Drone Systems and Applications

OPEN ACCESS | Review

A systematic review on metaheuristic approaches for autonomous path planning of unmanned aerial vehicles

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Abstract

In the path planning of UAVs, autonomous decision-making and control are challenging tasks in the uncertain 3D environment consisting of static and dynamic obstacles. Hence, the selection of appropriate path-planning approaches is essential. In the proposed work, we have considered the meta-heuristic approaches only for an in-depth review. Metaheuristic approaches have been remarkably known for solving complex problems, optimal solutions, and lesser computational complexity compared to deterministic approaches that produce an inefficient solution. An in-depth review has been made by considering the approaches used for path planning, their advantages, disadvantages, applications, the type of time domain (offline or online), type of environment (simulation or real time), hybridization with other approaches, single or multiple UAV system, and obstacle handled (static or dynamic). It is observed that current meta-heuristic methods face constraints like inadequate convergence rates, entrapment in local optima, and complex operations, necessitating continuous development of novel approaches. Implementation of path-planning approaches are very much limited to simulation study over experimental analysis. Hybrid algorithms emerge as a potential solution for tackling these hurdles and optimizing UAV navigation, particularly in dynamic environments involving multiple UAVs. The paper highlights key research gaps, trends, along with prospects in the field of research.

Key words: artificial intelligence, path planning, metaheuristic algorithms, UAV, mobile robot navigation

1. Introduction

Unmanned aerial vehicles (UAV) or drones are the vehicle that can take off and land vertically with high maneuverability (Yang et al. 2015). These vehicles are the perfect examples of robotics, in which artificial intelligence (AI) and mechanical motions take place simultaneously (Pandey et al. 2017). Modern robots should be able to make their own decisions according to the uncertainty present in the environment and work autonomously without the intervention of human operators or computers. Robots can sense the environment with the help of different sensors and cameras and AI helps it to react according to the environment. One such application of robotics is path planning, in which the robot will travel in a known, partially known, or completely unknown environment from start position to the goal (Dracopoulos 1998) and avoids the static and dynamic obstacles present in the path. Two-dimensional path-planning algorithms are simple and less time-consuming but are not always useful in a 3D environment, where a lot of complexities and uncertainties are present. Three-dimensional path planning or aerial navigation is an area of research that covers effective path planning, recording the path, controlling the movement, and avoiding static and dynamic obstacles in a 3D environment.

Optimization is important in all areas of engineering right from resource allocation, traveling, and scheduling. This optimization deals with the optimum utilization of man, machine, material, and money. In its simplest form, optimization is finding the maximum or minimum value of any function. For simple linear problems, optimization can be calculated by finding the double differentiation of a given function. However, the real-world problems are nonlinear, multimodal, multi-objective, and multivariate, which cannot be solved by simple linear programming methods. For solving these kinds of complex problems, metaheuristic algorithms are used. The term metaheuristic was first coined by Glover (1986) in his research paper. Metaheuristic algorithms tend to work for global optimization problems. Here the optimal solution is not always guaranteed. It is assumed that most of the time these algorithms will reach the optimal solution, but not necessarily all the time.

Table 1 shows the brief history of the development of a metaheuristic algorithm. Metaheuristic algorithms first came into existence in the 1960s, when evolutionary strategies (ES) and genetic algorithms (GA) were developed. But the major breakthrough was the development of simulated annealing (SA) by Kirkpatrick et al. (1983), which was inspired by the annealing process of metals. Another significant milestone was the development of artificial immune systems by Farmer et al. (1986). Since the year 1990, the term

Table 1. Brief history classical and modern approaches in unmanned aerial vehicles.

S. No	Year	Inventor	Name of algorithm
1.	1963	(Rechenberg 1989)	Evolutionary strategies (ES)
2.	1966	(Yuryevich and Wong 1999)	Evolutionary programming (EP)
3.	1975	(Holland 1992)	Genetic algorithm (GA)
4.	1980	(Fiechter 1994)	Tabu search algorithm (TS)
5.	1983	(Kirkpatrick et al. 1983)	Simulated annealing (SA)
6.	1986	(Timmis et al. 2004)	Artificial immune system (AIS)
7.	1992	(Dorigo and Blum 2005)	Ant colony optimization (ACO)
8.	1995	(Kennedy et al. 1995)	Particle swarm optimization (PSO)
9.	1996	(Storn and Price 1997)	Differential evolution (DE)
10.	2001	(Geem et al. 2001)	Harmony search (HS)
11.	2002	(Das et al. 2009)	Bacterial foraging algorithm (BFA)
12.	2005	(Pham et al. 2008)	Bee algorithm (BE)
13.	2005	(Teodorović et al. 2006)	Artificial bee colony (ABC)
14.	2008	(Yang 2010c)	Firefly algorithm (FA)
15.	2009	(Yang et al. 2009)	Cuckoo search (CS)
16.	2009	(Li et al. 2002)	Fish swarm algorithm
17.	2010	(Yang 2010a)	Bat algorithm (BA)
18.	2011	(Alatas 2011)	Artificial chemical reaction optimization (ACRO)
19.	2014	(Mirjalili et al. 2014)	Grey wolf optimizer (GWO)
20.	2013	(Findik 2015)	Bull optimization algorithm (BOA)
21.	2015	(Mirjalili 2016)	Dragonfly algorithm (DA)
22.	2015	(Rashedi et al. 2009)	Gravitational search algorithm (GSA)
23.	2017	(Siddique and Adeli 2017)	Chemical reaction algorithm (CRA)
24.	2021	(Abualigah et al. 2022)	Reptile search algorithm (RSA)
25.	2021	(Mohammadi-Balani et al. 2021)	Golden eagle optimizer (GEO)
26.	2022	(Nonita et al. 2022)	Intelligent water drop algorithm (IWDA)
27.	2022	(Xie et al. 2021)	Tuna swarm optimization (TSO)
28.	2022	(Dhouib 2021)	Dhouib-Matrix-4 (DM4)

"metaheuristic" has been well-known, and many researchers have started solving optimization problems using these algorithms. As a result, many metaheuristic algorithms for path-planning optimization problems were developed between 1990 and 2023.

Table 1 shows the list of classical and modern metaheuristic algorithms developed for solving NP hard optimization problems. Some algorithms like (GA), differential evolution (DE), ant colony optimization (ACO), particle swarm optimization (PSO), artificial bee colony (ABC), fish swarm algorithm (FSA), cuckoo search (CS), firefly algorithm (FA), bat algorithm (BA), grey wolf optimizer (GWO), SA, harmony search (HS), and gravitational search algorithm (GSA) have been implemented for path planning of UAV while some like ES, evolutionary programming (EP), TS, artificial immune system (AIS), bacterial foraging algorithm (BFA), BA, artificial chemical reaction optimization (ACRO), bull optimization algorithm (BOA), dragonfly algorithm (DA), chemical reaction algorithm (CRA), reptile search algorithm (RSA), Golden Eagle Optimizer (GEO), artificial water drop algorithm (AWDA), and tuna swarm optimization (TSO) have never been used for path planning of UAV. For several decades, researchers and scientists have developed numerous metaheuristic algorithms. We shall discuss GA, DE, ACO, PSO, ABC, FSA, CS, FA, BA, GWO, SA, HS, and GSA algorithms used for path planning of UAVs in a 3D environment in the current work. Because of the complexities involved, it is not possible to implement all developed algorithms for 3D path planning. For executing this complicated task, hybridization with other metaheuristic techniques is also implemented by the researchers (Patel and Patle 2020; Patle et al. 2021). Many researchers have done a review on path-planning algorithms, but these surveys are insufficient to provide detailed classification and in-depth knowledge of recently developed AI-based metaheuristic algorithms. Goerzen et al. (2010) have explained the methodology of path planning and reviewed all existing techniques of path planning. Beheshti (2013) has classified metaheuristic algorithms as nature-inspired against non-nature-inspired, population-based against single-point search, dynamic against static objective function, various against single neighborhood structure, and memory usage against memory-less methods. They discovered that existing algorithms have limitations such as trapping into local minima, slow convergence rate, and long computational time. These problems can be addressed by introducing new metaheuristic approaches. The use of different modern path-planning algorithms for mobile robot navigation is reviewed in reference Yang et al. (2016). In this review, the authors found that modeling of complex 3D environments, real-time planning, and complete information processing are still areas of possible study. Pandey et al. (2017) have studied the application of metaheuristic algorithms for aerial navigation and found that to overcome the problem of real-time path planning, modified metaheuristic algorithms are the best choice. A detailed classification of the metaheuristic algorithm is done irrespective of its application in Abdel-Basset et al. (2018). They classified metaheuristic algorithms as metaphor-based or non-metaphor-based. The application of path planning to 2D mobile robots using traditional and intelligent methods is discussed in Zafar and Mohanta (2018), Zhang et al. (2018), and Wahab et al. (2020). There has been a lot of research done on UAV path planning, such as in Zhao et al. (2018), where the author reviews path-planning algorithms that are only used for UAVs. Interception of targets in 3D path planning is a difficult task to perform. Sharma et al. (2021) have specifically reviewed multiple target-capturing capabilities of swarm intelligent UAVs. In Aggarwal and Kumar (2020), authors have classified the path-panning algorithms as cooperative techniques, representative techniques, and non-cooperative techniques. These literature reviews are extremely important and beneficial to new researchers interested in path planning in 2D and 3D environments.

It has been noted that no review study has been found in the existing research that covers all the methods of UAV path planning. The current literature fails to portray the hierarchical development of the field, including the contributions and progress made by each participant. As of now numerous metaheuristic techniques are developed for UAV path planning, but there is no publication available in the literature that analyzed the existing techniques in depth. Most of the review articles are based on a single category of algorithms and only parameters like obstacle avoidance and path planning are discussed. In current work, UAV path-planning algorithms are categorized into three groups and in-depth analysis has been done on each. After a thorough analysis, we have reviewed the various path-planning approaches and evaluated their strengths, weaknesses, and potential applications. We also considered factors such as time domain (offline or online), environment type (simulation or real time), hybridization with other approaches, the number of UAV systems involved (single or multiple), the type of obstacle addressed (static or dynamic), and optimization of path, time, and energy. This review paper covers all the presently utilized approaches for UAV path planning to assist the research community in comprehending the scope of work carried out in the field. This article provides an overview of the progress made in the field of UAV path planning to date. Reading it will give you an understanding of the research that has been conducted in this area. All the results and discussion parts are presented in graphical and tabulated form for easy understanding.

Section 1 of this article delivers an explanation of the introduction to UAV path planning and a critical review of all developed metaheuristic techniques. To realize the research gap in the topic, Section 2 provides a detailed study of all the algorithms that are implemented for UAV path planning, along with information on how these algorithms work, their inspiration, applications, benefits, and limitations. Section 3 presents the in-depth results and a discussion and comparison of all algorithms of UAV path planning used so far, and Section 4 concludes. By organizing the articles in this manner, the research gap in UAV path planning is made apparent, and readers gain a comprehensive understanding of the current state of the field.

2. Classification of metaheuristic algorithms used for aerial navigation

This paper categorizes metaheuristic algorithms as evolutionary algorithms, swarm intelligence algorithms, and trajectory algorithms. This classification is as per the author's perspective. Figure 1 shows the detailed classification of metaheuristic algorithms used for path planning and obstacle avoidance by UAVs.

Figure 2 shows the detailed classification of all the research papers downloaded for the current review. Approximately a total of 810 papers were downloaded from various reputed national and international journals. During the first scanning process out of these papers, 130 papers are removed due to duplicate downloads. The remaining 670 papers were scanned for their relevance by just reading the title and scrolling and 359 papers were eliminated. Now the remaining 311 papers are considered relevant and good for study and have gone through the study of abstract and conclusion. From this, 88 papers were rejected as they were not belonging to UAV application. Finally, the remaining 223 papers were considered for full-text assessment and went through a detailed study. From this study, again 67 papers were rejected, as those were not written for path planning applications. The remaining 156 publications are based on UAV route planning and related issues, and they are considered and mentioned in current work. These are divided into five categories Introductory papers (42 Nos), Evolution Algorithms (28 Nos), Swarm Intelligence Algorithm (61 Nos), and Trajectory-based Algorithm (25 Nos). Table 2 shows the detailed distribution of selected articles across different peer-reviewed journals.

2.1. Evolutionary algorithms

Evolutionary algorithms are population-based optimization methods in which the search sampling is based on the evolution theory of Darvin. These are heuristic-based approaches used for solving the optimization problem, which cannot be solved by linear programming. These are also called classical NP-hard problems. EA is based on biological evaluation, where groups of possible solutions to the given problem are created. The solution's quality is represented in terms of a fitness function, which indicates the quality of the solution. The group of solution updates will proceed towards a better solution (Leach 2007). There are three main streams of EA, GA developed by Holland (1992) in 1975, ES developed by Rechenberg (1989) in 1963, and EP developed by Yuryevich and Wong (1999) in 1966. Out of all this, GA is widely used and known as the best solution for optimization.

Fig. 1. Classifications of metaheuristic algorithm used for path planning of UAVs.

