Adaptive Strategies for Dynamic Obstacle Avoidance and Formation Control in Multi-Agent Drone Systems: A Review

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***Abstract*—Obstacle avoidance in multi-agent systems is a critical area of research driven by advancements in autonomous technology and artificial intelligence. This review examines various approaches to path planning, formation control, and communication architectures, focusing on their effectiveness in static and dynamic environments. The research contribution is a comprehensive analysis of current techniques based on a structured selection process evaluating peer-reviewed studies through computational efficiency, real-time adaptivity, and scalability. The findings highlight the strengths and limitations of classical methods, such as the Improved Artificial Potential Field (IAPF), and modern techniques like Reinforcement Learning (RL) and Model Predictive Control (MPC). Comparative analysis reveals that while these approaches improve adaptivity, they also introduce challenges such as high computational loads, difficulties in large-scale multi-agent coordination, and sensitivity of parameter tuning. Additionally, existing formation control strategies depend highly on stable inter-agent communication, making them vulnerable to delays and failures in decentralized networks. This review identifies key research gaps and suggests future directions, including hybrid RL-MPC formation control, adaptive path planning algorithms, and scalable communication protocols to enhance multi-agent system performance in real-world applications.**

Keywords*—*Multi-Agent Drone Systems; Dynamic Obstacle Avoidance; Adaptive Path Planning Algorithms; Real-Time Formation Control; Scalable Communication Protocols.

I. INTRODUCTION

In recent years, studies of multi-agent coordination have been increasing [1], including studies on multi-drone systems [2] and multi-robot systems [3]. This trend is driven by advancements in autonomous technologies and artificial intelligence [4] – [6]. Compared to single-agent systems, multi-agent systems have the potential to perform more complex tasks [7]. For example, multi-agent drone systems may facilitate the delivery of heavy goods [8], search and rescue operations [9], and agricultural monitoring [10] to increase productivity. These multi-agent collaborative tasks require the capability of navigating predetermined paths and maintaining formations in changing environments.

However, despite the significant potential of multi-agent systems, their implementation faces challenges, particularly in real-time navigation within dynamic and obstacle-filled environments [11]. While various path planning and formation control methods have been developed, these existing methods still face limitations in adapting to dynamic obstacles while maintaining formation. One critical research gap is the need for more adaptive and integrated strategies that simultaneously handle formation control and obstacle avoidance in dynamic environments. This review addresses this critical gap by analyzing recent developments in obstacle avoidance methodologies for multi-agent drone systems, particularly in path planning and formation control methods.

While this review concentrates on multi-agent approaches for drone systems, it also examines relevant algorithms from other multi-agent systems that benefit drone applications. The review examines how different methodologies perform under varying environmental complexity and their computational and communication requirements. This review aims to identify directions for developing more robust and adaptive multi-agent navigation frameworks suitable for real-world deployment by synthesizing findings across methodological approaches.

This review is structured as follows: Section II explains the review methodology. Section III discusses various obstacle avoidance methods based on the mentioned categories. Section IV presents the key findings and identified challenges. Finally, Section V concludes the review and provides directions for future research.

II. REVIEW METHODOLOGY

A. Selection Criteria

This review encompasses literature published between 2019 and 2024, focusing on methods applied to obstacle avoidance, path planning, and formation control. The article selection process was carried out using keywords such as "obstacle avoidance," "multi-agent systems," "multi-robot systems," and "multi-drone systems." This period is selected due to significant advancements in artificial intelligence-based path planning, autonomous navigation reinforcement learning applications, and multi-agent system technology improvements. Studies published before 2019 often lack the latest algorithmic enhancements and computational capabilities that have shaped modern multi-agent control systems.

To ensure this review's relevance and scientific rigor, the following criteria were used to select the studies for review:

(1) Publications from peer-reviewed journals and reputable conferences to ensure methodological robustness

(2) Publications that provided experimental or simulation validation of their proposed methods, and

(3) Publication that explicitly addressed multi-agent formation control, obstacle avoidance, and path planning.

Grey literature, such as industry reports and preprints, was omitted to maintain academic rigor. Furthermore, only English-language publications were considered to ensure consistency in analysis. Eighty-two articles were selected for further analysis. These articles were categorized based on the primary aspects: obstacle type, formation control, and path planning. These classifications are shown in Fig. 1.

This review seeks to consolidate existing knowledge and identify opportunities for hybrid approaches integrating multiple strategies for enhanced navigation and coordination in multi-agent systems. By systematically comparing methodologies, this study aims to guide future research toward more efficient and scalable multi-agent navigation frameworks.

B. *Limitations*

This review acknowledges several limitations in its methodology. First, the emphasis on English-language publications may have excluded relevant research published in other languages. Second, excluding grey literature may have overlooked emerging techniques from industry research that have not yet reached academic publication. Finally, the rapid evolution of this field means that very recent developments may not be fully represented in this review.

