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Analysis and Prospect of Existing Path Planning Algorithms for Multi-Drone Systems

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ABSTRACT

Drones are widely used nowadays in different sectors such as military, agriculture, surveillance, smart city measurements, logistics, and disaster rescue. In particular, multi-drone systems are gaining wider use for various problems, especially those requiring real-time navigation, simultaneous coordination, or collaboration between drones to attain various mission goals. One of the fundamental challenges for such systems is Path Planning, which requires computing an optimal collision-free trajectory from a source to a destination position in the presence of obstacles and moving agents. A wide range of algorithms, introducing nature-inspired metaheuristic methods like PSO, WOA, and LSO, have been developed to cope with this challenge. Reinforcement learning has also allowed drones to learn paths through environmental interaction and trial and error. Despite the strengths of those algorithms, they suffer from drawbacks, including computational complexity, scalability issues, being trapped in local minima, premature convergence, etc. This Review highlights the merits and demerits

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of existing Path Planning algorithms. It notes that while these algorithms have made considerable progress, they still suffer from limitations and do not yet account for the fractal and stochastic properties that appear in multi-drone systems. Fractal properties ensure solutions can adapt but remain valid and scalable throughout a hierarchy of environments. At the same time, stochastic methods enhance global exploration by weaving in a level of memory-less, random exploration of solutions. For future work, incorporating these features in the upcoming algorithms will make multi-drone performance even more robust, efficient, and adaptable and encourage their successful use in the real world.

1. Introduction

Drones are just a minor part of everyday life. The latest estimates, according to the Federal Aviation Administration, indicate that by the year 2025, there will be around 835,000 commercial Drones registered in the U.S., nearly double its current numbers. The autonomous aerial market (which includes Drone deliveries, urban air taxis, military applications, and industrial Drones) is estimated to have a market value of about $1.5 trillion by 2040 (Federal Aviation Administration, 2021). Multi-Drones can be very useful in high-risk tasks, making them ubiquitous in defense operations. Improvements in technology and lower prices have driven widespread uptake for commercial applications, where they shine in areas like surveillance, agriculture, search and rescue, inspections of infrastructure, and package deliveries. Logistics companies such as Amazon, UPS, and DHL are investigating autonomous Drones to minimize last-mile delivery expenses in answer to increasing expectations for

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speedier delivery services. Amazon, for instance, is growing a hybrid drone that can journey as much as 15 miles away to deliver small packages. Amazon is taking its next step in the Future of Drones with a huge new addition to Prime Air, the MK30 drone! This new platform has been designed from the ground up, has twice the range, and is much quieter than the previous generation drones. The MK30 can fly up to 15 miles to deliver packages weighing up to five pounds within 60 minutes. It has advanced technology, including a perception system for detecting and avoiding obstacles and the ability to weather light rain. Following the FAA's blessing on operations, the MK30 is now on track to help the company reach its goal of 500 million packages being delivered worldwide by the end of the decade. The table below highlights the major milestones in Amazon's development and implementation of drone delivery technology (Amazon,2024).

Table 1: Amazon milestones in the development and implementation of drone delivery technology

Year	Event	Description
2013	Prime Air Announced	Amazon announces its vision for 30-minute drone deliveries.
2016	First Drone Delivery in the UK	Successfully delivers a package in Cambridge, UK.
2019	Advanced Drone Model Unveiled	New design: 15-mile range and obstacle avoidance.
2020	Launch in Texas & California	Drone delivery begins in two U.S. locations.
2024	MK30 Drone Introduced & Arizona Launch	Quieter, longer-range MK30 deployed in Arizona.
2030	Future Goal: 500M Packages Annually	Aim to deliver 500M packages yearly using drones.

Advancements in drone technology and the increasing demand for drones in different industries have contributed to the rapid expansion of the commercial drone market over the past decade, including a multitude of applications, for instance, inspection of electrical infrastructure (such as power lines, solar

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panels, and wind turbines), bridge inspection, agriculture, logistics, and surveillance. Drone technology has been adopted globally to increase operational efficiency, cost-effectiveness, and innovative solutions. Google Trends was applied to analyze the search terms used in this manuscript (Google Trends, 2025). The trend analysis from 2010 to 2025 on the different keywords is shown in **Figure 1**.

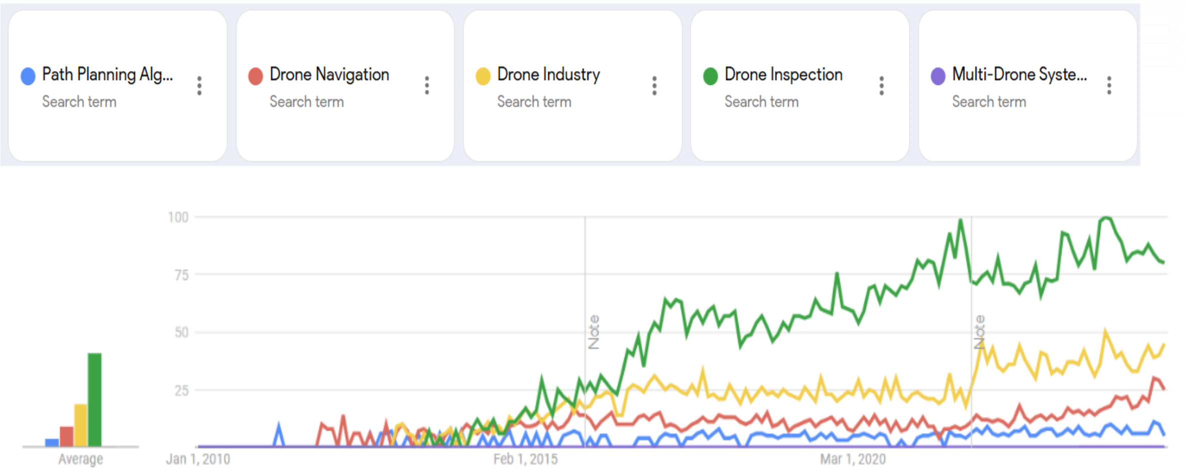

Fig 1: analysis of keywords searched in Google Trends since 2010

And here, **Figure 2** shows the growth rate of both commercial drone sales and commercial revenue generation (Ahmed et al., 2022).

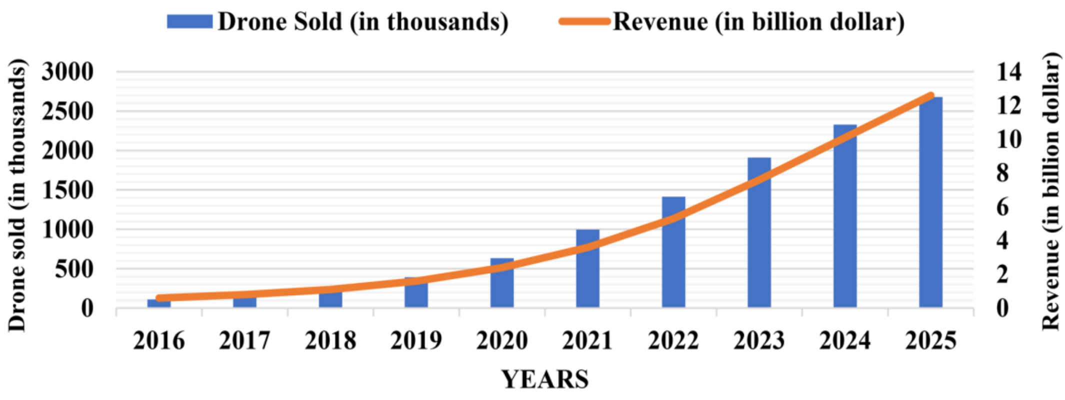

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Fig 2: Projected worldwide market growth for commercial drones

Path Planning is a crucial aspect of multi-drone systems, as it defines the optimal and secure trajectories through which drones perform their tasks. In various applications such as product delivery, disaster rescue, surveillance, and reconnaissance, Path Planning ensures optimal functionality. Drones navigate incredibly complex environments where they need to size up obstacles, avoid collisions, and respond to dynamic changes while staying energy-efficient and meeting mission objectives (Wu et al., 2023; He et al., 2021). Multi-drone systems involve designing algorithms capable of communicating and navigating multi-organism systems, which can be solved at least partially with modern path-planning algorithms. It has led to the development of many adaptations of optimization algorithms to solve this problem. For example, hybrid PSO has been utilized for cooperative path planning of multiple drones to ensure energy-efficient, collision-free paths (He et al., 2021). Likewise, bio-inspired algorithms like bio-inspired tuna swarm optimization and red-billed blue magpie optimizer have been proven to be very effective in solving 2D and 3D path planning (Fuetal.,2024; Wan et al.,2024).