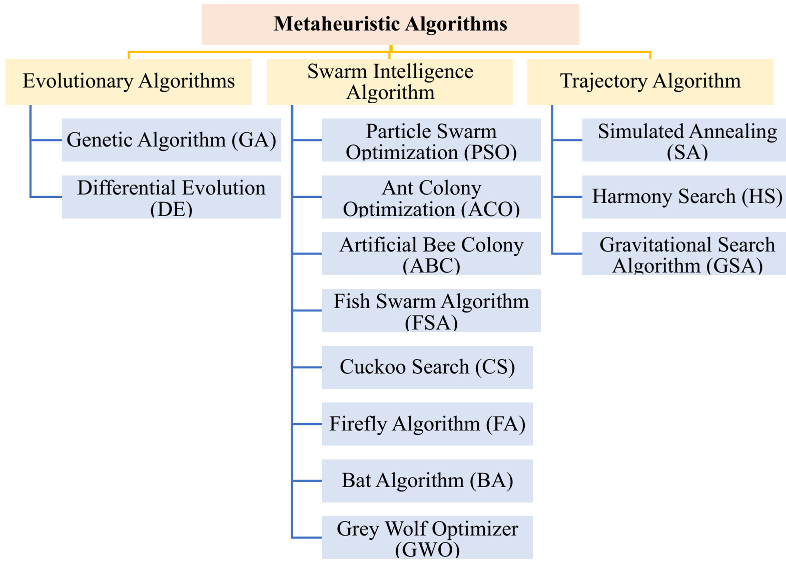
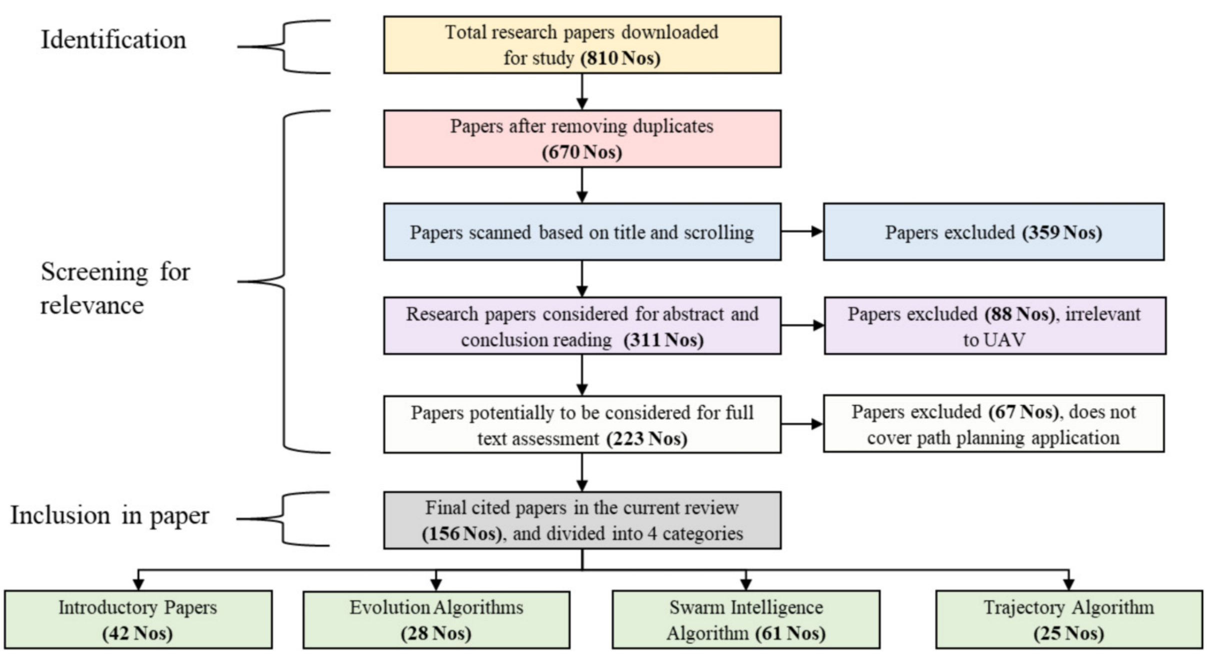


Fig. 2. Categorization of all the research papers considered for current review.



2.1.1. Genetic algorithm

Genetic algorithm was developed by Holland (1992) in 1975 and belongs to a subset of evolutionary computing. GA is an optimization algorithm based on natural selection and the survival of the fittest. In nature, genes with good survival traits survive for longer periods, giving offspring with similar gene material a better chance of survival. As a result of this, better-quality genes remain in the system, while the genes of inferior individuals die out during the process. This is the fundamental process of natural selection. The new solution (population) is produced by the iterative use of genetic operators on the existing individual solutions. The representation of chromosomes, their selection based on better traits, crossover, mutation, and fitness function computation are the key elements of GA (Fig. 3).

Genetic algorithm is a metaheuristic algorithm useful for solving complex (NP-hard) optimization problems. Since its development, GA has been used by many researchers in the different fields of control strategy in electric vehicles (Morteza et al. 2006), path planning of mobile robots (Patle et al. 2017), mobile manipulator path planning (Zhao et al. 1992), and underwater swarm robots (Vicmudo et al. 2014) to name few. These papers focus on the application of GA for path planning of UAVs. In the late 90s, Marin et al. (1999)

Table 2. Distribution of papers published in different peer-reviewed journals.

S. No	Publications	Number of papers	Percentage
1	MDPI Journals	6	3.85%
2	IEEE Transactions & Access	8	5.13%
3	IEEE journals	34	21.79%
4	Elsevier Science Publishers	38	24.36%
5	Springer	28	17.95%
6	SAGE Publications	4	2.56%
8	Hindawi	6	3.85%
9	Taylor & Fransis	3	1.92%
10	IOP Publishing	3	1.92%
11	Others	26	16.67%
	Total	**156**	**100%**

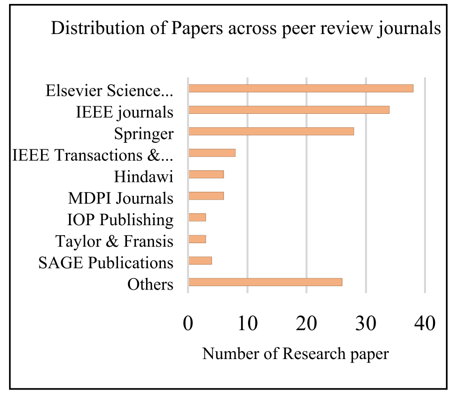
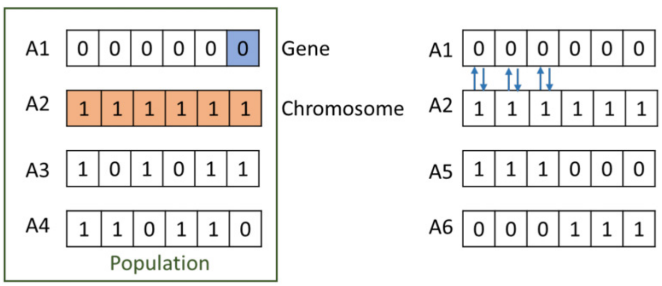


Fig. 3. Crossover and mutation procedure of genetic algorithm.



used GA to develop the rule that guides unmanned aerial vehicles. They used grid cells to model the uncertainty of the environment. They employed SAMUL evolutionary learning to generate this set of rules that guides the UAV. Nikolos et al. (2003) introduced modified breeder GA for offline and online path planning of UAVs. Here, B-spline curves are used to represent the calculated 3D path, with the control points being the evolutionary algorithm's artificial chromosome genes. In continuation to this, Hasircioglu et al. (2008) introduced a path planner algorithm for UAVs. They have also represented the path using these B-spline curves with its control point being the gene of the chromosome. GA outperforms other path-planning techniques since it explores the solution space but retains the best solution, which is already found.

However, for complex environments such as 3D terrain, GA tends to be slow due to its repetitive loop. To improve this unforeseen event Allaire et al. (2009) have applied field programmable gate array parallelly with GA. The computation time for the selection of the optimal path is further reduced by the introduction of a new algorithm called the vibrational genetic algorithm (mVGA) (Pehlivanoglu 2012). This algorithm focuses on new mutation applications and diversity. During the initial population phase, the mVGA uses the clustering method and voronoi diagram. They have compared the mVGA results with all existing algorithms and found that the results are the best in terms of computation time. For improving the path planning and obstacle avoidance, Wang and Chen (2014) suggested an improved GA based on prior knowledge. In certain application areas, the threatening zone, like an enemy radar's location and range, is known to us. These are treated as constraints for their optimization problem, which can also be called prior knowledge. To find a collision-free path for the UAV that is sharing the airspace with other UAVs, Cobano et al. (2011) used grid models and GA simultaneously to find safe trajectories. They have selected the best trajectory by using the Monte Carlo method with the consideration of different uncertainties such as winds, the limitations of sensors, and the accuracy of the vehicle model. Roberge et al. (2013) have used grid models and a GA simultaneously to find safe trajectories. Roberge et al. (2013) modified the conventional GA with multi-type genes to stochastically search a test solution.

GA is a global optimization tool for solving the path planning problems of UAVs where the global optimum solution is achieved generation by generation. Artificial neural network (ANN) can approximate all functions and is faster as compared to GA. But ANN gets a solution for the local optimum instead of the global optimum. So, to take advantage of ANN, Gautam (2014) combined ANN with traditional GA. They have used the output of GA to train ANN, which allows the UAV to plan its path better and faster as compared to GA alone. This hybridization helps GA perform better and find the optimal solution faster. Haghighi et al. (2020) hybridized GA with PSO to solve the open traveling salesman problem. Considering the importance of hybridization, GA is hybridized with fuzzy logic (FL) by Mazinan (2017).

UAVs can benefit significantly from engaging path-planning techniques offered by GAs. First, GA is great at efficiently exploring huge solution spaces, which makes them suitable for tough situations with multiple possible solutions. Additionally, they exhibit significant flexibility, being able to consider a variety of mission objectives and unpredictable situations. GA also offers resilience in handling ambiguous circumstances by continuously improving solutions. It is important to recognize that GAs have their limitations. One significant negative is their computational complexity, which may lengthen planning durations and restrict its use in real time. Additionally, due to the stochastic nature of their search, GAs could find it difficult to guarantee globally optimal solutions. Despite these drawbacks, GAs can be a useful tool for UAV route planning tasks when intelligently combined with other path-planning techniques.

2.1.2. Differential evolution

Differential evolution was developed by Storn and Price (1997) in 1996. DE is the part of evolutionary computation that optimizes the given problem by iterations and improves the candidate solution with regards to given criteria. Since the development of DE, many users have developed numerous techniques for optimization using DE. DE has been used in different areas of optimization. Parhi and Kundu (2017) used DE for path planning and obstacle avoidance of underwater robots, Blackmore et. al. (1997) did numerical control machine verification using DE, and Al-Dabbagh et al. (2014) used DE for controlling the manipulator's arm. Research articles (Neri and Tirronen 2010; Das and Suganthan 2011; Bilal et al. 2020) show a detailed survey of the present state of DE optimization techniques and their applications. After reading all these articles, it is evident that DE has emerged as the most frequently used algorithm for optimization problems. DE has all its properties due to which it is also best for navigation and path planning of UAVs in complex 3D environments for reaching the target with obstacle avoidance. Nikolos and Brintaki (2005) performed offline path planning with multiple UAVs to create 2D trajectory. The UAVs start from predefined initial point and reach the predefined target location. Avoidance of static obstacles and locating the collision-free path with other UAVs were the prime objective of their work. To enhance the performance of DE, Fu et al. (2013) proposed the hybridization of DE with quantum-based particle swarm optimization (QPSO) and named it DEQPSO. A new route planner using DEQPSO is designed for generating safe fly paths in the presence of different environmental constraints. They have compared the performance of DE-QPSO with real-valued GA, standard PSO, DE, QPSO, and hybrid particle swarm with differential evolution operator in terms of robustness, the convergence property, and solution quality and found it to be better among all tested optimization algorithms. This hybridization helps the DE improve its performance Yu and Wang (2013) have hybridized DE with GSO to take advantages of both algorithms. They have used GSO to identify the flight path of UAV by distance and search angle then this identified feasible path is modified within the search area in evolutionary process. Then UAV can locate the safe path by joining the selected points with threat avoidance and costing minimum fuel in the war zone. Adhikari and Kim (2017) proposed an adaptive fuzzy DE algorithm for 3D path planning of UAVs. The path-planning problem was assumed to be a multi-objective unconstrained optimization problem with the aim of minimizing energy requirement and finding the optimal cost. Here they have used the FL controller for determining the parameter values of DE. This hybrid algorithm when compared outperforms the conventional DE/rand/1 and DE/best/1. Hybridization of DE is also helpful in collaborative path planning with multiple UAVs. Path planning and obstacle avoidance of multiple UAVs is a critical task to perform, and a conventional DE algorithm will not be sufficient to perform this task optimally. In the year 2020, Ali et al. (2023) hybridized DE with maximum minimum ant colony optimization (MMACO) to make a new metaheuristic algorithm. This newly designed algorithm improves the performance of conventional DE by minimizing the lacunae of classical ACO and MMACO.

For the path planning of UAVs, DE has several advantages, including effective exploration of solution spaces with fewer function evaluations. Because DE is population-based, it shows resistance to local optima, making it suited for complicated and noisy environments. Additionally, DE's implementation can be made simpler by the comparatively simple parameter setting. DE does, however, have certain limitations. It may need careful calibration because of potential issues with high-dimensional problems and sensitivity to parameter adjustments. Additionally, DE's exploration–exploitation balance occasionally causes early convergence, which might provide less-than-ideal pathways. However, DE continues to be a viable method for UAV route planning, especially when customized parameter settings and hybridization with other algorithms are considered.