III. OBSTACLE AVOIDANCE METHODS

This section describes various multi-agent approaches for obstacle avoidance systems based on obstacle types, path planning, formation control, and communication architecture. The categorization is shown in Fig. 1 and described further in the following subsections.

A. *Obstacle Types*

Obstacles within an environment are classified into static, dynamic, and combined categories, as illustrated in Fig. 2. Static obstacles (e.g., walls, buildings) maintain fixed positions [17]-[28], [62], often addressed through path planning algorithms like Improved Artificial Potential Field (IAPF) [16] to determine the shortest path. Dynamic obstacles (e.g., pedestrians, vehicles) change position over time [29]-[34], requiring continuous real-time path adjustments that make Reinforcement Learning (RL)-based methods more appealing [34], [63]. Environments with combined static and dynamic obstacles [13], [16], [35]-[41] requires more integrated approaches for successful navigation.

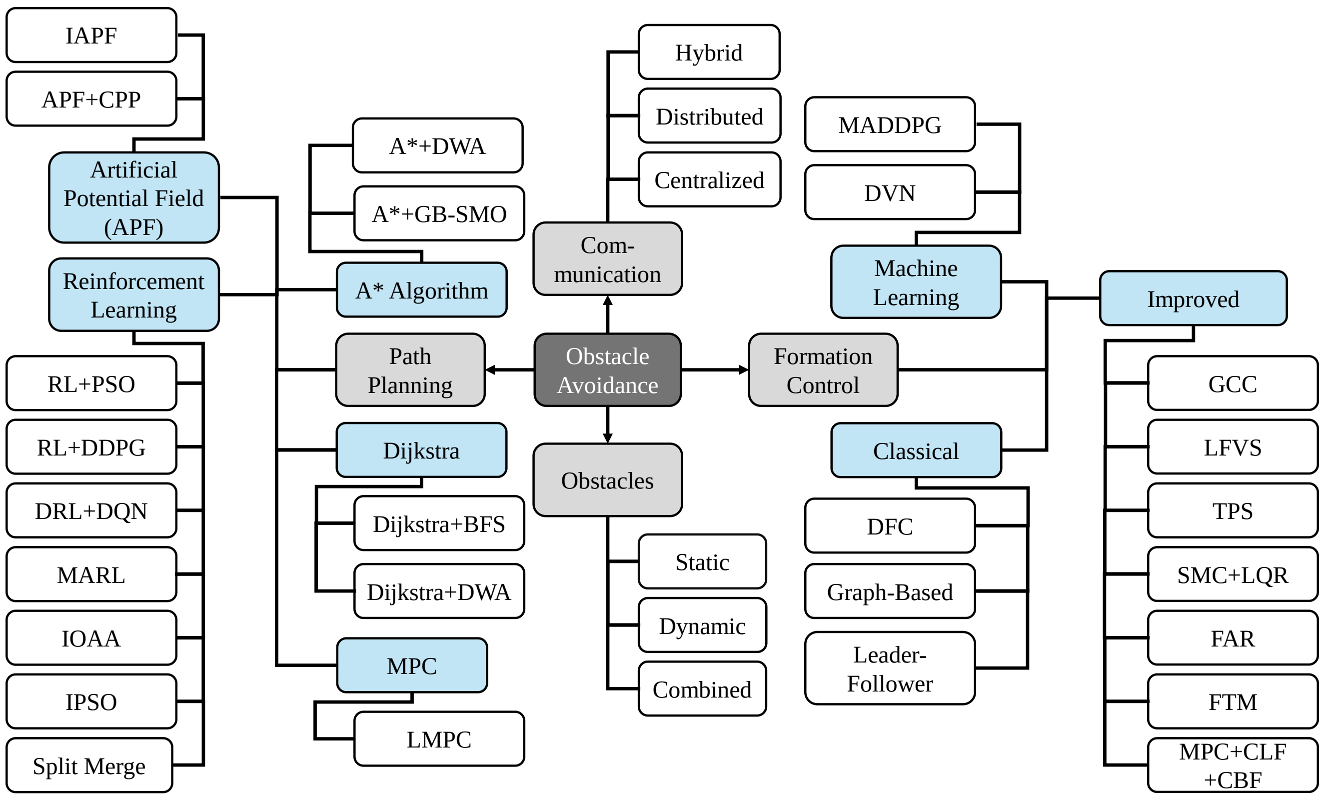

Fig. 1. Classification of obstacle avoidance methods

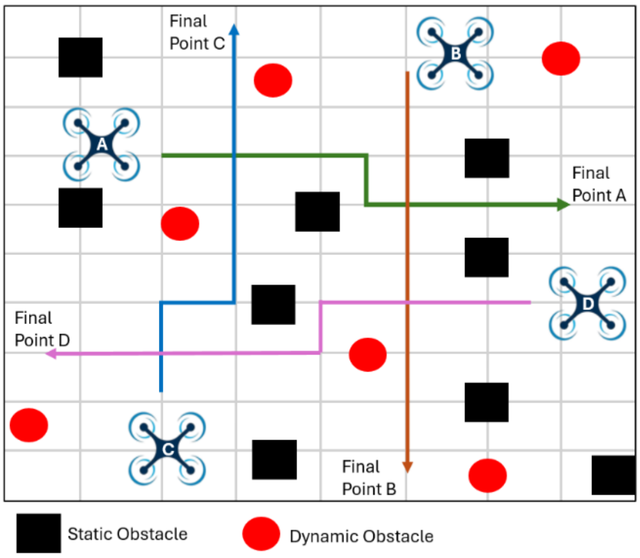

Fig. 2. A multi-agent drone system faces obstacle in a complex space

B. Path Planning

Path planning is crucial for navigation and obstacle avoidance in multi-agent systems, where each agent must find an optimal path to its goal while avoiding collisions. As shown in Fig. 3, path planning methods have evolved into three main categories: classical, optimization-based predictive models, and machine learning approaches. These categories are differentiated by their calculation approach, adaptivity to dynamic environments, and computational requirements. The following subsections discuss these categories.

1) Classical Methods: Classical methods in path planning utilize graph-based approaches and potential fields, such as the Dijkstra [18], A* [39], and Artificial Potential Field (APF) [40] Algorithms. These methods are well-known foundations and are often used as benchmarks. However, these methods struggle to handle dynamic environments, inter-agent interactions, and system constraints. The following subsections describe these classical methods.

