability among RL algorithms, underscoring the inherent difficulties associated with handling increasingly expansive state spaces.

The consistency of UAV components, including Electronic Speed Controllers (ESCs), motors, and GPS systems, remains a recurring challenge. Inconsistent hardware quality, stemming from insufficient quality control in certain components, has been a notable issue in various studies [67]. These inconsistencies can compromise the stability and reliability of UAVs, potentially leading to unexpected crashes or erratic behavior.

Sensor limitations play a pivotal role in the development of drone control systems. For instance, the use of laser distance sensors is highly suitable for critical altitude measurement during take-off and landing. However, laser distance sensors inherently possess a limited scope, typically covering distances of no more than 100 m. Overcoming this limitation and ensuring comprehensive altitude monitoring during a UAV's flight necessitates the integration of supplementary sensor technologies, such as barometers [44]. Additionally, the resolution of the camera also plays a crucial role in the systems that depend on the camera sensor to maintain effective tracking [53]. In innovative control systems such as gaze-based control, temporary loss of gaze tracking and slight offsets have been identified as issues that could impact control reliability and effectiveness [30].

While the simulations demonstrated the effectiveness of controllers under specific conditions with controlled dynamics, such as linear and non-linear environments, this review highlights a notable limitation. The translation of these findings to real-world scenarios, characterized by uncertainties, sensor noise, and non-linearities, presents a substantial challenge [59]. Moreover, considerable altitude errors are evident when altitude changes are applied, and track course errors arise due to wind turbulence [48].

Even though certain systems exhibit superior optimization accuracy, their computational efficiency might fall short when compared to alternative approaches. Furthermore, when dealing with multiple UAVs in the system, there is a notable increase in time overhead, which adds a layer of complexity to the operational efficiency [64].

The development of hybrid algorithms that combine the strengths of different methods could improve path optimization but also bring computational challenges. It becomes apparent that the optimization of the path declines as the number of critical nodes in the path increases, necessitating the use of path simplification methods to address the issue. However, the addition of the Dijkstra algorithm brings computational challenges, particularly when dealing with a wide range of critical nodes [92].

Some algorithms' performances depend on a threshold value defined in the parameters of the system. This means that selecting the correct threshold is crucial for optimal performance. However, the algorithm may struggle to maintain effectiveness if the threshold is set too high, leading to longer planning times and suboptimal paths [96].

Several limitations are commonly observed in existing UAV path planning approaches. One of these limitations is the absence of distance-based considerations regarding obstacles in certain methods [99]. Many of these approaches oversimplify the problem by assuming that UAVs cannot traverse obstacles. While this simplification streamlines the planning process, it does not consider the varying levels of risk associated with the proximity of UAVs to obstacles. This limitation hampers the adaptability of these algorithms in dynamic and intricate environments where precise risk assessment is essential.

Another significant challenge in UAV path planning occurred in the field of area coverage. Handling areas with intricate or non-convex shapes poses difficulties for many UAV systems [121]. Furthermore, the reliance on markers for field detection and coverage remains a common limitation. Researchers are actively exploring markerless solutions and advanced detection techniques to enhance the versatility of UAV field coverage.

One of the key limitations in UAV path planning is the insufficient ability to navigate complex and diverse obstacles [97]. Despite notable advancements in path planning algorithms, they often struggle when confronted with intricate and heterogeneous environmental challenges. This limitation restricts their capacity to adapt and plan efficient routes in scenarios where obstacles exhibit diverse shapes, sizes, and dynamic behaviors. Addressing this limitation remains a fundamental challenge, calling for the development of more robust and adaptive path planning techniques.

Additionally, the scalability and performance of path planning algorithms require further assessment. [100] highlighted the need for more extensive experiments involving a larger number of colonies. As the number of control points increases, challenges related to algorithm performance must be adequately addressed. Furthermore, some path planning algorithms have been predominantly tested in simulation environments, lacking real-world validation for path planning problems [101,114]. This limitation calls for a more comprehensive evaluation of these algorithms under real-world conditions.

Finally, certain path planning approaches, such as those [107,110], are primarily suitable for static environments. This constraint highlights the need for developing adaptive solutions capable of handling dynamic scenarios effectively.

### 5.2. Future research directions

As we delve into "What are the future research directions and potential areas for improvement in UAV/UAS/drone/swarm control systems and path planning?" this review aims to offer valuable insights into emerging trends and potential areas for improvement within the field. These insights will serve as a compass, guiding future research efforts and endeavors.