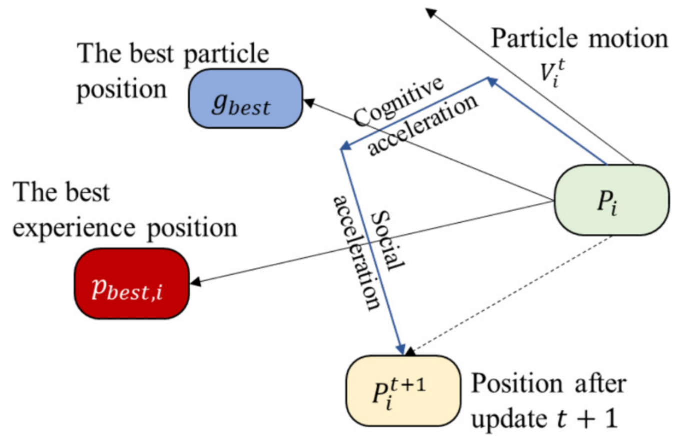
2.2. Swarm intelligence

Swarm intelligence is an AI technique inspired by the collective behavior of insects such as bees, wasps, and ants. Along with animal flocks like bird flocks, a group of fish shows similar swarm behavior. It is an intelligent multiple-agent system where the complex task is performed by the cooperation and coordination of individual members. The term swarm intelligence was first coined by Beni and Wang (1993) in the year of 1989 in the background of the cellular robotic system (CRS). Since the 1990s, many researchers have taken inspiration from nature and developed many swarm intelligence techniques for use in the optimization of different engineering problems. For example, ACO (Blum 2005), BA (Yang 2010*b*), PSO (Wang et al. 2018), fruit fly optimization algorithm (FFOA) (Pan 2012), bee algorithm (BE) (Yuce et al. 2013), FA (Fister et al. 2013), shuffled frog leaping algorithm (SFLA) (Eusuff et al. 2006), and CS (Yang et al. 2009) to name few. These algorithms have been used in numerous optimization applications, like the scheduling of trains, collective robots, the Internet of things, the computation of electric power, the path planning of mobile robots, and the trajectory planning of industrial manipulators. In the current study, we will concentrate on specific metaheuristic swarm intelligence-based techniques implemented for path planning and obstacle avoidance of UAV in a 3D environment.

2.2.1. Ant colony optimization

Ant colony optimization is pioneered by Dorigo and Gambardella (1997) as a part of his Ph.D. thesis. He has applied ACO to the traveling salesman problem and after a lot of experimentation, concluded that when compared, ACO outperforms then EA and SA. ACO is a materialistic optimization algorithm useful for solving complex combinatorial optimization problems with good solutions in less computational time (Dorigo and Blum 2005). This makes it useful for solving the path-planning problem of UAVs in uncertain environments. Zhang et al. (2010) have done the path-planning of UAVs based on ACO. They considered the target position as a food source of the ant that they are going to find; the defense region is assumed as the search space of the ant and divided into grids. The simulation shows that ACO can effectively accomplish the path planning, but as the path is generated in the grid environment it needs a smoothing factor to be added for UAV flying. ACO is modified by introducing a 3D grid design with an advanced climbing weight parameter (He et al. 2013). This modified algorithm outperforms the conventional ACO and shows a better result in terms of premature convergence, energy consumption, and exploration efficiency. They have implemented it for indoor UAVs. The premature convergence in UAV path planning is the major problem and is further reduced by introducing bidirectional searching in the traditional ACO (Cui et al. 2014). In bidirectional searching, the environment is modeled using grids, and an ant colony starts searching from both ends, i.e., start and destination, simultaneously. Cekmez et al. (2016) have introduced multi-colony ant optimization, which helps in reducing the premature convergence problem. In this multi-colony ant optimization, the ant colonies exchange valuable information among themselves to find the optimal solution. Experimental results showed that multi-colony optimization shows better results as compared to the single ant colony optimization approach. Guan et al. (2019) have added a genetic algorithm with a multi-ant colony optimization algorithm to reduce the slow convergence problem. In the large domain, conventional ACO slows down when finding the optimal path. To reduce this problem, the double-end colony optimization is used in which initially genetic algorithm is implemented to generate pheromones to accelerate the convergence. Chen et al. (2017*a*) performed effective UAV path planning under multiple static obstacle constraints. With their experiments, they found that as the obstacle number increases, the proposed ACO algorithm can find the shortest path between the goal and starting point. Dynamic path planning of a UAV that contains moving and static obstacles is a challenging task and is treated as a multi-objective optimization problem. Huang et al. (2018) proposed a new path-planning algorithm that combines the advantages of ACO and artificial potential fields (APF). Both static and dynamic constraints are considered when generating the artificial map. Cost function is established for each dynamic constraint and for finding the optimal path of UAV cost value of each path and the total cost is optimized using ACO. This combined method showed the smooth path planning of UAVs compared to only conventional ACO. Song et al. (2020) have combined the fuzzy with the improved ant colony algorithm. The conventional ACO is improved by introducing a rank-based ant system. This rank-based system works well with static obstacles but is not able to adapt to the dynamic environment. To find the optimal path in a dynamic environment, improved rank-based ACO is hybridized with FL and called FLACO. When compared to both conventional ACO and modified ACO for path planning in road networks, FLACO demonstrates superior results in terms of both convergence speed and path optimization. After reading all the literature, it is evident that conventional ACOs have the problems of slow convergence, a tendency to fall into local minima and low efficiency. These problems are solved by introducing some modifications to the classical ACO. Pu et al. (2020) have improved classical ACO in three steps. At the first step, global searchability is enhanced by a pseudo-random state transition strategy, in the second step convergence speed of the algorithm is increased by using pheromone updates and increments, and finally in the last step security of the path is ensured using the security value function. Li et al. (2021) have added greedy strategy (GS) to the classical ACO to obtain minimum mission time with multiple UAVs.

Fig. 4. Adaptive PSO.



ACO is a bio-inspired approach that shows great promise for UAV route planning. The key advantage of an ACO is its ability to efficiently manage complex and dynamic settings. It uses pheromone-based communication among agents to adapt rapidly to changing conditions and identify high-quality pathways in broad solution spaces, making it appropriate for a wide range of UAV missions. Scalability is enhanced by ACO's intrinsic parallelizability and adaptability for distributed systems. However, ACO may take more iterations to get optimal solutions, resulting in longer calculation times. Its performance is highly dependent on parameter adjusting and problem-specific parameters, and it may confront difficulties in high uncertainty or fast-changing dynamics. Despite these difficulties, ACO remains a tempting technique for UAV route planning, particularly when customized for mission objectives and backed by heuristic improvements.

2.2.2. Particle swarm optimization

Particle swarm optimization is a population-based, stochastic search algorithm that is inspired by the flocking of birds or fish. This algorithm is simple as compared to other evolutionary techniques because only a single objective function is required for defining the problem, and it does not depend upon any derivative of an objective function, as shown in Fig. 4. This algorithm was pioneered by Kennedy and James (1995).

Due to simplicity, many researchers have been attracted to PSO for solving the complex optimization problem of 3D path planning. In Jung et al. (2006), the author used the PSO to find the optimal path of a UAV in a 3D environment for reducing enemy threats and fuel usage. The optimal path is generated with the help of a B-spline curve for static situations where all the flight trajectories were known beforehand. However, in real-world situations where the terrain and obstacles change in real time, dynamic path planning is required. Cheng et al. (2014) used an improved PSO named adaptive chaotic PSO for real-time dynamic path planning. This improved method outperforms both standard and immune PSO in terms of local and global path planning. The standard PSO is also improved by introducing the competition strategy, which improves particle search ability and convergence speed. This improvised method, which is named GBPSO (Huang et al. 2018), is able to optimize the global best solution in the particle evolution process. PSO's performance was improved further by combining it with a GE as a hybrid algorithm (Haghighi et al. 2020). This hybrid form of PSO combines the benefits of both the genetic algorithm and PSO. In 2020, Haghighi et al. (2020) compared the performance of hybrid PSO with that of a traditional GA and a standard PSO alone and found that the hybrid PSO gave better results for cooperative UAVs. In continuation of this hybridization, Abhishek et al. (2020) have hybridized the conventional PSO with the HS algorithm and the GA separately. In contrast to the individual GA or PSO, they discovered that this hybridized algorithm is not biased in terms of exploitative and exploratory searches.

Due to simplicity and ease of implementation, PSO has garnered a reputation as a great method for UAV route planning. PSO navigates complicated solution spaces effectively by mimicking particle social behavior, frequently converging swiftly to near-optimal solutions, which is advantageous for real-time applications. Furthermore, PSO can solve both single-objective and multi-objective optimization problems, increasing its flexibility. Nonetheless, PSO has boundaries, including issues with multimodal and high-dimensional search spaces, as well as sensitivity to its parameters and settings, which need careful tuning. Furthermore, PSO may not always guarantee globally optimul solutions. PSO, when used wisely and in combination with hybrid techniques and parameter adaptation mechanisms, remains a powerful tool in UAV route planning.

2.2.3. Artificial bee colony

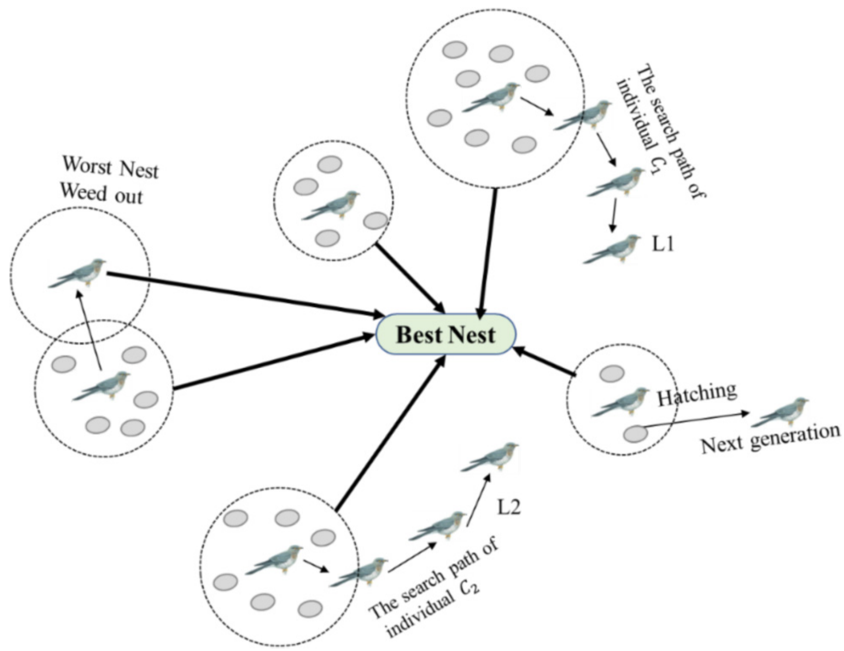
Artificial bee colony is a metaheuristic, swarm-based intelligence system based on the foraging behavior of the honeybee. ABC was pioneered by Karaboga in 2005 (Yuce et al. 2013), and is used for the optimization of complex numerical problems. ABC is inspired by the foraging behavior of the bees when they are in search of good-quality food or nectar. This foraging behavior helps in finding the optimum solution quickly, which makes ABC an effective algorithm for solving UAV path-planning problems. Cao et al. (2013) have used the ABC algorithm for optimal route planning and threat avoidance of unmanned combat aerial vehicles. They improved the conventional ABC algorithm using the balance evolution strategy (BES). In this improved algorithm, the convergence information obtained during iteration stage is completely used to modify the exploration accuracy, which creates balance between global and local exploration. The performance of the conventional ABC algorithm can also be improved by using the memory-saving optimization algorithm of compact ABC (Pan et al. 2017). In this compact algorithm, the original design variable of ABC is replaced by a probabilistic solution. This entire improvement in conventional ABC is done for a static environment. For avoiding the dynamic threats, an improved ABC (IABC) algorithm is proposed by Tian et al. (2018). They have used IABC as it requires a very small number of control parameters and gives fast convergence in real-time path planning. They depicted that IABC is faster than conventional ABC in terms of path planning and threat avoidance in a real-time situation for single and multi-UAVs. Muntasha et al. (2021) have designed an anti-collision system for the swarm of drone. In the proposed system, the ABC is used to optimize the velocity of the UAV, its obstacle-avoiding capability, and the selection of an optimal path with collision avoidance with other UAVs. Many trials were simulated, and they found that for the swarm of 12 and 20 drones, collisions were negligible, but for a larger number of drones, say 50, there were 12 collisions.

ABC technique has emerged as a great option for UAV navigation, because of its simplicity and computational efficiency. This makes it very suitable and reliable for real-time applications. ABC efficiently explores solution spaces, drawing inspiration from honeybee foraging behavior. On the other hand, it struggles with high-dimensional and multimodal problems and can be sensitive to parameter choices and initialization, requiring careful tweaking. Furthermore, it does not always guarantee globally optimal solutions. However, when designed correctly and paired with problem-specific heuristics, ABC remains a significant tool in UAV route planning, particularly for resource-constrained platforms.

2.2.4. Fish swarm algorithm (FSA)

The FSA is proposed by Li et al. (2002) as a metaheuristic technique inspired by the swarming behavior of a fish colony. The FSA is an optimization technique that is modeled on the way that schools of fish move together to find food. Due to the exploration behavior of fish colonies, the FSA avoids trapping into local minima, which is helpful in the autonomous navigation of UAVs in 3D environments. Ma and Lei (2010) have used an artificial fish school algorithm to eliminate the 2D radar threat environment for Unmanned combat aerial vehicle (UCAV). The artificial FSA (AFSA) uses the local searching method, which makes it effective in global optimization. They compared the performance of AFSA with that of PSO and found that AFSA was more effective in finding shorter distances for flight and threat avoidance. Due to the global optimization capability of FSA, Yang et al. (2021) have combined the AFSA with PSO for dynamic path planning in flight to prevent developing the threat. The behavior evolution strategy of FSA helps overcome the premature convergence phenomenon of PSO effectively. By combining AFSA with PSO, they found that the rate of convergence increased, safe and simplified path planning was achieved, and ultimately the total flight cost was reduced.