The combination of multiple-optimization approaches also enhances multi-drone path planning. By way of illustration, adaptive genetic algorithms coupled with artificial bee colony methods have demonstrated efficacy for disaster rescue tasks, optimized task assignments, and effective path planning (Liu et al., 2021; Xiong et al., 2023). Likewise, the BINN-HHO algorithm has been applied to exact and dependable Path planning in multi-drone frameworks (Li et al., 2022). However, challenges like scalability, real-time development, and unavailability of complete information persist. Xiong et al. (2023) focused on multi-drone optimization with an emphasis on efficient assignment of missions and 3D Path planning for disaster rescue, ensuring high efficiency and scalability to coordinate drones in emergencies where fast response times and adaptability are key aspects of successful mission deployment, thus establishing a very

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relevant connection to the Review by emphasizing the need for responsive and scalable drone management solutions in time-critical scenarios, as well as adaptive path planning concerning the reviewed content relating to practical implementations of multi-drone systems for emergency use. As we described previously, path planning is the process of determining an ideal or near-optimal path that avoids obstacles and meets some predefined criteria, as shown in **Figure 3**, from a large number of feasible paths (Wang et al., 2024).

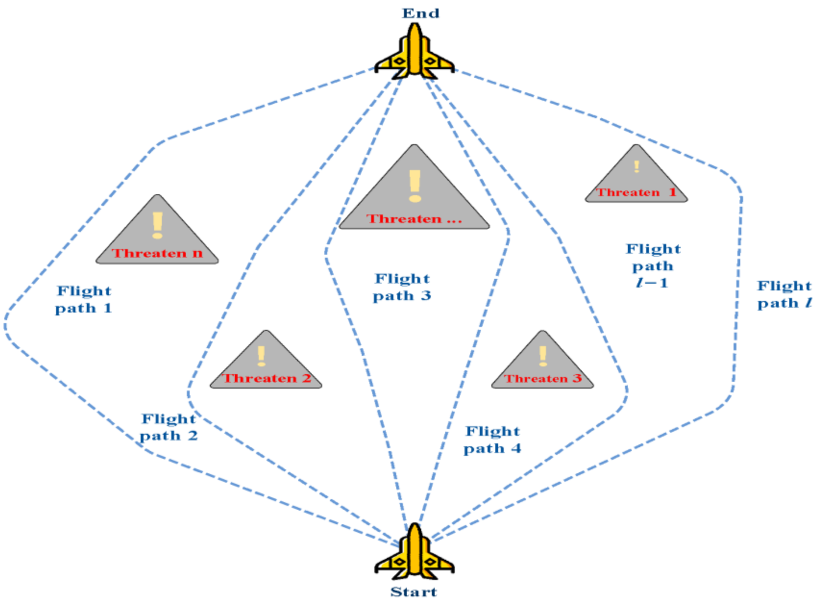

Fig 3: Obstacle avoidance path for drones.

This Review is structured as follows: Section 2 addresses the challenges in multi-drone pathing, Section 3 deals with path planning algorithms, and Section 4 focuses on the stochastic and fractal properties in path planning. In Section 5, we offer some analysis of algorithm performance and challenges. The final Section is about the main takeaways and avenues for future research.

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2. The Multi-Drone Path Planning Challenges

To improve the efficiency and effectiveness of multi-drone Path Planning, several notable issues must be resolved, Including Dynamic and Complex Environments, Communications and Coordination, Conflict Resolution & Collision Avoidance, Computational Complexity, Unknown Environments, Energy Efficiency, Dynamic environments, Scalability, Extra considerations, Heterogeneous drone systems, and Environmental interference. Below are some of those challenges:

Energy Constraints: UAVs need to optimize energy usage through path planning because they have limited battery life. Path planning is especially critical for drones to complete their missions without exceeding operational constraints, particularly for extended operations. Weather Conditions Performance of drones can be greatly affected by undesired weather events, including wind, rain, and poor visibility.

Weather conditions: These must be accounted for in path planning algorithms that change routes based on the weather in real-time so that drones function optimally and can work around the adverse conditions caused by changing weather.

Dynamic Environments: In multi-drone adaptations, routing and plotting need to be adaptive in close to real-time since environmental situations like moving obstacles or landforms can emerge at the very last minute, requiring thorough in situ route reassignment to enable safe navigation, path planning algorithms need to be adaptable and react to such changes.

Obstacle Avoidance: A key challenge in multi-drone path planning is navigating safely through environments with static and dynamic obstacles. Algorithms must prevent obstacle collisions and resolve other challenges while speeding up mission completion to conduct successful operations (Gugan & Haque, 2023).

3. Path Planning Algorithms

Generally, in this study, Path Planning based on algorithms can be categorized into three main groups: Intelligent algorithms, Traditional algorithms, and Hybrid algorithms. One of the approaches for Path Planning is the use of Traditional algorithms, such as Dijkstra's algorithm and the A* algorithm, which rely on deterministic methods to find optimal paths, with Dijkstra's focusing on the shortest Path and A* enhancing this with heuristic functions for efficiency. (Aggarwal & Kumar, 2020).

The second approach for optimizing path planning is using intelligent algorithms inspired by natural or biological processes, which are divided into two subcategories: Swarm intelligent algorithms and artificial intelligent algorithms. Swarm Intelligent algorithms, such as in colonies of ants, flocks of birds, or schools of fish, focus on decentralized control and the interaction of simple agents that work together to achieve a global optimization objective. for example, algorithms like Improved Tuna Swarm Optimization (Wang, Xu, and Hu, 2024)., Lion Swarm Optimization (Yang, Jiang, & Li, 2020). all of which mimic collective behaviors in nature for optimization.

Artificial Intelligence algorithms use machine learning, neural networks, and other AI techniques to refine decision-making and optimization processes. Their goal is mostly to improve through experience or training, including neural networks (used to model complex patterns for path planning) and reinforcement learning (optimize decision-making based on feedback in dynamic environments).

A third approach involves Hybrid algorithms, which combine elements of two or more algorithms, maybe combining traditional and intelligent methods or combining two swarm intelligent algorithms to leverage their respective

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strengths, such as Binary Neural Networks with Harris Hawks Optimization (Li et al., 2022). and Genetic Algorithm with Artificial Bee Colony (Liu et al., 2021).
Figure 4 illustrates the Classifications of Path Planning based on Algorithms (Luo, Tian, & Wang, 2024).