a) Dijkstra's Algorithm: Dijkstra's algorithm is one of the earliest graph-based path-planning methods. The approach constructs a graph consisting of nodes and edges, in which the nodes represent the possible locations to visit, and the edges represent the length of the path between nodes. The algorithm starts at the source node and iteratively selects and then visits the closest neighbor node until it finally arrives at the destination node through the smallest number of nodes. Despite its concise idea and programming, its computational load grows exponentially with the number of nodes, boundaries, and obstacles; hence, limiting scalability to large-scale multi-agent systems. Improvements to Dijkstra's Algorithms have been explored by augmenting with Breadth-First Search (BFS) [18] for enhanced path finding in environments with formation constraints and dense obstacles. Another approach [52]-[53] combines Dijkstra's Algorithm with the Dynamic Window Approach (DWA) for real-time obstacle avoidance in unknown environments. This method employs Dijkstra as a global planner and DWA as a local reactive planner for dynamic obstacle avoidance.

b) A Algorithm:* The A* algorithm is also a graph-based path planning method. It assigns costs to all edges in the graph, so its total cost can rank all paths connecting two nodes. The algorithm starts at the source node and estimates the distance to the destination node. Based on the estimation, it selects the lowest-cost edge to visit the next node. Then the algorithm iterates the distance estimation, edge selection, and node visit until the destination node is reached. The algorithm maintains a node list to avoid re-evaluating nodes [11], hence faster convergence. However, it does not always guarantee the absolute shortest path and often requires distance estimation adjustments for complex tasks [54]. A study of strategic maps and mazes [55] showed that the A* Algorithm provides the shortest path 85% of the time. Its performance improvements include integration with Gradient-Based Sequential Minimal Optimization (GB-SMO) for smoother trajectories [39] and combination with DWA for real-time adjustment to moving obstacles [45].

c) Artificial Potential Fields (APF): The Artificial Potential Fields (APF) Algorithm has long been used in path planning for multi-drone systems. The standard form of the APF algorithm guides agent movements using attractive and repulsive potentials among drones [1], [21], [29]. While computationally efficient, standard APF suffers from local minima issues, where agents may become trapped near obstacles. Improved APF (IAPF) methods [13], [15], [37], [22] modify repulsive forces to reduce these problems, while hybrid approaches like APF with Coverage Path Planning (CPP) [46] enhance obstacle handling capabilities.