Fig. 5. The migration and brood parasitism of cuckoos.



One of the primary characteristics of FSA is its ability to effectively explore solution areas, which is inspired by the coordinated behavior of a school of fish. This versatility allows FSA to effectively navigate complex and dynamic situations, making it suitable for UAV route planning tasks. FSA frequently achieves high-quality results in a reasonable period, which is critical for real-time applications. In addition, FSA is easy to set up and requires little parameter modification. It can handle both single-objective and multi-objective optimization issues. FSA does, however, have certain limits. When dealing with issues with high-dimensional solution spaces or complicated restrictions, it may encounter difficulties, perhaps resulting in poor solutions. The algorithm's performance might be sensitive to parameter values, necessitating careful tuning for the best results. Furthermore, the FSA does not ensure global optimality and may result in early convergence.

2.2.5. Cuckoo search (CS)

Cuckoo search, a novel metaheuristic optimization algorithm, was proposed by Yang et al. (2009). This algorithm is built on the parasitic nature of cuckoo birds and the lethal flight behavior of several birds. Figure 5 shows the migration and brood parasitism behaviors of cuckoo birds. Due to the high convergence and accuracy of the CS algorithm, it has been used in many engineering optimization problems, like mobile robot navigation (Mohanty and Parhi 2013), and UAV path planning, to name a few.

Path planning for UAVs is a difficult problem due to the greater number of control points and threats. The current literature review shows that the CS algorithm alone is not sufficient to solve this NP-hard problem and needs to be hybridized with other developed algorithms. Xie and Zheng (2016) used an improved hybrid CS algorithm that combines the mutation and crossover of genetic algorithms. This hybridization of an algorithm helps in achieving a faster solution and a higher success rate compared to the traditional CS algorithm. To improve the robustness of the conventional CS algorithm, Luan et al. (2016) have combined it with ACO. This hybridization eliminates the manual alteration of process parameters, unlike the conventional CS algorithm. By performing this hybridization, they observed that the performance of conventional CS is improved in terms of getting a shorter path compared to other algorithms. Wang et al. (2019) have suggested a novel hybrid intelligent algorithm that combines the genetic algorithm's global search capability with the adaptive CS algorithm's local search capability to enhance the algorithm. Their simulation result depicts that the proposed algorithm can avoid obstacles in a three-dimensional environment without colliding and performs better compared to a single intelligent algorithm. To improve the low convergence speed of conventional CS, El Gmili et al. (2019) have proposed a new algorithm by combining PSO with conventional CS and named it as PSO-CS algorithm. The social thinking ability of PSO and the local search capability of CS are combined, and the resultant algorithm increases the convergence speed. To achieve faster convergence and avoid obstacles, Song et al. (2020) have proposed a new CS algorithm based on compact and parallel techniques. The compact CS technique saves the memory of the UAV, and the parallel technique increases its accuracy and achieves faster convergence. Hu et al. (2019) have studied the trajectory planning of quadcopters using the CS algorithm for goods delivery applications. They have explained the basic CS algorithm first, and then the trajectory planning is applied to conventional CS.

The CS algorithm has been known as an optimization technique with potential uses in UAV route planning that is inspired by nature. CS has benefits like simplicity, adaptability to changing situations, and effective solution space searching. High-dimensional solution spaces or complex restrictions, sensitivity to parameter choices, and probable premature convergence are obstacles it could have to overcome. Despite these challenges, CS algorithms have great potential to improve UAV path planning when used in situations that make use of its flexibility and are backed by tactics for parameter tweaking.

2.2.6. Firefly algorithm (FA)

The FA, developed in 2008 by Yang et al. (Fister et al. 2013), is a modern, nature-inspired stochastic metaheuristic algorithm that can be applied to solve all kinds of NP-hard optimization problems. It belongs to the group of stochastic algorithms, which means it will use randomization to search a set of solutions. Since its inception, it has been used in many engineering optimization problems like image processing scheduling and path planning for mobile robots and UAVs (Yang 2010*c*). Initially, path planning of UAVs was done with traditional FA, but with the introduction of new constraints, a modified FA algorithm was proposed by Wang et al. (2012*b*). They have done the modification in the information exchange process between the top fireflies during the light-intensity updating process. Liu et al. (2015) have used the FA for 3D path planning of underwater robots. The 3 D path planning requires high convergence speed, which was a drawback of the conventional FA. The authors have achieved this by modifying some parameters, and an operating parameter is used to adjust the random movement. The obstacle avoidance was improved by introducing an excluding operator, and a contracting operator to enhance the convergence speed and sharpness of the path. This slow convergence problem of the conventional FA is addressed by Chen et al. (2017*b*). They replaced the traditional fixed step size with a Gaussian random walk, which improved the searchability of the conventional FA.

The FA has grown in popularity as a bio-inspired optimization approach with great application in UAV path planning. FA's capabilities include the capacity to handle complicated, multimodal, and noisy search spaces, as well as the ability to rapidly converge to near-optimal solutions. However, FA may be sensitive to parameter selection and can converge to local optima, with decreasing efficacy in high-dimensional solution spaces. FA is still a feasible option for UAV route planning, especially when carefully built and used in settings that play to its strengths.

2.2.7. Bat algorithm

The BA is a metaheuristic algorithm inspired by the echolocation behavior of bats and was proposed by Yang (2010*a*). Microbats have the ability of echolocation, which helps them locate their prey, find their path, and differentiate among various insects. Frequency tuning and variation are used for mimicking the real function, which is like other swarm intelligence algorithms. The BA has the capability of automatic zooming. It converges towards the most promising solution among the available solutions by switching from random exploratory moves to local exploitation. Apart from this, the BA also has better control over its parameters, which helps it toggle from exploration to exploitation (Yang and He 2013). These features of BA make it useful in the path planning of UAV applications. Wang et al. (2012*a*) have used mutation in traditional BA by mutating among the bats in the process of solution updating. Due to this mutation, the UAV can locate a safe path with the minimum amount of fuel by connecting the selected nodes of coordinates with threat avoidance. This mutated algorithm when compared outperformed other population-based algorithms like DE, ES, ACO, and PSO in terms of global convergence speed. Apart from mutation, some researchers have modified the conventional BA with the fusion of some other intelligent technique and named it the Improved BA (IBA). Wang et al. (2016) have combined DE with the BA and named it the IBA. They have used DE for selecting the most appropriate bat population. For smoothing the path of the UAV, B-spline curves are implemented. The traditional BA is also improvised by introducing crossover in the GA (Xi et al. 2018). This improvement has expanded the search space, and as a result, convergence speed has also increased. The low convergence speed, tapping into local optimum, and lack of robustness are the major problems for path planning of UAVs with traditional metaheuristic algorithms. To overcome this, Lin et al. (2019) have proposed an IBA combining an APF with the chaotic BA and named it CP-FIBA. They combined three different methods: an APF is applied to conventional BA to improve the convergence speed. To enhance the adaptive inertia, an optimal success strategy is implemented, and at last, the chaos method is used to prevent falling into a local optimal solution. To improve the local search ability of conventional BA, Zhou (Zhou et al. 2021) has proposed an improved BA combining an artificial bee colony with traditional BA. They found that the time required to achieve the optimal solution is reduced by 50% and the quality of the solution is increased by 14% compared to the conventional algorithm.

The BA algorithm is used by researchers for UAV navigation due to its adaptation to dynamic situations and rapid exploration of solution spaces. However, BA may encounter difficulties when dealing with high-dimensional solution spaces or complicated restrictions, as well as its sensitivity to parameter choices and probable premature convergence. Despite these obstacles, BA shows potential in UAV route planning, particularly when used in scenarios that take advantage of its versatility and are assisted by parameter tweaking procedures.

2.2.8. Grey wolf optimizer

A grey wolf optimization algorithm was proposed by Mirjalili et al. (2014) and inspired by the leadership and hunting behavior of grey wolves. GWO has been researched by many researchers in the last decade due to its simplicity, low storage requirement, and low number of decision variables. Some of the researchers have used other meta-heuristic algorithms with conventional GWO to improve exploration and exploitation. The parallelism approach is also used for improving the quality of the solution in conventional GWO.

Dewangan et al. (2019) have used GWO for the path planning of multiple UAVs. All UAVs start from different points and reach their goal in a collaborative environment within a single map. They compared the performance of GWO with well-established heuristic algorithms like A*, D*, and Dijkstra and metaheuristic algorithms such as PSO, BA, Whale Optimization Algorithm (WOA), and Glow Swarm Optimization (GSO) and found that conventional GWO outperforms other algorithms in terms of time taken and average cost. Jarray and Bouallègue (2020) implemented the conventional GWO for trajectory planning for a single UAV in a static obstacle environment. They performed numerical analysis and compared it with many developed metaheuristic algorithms in four different scenarios and found the performance satisfactory in terms of path length. To improve the performance of GWO, model predictive control (MPC) is combined with an improved GWO (Yao et al. 2016). First, the problem of target tracking is modeled in an urban environment. To reduce the computational complexity, they use an intelligent GWO with the advantages of good searchability and stability.

Generating the locally optimal solution is the key feature to be introduced in any path-planning algorithm. Ge et al. (2019) have hybridized the conventional GWO with the FFA. Initial paths for an oilfield were generated with basic GWO, and then the FFA was responsible for performing local optimization of the optimal solution. To handle the exploration and exploitation feature, Qu et al. (2020*a*) combined the simple GWO with the modified symbiotic organism search (MSOS) algorithm. Initially, the GWO phase is made easy for improvising the convergence rate and maintaining the exploration ability. The further commercialization step of SOS is modified to improve the exploitation capability. The convergence analysis shows this hybridization outperformed the basic GWO and SOS algorithms. Chengzhi et al. (2020) addressed four operations: exploration, exploitation, optimal adjustment, and geometrical justification for each individual. They improvised conventional GWO by introducing reinforcement learning. Improved GWO is for path planning of multiple UAVs by Xu et al. (2020). They developed a threat model and combined it with fuel consumption within the limitations of space and time. This multi-constrained objective function is solved by improved GWO. They found that the proposed algorithm can generate the collaborative path for multi-UAV in terms of fast convergence and lower path cost. To control the collaborative movement of multiple UAVs, Wang et al. (2020) proposed a distributed MPC framework for each of the UAVs to share the information. Next, the local finite horizon optimal control problem is solved using the chaotic GWO approach, which was created based on chaotic initialization and chaotic search. Finally, an event-triggered strategy is used to lower the computational timing. The problem of slow convergence of multi-UAV systems is addressed by Jiaqi et al. (2022) and Zhang et al. (2021). To improve the conventional GWO, they implemented the adaptive path-planning method. The spiral update positioning method inspired by the whale algorithm is used. They found that with this improvement flight time is shortened by 22.8% and achieves a shortened convergence time. Collaborative movement of UAVs is also optimized by introducing distributed MPC (Lv et al. 2022) and Parallel Cooperative Coevolutionary Grey Wolf Optimizer (PCCGWO) (Jarray et al. 2022). For improvement in existing GWO, many researchers have hybridized with different existing metaheuristic algorithms. Yu et al. (2023) proposed the hybridization of DE with conventional GWO to enhance the exploitation and exploration features. The position update equation is modified in such a way that beta, delta, and omega wolves move around alpha wolves to enhance exploitation.

GWO has gained a lot of popularity among researchers because of its effectiveness in exploring solution fields and rapidly convergent towards high-quality solutions. GWO may encounter difficulties due to high-dimensional solution spaces or complicated restrictions, sensitivity to parameter choices, and the possibility of premature convergence. However, when intelligently built and implemented in settings that correspond with its capabilities, GWO remains a potential strategy in UAV path planning.

2.3. Trajectory-based algorithm

In an earlier section, we discussed population and swarm-based algorithms like ACO, GWO, CS, and FA, which use multiple agents in the search space to find the optimal solution, but in trajectory-based algorithms, only one agent moves around the search space in piecewise fashion to find the optimal solution. A good solution is accepted, while the not-so-good solution is accepted with some probability. All the moves follow a trajectory with all nonzero probability values for reaching the global optimal solution. Many trajectory-based algorithms are being developed, like simulated annealing, tabu search, memetic algorithms, and harmony search. The main advantage of these algorithms is that they avoid trapping in local minima, unlike the swarm-intelligent algorithms.

2.3.1. Simulated annealing

Simulated annealing is based on a probability approach for finding the global optimum solution. This approach is useful for solving the unconstrained or bound-constrained optimization problem where the search space is discrete and large. The SA algorithm is proposed by Kirkpatrick et al. (1983) and is modeled by mimicking the annealing process of metallurgy where metals are heated and allowed to cool down slowly at a controlled temperature to decrease defects and alter their physical properties. SA is used in many engineering optimization problems like structural optimization, mobile robot navigation, telescope phasing, and path planning of UAVs (Gao and Tian 2007; Kolahan et al. 2007; Adler and Ribak 2021). For path planning of UAV, SA is combined with GA by Meng and Xin (2010). They used the metropolis acceptance feature of SA to deal with the local minimum problem of GA. This hybridization of SA and GA is done by Wang et al. (2022) also to solve the cooperative search problem of multiple UAVs in a large area. The proposed large search area is divided into smaller areas and task allocation for UAVs is regarded as a multiple travel salesman problem. Then optimization of the offspring of GA is done by implementing the advantages of SA with it. Multi-UAV path planning in a cooperative environment with multiple constraints is a complicated task to perform. Yue and Zhang (2018) have implemented K-means algorithm with conventional SA. At first for the cruise, the target zone, no-fly zone, and a valid zone is established in the target mission area. Secondly, for clustering the target points K-means algorithm is implemented. Behnck et al. (2015) have modified the conventional SA to generate or inspect multiple point of interest (POI). The energy function of SA was used to calculate the mismatch between UAV specialty and POI type. The SA method is also used for generating the optimal path in a 2D radar environment (Turker et al. 2015). The solution generated from a simple SA algorithm is optimized by introducing a threat avoidance approach, which helps it to avoid circular radar threats. The threat avoidance approach is based on the addition of some virtual points near the radar area to escape it.