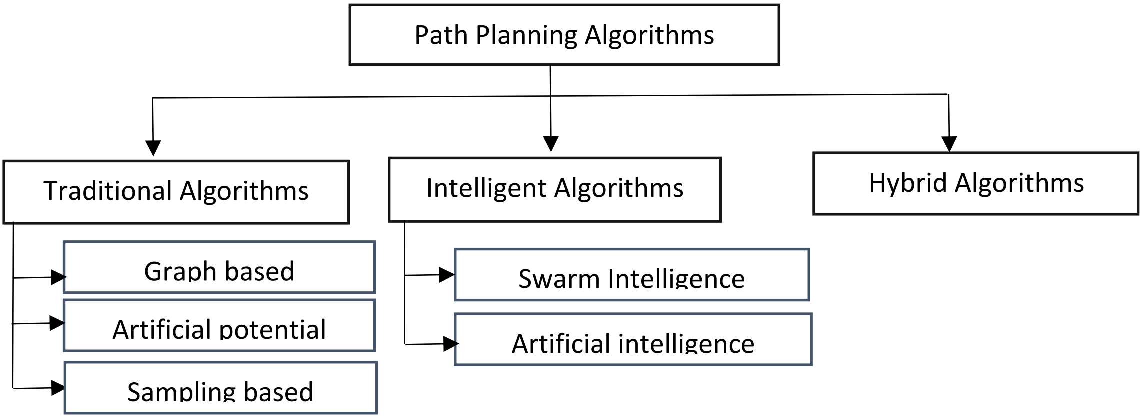

Fig 4: Classification of Path Planning Algorithms

3.1 Traditional Algorithms

Drone path planning has traditionally depended on algorithms (e.g., graph search or dynamic programming) to navigate from start to destination. Though extremely dependable, these techniques are often computationally costly and cannot easily scale for high-state space dimensions in dynamic and complex environments. Probabilistic methods like using a PRM are also helpful in obstacle avoidance. However, the approaches are more suitable for predefined scenarios rather than real-time obstacles. Mainly Traditional Algorithms, according to Luo, Tian, and Wang (2024), fall into three types: Graph-Based Algorithms, Artificial Potential Fields and Sampling-Based Algorithms:

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3.1.1 Algorithms based on Graph

These are map-based and computationally efficient for smaller problems. This Review discusses one of these algorithms, Dijkstra's algorithm, which provides an optimal path in static environments.

Dijkstra's Algorithm

Dijkstra's algorithm is one of the most fundamental and widely used algorithms for finding the shortest Path in a weighted graph. It is used in many drone path planning applications due to its simplicity and effectiveness. It is effective in well-defined environments with fixed obstacles, returning solid simulation results. As an example of how effective the algorithm can be when it is used in flying drones, it successfully tends to move around obstructions on its Path for a considerably shorter distance than the other approaches of navigation so that minimum resources in the sense of battery usage and travel time will be spent towards the destination (Dhulke, Durdu & Terzioğlu, 2020). **Fig 5** shows the example of nodes of Dijkstra's Algorithm.

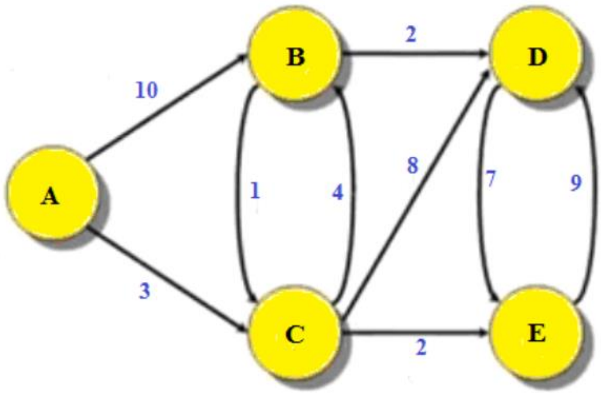

Fig 5: Example nodes for Dijkstra's algorithm

Despite the strengths of Dijkstra's algorithm, there are still some weaknesses:

One limitation of Dijkstra's algorithm is that it's designed for a static environment, making it less effective in real-time applications where obstacles or environmental factors may be changed unexpectedly. This is because the Path computed might become invalid due to the usage of the static environment while considering the dynamic environment (Wu et al., 2023; He, Qi, & Liu, 2021), which requires some form of re-computation or real-time updates that Dijkstra's algorithm isn't able to cope with in real-time.

Another limitation of Dijkstra's algorithm is that it is expensive to compute anymore as the state space grows. The high computational expense and time delays associated with Dijkstra's make it inappropriate for time-sensitive applications, especially in multi-drone systems where large search areas and many waypoints are common (He, Qi, & Liu, 2021; Dhulke, Durdu, & Terzioğlu, 2020).

Lastly, Although Dijkstra's method will always find the optimal Path, it fails to consider the trajectory's smoothness. The generated Path can be fragmented, which may cause an inefficient flight path for a drone. However, this poses a problem that can form several additional post-processing steps, increasing computational complexity (Dhulke et al., 2020; Wu et al., 2023).

3.1.2 Artificial Potential Fields (APF)

The Artificial Potential Fields (APF) methods look towards providing paths using attractive forces in the direction of the goal and repulsive forces from obstacles (Aggarwal & Kumar, 2020). These methods are computationally efficient and effective in static or slightly dynamic environments. But they also have some unique challenges:

1-Local Minima Problem: Since the forces that attract and repel the APF methods cancel each other out of the algorithm, it gets stuck in local minima and cannot find a path.

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2-Oscillatory Behavior: On narrow passages or closely spaced obstacles, the algorithm may give rise to oscillatory behavior, which may reduce the efficiency of the navigation and result in collision.

3-Limited Global Awareness: The local nature of the pathfinding of APF could result in less-than-optimal paths.

4-Scalability challenges: APF is computationally efficient for easy environments but has scalability issues for complex or large-scale scenarios.

3.1.3 Sampling-Based Algorithms

Sampling-based methods like RRT and PRM are among the best solutions for high-dimensional space problems. Typical approaches to path generation involve random sampling points in the environment and connecting them to form feasible paths. While RRT* and NPQ-RRT* offer superior path quality, computational efficiency comes at the price of high resources, sidelining them for real-time applications.

3.1.3.1 Probabilistic Roadmaps (PRM)

PRM is one of the existing algorithms used for Path Planning in static environments. A graph is then constructed by randomly sampling collision-free points of feasible paths connecting. As Li et al. noted, better versions are based on adaptive sampling and dynamic weighting that improve computational efficiency and the quality of the Graph. As shown in **Fig 6**, road map edges are created by local planners, so they reside entirely in the free space. The thick line indicates the shortest Path on the roadmap from the robot's start to the goal position. (Aggarwal & Kumar, 2020)

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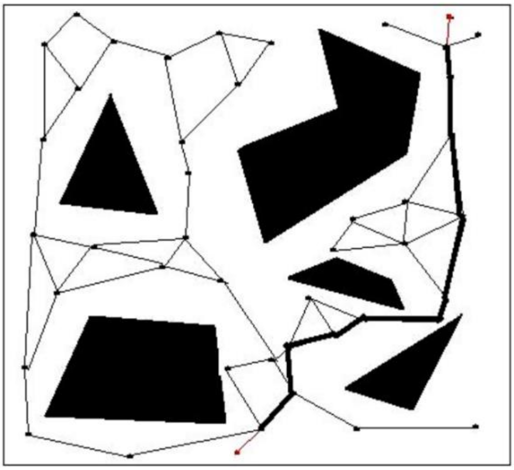

Fig 6: Probabilistic roadmaps

However, the PRM algorithm is becoming increasingly sophisticated in its design and drawing of local planners, which takes the random sampling technique into account. However, there are also several problems with improving the traditional PRM algorithm, such as low operational efficiency, an overly long path, and improperly avoided obstacles (Li et al., 2022).

3.1.3.2 A Star Algorithm

The A star or (A*) algorithm is commonly employed in Drone Path Planning to calculate the shortest Path by assessing the cost from the current node to both the starting and goal points. It operates on a map grid to find an optimal path. The A* algorithm has advantages and disadvantages, and comparisons are often made with other techniques like genetic algorithms and Ant Colony Optimization (ACO). Models also use it to plan safe paths while minimizing the drone's fuel consumption. Additionally, studies have compared several path-planning algorithms, including the Floyd algorithm, ACO, and Dijkstra, focusing on their real-time pathfinding capabilities. It has been found that Dijkstra, which is similar to A*, performs better than the other algorithms in finding an optimal drone path (Aggarwal & Kumar, 2020).