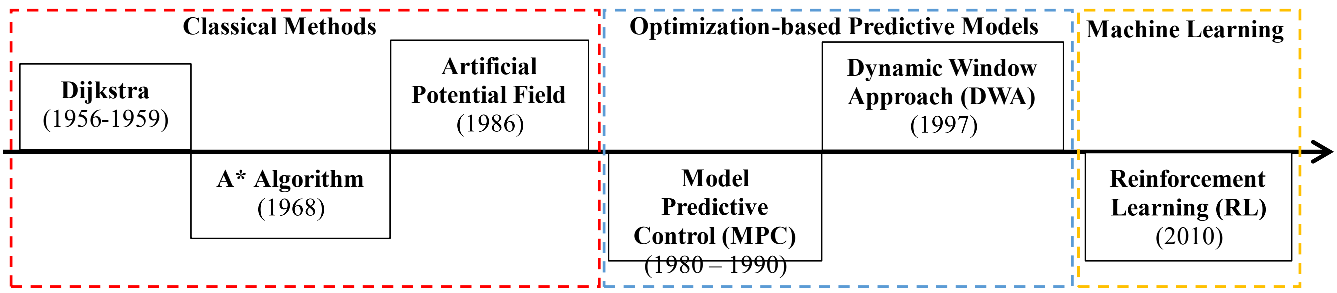

Fig. 3. The evolution of path planning method

2) Optimization-based Predictive Models: This approach utilizes optimization techniques to plan efficient paths under various constraints. Model Predictive Control (MPC) has been applied in multi-agent path planning [14], [24], [31], [60], optimizing trajectories and minimizing energy while explicitly considering constraints such as safe inter-agent distances and obstacle avoidance. MPC predicts the future system's behavior and optimizes the control sequence to minimize specific cost functions. Despite its optimality, MPC implementation faces computational challenges, especially for large-scale multi-agent systems in complex environments, due to its requirement for iterative optimization at every control step.

Several advancements have been proposed to address these computational challenges. Lyapunov-Based MPC (LMPC) [20] incorporates Lyapunov functions to ensure system stability [80]. LMPC effectively transitions formations from tracking to containment, outperforming classical control methods with faster responses and more precise tracking performance.

3) Machine Learning Methods: These data-driven approaches facilitate adaptive navigation in complex environments. Reinforcement Learning (RL) has advanced rapidly in multi-agent path planning. Its early studies explore Reinforcement Learning Particle Swarm Optimization (RLPSO) [26] to improve training efficiency and adaptivity, and Deep Deterministic Policy Gradient [34].

Deep Reinforcement Learning (DRL) with Double Deep Networks (DQN) [35] processes environmental observations using Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) to generate navigation actions, demonstrating adaptivity across varying scenarios despite challenges from communication delays. Multi-Agent Reinforcement Learning (MARL) [44] enhances adaptivity in complex, high-density scenarios, though computing inter-agent relationships via Deep Value Networks (DVN) increases execution time.

Recent advances integrate nature-inspired and hybrid approaches: The Improved Obstacle Avoidance Algorithm (IOAA) [17] maintains formation integrity by adjusting inter-agent angles without disrupting overall trajectory. Next, the Improved Particle Swarm Optimization (IPSO) [37] combines modified PSO for global planning with customized Artificial Potential Field for local refinement. Finally, the Split-Merge strategy mimics pigeon behavior to dynamically adjust speeds [47].

The analysis of path planning methods across classical, optimization-based predictive models, and machine learning categories reveals distinct trade-offs summarized in Table I. Dijkstra's Method guarantees optimal solutions but becomes inefficient in large environments due to high computational complexity. A* offers faster processing at the expense of adapting to dynamic changes. Artificial Potential Field (APF) provides high responsiveness but suffers local minima issues and requires parameter tuning. Model Predictive Control (MPC) accurately incorporates system constraints but demands significant computational resources. Reinforcement Learning (RL) demonstrates superior adaptivity to dynamic environments, though its effectiveness depends on training data quality.

C. Formation Control

Formation control is essential for multi-agent systems, ensuring agents maintain formation while navigating toward goals and avoiding obstacles. Formation control methods have evolved into three categories: classical, improved control-based, and machine learning-based approaches.

1) Classical Methods: These foundational approaches for multi-agent coordination focus on maintaining desired formations during navigation. As shown in Fig. 4, classical methods include leader-follower [11], virtual structure [12], behavior-based [13], decentralized [61], and distributed [75] approaches. The leader-follower method (early 1970s-1980s) represents the earliest form of formation control, while distributed formation control (early 2000s) was developed to address previous limitations.

In the leader-follower approach, the obstacle avoidance strategy is typically applied to the leader, with information relayed to the followers [23] to adjust their formation. Despite being intuitive, this method has two key limitations: vulnerability to failure if the leader malfunctions, and reduced robustness against external disturbances and rapid formation changes.

Many studies [1], [21], [23], [33], [35], [48], [64]-[65], [70] have modified the leader-follower approaches to address their inherent limitations. Despite these improvements targeting robustness and adaptivity, classical formation control methods still struggle with dynamic environments and unexpected disturbances, driving the development of more flexible and robust approaches for complex scenarios.

TABLE I. TRADE-OFFS OF PATH PLANNING METHODS

Method	Advantages	Disadvantages	Trade-Offs	Common Application
Dijkstra	Guarantees the shortest path and is optimal for global pathfinding	Inefficient for large environments and high computational complexity	Guarantees optimal solutions, but it is slow	Static navigation
A*	Faster than Dijkstra	Can get stuck in local paths and not be flexible to changes in dynamic environments	Fast but lacks adaptivity	Robotics
APF	Responsive and simple implementation	Prone to local minima	Fast but requires parameter tuning	Drones and robots
MPC	Considers system constraints and accounts for forward predictions	Requires high computation	Accurate but computationally expensive	Drone control
RL	Adaptive to dynamic environments	Requires extensive training data	Flexible, but depends on training quality	Autonomous navigation