Due to large a number of constraints and possible solutions, the UAVs fall into the local optimum solution. The hybridization of SA with PSO helps in avoiding this local optimal trapping (Wang et al. 2021). Huang et al. (2022) suggested such hybridization where the metropolis criterion and annealing mechanism is used to modify the particle state. This modification is done through the SA probability jump strategy which reduces the probability of particles falling into the local optimum solution and improves its performance. Similarly, Wangsheng et al. (2021) also suggested a method to avoid the local optimum selection of PSO. At first, the algorithm is distributed evenly in the search space by the tent reverse learning method. Then an annealing algorithm is applied which gives better local path judgement. To ensure the collision-free and smooth path, SA is hybridized with chaotic Aquila optimization (Ait-saadi et al. 2022). In this hybridization, SA provides the balance between exploration and exploitation. The proposed algorithm is compared with nine different already developed metaheuristic algorithms and they found that the path cost and fitness values were 19% and 36%, respectively.

The SA algorithm is renowned for its ability to navigate challenging and complicated solution spaces while eluding local optima. SA may be difficult in high-dimensional solution spaces and dynamic situations, requiring several iterations and careful cooling schedule selection. SA is still a strong choice for UAV planning, especially when coupled with heuristics tailored to the issue at hand and hybridization with other algorithms.

2.3.2. Harmony search

The harmony search algorithm is a metaheuristic optimization technique useful to many researchers in performing the optimization of real-life problems. This algorithm is inspired by the improvisation process of music, in which the musician searches for the accurate note to develop the perfect harmony (Alia and Mandava 2011). To improve the performance of conventional HS, two different procedures are used by the researchers: (1) improvement in parameter setting and (2) hybridization of conventional algorithms with already developed metaheuristic algorithms (Alia and Mandava 2011). HS algorithm along with its variants has been used in the path planning of UAVs. Yao-zhong and Lan (2018) have focused on the problem of multiple UAV cooperative reconnaissance. They have improvised on the traditional HS algorithm by using mutation and crossover along with an adaptive approach for adjusting the parameters. As a result, the convergence rate is enhanced and the ability to avoid local optimum is increased. Wu et al. (2017) have also worked on path planning for multiple UAVs in complex three-dimensional environments. They extended the Pythagorean hodograph (PH) with some constraints. The HS algorithm was implemented to optimize the parameters of PH curves. The HS algorithm is useful for solving multi-objective optimization problems because it can iterate over bulk solutions in its Harmony Memory (HM) memory and archive the true optimal region (Huang and Chen 2020). Abhishek et al. (2020) have hybridized the HS algorithm with PSO and named as hybrid PSO-HSA. This hybridization helps in maintaining the balance between exploitative and exploratory search. The previously developed metaheuristic algorithms were biased towards either exploitation or exploration, which increases the probability of falling into a local optimum. They compared this hybrid algorithm with eight different renowned metaheuristic algorithms and found performance to be better in terms of cost function, travel distance, and time.

The HS algorithm gained a lot of attention due to its rapid search capability of solution spaces and ability to handle complex and dynamic settings. High-dimensional solution spaces or complicated restrictions, sensitivity to parameter choices, and probable premature convergence are among potential obstacles to the HS algorithm. However, HS shows potential in UAV route planning, particularly when carefully built and employed in settings that capitalize on its capabilities.

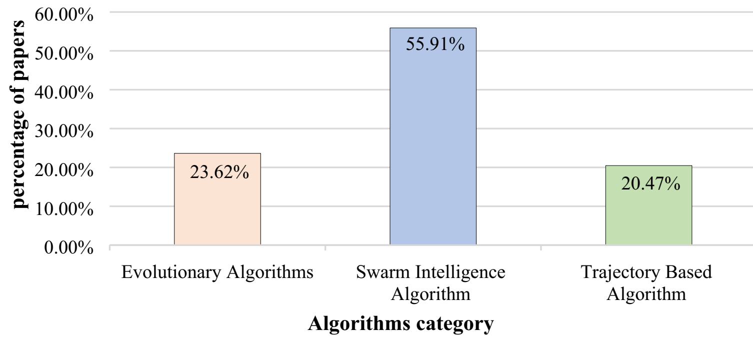
2.3.3. Gravitational Search Algorithm

The Gravitational Search Algorithm is inspired by the law of nature, which falls under the category of gravitational kinematics. It is based on Newton's law of gravity and law of motion, which states that "every particle in the universe attracts every other particle with a certain force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between them" (Rashedi et al. 2009).

For solving multi-objective nonlinear optimization problems, many variants of GSA have been developed by researchers in the last decade, like binary discrete single-objective GSA (Rashedi et al. 2018). To deal with real-world optimization problems, GSA has also been hybridized with other metaheuristic algorithms. Li and Duan 2012 have combined PSO with GSA to introduce the memory and social information functions in GSA and to avoid the problem of trapping into the local optimum. This hybridization helps improve the quality of the optimal solution. The convergence speed of the process is increased by introducing the weighted value of inertial mass in every iteration. Similarly, optimize

 Drone Syst. Appl. 12: 1–28 (2024) | dx.doi.org/10.1139/dsa-2023-0093

Fig. 6. Distribution of papers as per algorithm category.



the heading angle of agricultural UAVs. Tian et al. (2020) have hybridized a GSA with A* algorithm. Xu et al. (2021) implemented a mixed strategy-based GSA in which an adaptive adjustment strategy and a Cauchy mutation strategy are developed. The adaptive adjustment strategy helps in adjusting the gravitational constant attenuation factor, which enhances the balance between exploration and exploitation search. The Cauchy mutation strategy helps in avoiding the premature convergence problem.

GA has potential applications in UAV route planning and is known for effectively searching solution spaces and converging to high-quality solutions. GA is an optimization approach inspired by the laws of gravity and potential energy. High-dimensional solution spaces or complicated constraints, sensitivity to parameter choices, and probable premature convergence might all present problems for GSA. However, GSA still has a promise for UAV route planning when carefully set up and used in situations that play to its advantages.

2.4. Other metaheuristic algorithms

Apart from these algorithms, there are many modern metaheuristic algorithms available that are not yet implemented for UAV path planning but have great potential for this. Like the dragonfly algorithm (DA) developed by (Mirjalili 2016) improves the initial random population and converges the solution towards optimum. Reptile search algorithm (Abualigah et al. 2022) inspired by the movement of crocodiles and have a powerful search process mechanism that helps in finding the optimum solution for complex engineering problems. Another method, Dhouib-Matrix-4 (DM4), proposed by Dhouib (2021) reduced the number of initial parameters, which helps it in reducing the time taken for optimal solution. Due to this advantage, DM4 is implemented in many applications like finding the shortest drilling path in PCB (Dhouib 2022), optimization of the drilling process (Dhouib and Pezer 2022), hierarchical coverage repair for wireless sensor network (Dhouib 2023*a*), performance improvisation of CNC machine (Dhouib 2023*a*), and shortest path planning for mobile robots (Dhouib 2023*b*). Looking at these advantages, the mentioned algorithms can be implemented for UAV path planning and can accommodate the complexity involved in it. The hybridization of DA with DM4 can help the UAV to plan the optimum path in the minimum time.

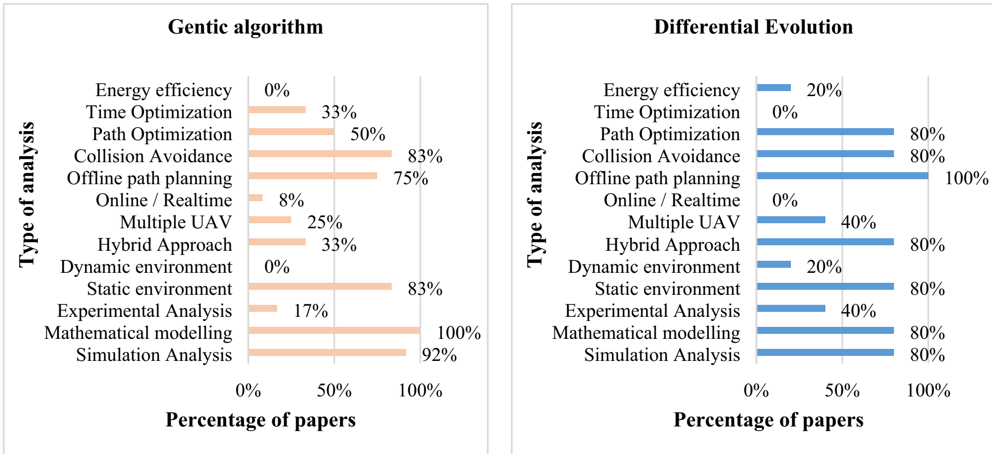
3. Results and discussions

After a rigorous discussion and evaluation of the research papers cited in this paper, the path-planning algorithms are classified into three groups: evolutionary algorithms, swarm-based algorithms, and trajectory-based algorithms. However, this classification is based on individuals' perspectives, as some algorithms can be classified into multiple groups, like GA, which can be classified as evolutionary and swam-based algorithms. These algorithms generate a possible set of solutions but do not guarantee the actual solution. They are useful for solving the classical NP-hard problems. Figure 6 depicts that; in literature, all the categories of algorithms are similarly implemented for path planning but compared to other algorithms swarm-inspired algorithms are widely used due to its simplicity and high convergence rate. To solve the path-planning problem of the UAV, which is multidimensional and multi-objective, the conventional evolutionary algorithms are either improved by introducing new parameters in the mutation stage or by hybridizing with the modern intelligent technique. Hybridization helps the conventional algorithms overcome lacunas like slow convergence due to repeating loops trapping at the local optimum. The swarm intelligence algorithms also have similar drawbacks of premature convergence and low local optimization ability. To overcome this drawback, swarm intelligence algorithms are hybridized with other metaheuristic algorithms. Besides these drawbacks, swarm algorithms are flexible and easy to implement, which attracts a huge number of researchers to work on them. The application of swarm intelligent algorithms to dynamic path planning where obstacles or goals are in a moving state is still a grey area of research. For avoiding the convergence of locally optimal solutions, trajectory-based algorithms are very useful, as in this algorithm, only a single agent moves around the search space to find the optimal solution. In the literature, trajectory-based algorithms are mostly used with static obstacle conditions.

3.1. Analysis of evolutionary algorithms

In this subsection, the evolutionary algorithms are analyzed based on parameters like simulation analysis, mathematical modeling, experimental analysis, static environment, dynamic environment, hybrid approach, multiple UAV, online/real time, offline path planning, collision avoidance,

Fig. 7. Analys of evolutionary algorithm based on UAV flying condition and obstacle position.



(a) % Analysis of GA with different parameters **(b) % Analysis of DE with different parameters**

path optimization, time optimization, and energy efficiency. It can be seen from Fig. 7 that simulation analysis and mathematical modeling are very first preferences of the researchers and almost in all the research papers these are used, while the experimental analysis is found very less in the literature. Both GE and DE algorithms are implemented for static environments only, while the implementation of these algorithms in the dynamic environment is not found in the literature. Evolutionary algorithms are fast in processing but are not able to decide the uncertainty present in the environments. Optimization of path is the primary concern of the researchers; they have not implemented these algorithms for energy and time optimization.