The A star algorithm is a widely used path planning algorithm but has several limitations in drone applications. One key drawback is its computational complexity, which increases as the environment's size and the number of nodes in the grid grows. This can make it computationally expensive and unsuitable for real-time applications requiring quick decisions. Additionally, the algorithm's performance is highly sensitive to the heuristic function used to estimate the cost of the goal. If the heuristic is poorly designed, the algorithm may not find an optimal path or perform inefficiently. Furthermore, A is unsuited for dynamic environments* where obstacles may appear or move in real-time. In drone Path Planning scenarios where the environment is constantly changing, A* may require frequent recalculations or adjustments, making it less efficient than other algorithms designed for dynamic obstacle avoidance (Aggarwal & Kumar, 2020).

3.2 Intelligent Algorithms

AI algorithms significantly advance drone path planning, employing advanced methods to navigate dynamic environments. Techniques based on AI technologies like machine learning and metaheuristic algorithms especially focus on route optimization, creating the best possible routes based on real-time data and constantly evolving conditions. The biggest advantage of intelligent algorithms is their ability to learn and react to new developments. In particular, scenarios such as disaster management, surveillance, and urban navigation demand executing complex plans where unpredictable scenarios are common (Wu et al., 2023; He et al., 2021).

3.2.1 Swarm Intelligence

Swarm intelligence, which mimics the collective behavior of animals like birds and insects, is used in algorithms based on Particle Swarm Optimization (PSO), which is applied in drone path planning. This has enabled, in particular, the coordination of several drones for tasks that require extensive territorial coverage or complex collective actions. Swarm intelligence bolsters efficiency and adaptability in multi-drone operations by simulating natural group behavior. Yet, with these algorithms, challenges arise regarding their implementation, requiring a significant amount of computing and efficient communication between drones to guarantee no overlap occurs in their dispatch paths for the safety of operations (Fu et al., 2024; He et al., 2021; Li et al., 2022).

Improved Tuna Swarm Optimization (SLTSO)

The enhanced version of Tuna Swarm Optimization (ITSO), also known as Sine–Levy Tuna Swarm Optimization (SLTSO), is a modification of the standard Tuna Swarm Optimization (TSO) algorithm operating to avoid the limitations of TSO. Thus, it applies innovative techniques like Levy flight to make global search more effective, a golden sine strategy to fast convergence, and elite opposition-based learning to improve population diversity and mitigate premature convergence. One major improvement is Levy flight, which can make random long-distance gap jumps to improve searching behavior. This translates the new position of a solution after a Levy flight as:

$$X_i(t) = X_i(t) + \lambda . C_1 \otimes Levy, \tag{1}$$

Where λ (lambda) is the step weight, C1 is the scaling factor, and levy represents a step size derived from the Levy distribution.

Another enhancement is the golden sine strategy, accelerating convergence by condensing the solution space while maintaining diversity. The position update using the golden sine strategy is defined as:

$$\mathrm{x_{g,i}(t) = x_i(t).\left|sin\ (rg_1)\right| + rg_2.sin(rg_2)\,.\left|c_1T_{pos} - c_2x_i(t)\right|}, \tag{2}$$

where rg_1 and rg_2 are random numbers, c1, and c2 are golden ratio coefficients, and T_{pos} is the current best solution.

The elite opposition-based learning (EOBL) mechanism improves population diversity by generating reverse solutions of elite individuals:

$$\mathrm{x_{i,j}^{E} = c.\left(lb_j + ub_j\right) - X_{i,j}}, \tag{3}$$

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where c is a random number between 0 and 1, lbj and ubj are the lower and upper bounds of the search space, and $X_{i,j}$ represents the position of elite individuals. This approach helps avoid local optima by expanding the search scope.

The greedy strategy is employed after position updates via Levy flight to refine the solution further. This strategy ensures that only positions with improved Fitness are retained. The selection rule is:

$$X_i\,(t+1) = \begin{cases} x_i(t), & \text{if Fitness } (x_i(t)) \leq \text{Fitness}(\, x_i'(t)) \\ x_i(t), & \text{Otherwise,} \end{cases} \qquad (4)$$

xi(t) represents the original position, xi'(t) is the updated position after the Levy flight, and Fitness measures the solution's quality. By retaining only the better position, the algorithm avoids unnecessary computations and accelerates convergence.

Therefore, the improvements help CA overcome the drawbacks of TSO, such as faster convergence, better global searching capability, and more robustness. These enhancements allow SLTSO to be particularly performed on drone Path Planning in non-straightforward surroundings (Wang, Xu, and Hu, 2024).

Although the Sine–Levy Tuna Swarm Optimization (SLTSO) algorithm has greatly improved, it still has some limitations. The algorithm adds extra parameters like the levy flight to the golden sine strategies that must be tuned correctly for proper performance. Note that the Balance between exploration and exploitation remains a challenge, specifically in optimization problems that are highly complex or dynamic. The improvements, although facilitating global and local search, introduce a significant overhead compared to the baseline TSO and can limit the application of such enhancements in resource-poor environments or real-time applications. Additionally, the criteria used to assess the algorithm's accuracy are unique to the problem at hand, potentially requiring some tuning in the method of operation for it to be applied to different areas. Moreover, similar to other metaheuristic approaches, SLTSO is not theoretically guaranteed

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to achieve the global optimum, nor is it free from getting trapped in local optima in highly complex search spaces. (Wang, Xu and Hu, 2024).
The SLTSO algorithm changes the position updating method for discoverers while keeping the time complexity the same as the original TSO algorithm. Both algorithms run in O(N·D·T) on overall time complexity, which guarantees no more computations from SLTSO enhancements.

Sinh–Cosh-Enhanced Dung Beetle Optimization (SCDBO)
Introduced as an optimization method in 2022, the Dung Beetle Optimization (DBO) algorithm is inspired by the dung beetle's natural behaviors, such as rolling dung balls, foraging, and stealing dung balls. It is one of the popular and fast convergence to optimal solutions. However, in more complicated cases, its performance can be restricted. The initial population is usually not very diverse; hence, it is limited in its ability to perform a global search. In addition, the algorithm also struggles with balancing between exploration and exploitation, which could lead to being trapped in local optima. During spawning, the problem is aggravated as the swarm is clustering around the local optima of a solution given out by every agent, resulting in redundancy and rebuffing the possibilities by letting the scouts work through unproductive iterations and raising inefficiency.
These challenges motivated us to develop the Sinh-Cosh-Enhanced DBO (SCDBO). Using the hyperbolic sinh and cosh functions to integrate the algorithm seeds diversity expands the range for exploration to improve the diversity of the initial population. It helps explore the search space more effectively, especially in the initial stages. The positional update for this phase is in the form of:

$$x_i(t+1) = x_i(t) + r_1 . W_1 . x_i(t), \qquad \text{where } W_1 = r_3 . \alpha_1 . (\cosh(r_4) + u . \sinh(r_4) - 1). \qquad (5)$$

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The SCDBO also introduces a two-phase exploration strategy. The first phase emphasizes expanding the search range, while the second phase shifts to undirected exploration to diversify potential solutions further. This is represented mathematically as:

$$x_i\,(t+1) = \begin{cases} x_i(t), +|\varepsilon.W_2.X_{best} - x_i(t)|, & \text{if } r_5 > 0.5 \\ x_i(t), -|\varepsilon.W_2.X_{best} - x_i(t)|, & \text{if } r_5 \leq 0.5 \end{cases}$$

(6)

Where ε is a small constant that controls the impact of the best-known solution, ensuring a balance between exploration and exploitation. By employing these strategies, SCDBO accelerates convergence, improves stability, and enhances the algorithm's ability to escape local optima. These improvements make SCDBO a more robust choice for solving complex optimization problems such as drone path planning (Wang et al., 2024). Despite the enhancements to the modified Sinh-Cosh-Enhanced Dung Beetle Optimization (SCDBO) algorithm, some drawbacks remain. Compared with the original DBO, the SCDBO has a higher computational cost because of the introduction of hyperbolic functions and multi-phase strategies, leading to less efficiency in real-time applications or high-dimensional problems.