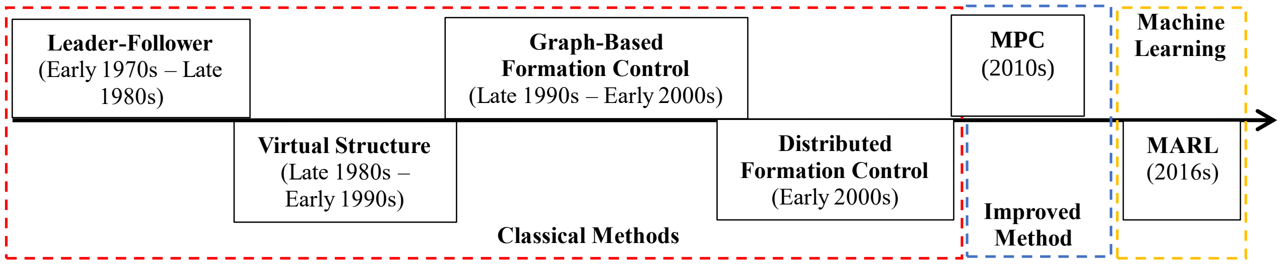

Fig. 4. The evolution of formation control method

As an alternative to the leader-follower approach, the virtual structure method defines the formation as a rigid geometric structure. The agents maintain their relative positions to virtual points on that structure. This strategy has been used with drones [40], which defined the virtual structure points as routes to follow. Although this concept was easy to implement, the virtual structure method was often less flexible in dealing with obstacles and dynamic formation changes. Validation in real-world environments with complex obstacles is still required, especially given the simulation-based limitations of [40].

Graph-based formation control represents the formation and environmental constraints as a graph. The nodes and edges in the graph represent agent configurations and their relationships, respectively. Graphs were used to represent valid configurations, determine formations that satisfy constraints, and plan optimal paths while maintaining graph connectivity [18], [29]. Although effective in static environments with previously known environmental information, the computational complexity and the need for global information limited its application in dynamic environments. Time-consuming mapping of the configuration space became a significant obstacle.

Finally, Distributed Formation Control (DFC) offered improvements in robustness and scalability. This method allowed each agent to make control decisions based on local information, reducing reliance on global information. DFC has been implemented in environments with static obstacles [16]. DFC was also utilized with virtual control commands to maintain the formation during obstacle avoidance [40]. This approach focused on formation maintenance through local interactions between agents, making it more adaptive to environmental changes and individual agent failures.

2) Improved Methods: The multi-drone formation control continued to address the limitation of classical methods and enhance performance in complex environments. Early approaches explored leader-follower methods with gain and corrective control [17], employing observer-based controllers for precision. However, these methods were restricted to static obstacles. The combination of leader-follower and virtual structure (LFVS) [27] augmented the accuracy of virtual structures with the flexibility of leader-follower methods but relied heavily on vulnerable communication infrastructures. Other approaches utilized thin plate splines (TPS) to minimize formation deformation [27], while sliding mode control (SMC) and Linear Quadratic Regulator (LQR) were explored in the leader-follower context [49]. However, SMC proved sensitive to plant-model mismatches.

Recent studies introduce the Formation Assignment and Rotation (FAR) method [19], which uses alternating optimization to maintain formation alignment under disturbances. The Fixed-Time Methods (FTM) [50] ensure accurate estimation of the leader's position and velocity of the followers within a fixed time, although they require precise parameter tuning. A non-smooth consensus approach with backstepping [51] effectively separates position and orientation control but is susceptible to chattering.

Building on this development, current trends include Model Predictive Control (MPC) and its variations for their predictive capabilities and robust constraint handling. Notable variants included distributed MPC [24], [59], [68], [71], and two-layer distributed MPC [43], which separated translational and attitude control to reduce computational and communication load. Dual MPC combines the Control Lyapunov Functions (CLFs) to stabilize the formation and enhance the optimization convergence, with Control Barrier Functions (CBFs) for collision avoidance [51] to enhance its adaptability in dynamic environments.

Despite the predictive capability and constraint handling advancements offered by MPC and its variants, these methods still depend on predefined models and careful parameter tuning. As environments become more dynamic and less predictable, such limitations have prompted a shift toward learning-based approaches.

3) Machine Learning: In increasingly complex and dynamic environments, studies in multi-agent formation control shifted towards Reinforcement Learning (RL) approaches [66], [75], particularly Multi-agent Reinforcement Learning (MARL). MARL offers better learning capabilities and adaptivity than classical methods, especially in handling uncertainties, environmental dynamics, and complex objectives.