As we reviewed and detailed extensively the current state-of-the-art control algorithms and path planning techniques, and the challenges and limitations, we found some gaps to be filled and future research directions. One notable avenue for future research, inspired by [36], involves more flexible exploration strategies that maintain connectivity while accommodating scenarios with a reduced number of UAVs. Furthermore, understanding the trade-off between connectivity and coverage can inform the design and operation of UAV fleets, particularly in scenarios where network connectivity is vital.

There is an opportunity to investigate gaze-based drone interaction in combination with near-eye displays, which are favored by drone professionals. Additionally, exploring the use of binocular eye data for measuring convergence and automatically selecting among multiple interfaces at various distances could enhance control. Combining gaze control with head movements, facial expressions, and hand gestures could result in richer interaction possibilities and more robust filtering for accidental commands [30].

In the pursuit of advancing machine learning and RL, future research should focus on addressing the challenges presented. A critical direction involves optimizing state spaces to cope with complexity more effectively. Furthermore, researchers should prioritize efforts to reduce training times and improve the overall efficiency of RL models. By tackling challenges related to robustness, adaptation, and designing more expressive reward functions, the field can expedite training processes, yielding more reliable and efficient RL models.

UAV sensor enhancement through the addition of technologies such as LiDAR for depth information and improvements in computational speed can significantly boost the effectiveness of path planning algorithms. Another promising research direction involves the online coupling of control and communication to enhance real-time control capabilities. This dynamic coupling can empower more responsive and adaptive UAV systems, facilitating improved decision-making in changing environments.

Given the small size of the drones, the tracking applications encountered difficulties in precisely identifying and following the targets. To address this limitation in future work, it is imperative to consider employing cameras with higher resolutions capable of tracking smaller objects effectively. Furthermore, to bridge the gap between idealized simulations and real-world applications, it is essential to introduce more realistic dynamics and sensor noise into simulation environments.

Incorporating external sensors like laser range finders to map unknown terrains and conducting flight tests to assess collision avoidance algorithms' performance with larger obstacles are avenues for future research. Additionally, the development of more complex algorithms that combine path prediction and machine learning approaches to avoid collisions efficiently is one of the future trends in the field of UAV research. Furthermore, research into hybrid algorithms that combine different methods to provide high-quality paths for complex scenarios while maintaining computational efficiency holds promise.

The development of techniques for automatically optimizing threshold values based on specific environment and obstacle characteristics is a prospective area of study. Additionally, efforts will focus on further reducing computational time without sacrificing search accuracies, ensuring efficient path planning. Moreover, future research and development endeavors should give top priority to overcoming limitations by integrating risk assessment that takes into account the distance between UAVs and obstacles into path planning algorithms. This strategic move will facilitate the development of more comprehensive and dependable path planning solutions for UAV missions, ultimately enhancing safety and adaptability.

The concept of explainability and interpretability is gaining prominence in the domain of drone control systems. As these systems become increasingly sophisticated, understanding and interpreting the decisions made by AI-driven algorithms is essential, particularly in critical applications such as surveillance, search and rescue, and autonomous navigation. Researchers should explore methods to make control systems more transparent, enabling operators to comprehend the reasoning behind UAV actions. This focus on explainability not only enhances trust in AI-driven UAV systems but also contributes to the ethical deployment of autonomous technologies.

To further enhance the capabilities of UAVs, researchers should concentrate on refining real-time adaptation mechanisms. Developing algorithms that allow UAVs to dynamically adjust their behavior in response to evolving environmental conditions and mission objectives is necessary. By focusing on real-time adaptation, researchers can ensure that UAVs operate with increased resilience and versatility, adapting to unforeseen challenges and optimizing their performance in dynamic scenarios.

In the context of cybersecurity, researchers should prioritize the development of advanced threat detection and mitigation strategies within UAV control systems. As UAVs become integral to critical applications, safeguarding them against cyber threats is paramount. Researchers should explore innovative approaches to identify and neutralize potential cybersecurity vulnerabilities, ensuring the secure and reliable operation of UAVs in the face of evolving digital risks.

To address the energy efficiency concerns associated with UAVs, researchers should concentrate on optimizing control systems and path planning algorithms for power consumption. Exploring lightweight algorithms, energy-efficient hardware designs, and sustainable power sources will be essential. Focusing on energy-efficient systems will not only extend UAV flight times but also contribute to environmentally friendly and sustainable UAV operations, aligning with global efforts towards green technology.