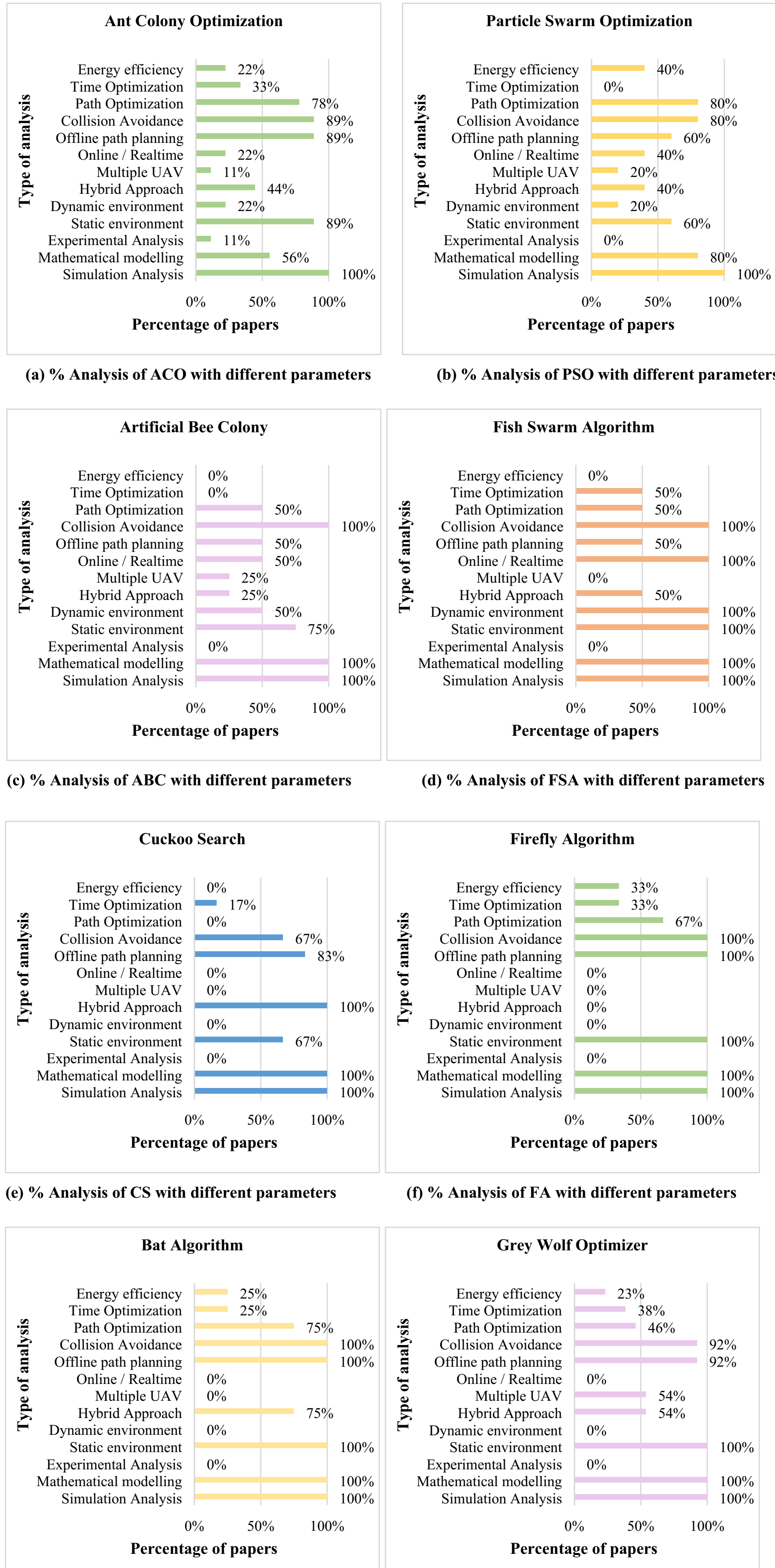
3.2. Analysis of swarm intelligence algorithms

There are some algorithms like PSO, ABC, FSA, CS, FA, and GWO that have not yet been explored for experimental analysis for path planning of UAVs and have a great potential field to work on as shown in Fig. 8. Path planning of UAV in a static environment where obstacles and goals are in stationary conditions is greatly explored in the literature and there are some techniques like FSA, FA, BA, and GWO that have all the articles (100%) available for static environment only. At the same time, path planning in dynamic environments brings a lot of challenges and controlling factors, which leads to very little research in this area. Algorithms, like CS, FA, BA, and GWO, are never implemented for dynamic path planning for UAVs and have huge research potential. To achieve the optimal smooth path from the initial to the target position with obstacle avoidance, researchers have combined two or more metaheuristic algorithms to take advantage of both algorithms. GA, PSO, ABC, and FL are mostly used with other techniques such as hybrid algorithms. Algorithms like CS and GSA are always (100%) found combining with other algorithms in the literature. There are some application areas like military and agriculture, which require multiple UAVs to fly simultaneously in a collaborative environment where each UAV will communicate with others to avoid collision, avoid obstacles, and reach the target. Researchers have explored this area also in some algorithms, but a very limited number of papers are available. Algorithms like FSA, CS, FA, and BA have never been explored for multiple UAV path planning and have a potential field to study. From the study, it is also clear that simulation or experimental analysis in online/real time where the environmental map is not known to the UAV is very limited in the literature. Only a few techniques like ACO, PSO, ABC, and FSA are implemented for online path planning, whereas offline path planning is a widely researched topic among researchers. All the techniques studied in the current work are implemented for offline path planning. Collision avoidance is the most basic objective of path planning and hence all the algorithms are implemented for it. Algorithms like ABC, FSA, FA, and BA are fully (100%) implemented for collision avoidance. Finding the optimal and smooth path is also analyzed vastly in the literature. Algorithms like ACO, PSO, and BA are greatly implemented for path optimization, whereas the CS algorithm is not yet implemented for the optimization of path. As compared to path, time optimization is comparatively low in literature. Researchers are more focused on archiving the obstacle-free, smooth, and optimum path. Algorithms like PSO and ABC are not yet implemented for time optimization and leaving the grey area for research. Similarly, energy efficiency is a key parameter for path planning of UAVs and very few techniques (ABC, PSO, FA, BA, and GWO) are implemented for it. Algorithms like ABC, FSA, and CS are not yet implemented for energy efficiency.

3.3. Analysis of trajectory-based algorithms

These algorithms help in avoiding the trapping of local minima, which makes it useful for UAV applications. SA, HS, and GSA are widely used for path planning of UAVs in simulation-type study. Their implementation for experimental analysis is found very less in the literature as shown in Fig. 9. In trajectory-based algorithms, single agent moves in the entire search area to find the optimal solution which makes it difficult to find the optimal path if the environment is changing dynamically as a result most of the research work

Fig. 8. (*a–h*) Analysis of swarm intelligence algorithm based on unmanned aerial vehicles (UAV) flying conditions and obstacle position.



(a) % Analysis of ACO with different parameters

(b) % Analysis of PSO with different parameters

(c) % Analysis of ABC with different parameters

(d) % Analysis of FSA with different parameters

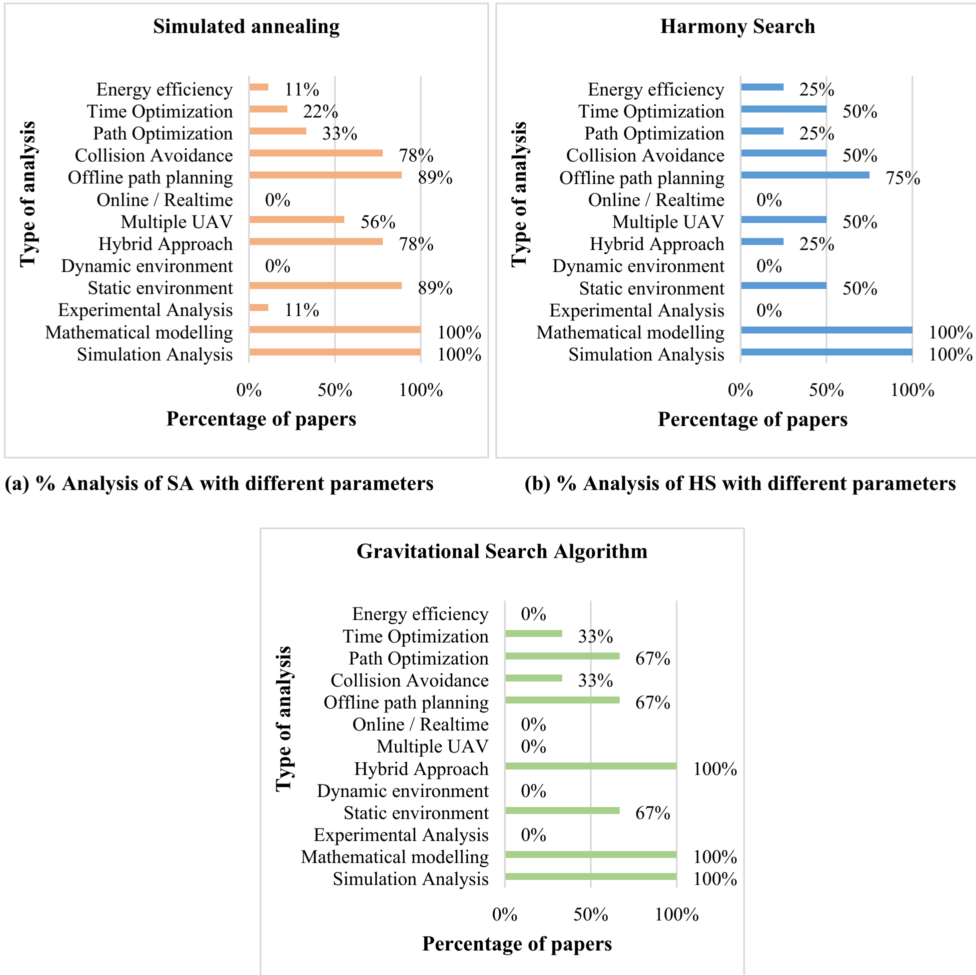
(e) % Analysis of CS with different parameters

(f) % Analysis of FA with different parameters

(g) % Analysis of A with different parameters

(h) % Analysis of GWO with different parameters

Fig. 9. (*a*–*c*): Analysis of trajectory-based algorithm on unmanned aerial vehicles (UAV) flying condition and obstacle position.



(a) % Analysis of SA with different parameters

(b) % Analysis of HS with different parameters

(c) % Analysis of GSA with different parameters

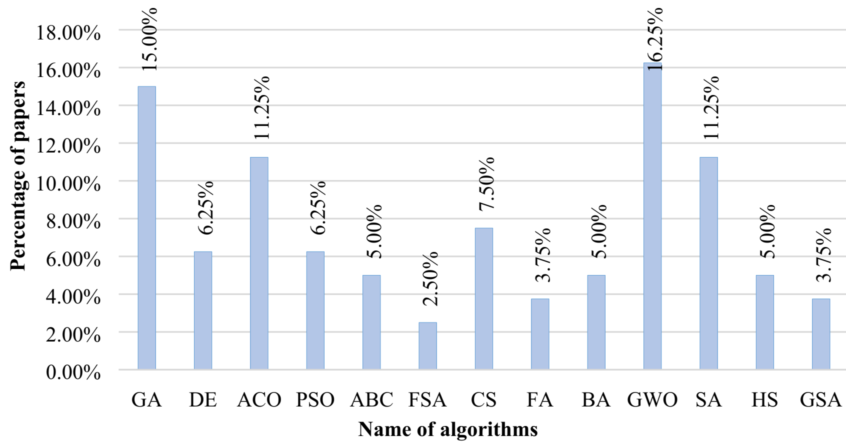
was done based on the static environment only and implementation in dynamic environment is not found it the literature. These algorithms are not able to find the optimal path alone and hence hybridized with other metaheuristic techniques, which helps them to identify the smooth and obstacle free path. SA and HS are implemented for path planning of multiple UAVs also, while the GSA has not been implemented for this. Along the path of path optimization, these algorithms are implemented for time and energy optimization.

After a rigorous study of charts of individual algorithms shown in Figs. 7–9, it can be concluded that there is huge research going on in the field of path planning of UAV and yet there are many areas or parameters left for study. Path planning and collision avoidance in static environments are studied with simulation analysis by most of the researchers. Algorithms like CS, FA, BA, and GSA have great potential and are not yet used for experimental analysis, dynamic environments, and online path planning. We also found that hybridization is performed with most of the algorithms, which increases its capability in path and time optimization. There is vast scope in developing a hybrid algorithm that can be implemented in a dynamics environment with multiple UAVs for time and energy optimization.

3.4. Overall analysis

In this section, all the algorithms are compared among each based on certain parameters. Figure 10 depicts the analysis of several research papers written on the path planning of UAVs using different metaheuristic algorithms. GA, ACO, GWO, and SA algorithms are more popular among the researchers. Swarm algorithms like ABC and FSA have great potential for optimization, but they are more prone to trapping in local optimum solutions, which makes it difficult to plan the path in a 3D environment. Similarly, algorithms like FA and BA also have tremendous scope in optimization due to their simplicity and random exploratory moves for local exploration, which helps them to converge towards the most promising solution. However, these algorithms have a slow convergence speed, which is a major drawback for the 3D path planning of UAVs. To overcome this, a few researchers have improvised it either by mutating the process parameters or by hybridizing with GA, APF, or ABC.

Fig. 10. Analysis of path-planning technique based on number of papers studied.



In Table 3, a detailed analysis of navigational techniques used for path planning for UAVs in a three-dimensional environment has been done. Each technique has been analyzed with parameters like study type, simulation-based, mathematical modeling or experimental analysis, application for multiple UAVs, use as a hybrid approach, capability of static or dynamic obstacle avoidance, online/real-time or offline results, collision avoidance, path optimization, time optimization, and energy efficiency. Table 3 shows that algorithms like GA, ACO, CS, GWO, and SA are more popular among researchers than other algorithms. In literature, the GA algorithm is the most used algorithm for simulation and real-time use for static path planning. Most of the navigational techniques like ACO, PSO, SA, CS, BA, SA, and HS are hybridized with GA only to improve their performance. The real-time and experimental analysis of path planning for UAVs is very limited in the literature due to its complexity and the high number of control points involved. Table 3 also demonstrates the detailed analysis of obstacle avoidance in static and dynamic environments. Dynamics environment involves either moving obstacle avoidance or moving target achievement or both.

In Fig. 11, a comparison of the research papers published on the path planning of UAVs is done based on simulation analysis, mathematical modeling, and an experimental study. Approximately, all the researchers have done mathematical modeling and analysis in computer-based simulation only. Experiments on UAV path planning are very limited (approximately 8% of the literature) as they involve a lot of constraints due to the three-dimensional environment. These constraints affect the performance of UAVs, and some authors find large differences in simulation and experimental results. So, the experimental investigation of path-planning algorithms is still a grey area for research. Due to these constraints, researchers are more focused on the minimum requirement of path-planning algorithms, i.e., collision avoidance and path optimization, evident from Fig. 12. Among all the cited papers in Table 3, around 83% of papers are based on collision avoidance either with obstacles or with other UAV in collaborative environments. Some researchers have worked on path optimization (around 52%) and time optimization (around 27%). They tried to generate an obstacle-free optimized path where UAV can reach the target in minimum time. They hybridized the existing conventional algorithms with other metaheuristic algorithms to increase the convergence speed towards the optimum solution and ultimately optimized the time. Based on the analysis of the paper, we can say very few, around 15% of papers are present for energy optimization. Hence energy optimization with obstacle avoidance and path optimization is a potential field to study. There are more than 40 metaheuristic optimization algorithms that have been developed by researchers in the last few decades. However, all the algorithms are not suitable for three-dimensional path planning of UAVs due to the complexity involved in it.