Furthermore, the algorithm relies on tuning parameters like sensitivity coefficients and constants, whose inappropriate configuration can hinder its realization. Although SCDBO enhances global exploration and alleviates the risk of local optima, it is still susceptible to premature convergence when faced with highly deceptive optimization landscapes. Its enhancements are problem-specific, and thus, the algorithm should be tuned to demonstrate good performance in new domains. Lastly, as with other metaheuristic algorithms, the SCDBO does not guarantee obtaining the global optimum, nor does it show scalability on large-scale or complex optimization (Wang et al., 2024).

The SCDBO algorithm has a time complexity of $O(T_{max} \cdot N)$ similar to the DBO algorithm, with T_{max} as the maximum iterations and N as the population size. Conditional updates add a minor $O(T_{max})$, but the complexity remains comparable.
Lastly, it deals with the lack of randomness in the population initialization process, the slow speed of search, and the deficiency in the global search capability of the Dung Beetle Optimization DBHO algorithm. The SCDBO incorporates hyperbolic sine (sinh) and cosine (cosh) functions into the integration process, improving search efficiency and global exploration. Although SCDBO outperforms regular DBO, it is important to know that no single optimization algorithm can solve all optimization problems effectively, commonly referred to as the No Free Lunch theorem. As a result, SCDBO might still face difficulties when applied to domain-specific or niche problems. More research and development are needed to resolve minor issues and apply them to optimization problems.

Lion Swarm Optimization (LSO)

Lion Swarm Optimization (LSO) is an improved swarm intelligence algorithm based on the social behavior of lions, such as the behavior of lion kings, lionesses, and cubs. With LSO, favorable performance is achieved as a simple method for finding optimum paths in 2D environments, aided further by Dijkstra's classical algorithm for better search space initialization in the context of drone path planning. This hybrid method exploits Dijkstra's efficiency at computing initial paths and LSO's ability to improve those paths iteratively. What makes LSO stand out among high-dimensional and complex path-planning problems is its usage. Adopting a multi-group cooperation mechanism will not compromise its global search capability. However, the diversity of solutions in the solution space can be effectively ensured to avoid the situation of local extremum. Lion kings are currently the best solutions, which move locally, lionesses move on a larger scale while progressively restricting the search space, and cubs contribute by

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obtaining exploration and competition. This method is especially useful when there are many obstacles in the way. Dijkstra's structured graph-based pathfinding, combined with LSO's adaptive optimization, allows drones to calculate the shortest, safest, and most efficient paths. Simulations have demonstrated that LSO performs better than other algorithms, like Ant Colony Optimization, regarding convergence speed and stability (Yang, Jiang, & Li, 2020).

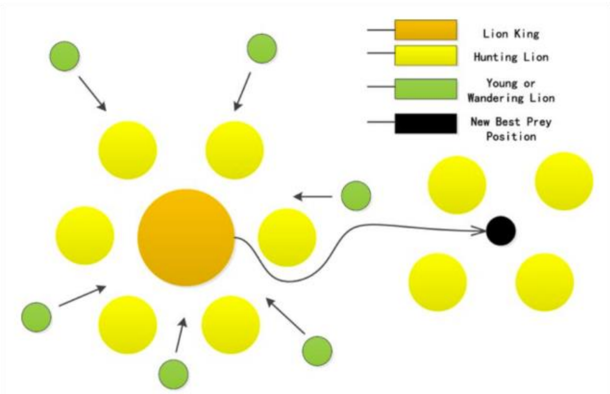

Fig 7: Schematic diagram of lion swarm optimization algorithm

Figure 7 shows the Cooperative Mechanism of Lion Swarm Optimization (LSO), during which the Swarm is Divided into Roles to Achieve the Optimum Solution. The lion king (orange) emits the best solution so far and prefers to optimize fine-tuning locally.

The main weakness points of Lion Swarm Optimization (LSO) are:
Local optima and convergence speed: In complex environments, LSO may oscillate and get caught in local optima, yielding sub-optimal solutions.

Computing Cost: It is very computing intensive and unsuitable for online processing, especially for large-scale Path planning with many obstacles.

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Parameter Sensitivity: The performance of these algorithms is very sensitive to parameter tuning (population size, iteration count, etc.) , making them hard to use in different domains.

Scalability Issues: The performance of LSO de. A spectral method, LSO does not scale well with complexity.

No Guarantee of Global Optimality: Because LSO cannot guarantee the finding of a global optimum, it may produce less-than-optimal path-planning solutions.

3.2.2 Algorithms based on Artificial Intelligence techniques

Artificial Intelligence (AI) has transformed drone Path Planning with recent advancements in reinforcement learning techniques. Such environments are often dynamic and unpredictable, making traditional path-planning algorithms fail. On the other hand, approaches based on AI, like reinforcement learning, provide more efficient and adaptable solutions to drones by allowing them to make informed decisions based on feedback from the environment.

Recently, multi-drone path planning systems that apply reinforcement learning models have proven their strength. Expert systems thrive in complex ecosystems with incomplete information and dynamic adaptation. One such strategy is centralized training with decentralized execution frameworks, allowing drones to work together when navigating the environment and learning the best Path while avoiding obstacles. These algorithms implement actor-critic architecture for exploration versus exploitation management, enhancing adaptability in dynamic environments (Chen et al., 2022). These models go a step further to tackle difficult questions of partial observability by incorporating techniques such as recurrent neural networks, which allow drones to use historical data to inform their decision-making.

Moreover, these AI-based Path-planning techniques require a huge computational load for training and have scalability issues when the number of

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drones increases. Yet their key contributory strengths are those necessary for handling real-time adaptation and complex multi-agent interactions, rendering them irrelevant to traditional drone use cases. **Figure 8** illustrates the actor-critic architecture of reinforcement learning on Drone path planning. Above the actor, the critic evaluates the value of the actor's actions, allowing it to optimize the decision-making process. Exploration and exploitation are balanced in this context, allowing for real-time virtual collision-free navigation and boosting adaptability and efficiency in constantly changing surroundings.

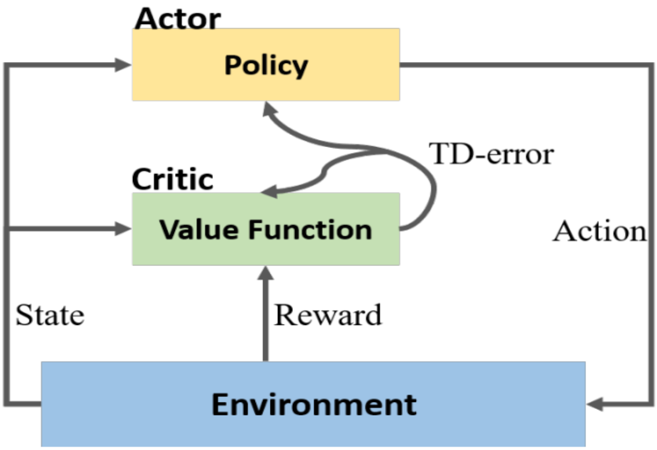

Fig 8: Algorithm of Actor-critic

Reinforcement Learning (RL)

Drones use Reinforcement Learning for optimal policies via trial and error in simulated environments. Deep Q-learning (DQL) and Multi-Agent Reinforcement Learning (MARL) support collaborative decision-making in multi-drone systems. However, these methods are computation-heavy and need carefully designed reward structuring.

4.3 Hybrid Algorithms

Hybrid Algorithms utilize multiple optimization methods to provide more efficient decision-making capabilities and better flexibility within challenging or varied environments. Improved, tackles generic operational issues by utilizing the complementary properties of different algorithms to obtain customized solutions that cannot be reached individually by the single methods.

BINN with HHO Algorithm

Incorporating bioinspired neural networks (BINN) along the Harris Hawks optimization (HHO) algorithm is a significant development in multi-drone path planning, especially when dealing with complex and dynamic three-dimensional environments. This hybrid framing allows the combined properties of the respective methodologies to increase global exploration ability while other guides to local exploitation, plus tackles issues like obstacle avoidance or dynamic Path re-planning.