One notable application of MARL is the Multi-agent Deep Deterministic Policy Gradient (MADDPG) [36], extended with Prioritized Experience Replay-MADDPG (PER-MADDPG). This algorithm uses centralized training using experience buffer and decentralized execution (Centralized Training with Decentralized Execution - CTDE). The reward function encouraged agents to maintain formation, avoid collisions, maintain communication, and move collectively toward a target. PER accelerates learning by prioritizing more informative experiences, although it risks overfitting to high-priority samples. An importance sampling mechanism mitigates this problem by correcting the bias introduced by priority sampling.

MADDPG has been applied to multi-agent drone systems to maximize secure capacity by optimizing the agent trajectory, transmission power from the agent transmitter, and jamming power from the agent jammer [58]. This simulation study implements the joint trajectory design of agents. The continuous action attention MADDPG (CAA-MADDPG) method is recommended for further exploration to improve learning efficiency and convergence.

In addition to policy gradient-based approaches like MADDPG, the use of Deep Value Networks (DVN) for formation control was also explored [44]. This study controls formation control through selective communication using DVN-based message selection. This approach allows agents to select relevant messages from nearby agents based on relationships calculated from agent-level and sensor information to maintain communication efficiency under limited bandwidth. However, this approach assumes perfect agent-level information that is often unrealistic in the real world. Furthermore, calculating inter-agent relationships using DVN can significantly increase total execution time, especially with many agents.

The discussion on the three categories of formation control methods (classical, MPC, and machine learning) presents distinct trade-offs among these approaches. Table II summarizes key comparisons among these methods. Classical methods, such as the leader-follower and virtual structure-based approaches, offer simplicity and ease of solutions but lack flexibility in dynamic environments. In contrast, graph-based and distributed control strategies provide greater adaptivity to environmental changes, though they require more complex coordination mechanisms. Fixed-Time Control methods ensure guaranteed convergence within a predefined time frame but are less responsive to sudden disturbances. MPC delivers high precision and robustness in trajectory planning but has significant computational demands. Meanwhile, machine learning techniques, including reinforcement learning and deep neural networks, excel in adapting to uncertain and evolving scenarios, albeit at the cost of extensive training requirements and data dependency [77], [79].

D. Communication Architecture

Multi-agent drone systems require a solid communication architecture for effective formation coordination and obstacle avoidance in complex environments. Current approaches can be categorized into centralized, decentralized, and hybrid communication strategies, each with distinct implications for scalability and resilience in dynamic environments.

TABLE II. TRADE-OFFS OF FORMATION CONTROL METHODS

Method	Advantages	Disadvantages	Trade-Offs	Best Suited for
Leader-Follower	Simple and easy to implement Centralized processing in the leader	High dependency on the leader (prone to failure if the leader fails) Less adaptive to formation changes and a dynamic environment	Easy to implement, but lacks flexibility in dynamic environments If the leader fails, the formation may collapse	Fixed formations with predefined paths
Virtual Structure	Maintains a rigid formation Simplifies path planning with centralized coordination	Less flexible in environments with many obstacles Not easily adaptable to dynamic changes	Stable but less adaptive to external disturbances	Convoy drones or robots with fixed formations in static environments
Graph-Based Control	Can handle formation topology changes flexibly Offers a mathematical approach to formation optimization	Requires complex computations Relies on global information or inter-agent communication	Enables flexible formations but requires more computation and communication	Navigation with frequent formation changes, such as drone swarms
Distributed Formation Control	More robust, as each agent can make its own decisions More scalable for large multi-agent systems	Requires more complex inter-agent coordination Not always optimal for tight formations	More adaptive to individual agent failures, but requires stable inter-agent communication	Dynamic environments with formation changes and autonomous agents
Fixed-Time Methods (FTM)	Ensure convergence within a fixed time Reduces uncertainty in formation movement	Sensitive to parameter tuning Less flexible in highly dynamic environments	Guarantees convergence time but lacks flexibility for sudden changes	Applications requiring stable formations within a set timeframe
Model Predictive Control (MPC)	Can handle physical constraints and short-term optimization Can anticipate environmental changes	Computationally heavy, requiring high processing power Not always real-time for large-scale agents	Accurate and predictive, but computationally expensive	Drone control in complex environments with many obstacles
Reinforcement Learning	More adaptive to dynamic environments Can learn from experience and improve performance	Requires extensive training data Prone to overfitting in specific scenarios	Adaptive and flexible, but requires extensive training and is computationally expensive	Systems in unpredictable environments require rapid adaptation.
Deep Value Networks (DVN)	Optimizes inter-agent communication under limited bandwidth Can select relevant information	Assumes ideal inter-agent information Computationally complex for many agents	Reduces communication needs but increases computational complexity in processing information	Systems with limited communication but requiring high coordination

Centralized approaches primarily utilize Wi-Fi with RTK positioning [47]. This architecture enables high-bandwidth data transfer (up to 54 Mbps) and supports complex coordination algorithms running on the ground control station (GCS). However, this centralization creates a critical single point of failure—if the GCS connection is lost or degraded, the entire system's functionality is compromised. Additionally, as the number of agents increases, bandwidth limitations and network congestion become significant barriers to real-time performance [47].