Figure 13 shows the detailed analysis of path-planning algorithms in percentage of papers under various categories like single vs. multiple UAV, static vs. dynamic analysis, path vs. time optimization, simulation vs. experimental analysis, collision avoidance vs. without collision avoidance, and hybrid approach vs. standalone algorithms. It can be observed that path planning of multiple UAVs in a collaborative environment is less as compared to a single UAV due to the many control points and parameters involved in multiple UAVs. Dynamic analysis where an obstacle and/or goal is in a moving position is a critical task to perform and is evident from the analysis also. Out of the total papers, only 10% of the papers covers dynamic analysis. Currently, most of the researchers are focusing on path optimization only as a basic requirement from path-planning algorithms. Optimization of processing time or flight time is found comparatively low (around 26%) in the literature. Most of the work is performed by the researchers in simulation only. Experimental analysis involves a lot of factors that restrict the performance of UAVs and are difficult to control, as a result only 8% of papers are found that cover Experimental analysis. Figure 13 also shows that collision avoidance is considered a basic requirement of UAV path-planning algorithms and around 82% of papers are present in it. To achieve this complicated task of path planning in dynamic environments and with multi-

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Table 3. Analysis of various path-planning techniques.

S. No	Technique	Citation	Simulation	Mathematical modelling	Experimental analysis	Static obstacle avoidance	Dynamic obstacle avoidance	Hybrid approach	Application as multiple UAV	Online/real time	Offline path planning	Collision avoidance	Path optimization	Time optimization	Energy efficiency
1	GA	Marin et al. (1999)	N	Y	N	N	N	N	N	N	N	N	N	N	N
2		Nikolos et al. (2003)	Y	Y	N	N	N	N	N	N	N	N	Y	N	N
3		Hasircioglu et al. (2008)	Y	Y	N	Y	N	N	N	N	Y	Y	Y	N	N
4		Allaire et al. (2009)	Y	Y	N	Y	N	N	N	N	Y	Y	N	Y	N
5		Pehlivanoglu (2012)	Y	Y	N	Y	N	N	N	N	Y	Y	Y	Y	N
6		Wang and Chen (2014)	Y	Y	N	Y	N	N	N	N	Y	Y	Y	N	N
7		Cobano et al. (2011)	Y	Y	Y	Y	N	Y	Y	N	Y	Y	N	N	N
8		Roberge et al. (2013)	Y	Y	N	Y	N	N	N	Y	N	Y	N	Y	N
9		Deng et al. (2013)	Y	Y	N	Y	N	N	Y	N	Y	Y	Y	N	N
10		Gautam (2014)	Y	Y	N	Y	N	Y	N	N	Y	Y	N	N	N
11		Haghighi et al. (2020)	Y	Y	N	Y	N	Y	Y	N	Y	Y	Y	N	N
12		Mazinan (2017)	Y	Y	Y	Y	N	Y	N	N	Y	Y	N	Y	N
13	DE	Nikolos and Brintaki (2005)	Y	Y	N	Y	Y	N	Y	N	Y	Y	N	N	N
14		Fu et al. (2013)	Y	Y	Y	N	N	Y	N	N	Y	N	Y	N	N
15		Yu and Wang (2013)	N	Y	Y	Y	N	Y	N	N	Y	Y	Y	N	Y
16		Adhikari and Kim (2017)	Y	N	N	Y	N	Y	N	N	Y	Y	Y	N	N
17		Ali et al. (2023)	Y	Y	N	Y	N	Y	Y	N	Y	Y	Y	N	N
18	ACO	Zhang et al. (2010)	Y	N	N	Y	N	N	N	N	Y	Y	Y	N	N
19		He et al. (2013)	Y	N	N	Y	N	N	N	N	Y	Y	Y	Y	N
20		Cekmez et al. (2016)	Y	N	Y	Y	N	N	N	N	Y	Y	N	N	N
21		Guan et al. (2019)	Y	N	N	Y	N	Y	N	N	Y	Y	N	Y	Y
22		Chen et al. (2017b)	Y	Y	N	Y	N	N	N	N	Y	Y	Y	N	N
23		Huang et al. (2018)	Y	Y	N	Y	Y	Y	N	Y	Y	Y	Y	N	Y
24		Song et al. (2017)	Y	Y	N	Y	Y	Y	N	Y	Y	Y	Y	N	N
25		Pu et al. (2020)	Y	Y	N	Y	N	N	N	N	Y	Y	Y	N	N
26		Li et al. (2021)	Y	Y	N	N	N	Y	Y	N	N	N	Y	Y	N
27	PSO	Jung et al. (2006)	Y	N	N	Y	N	N	N	N	Y	Y	Y	N	Y
28		Cheng et al. (2014)	Y	Y	N	Y	Y	N	N	Y	N	Y	Y	N	N
29		Huang et al. (2018)	Y	Y	N	N	N	N	N	Y	N	Y	Y	N	N
30		Abhishek et al. (2020)	Y	Y	N	N	N	Y	Y	N	Y	N	N	N	N
31	ABC	Cao et al. (2013)	Y	Y	N	Y	N	Y	N	N	Y	Y	N	N	N
32		Pan et al. (2017)	Y	Y	N	Y	N	N	N	N	Y	Y	Y	N	N
33		Tian et al. (2018)	Y	Y	N	Y	Y	N	N	Y	N	Y	N	N	N
34		Muntasha et al. (2021)	Y	Y	N	N	Y	N	Y	Y	N	Y	Y	N	N

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Table 3. (*continued*).

S. No	Technique	Citation	Simulation	Mathematical modelling	Experimental analysis	Static obstacle avoidance	Dynamic obstacle avoidance	Hybrid approach	Application as multiple UAV	Online/real time	Offline path planning	Collision avoidance	Path optimization	Time optimization	Energy efficiency
35	FSA	Ma and Lei (2010)	Y	Y	N	Y	Y	N	N	Y	Y	Y	N	N	N
36		Yang et al. (2021)	Y	Y	N	Y	Y	Y	N	Y	N	Y	Y	Y	N
37	CS	Xie and Zheng (2016)	Y	Y	N	Y	N	Y	N	N	Y	Y	N	N	N
38		Luan et al. (2016)	Y	Y	N	N	N	Y	N	N	Y	N	N	N	N
39		Wang et al. (2019)	Y	Y	N	Y	N	Y	N	N	Y	Y	N	N	N
40		El Gmili et al. (2019)	Y	Y	N	N	N	Y	N	N	N	N	N	N	N
41		Song et al. 2020)	Y	Y	N	Y	N	Y	N	N	Y	Y	N	Y	N
42		Hu et al. (2019)	Y	Y	N	Y	N	Y	N	N	Y	Y	N	N	N
43	FA	Wang et al. (2012*b*)	Y	Y	N	Y	N	N	N	N	Y	Y	N	N	Y
44		Liu et al. (2015)	Y	Y	N	Y	N	N	N	N	Y	Y	Y	Y	N
45		Chen et al. (2017*b*)	Y	Y	N	Y	N	N	N	N	Y	Y	Y	N	N
46	BA	Wang et al. (2012*a*)	Y	Y	N	Y	N	N	N	N	Y	Y	N	N	Y
47		Wang et al. (2016)	Y	Y	N	Y	N	Y	N	N	Y	Y	Y	N	N
48		Xi et al. (2018)	Y	Y	N	Y	N	Y	N	N	Y	Y	Y	N	N
49		Lin et al. (2019)	Y	Y	N	Y	N	Y	N	N	Y	Y	Y	Y	N
50	GWO	Dewangan et al. (2019)	Y	Y	N	Y	N	N	Y	N	Y	Y	N	Y	Y
51		Jarray and Bouallègue (2020)	Y	Y	N	Y	N	N	N	N	Y	Y	N	N	Y
52		Yao et al. (2016)	Y	Y	N	Y	N	Y	Y	N	Y	Y	N	Y	N
53		Ge et al. (2019)	Y	Y	N	Y	N	Y	N	N	Y	Y	Y	N	N
54		Qu et al. (2020a)	Y	Y	N	Y	N	Y	N	N	Y	Y	Y	N	N
55		Qu et al. (2020b)	Y	Y	N	Y	N	Y	N	N	Y	Y	Y	N	N
56		Xu et al. (2020)	Y	Y	N	Y	N	N	Y	N	Y	Y	N	N	N
57		Wang et al. (2020)	Y	Y	N	Y	N	Y	Y	N	Y	Y	N	N	N
58		Jiaqi et al. (2022)	Y	Y	N	Y	N	N	Y	N	Y	N	N	Y	N
59		Zhang et al. (2021)	Y	Y	N	Y	N	N	N	N	Y	Y	Y	N	N
60		Lv et al. (2022)	Y	Y	N	Y	N	N	Y	N	Y	Y	N	Y	N
61		Jarray et al. (2022)	Y	Y	N	Y	N	Y	Y	N	Y	Y	Y	Y	Y
62		Yu et al. (2023)	Y	Y	N	Y	N	Y	N	N	Y	Y	Y	N	N
63	SA	Meng and Xin (2010)	Y	Y	N	Y	N	Y	N	N	Y	Y	N	N	N
64		Wang et al. (2022)	Y	Y	N	N	N	Y	Y	N	N	N	N	N	N
65		Yue and Zhang (2018)	Y	Y	N	Y	N	Y	Y	N	Y	N	Y	N	N
66		Behnck et al. (2015)	Y	Y	Y	Y	N	N	Y	N	Y	Y	Y	N	N
67		Turker et al. (2015)	Y	Y	N	Y	N	N	N	N	Y	Y	N	N	N
68		Wang et al. (2021)	Y	Y	N	Y	N	Y	Y	N	Y	Y	Y	N	N
69		Huang et al. (2022)	Y	Y	N	Y	N	Y	Y	N	Y	Y	N	Y	N
70		Wangsheng et al. (2021)	Y	Y	N	Y	N	Y	N	N	Y	Y	N	N	N
71		Ait-saadi et al. (2022)	Y	Y	N	Y	N	Y	N	N	Y	Y	N	Y	Y

Table 3. (*concluded*).

S. No	Technique	Citation	Simulation	Mathematical modelling	Experimental analysis	Static obstacle avoidance	Dynamic obstacle avoidance	Hybrid approach	Application as multiple UAV	Online/real time	Offline path planning	Collision avoidance	Path optimization	Time optimization	Energy efficiency
72	HS	Yao-zhong and Lan (2018)	Y	Y	N	N	N	N	Y	N	Y	N	N	Y	N
73		Wu et al. (2017)	Y	Y	N	Y	N	N	Y	N	Y	Y	Y	N	N
74		Huang and Chen (2020)	Y	Y	N	N	N	N	N	N	N	N	N	N	N
75		Abhishek et al. (2020)	Y	Y	N	Y	N	Y	N	N	Y	Y	N	Y	Y
76	GSA	Li and Duan (2012)	Y	Y	N	Y	N	Y	N	N	Y	Y	Y	N	N
77		Tian et al. (2020)	Y	Y	N	N	N	Y	N	N	N	N	N	N	N
78		Xu et al. (2021)	Y	Y	N	Y	N	Y	N	N	Y	N	Y	Y	N

Note: Y, considered; N, not considered.

Fig. 11. Analysis of path-planning technique based on simulation, mathematical modelling, and experiment.

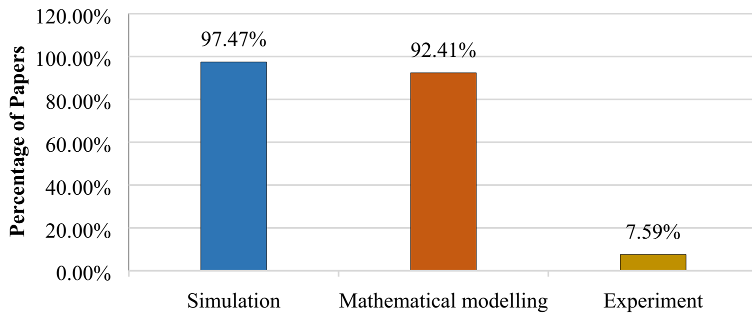


Fig. 12. Analysis of path-planning technique based on simulation, mathematical modelling, and experiment.

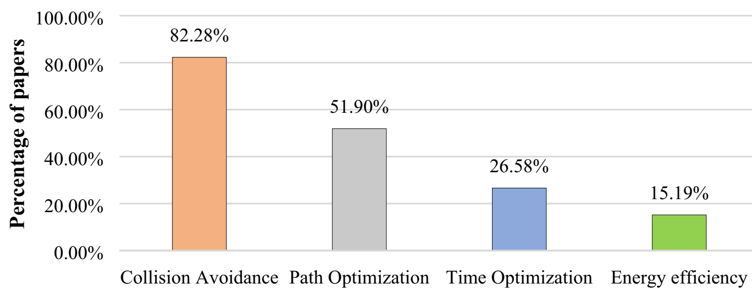


Fig. 13. Analysis of unmanned aerial vehicles (UAV) path-planning metaheuristic algorithms in percentage of papers.