The simulation results show that the BINN-HHO algorithm significantly improves path length, obstacle avoidance, and convergence speed compared with single algorithms like PSO and standard HHO. Thus, BINN-HHO is well suited for real-time adaptability and precision, including surveillance, disaster response, and military operations (Li et al., 2022).

The main limitation of the BINN-HHO algorithm is that it is computationally expensive, particularly in the initialization phase, and for better performance in high dimensional dynamic environments. Yet such an approach strikes a fine trade-off between classical local path planning and the study of global path planning, which may fail to scale up in scenarios with fast-moving objects or in extremely uncertain environments requiring real-time adjustments. It relies on high-quality sensor data that can create issues when sensors provide inaccuracies impacting path planning or obstacle avoidance. These limitations show the need for optimizations to make more complex or resource-constrained systems more efficient and scalable.

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GA with ABC Algorithm

Combining the Genetic Algorithms (GA) and Artificial Bee Colony (ABC) methods provides a promising implementation of a solution to the main challenges associated with global exploration and local optimization of Drone Path Planning. In scenarios where dynamic obstacles or mission-critical operations are present, the hybrid GA and ABC improve overall performance by combining GA's global search capability with the local search efficiency of the ABC algorithm. The GA-ABC hybrid algorithm has several practical applications, and it is especially promising in disaster response and mission-critical operations for drones. One example is the importance of flight planning in minimizing energy expenditure and steering clear of hazards during safe navigation. In addition, the hybrid algorithm performs task allocation and path optimization simultaneously, conducive to better coordination of multi-drone systems. This flexibility enables real-time operations in dynamic environments, making reinforcement learning a solution to some applications with unpredictable scenarios (Liu et al., 2021). Even though the hybrid GA-ABC approach works properly, it has some disadvantages, such as increased computational complexity, which makes such algorithms fairly difficult to use on large-scale multi-drone systems. Also, fine-tuning parameters can be tedious and time-consuming; the algorithm's performance is extremely sensitive to them, and you may need to tweak mutation rate, colony sizes, etc. However, its flexibility and efficiency make it a good candidate for modern drone path planning.

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Table 2: Analysis of Drone Path Planning Algorithms Discussed in this Review

Reference	Type	Objectives	Algorithm	Optimization	Env.	Performance measure	Limitations
Wu et al. [1]	Traditional	Find the shortest Path in weighted graphs	Dijkstra's algorithm	Minimizes total path cost, suitable for weighted graphs	2D	Total distance traveled, time complexity O(V^2) for dense graphs	High computational cost for dense graphs, not suitable for real-time applications
He et al. [2]	Traditional	Find the shortest Path in grid-based environments	A* algorithm	Uses heuristics to minimize path cost faster than Dijkstra in some cases	2D	total distance traveled, faster pathfinding with heuristic, time complexity	Heuristic effectiveness depends on the environment, limited scalability in the large area
Aggarwal et al. [8]	Traditional/ Review	Review of drone path-planning techniques	Comparative Analysis	Evaluate strengths and weaknesses of algorithms	2D/3D	Holistic analysis of performance trade-offs	Limited empirical data for specific algorithms
Dhulke et al. [14]	Traditional	Application of Dijkstra's algorithm in drone path planning	Dijkstra's algorithm	Efficient pathfinding in predefined scenarios	2D	Reliable obstacle avoidance, resource optimization	Limited adaptability to dynamic environments, computational intensity in complex settings
Li et al. [13]	Traditional	Improve path planning with dynamic obstacle avoidance	improved PRM	Enhances energy efficiency and adaptability to dynamic environments	3D	Real-time adaptability, reduced energy consumption	Computational demands, limited performance in environments with highly dynamic obstacles
Wang et al. [4]	Swarm Intelligent	Optimize exploration and exploitation in dynamic scenarios	Improved Tuna Swarm Optimization (TSO)	Improved global exploration and local exploitation	3D	Energy efficiency, path length, convergence speed	Requires tuning of parameters, slower convergence in the highly complex environment

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Yin et al. [13]	Swarm Intelligent	Enhance 3D Path planning in dynamic meteorological environments	Enhanced WOA	Introduces quasi-opposition learning and dynamic adjustments for improved efficiency	3D	Convergence speed, energy efficiency, better obstacle avoidance	High sensitivity to parameter settings, computational overhead in real-time scenarios
Fu et al. [5]	Swarm Intelligent	Enhance convergence in obstacle-rich environments	Red-Billed Blue Magpie Optimizer (RBMO)	Novel metaheuristic for adaptive path planning	2D/3D	Convergence speed, effective obstacle avoidance	High computational cost, dependency on communication between Drones
Wang et al. [9]	Swarm Intelligent	Improve convergence and stability in complex environments	Sinh–Cosh-Enhanced Dung Beetle Optimization	Enhances exploration and exploitation using sinh-cosh functions	3D	Faster convergence and greater stability in optimization problems	Computational complexity, parameter sensitivity, and scalability issues
Yang et al. [15]	Swarm Intelligent	2D path planning inspired by lion behavior	Lion Swarm Optimization	Adaptive exploration and exploitation for 2D path planning	2D	Fast convergence, adaptability to dynamic obstacles	High computational cost, limited scalability to 3D or Multi-Drone systems
Li et al. [3]	Hybrid	Mission assignment and Path planning for Multi-Drones	GA with ABC	Combines GA's	3D	Task completion time, energy efficiency, adaptability in changing dynamics	Parameter tuning complexity, increased computational demands for large-scale systems
Liu et al. [6]	Hybrid	Optimize mission assignments and 3D Path planning in disaster rescue	Multi-Agent Reinforcement Learning (MARL)	Collaborative path optimization, adaptive to dynamic conditions	3D	Adaptability in emergency scenarios, collision avoidance	Requires extensive training, scalability issues in large-scale disaster response systems
Wang et al. [12]	Hybrid	Enable Multi-Drones to plan collision-free paths in uncertain environments autonomously.	Whale-Inspired Deep Q-Network (WDQN)	Combines WOA with reinforcement learning for enhanced adaptability and learning efficiency	2D/3D	Learning efficiency, Path planning success rate, collision-free paths	Requires extensive training, scalability issues, and computational demands
Chen et al. [10]	Reinforcement Learning	Threat-oriented collaborative Path planning for reconnaissance	Actor-Critic Reinforcement Learning	Balances exploration and exploitation in real-time reconnaissance missions	2D/3D	High adaptability to incomplete information, mission success rate	High computational cost, limited generalization to unseen scenarios
Zhao et al. [11]	Reinforcement Learning	Multi-agent collaborative path planning and following	Multi-Agent Reinforcement Learning (MARL)	Promotes coordinated navigation and collision avoidance	2D/3D	High scalability, adaptability to dynamic environments	Scalability issues, as the number of agents increases, require extensive training

However, none of these existing approaches to multi-drone Path planning have explicitly leveraged fractal and stochastic properties. This strategy leads to a strong exploration of the solution space. However, the randomness helps avoid converging too quickly into suboptimal solutions. Fractal techniques add hierarchical and recursive structure to the design process, allowing for better global search while permitting fine-grained local refinements. These combined properties can yield better adaptability, scalability, and efficiency algorithms. This integration can greatly enhance collision avoidance, energy optimization, and real-time re-planning in dynamic obstacle-rich environments typical of multi-drone systems.

Future work suggests including fractal and stochastic properties in multi-drone Path Panning algorithms. By making the method more adaptable, efficient, and robust in the face of challenges such as navigating complex and dynamic environments, this new and unique approach is meant to overcome issues currently faced.

4.Fractal and Stochastic Properties

Stochastic methods bring randomness to the search process, resulting in a more thorough exploration of the solution space and less possibility of getting trapped in the local optimal (Salimi,2015).