Considering the increasing integration of UAVs in urban environments, researchers should prioritize path planning algorithms that address urban challenges. Urban environments pose unique obstacles such as buildings, traffic, and restricted airspace. Research efforts should focus on developing path planning strategies that navigate these challenges efficiently, ensuring safe and effective UAV operations in urban settings. By tailoring algorithms to urban complexities, researchers can unlock the full potential of UAVs in applications like delivery services and infrastructure inspection.

Another important aspect to consider is the role of regulations and legal frameworks in the development and deployment of UAV systems. As drone technology becomes more sophisticated and widespread, the need for clear and comprehensive regulations becomes increasingly apparent. These regulations must address issues such as airspace management, privacy concerns, and operational safety. The evolving regulatory landscape will play a significant role in shaping the future of UAV technology, potentially influencing the design and functionality of UAV control systems.

One of the significant limitations is the lack of standardized testing and validation procedures. Many studies rely on custom-built testing environments and scenarios, making it challenging to compare results across different research projects. This inconsistency can limit the development of universally accepted benchmarks for UAV systems. To address this issue, future research should focus on creating standardized testing frameworks that allow for consistent evaluation of UAV systems' reliability, safety, and efficiency. Such frameworks could facilitate broader collaboration among researchers and industry experts, promoting a more cohesive approach to UAV system development and reducing the barriers to technology adoption.

The evolution of swarming algorithms is shaping the collaborative dynamics of UAV fleets. While existing control schemes emphasize coordination and efficiency, ongoing research delves into the integration of swarm intelligence principles, social behaviors, and evolutionary strategies. This holistic approach envisions UAV swarms that exhibit emergent behaviors, self-organization, and adaptability in response to environmental changes. The exploration of bio-inspired swarm algorithms aims to emulate collective decision-making processes, potentially revolutionizing the capabilities of UAV fleets in dynamic and unpredictable environments. Therefore, this is another future research direction that researchers should actively pursue to unlock the full potential of collaborative UAV missions.

Finally, the utilization of multi-UAV systems holds significant promise for future work. These systems involve the coordinated operation of multiple UAVs, working together to achieve complex objectives. Swarm intelligence, with its principles of decentralized decision-making and collaboration, can play a pivotal role in coordinated movements among UAVs, enhancing their responsiveness and adaptability in dynamically changing environments. The advantages are multifaceted. They can collectively cover larger areas, enhance redundancy for mission-critical tasks, and facilitate collaborative efforts for applications such as search and rescue, surveillance, and environmental monitoring. Future research should focus on the development and optimization of UAV swarm control and path planning algorithms that can efficiently coordinate and manage fleets of UAVs. These algorithms will need to address challenges related to communication, collision avoidance, and dynamic task allocation, ultimately leading to more efficient and adaptable UAV missions.

## 6. Conclusion

This systematic review summarized the current state-of-the-art UAV/UAS/drone/swarm control systems and path planning techniques, existing challenges and limitations, and possible future research directions. As we reflect on the advancements in these diverse areas of UAV research, it is evident that the past decade has seen significant progress in enhancing the capabilities, safety, and adaptability of UAV systems. The review underscores the evolution of UAVs, not as standalone entities but as integral components within swarm intelligence and nature-inspired algorithms. Notably, the incorporation of swarm intelligence principles has contributed to flexible exploration strategies, maintaining connectivity, and facilitating collaborative decision-making—a trend likely to shape the future of UAV technology. These developments not only contribute to the expanding field of UAV technology but also have a profound impact on various sectors, ranging from security and surveillance to entertainment and beyond. Nature-inspired algorithms, including swarm intelligence, have played a key role in steering these developments, fostering adaptability and cooperative decision-making among UAVs. Looking forward, the trajectory of UAV research holds promise, with researchers and industry experts poised to expand the capabilities of UAV systems. Swarm intelligence, alongside the continued exploration of nature-inspired algorithms, will undoubtedly remain integral to this journey, guiding the path toward more intelligent, adaptive, and collaborative UAV systems. These advancements not only contribute to the ongoing expansion of UAV technology but also affirm the pivotal role of UAVs in shaping contemporary technological landscapes.

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## CRediT authorship contribution statement

**Berk Cetinsaya:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Dirk Reiners:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Carolina Cruz-Neira:** Writing – review & editing, Supervision, Project administration.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

No data was used for the research described in the article.

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