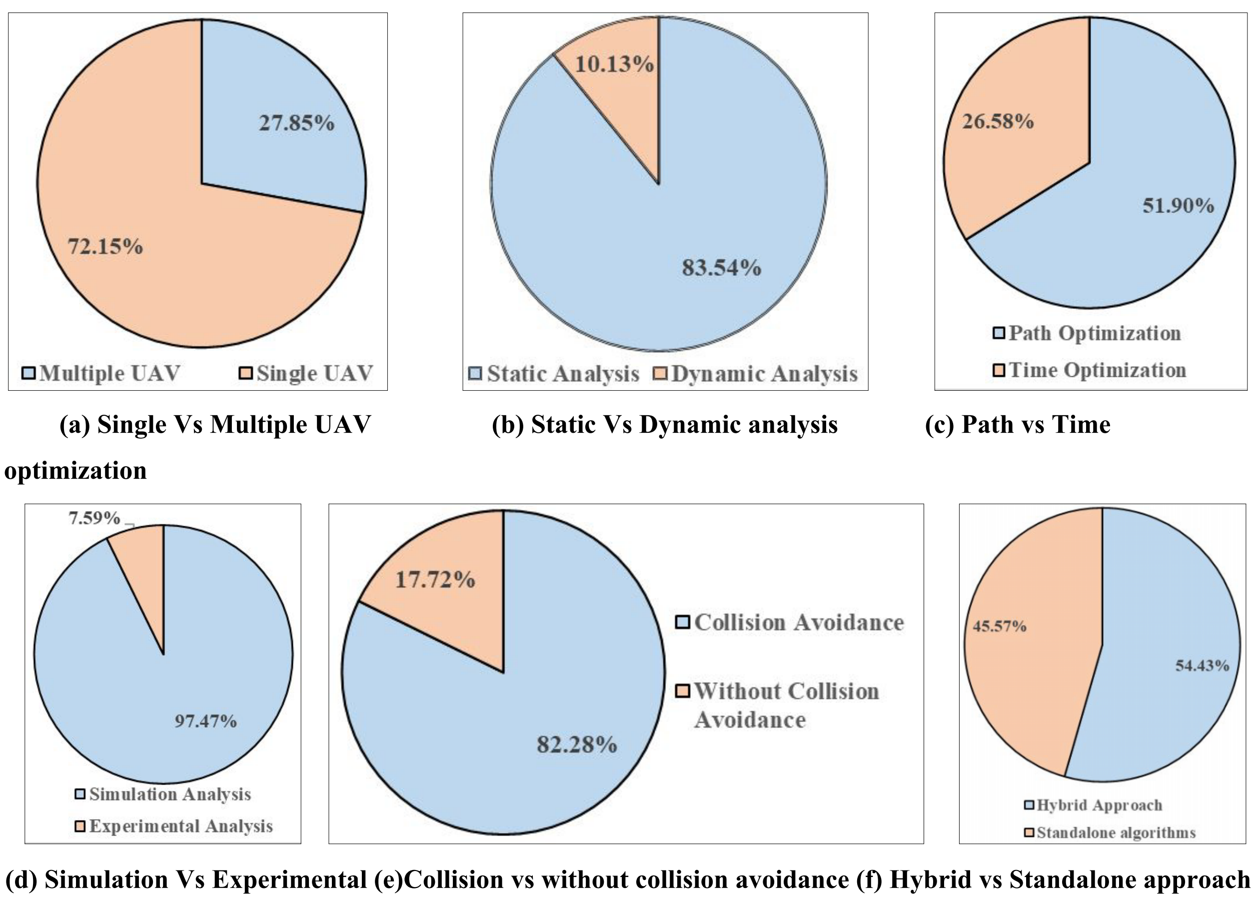


Fig. 14. Analysis of path-planning technique based on simulation and experimental analysis.

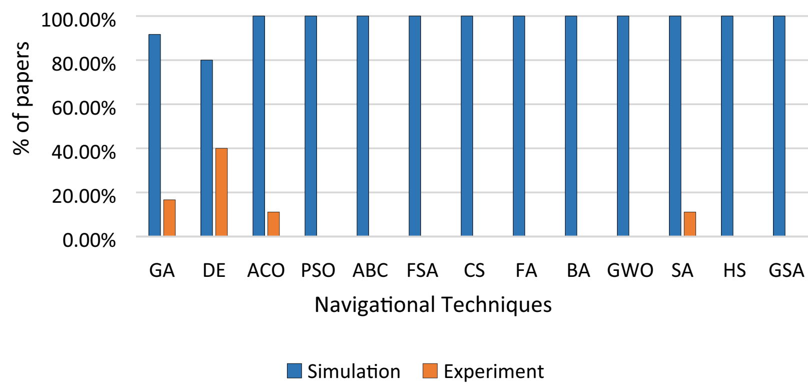
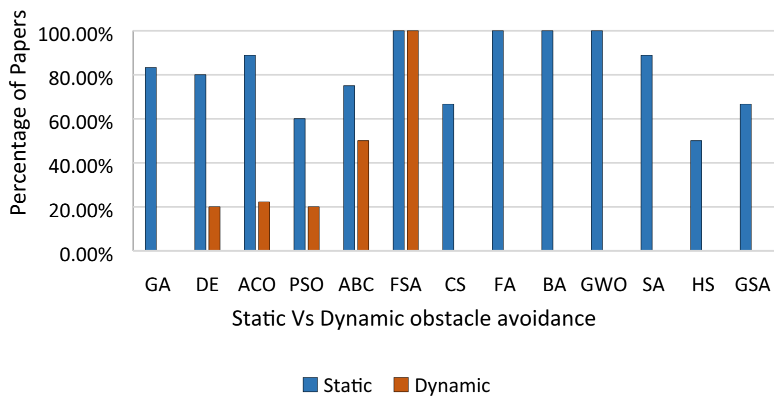


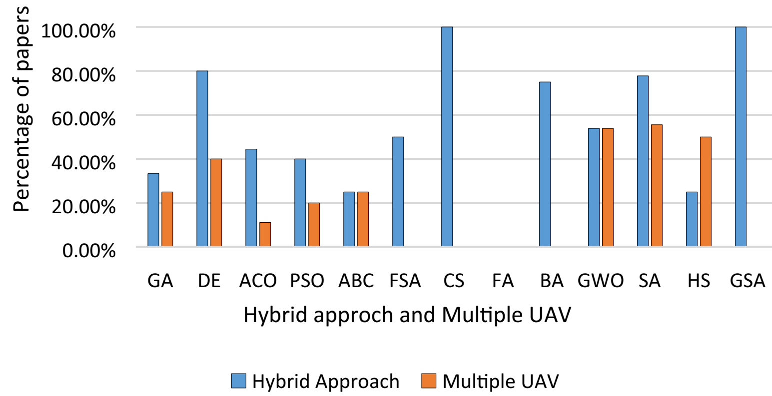
Fig. 15. Analysis of path-planning technique based on static and dynamic obstacle avoidance.



ple UAVs, many researchers have implemented a hybrid approach where two or more metaheuristic algorithms were combined to take the benefits of both the algorithms. This hybridization helps in reducing the convergence timing, avoiding trapping into local minima and optimizing or smoothing the path of UAV.

Figure 14 depicts that very few researchers have implemented only GA, DE, ACO, and SA algorithms for real-time analysis, and almost all the research papers are based on simulation analysis only. It can be observed from Fig. 15 that the swarm intelligence algorithms ACO, PSO, ABC, and FSA are dominant in the dynamic path-planning approach. All the swarm intelligence algorithms studied in this paper have been implemented for static and dynamic path planning. Trajectory-based algorithms are implemented only for static obstacle avoidance. There are many metaheuristic algorithms developed so far, but to deal with multi-objective, multi-dimensional, and multimodal optimization problems like the path-planning problem of UAVs, no single traditional technique is sufficient. To achieve fast convergence, an improved solution, avoiding trapping in local minima, a better environment, exploring capacity, quick response and action, self-decision-making ability, and operation flexibility, conventional algorithms are improved either by introducing new parameters into their operation or by hybridizing with other metaheuristic techniques. From Fig. 16, it is visible that, except for FA, all other algorithms are hybridized with some other metaheuristic algorithms to take advantage of both algorithms. Algorithms like CS and GSA are found in literature only in hybridized form. Hybridization of algorithms with GE and FL is very common in literature, as these algorithms help improve the solution quality while consuming a considerable amount of computational time. Hybridization with PSO helps the algorithms take advantage of PSO, i.e., avoid trapping in the local minima. ACO provides robustness to the solution if it is hybridized with other metaheuristic techniques. Similarly, swarm intelligence-based algorithms provide a good exploitative and explorative search feature in hybridization. This hybridization also helps in the path planning of UAVs in a collaborative environment. Movement of UAVs in a collaborative environment involves the path planning and target achievement of multiple UAVs simultaneously without collision. This requires huge computation, communication between UAVs, fast convergence, and a robust design. A single algorithm is not able to perform this optimization task alone and needs to be hybridized with other algorithms. Figure 16 shows that old algorithms like GA, DE, ACO, PSO, ABC, GWO, SA, and HS, which have evolved over many years, have been used for multiple UAV path planning in collaborative environments. Some newly developed algorithms like FSA, CS, FA, BA, and GSA have not yet been used for multiple UAVs.

Fig. 16. Analysis of path-planning technique based on hybrid approach and multiple unmanned aerial vehicles (UAVs).



3.5. Comparison between metaheuristic algorithms and deterministic optimal methods

On the other hand, where metaheuristic algorithms have shown great significance in solving the complex optimization problem, it is important to discuss their inherent weaknesses and limitations, specifically when compared with the deterministic approach. In the current section, we shall address the limitations and weaknesses of metaheuristic approaches with specific reference to the novel Dhouib-Matrix-SPP (DM-SPP) method. DM-SPP deploys a deterministic column–row technique and has demonstrated superior performance in specific scenarios. A major limitation of metaheuristic algorithms lies in their iterative stochastic nature, which implies a process of exploring and exploiting the search space to identify near-optimal solutions. This iterative process often requires a substantial number of iterations and may demand randomness in solution selection, which leads to variability in solution quality. Therefore, metaheuristic algorithms may experience large computational times, especially when addressing complex optimization problems. Moreover, the stochastic nature of metaheuristics may pose challenges in ensuring convergence to global optima, particularly in multimodal search spaces where the presence of numerous local optima can impede exploration. Unlike metaheuristic algorithms, deterministic optimal methods like the DM-SPP method provide benefits in computational efficiency and reliability as it does not require any randomization. These methods provide consistent results and do not require any repeated iterations or randomness in solution selection. Specifically, the DM-SPP method offers a streamlined path-planning approach that bypasses the iterative nature of metaheuristics by effective utilization of matrix operations and optimization techniques. The DM-SPP method can quickly calculate optimal paths with minimal computational time. This makes it well-suited for real-time applications where speed in decision-making is crucial like UAV aerial navigation. Further, the DM-SPP method guarantees the theoretical optimal solution and assures that the obtained solution is the global optima or near to optima for the given objective function. The deterministic reliability of methods like the DM-SPP is particularly advantageous in safety-critical applications like UAV path planning. In this context, the precision and efficiency of the path significantly impact mission success and risk mitigation. In summary, although metaheuristic approaches have proven effective for addressing complex optimization challenges, it is important to acknowledge their limitations, particularly when compared with deterministic optimal approaches like the DM-SPP. By acknowledging these limitations and recognizing the merits of deterministic methods, researchers and practitioners can make informed choices when selecting path-planning algorithms tailored to their applications' specific requirements and constraints.

4. Conclusions

In the current work, a comprehensive analysis of AI-based metaheuristic algorithms used for path planning of UAVs is done. More than 150 articles are reviewed from various major international journals and conference proceedings. Metaheuristic algorithms are classified as evolutionary algorithms, swarm-based algorithms, and trajectory-based algorithms. Implementation of these algorithms is discussed with parameters like static or dynamic obstacle avoidance, use as a hybrid approach, implementation for multiple UAVs, simulation, or experimental study. The following are the key points of the current study:

- In addressing every problem, no single meta-heuristic method beats all others. Existing algorithms additionally have drawbacks such as inadequate convergence rates, becoming trapped in local optima, applying complicated operators, requiring extensive processing time, requiring frequent parameter modifications, and being constructed just for either real or binary search spaces. As a result, developing fresh meta-heuristic methods to solve these disadvantages remains a constant task.
- Path planning of UAVs in a 3D environment is a complicated task that involves a lot of computational intelligence and many control points, which makes it difficult to implement the algorithms in a real-time situation. Hence, most of the work in the literature is found only in simulation

analysis and mathematical modelling. The work related to experimental analysis is very limited and limited to a few algorithms like GA, DE, ACO, and SA. There is a vast scope in developing a hybrid algorithm for implementation in experimental analysis.
- Most of the work in the literature is on obstacle avoidance in the static condition only, whereas path planning in the dynamic environment is much more difficult due to the high number of control points and fast convergence requirements.
- There are very few papers available in the literature on which a standalone algorithm is used for path planning of UAVs, and in those papers also there are a lot of drawbacks. Most of the researchers have hybridized the conventional algorithms with modern, developed algorithms to take advantage of both.
- The paper involved in path planning in a collaborative environment with multiple UAVs is less compared to single UAV path planning.
- Algorithms like PSO, ABC, FSA, CS, FA, BA, and HS have tremendous potential for optimization but have not been applied much for the navigation of UAVs. There is scope for developing new parameters and hybridizing them with other metaheuristic algorithms for UAV path planning.
- There is vast scope in developing a new metaheuristic hybrid algorithm that can be implemented in a collaborative environment and can be implemented in real-world experimental analysis.

Article information

History dates

Received: 28 October 2023
Accepted: 24 April 2024
Version of record online: 6 June 2024

Copyright

Data availability

This manuscript does not report any data.

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Validation: SS
Visualization: SS
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Writing – review & editing: SA

Competing interests

The authors declare there are no competing interests.

Funding information

No funding was received to assist with the preparation of this manuscript.

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