Self-similarity: Fractal models highlight self-similarity, in which patterns or behavior recur across different scales. This becomes especially handy in solving problems with hierarchical or recursive structures, frequently in optimization problems.

Fractals in Path Planning: The algorithms can refocus near regions of interest after exploring the search space for the first time in less time, as the search space does not have to be explored again. Accomplishing this equilibrium between local

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intensification and global exploration is critical to solving problems effectively. Owing to their recursive and iterative nature, fractals exhibit good scaling for optimization problems ranging from small to large-scale applications. Also, the fractal nature allows the algorithms to navigate complex, serrated, or rough solution landscapes, adapting organically to these structures (Salimi, 2015). As shown in **Fig. 9,** Fractals are self-similar structures in nature, geometry, and algebra.

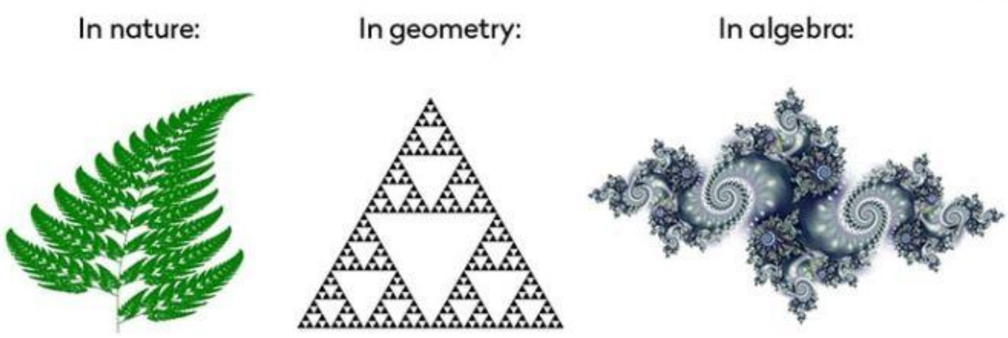

Fig 9: Fractals: Patterns in Nature, Shapes, and Math

However, stochastic and fractal properties are necessary to scale multi-drone Path Planning through improved adaptability and robustness. The randomization of stochastic methods helps for better global exploration and escaping local optimums where fractal properties allow the exploitation of minimizing paths across orders of multiscale systems. Although such properties have great potential, few existing algorithms explicitly consider them, including metaheuristics (for example, ITSO, WOA), Traditional algorithms, Reinforcement learning, and the vast majority of hybrid algorithms. Existing approaches find it difficult to adapt in real-time, especially in environments with obstacles and rapidly changing conditions.

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5. Discussion

Drone Path Planning is crucial in disaster response, surveillance, and environmental monitoring applications where coordination efficiency and adaptability are essential. Although there have been significant advancements in the area, technical and operational challenges remain, particularly in dynamic obstacle-rich environments. Deterministic and trustworthy traditional algorithms (e.g., Dijkstra's, A*) and/or purely rely on a deterministic and reliable nature.

Nonetheless, their computational inefficiency and limited adaptability to dynamic scenarios restrict their potential usage in the real-time operations of multi-drones. Conversely, intelligent algorithms Inspired by swarm intelligence, such as Improved Tuna Swarm Optimization Sinh–Cosh-Enhanced Dung Beetle Optimization, exhibit favorable performance in portions of adaptability and robustness in changing environments. These approaches exploit bio-inspired mechanisms to achieve exploration vs exploitation trade-off, thereby ameliorating some of the troubles of algorithms. Hybrid algorithms (e.g., BINN with HHO and GA with ABC) add even more flexibility by employing synergies between techniques.

Although reinforcement learning Algorithms show great potential for training real-time adaptability, they require significant training time and struggle to generalize across different situations, which is even more pronounced in multi-drone cases where interaction complexity grows. Through the practical deployment of these algorithms, the importance of reliable sensor data, efficient computational frameworks, and robust communication systems becomes clear in providing collision-free navigation and the mission's ultimate success. Moreover, multi-drone systems are integrated into critical applications. Hence, ethical and regulatory aspects like privacy, airspace management, and safety standards must be resolved to ensure widespread acceptance.

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Figure 10 demonstrates the geographical distribution of research articles included in this Review. More studies are published from China (7 articles); the rest are from the USA (5 , Germany:2, India:1, Turkey 1 , and the UK: 1).

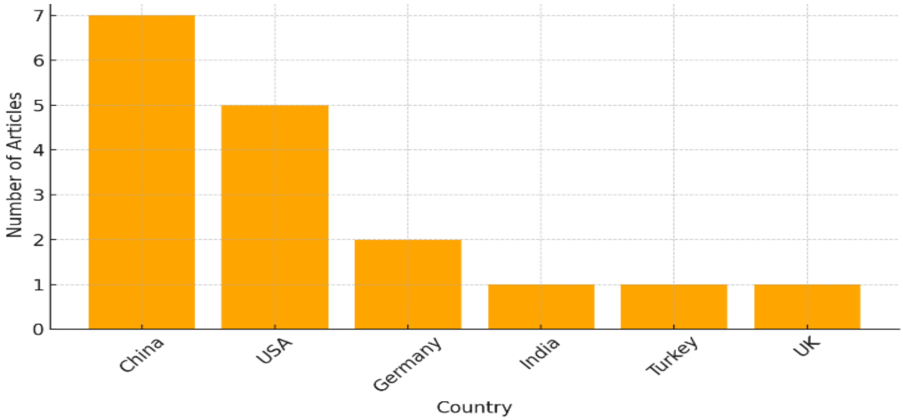

Figure 10: Distribution of References based on Country

Classify reviewed works according to the utilized algorithm types. To address this, the Swarm Intelligence algorithms currently lead the research landscape with seven studies indicating the versatility and popularity of these approaches for resolving complex path planning problems, as shown in **Figure 11**.

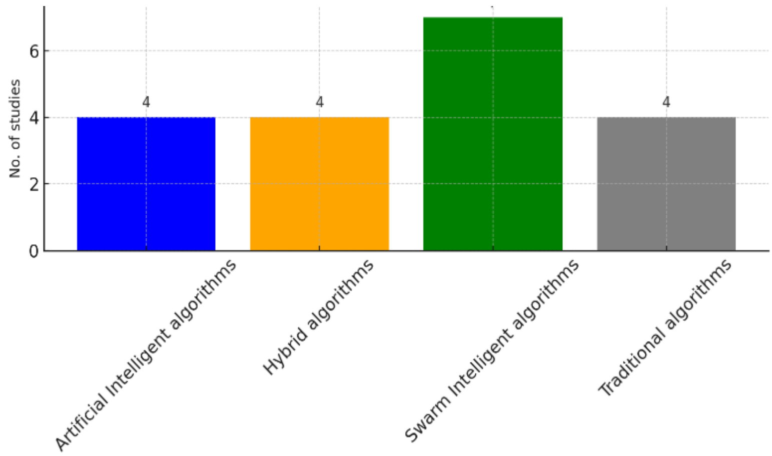

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Figure 11: Distribution of Path Planning algorithms

6. Conclusion

This Review emphasizes the importance of adaptive path-planning algorithms for multi-drone systems in disaster response, surveillance, and logistics applications. Traditional algorithms like Dijkstra's and A*, while effective in structured environments, face limitations in scalability and adaptability when applied to dynamic, real-time contexts. Nature-inspired swarm intelligence provides improved adaptability and efficiency, allowing multiple drones to explore complex environments; however, it also comes with limitations, such as the need for a high computational cost, extensive parameter tuning, and the threat of premature convergence where the algorithm cannot explore better solutions and focuses on suboptimal parts of the search space. This system helps concurrent systems to adapt in real-time when they collaborate; however, it requires extensive training and does not generalize well across unexpected and dissimilar scenarios, particularly multi-drone environments. Hybrid algorithms that integrate the strengths of various techniques mitigate these shortcomings by providing a balanced approach to global optimization, real-time adaptability, and computational efficiency. While they mitigate some concerns about premature convergence, they present others, including higher computational costs and a requirement for careful parameter tuning. In this context, hybrid algorithms might be a limited yet efficient solution for multi-drone systems in the sense of performance and scalability. Upcoming with their nature of stochastic and ability to model complex systems, they had shown a unique potential to be explored in multi-drone path planning. Fractal patterns experienced in nature provide a strong lens for optimizing exploration and exploitation, enabling algorithms to traverse enormous and irregular search spaces effectively and responsibly, spiking to local optima. Such features make these properties particularly suitable for the new challenges imposed by multi-

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drone systems, requiring flexible adaptation to dynamic environments, scalability, and solid navigation performance. Integrating fractal-based principles with real-life scenarios, specifically Path Planning algorithms, we work to improve adaptability and meet the stochastic behavior of multi-drone systems. This Review framework is expected to significantly increase the navigation efficiency, adapt to the dynamism of the operational environment, and ultimately enhance performance in complex, large-scale applications.