In contrast, decentralized architectures like Zigbee networks [13], [37], [57], distribute processing across the agents. Each agent handles local decision-making while maintaining mesh communication (typically 250 Kbps), making the system more resilient to individual node failures. Zigbee-based systems can maintain 85% of their coordination capabilities even when 30% of communication links are disrupted [13]. However, this resilience comes at the cost of reduced bandwidth, limiting the complexity of information that can be exchanged in real-time.

Hybrid architecture emerges as a promising solution to address the limitations of centralized and decentralized approaches. The Double-Wave Swarm (DWS) approach [56] uses wave propagation algorithms for message exchange and subtask coordination, enabling dynamic adaptation of communication pathways based on environmental conditions. While DWS improves robustness in changing environments, it still faces challenges with message overhead, which increases quadratically with agent numbers.

Recent studies have explored adaptive communication strategies that dynamically adjust topology and bandwidth allocation based on mission phases and environmental constraints. For instance, systems implementing dynamic role assignment [37] can reassign communication relay functions among agents when network degradation is detected, maintaining connectivity in challenging radio environments. However, these adaptive approaches remain computationally intensive and require further optimization for large-scale deployments.

IV. RESULTS AND DISCUSSION

This study reviews eighty-two publications on obstacle avoidance in multi-agent systems, encompassing path planning, formation control, or both. It focuses on operational efficiency and agent coordination, evaluating methods and their applicability in large-scale multi-agent drone systems.

A. *Synthesis of Obstacle Avoidance Methods*

Various methods address obstacle avoidance in multi-agent drone systems. Promising approaches include Improved Artificial Potential Field (IAPF) [22] for static obstacles and Reinforcement Learning (RL) [34] for dynamic obstacles. These methods show potential in controlled environments, but still face significant challenges when applied to more complex and dynamic settings.

1) Improved Artificial Potential Field (IAPF): IAPF has proven efficient in avoiding stationary objects. However, it struggles with static and dynamic obstacles in constantly changing environments. Therefore, IAPF requires major adaptation to handle real-world scenarios in which dynamic obstacles may suddenly appear.

2) Reinforcement Learning (RL): RL can adjust agent behavior based on previous experiences, enabling adaptive responses to environmental changes. However, it requires long training times and substantial computational resources, which limits its application in large multi-agent systems that require real-time responses.

3) Hybrid Approach: Combining classical and machine learning methods offers a more flexible solution. These approaches may leverage the advantages of both worlds: the efficiency of classical methods and the adaptivity of machine learning methods. However, real-world experiments with these hybrid methods are still limited, raising uncertainties about their reliability in more complex environments.

B. *Comparison of Path Planning Methods*

Classical path planning methods such as Dijkstra [18], A* Algorithm [39], and Artificial Potential Field (APF) [40] are strong foundations, although their limited adaptivity and reliance on prior environmental knowledge limit their real-world applications. Model Predictive Control (MPC) and Reinforced Learning (RL) methods provide greater flexibility but require substantial computational resources and precise parameter tuning, challenging their implementation in large-scale multi-agent systems. Table III compares these approaches based on computational complexity, dynamic environment adaptivity, initial information requirements, and solution optimality.

TABLE III. COMPARISON OF PATH PLANNING PERFORMANCES

Criterion	A*	Dijkstra	APF	MPC	RL
Computational Complexity	Medium (depends on heuristic)	High	Low	High (depends on prediction horizon)	High (during training), Low (after training)
Adaptivity to Dynamic Environment	Low (requires replanning)	Low (requires replanning)	Fair (reactive)	Good (predictive)	Excellent (learns from experiences)
Needs of Initial Information	Map/graph heuristic	Map/graph	Map/graph, potential function	System model, constraints, objective	Environment (interactions)
Solution Optimality	Optimal (If the heuristic was admissible)	Optimal (guaranteed)	Not guaranteed optimal (local minima)	Depends on the problem formulation and horizon	Depending on the algorithm and exploration, can approach the optimal

C. Formation Control Approaches

Formation control of multi-agent systems requires adaptivity to communication challenges and rapid formation changes. Classical methods such as Leader-Follower, Virtual Sstructures, and Graph-based methods have long been used in formation control. However, these methods suffer when facing communication failures.

On the other hand, Model Predictive Control (MPC) [51] offers adaptive solutions by considering future predictions and system constraints, although it suffers from high computational load and reliance on parameters that require precise tuning. Multi-agent Reinforcement Learning (MARL) [44] has shown better adaptivity to dynamic conditions and environmental uncertainty, although communication between agents is often slow, which hinders decision-making, particularly in environments with bandwidth limitations or poor communication conditions.