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شیکردنەوە و لێکدانەوەی ئەلگۆریتمە بەردەستەکانی پلاندانانی ڕێڕەو بۆ سیستەمی فڕۆکە بێ فڕۆکەوانەکان

پوختە:

فڕۆکەی بێ فڕۆکەوان لەم ڕۆژگارەدا بەشێوەیەکی بەرفراوان لە کەرتە جیاوازەکانی وەک سەربازی، کشتوکاڵ، چاودێری، پێوانەی شاری زیرەک، لۆجستیک و ڕزگارکردن لەکاتی کارەساتەکان بەکاردەهێنرێت. بەتایبەتی، سیستەمی فڕۆکەی بێ فڕۆکەوان بۆ کێشەی جۆراوجۆر بەکاردەهێنرێت بەتایبەتی ئەوانەی کە پێویستیان بە ڕێنیشاندەری ڕاستەقینە، هەماهەنگی هاوکات یان هاوکاری نێوان فڕۆکە بێ فڕۆکەوانەکان هەیە بۆ گەیشتن بە ئامانجە جۆراوجۆرەکان. یەکێک لە ئاستەنگە بنچینەییەکانی ئەم جۆرە سیستەمانە پلاندانانی ڕێگایە، کە پێویستی بە ژماردنی باشترین ڕێڕەوی بێ بەرکەوتن هەیە لە شوێنی سەرچاوەوە بۆ شوێنی مەبەست بێ بوونی بەربەست و هۆکارە جوڵاوەکان. ژمارەیەکی فراوان لە ئەلگۆریتمەکان بۆ ڕووبەڕووبوونەوەی ئەم تەحەدایە پەرەیان پێدراوە وەکو ئالگۆریتمی مێتاهیورستیک کە سەرچاوەیان لە سروشت وەرگرتووە وەکو ئەلگۆریتمی(LSO) و (WOA) و (PSO) . هەروەها فێربوونی بەهێزکردن بەکارهاتووە بۆ ڕێگەدان بە فڕۆکەی بێفڕۆکەوان بۆ فێربوونی ڕێگاکان لە ڕێگەی کارلێکردنی ژینگەیی وڕێگەی تاقیکردنەوە و هەڵە. سەرەڕای بەهێزی ئەو ئەلگۆریتمانە هێشتا دووچاری کەموکورتی دەبنەوە، لەوانە ئاڵۆزی ژمێریاری، کێشەی پێوانەکردن، گیربوون لە

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مینیمای ناوخۆیی، لێکنزیکبوونەوەی پێشوەختە و هتد. ئەم پێداچوونەوە تیشک دەخاتە سەر سوود و زیانەکانی ئەلگۆریتمە بەردەستەکانی پلاندانانی رێڕەو وە ئاماژە بەوە دەکات کە هەرچەندە ئەم ئەلگۆریتمانە پێشکەوتنێکی بەرچاویان بەدەستهێناوە بەڵام هێشتا بەدەست سنوردارییەوە دەناڵێنن و هێشتا ئەو تایبەتمەندییە فراکتال و ستۆکاستیکانە لەبەرچاو ناگرن کە لە سیستەمە فرە بێ فڕۆکەوانەکاندا دەردەکەون لەبەرئەوەی تایبەتمەندیەکانی فراکتال دڵنیایی دەدەن کە چارەسەرەکان دەتوانن خۆیان بگونجێنن بەڵام بە دروستی دەمێننەوە و توانای پێوانەکردن بە درێژایی هەرەمی ژینگە دەمێننەوە، لە کاتێکدا شێوازەکانی ستۆکاستیک گەڕانی گشتی زیاد دەکەن بە چنینی ئاستێکی بێ بیرەوەری و گەڕانی هەڕەمەکی چارەسەرەکان. وە بۆ کارەکانی داهاتوو پێشنیار دەکرێت بە تێکەڵکردنی ئەم تایبەتمەندیانە لە ئەلگۆریتمەکانی داهاتوودا کە بەمەش ئەدای فرۆکە بێ فڕۆکەوانەکان بەهێزتر و کاراتر و گونجاوتر دەکات و هانی بەکارهێنانی سەرکەوتوویان دەدات لە جیهانی ڕاستەقینەدا.

تحليل وتوقع خوارزميات تخطيط المسار الموجودة للأنظمة متعددة للطائرات بدون طيار

الملخص:
اكتسبت مؤخراً الطائرات بدون طيّار (Drones) رواجاً وأهميةً متزايدة في مختلف المجالات والتطبيقات، بما في ذلك المجالات العسكرية والمدنية. ومع ذلك، فإنَّ التطوير المستمر لهذه الطائرات يتطلب مواجهة العديد من التحديات والمشاكل مثل: تخطيط المَسار، والتنظيم والتكامل، وكذلك استهلاك الطاقة والاتصالات والشبكات، فضلاً عن التحديات المتعلقة بالأمن والخصوصية وقيود التشغيل. وتبعاً لذلك، تُعد مشكلة تخطيط المَسار أحد أكثر المشكلات أهميةً؛ أي بمعنى إيجاد أفضل مسار من نقطة البداية (المصدر) الى نقطة النهاية (الوجهة)، مع تجنب الاصطدامات عن طريق خفض التكلفة (أي تكلفة الوقت والطاقة والموارد الأخرى). تم تطوير مجموعة واسعة من الخوارزميات ، التي تقدم طرقا مافوقة الاكتشاف المستوحاة من الطبيعة مثل PSO و WOA و LSO ، للتعامل مع هذا التحدي. كما تم استخدام التعلم المعزز للسماح للطائرات بدون طيار بتعلم المسارات من خلال التفاعل البيئي والتجربة والخطأ. على الرغم من نقاط القوة في هذه الخوارزميات ، إلا أنها تعاني من عيوب ، بما في ذلك التعقيد الحسابي ، وقضايا قابلية التوسع ، والمحاصرين في الحد الأدنى المحلي ، والتقارب المبكر وما إلى ذلك. تسلط هذه المراجعة الضوء على مزايا وعيوب خوارزميات تخطيط المسار الحالية. ويشير إلى أنه في حين أن هذه الخوارزميات قد أحرزت تقدما كبيرا ، إلا أنها لا تزال تعاني من قيود ولا تأخذ في الحسبان بعد مثل هذه

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الخصائص الكسورية والعشوائية التي تظهر في أنظمة الطائرات متعددة الطائرات بدون طيار. تضمن الخصائص الكسورية أن الحلول يمكن أن تتكيف ولكنها تظل صالحة وقابلة للتطوير عبر التسلسل الهرمي للبيئات ، بينما تعزز طرق ستوكاستيك الاستكشاف العالمي من خلال نسج مستوى من الاستكشاف العشوائي للحلول بدون ذاكرة. بالنسبة للعمل المستقبلي ، فإن دمج هذه الميزات في الخوارزميات القادمة سيجعل أداء الطائرات متعددة الطائرات بدون طيار أكثر قوة وكفاءة وقابلية للتكيف ويشجع على استخدامها بنجاح في العالم الحقيقي.