D. Communication Architectures

A comparison of the communication architecture between Zigbee Network and Wi-Fi is critical for multi-agent drone applications. Zigbee should be used if connections to the control station are unstable. In contrast, Wi-Fi is preferred when connections are stable and sufficient bandwidth is available. Table IV compares these protocols. Zigbee uses distributed processing with less ground station dependence but offers lower bandwidth and shorter range. Wi-Fi employs centralized processing with higher ground station dependence, greater bandwidth, and wider range through routers and access points. Zigbee typically implements mesh structures regarding network topology, whereas Wi-Fi uses star configurations centered on ground stations.

TABLE IV. COMPARISON OF COMMUNICATION ARCHITECTURE: ZIGBEE VS WI-FI NETWORK PROTOCOLS

Feature	Zigbee Network	Wi-Fi
Processing	Distributed	Processing
Ground Station Dependence	Lower	Higher
Bandwidth	Lower	Higher
Range	Shorter (typically)	Longer (with routes and Aps)
Network Topology	Mesh (potential)	Star (ground station as the center)

E. Identified Research Gaps and Future Directions

The synthesis of existing methods reveals several research gaps that must be addressed to advance multi-agent drone systems in real-world applications.

1) Computational Efficiency and Adaptivity: Modern algorithms, such as RL and MPC, offer adaptivity in dynamic environments but need significant computational overhead. In contrast, classical methods like A* and APF are computationally efficient but lack flexibility. Future development must bridge this gap, whereas high adaptivity can be achieved through low computation load, particularly for real-time, large-scale systems.

2) Integration of Machine Learning and Classical Methods: Hybrid methods that combine the structure of classical algorithms with the learning capability of data-driven models present a promising path forward. However, further exploration is needed to determine their reliability and robustness in real-world, dynamic environments.

3) Reducing Dependency on Sensitive Parameters: Many current methods are susceptible to parameter settings, which can compromise system stability. Developing more robust algorithms with self-adaptive or parameter-insensitive designs would enhance real-world applicability.

4) Improved Communication Efficiency: Efficient and reliable inter-agent communication remains a bottleneck, especially in bandwidth-limited or interference-prone environments. Adaptive communication strategies, such as multi-hop or self-healing network topologies, are necessary to maintain coordinated behavior in the field.

5) Real-World Validation: While many techniques succeed in simulation, few have undergone rigorous real-world validation. Extensive field testing is essential to evaluate algorithmic resilience under unpredictable operational conditions.

V. CONCLUSION

This paper reviews various obstacle avoidance approaches in multi-agent drone systems, focusing on path planning, formation control, and communication architectures. The analysis identifies key advantages and limitations of existing methods and provides insights into potential research directions.

Classical Path Planning methods, such as A*, Dijkstra, and Artificial Potential Field (APF), remain fundamental but struggle in dynamic environments due to their reliance on prior knowledge and limited adaptivity. Modern approaches, including Reinforcement Learning (RL) and Model Predictive Control (MPC), offer greater flexibility but have high computational costs and parameter sensitivity, making large-scale real-time implementation challenging. Hybrid methods that integrate classical and machine learning techniques, such as RL-based heuristic search or MPC with neural network-based optimization, show promise but require further validation in real-world applications.

Classical Formation Control strategies like leader-follower, virtual structures, and graph-based methods ensure structured coordination but are highly dependent on stable communication and sensitive to parameter tuning. Advanced approaches such as MPC and Multi-Agent Reinforcement Learning (MARL) improve adaptivity, but face challenges related to computational complexity and inter-agent communication delays. Future research should explore hybrid RL-MPC frameworks to enhance formation control in highly dynamic environments and develop decentralized learning-based methods to mitigate the impact of communication disruptions.

Regarding communication, Zigbee offers decentralized, resilient networks with lower bandwidth, while Wi-Fi provides higher bandwidth but relies on centralized control, making it vulnerable to failures. Future research should investigate adaptive communication strategies, such as multi-hop networking with dynamic topology adjustments, to ensure reliable coordination in large-scale multi-agent systems.

While this review comprehensively analyzes existing approaches, it also acknowledges their limitations. The selected studies may introduce potential biases, and the scope primarily focuses on algorithmic aspects, not hardware constraints or energy efficiency considerations. This review does not discuss the ethical, logistical, or technical barriers to operating the systems in complex operational environments. Addressing these aspects in future research would provide a more holistic understanding of multi-agent obstacle avoidance in real-world applications.

This review contributes to the field by identifying critical barriers to effective multi-agent drone obstacle avoidance, such as computational efficiency in dynamic environments, formation resilience during communication disruptions, and adaptive networking protocols. The urgent research priority is developing lightweight, decentralized algorithms that maintain performance despite intermittent connectivity. Addressing this challenge would enable deployment in complex applications, such as package delivery, search and rescue operations, and industrial process monitoring. Future experimental work should test the hypothesis that hybrid approaches combining classical fidelity with learning-based adaptivity can achieve reliability and flexibility in real-world environments. These advances would transform autonomous multi-agent drone systems from controlled laboratory demonstrations into robust solutions for complex real-world challenges.

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