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SURVEY ARTICLE

UAV Path Planning Using Optimization Approaches: A Survey

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Abstract
Path planning is one of the most important steps in the navigation and control of Unmanned Aerial Vehicles (UAVs). It ensures an optimal and collision-free path between two locations from a starting point (source) to a destination one (target) for autonomous UAVs while meeting requirements related to UAV characteristics and the serving area. In this paper, we present an overview of UAV path planning approaches classified into five main categories including classical methods, heuristics, meta-heuristics, machine learning, and hybrid algorithms. For each category, a critical analysis is given based on targeted objectives, considered constraints, and environments. In the end, we suggest some highlights and future research directions for UAV path planning.

1 Introduction

Unmanned Aerial Vehicles (UAVs) are a class of flying, mobile robots able to perform various tasks and navigate in dynamic environments. In the beginning, UAVs were dedicated for military applications, by 1930. They were experimented during the second world war [1]. A few years after, the deployment of UAVs appeared in civil applications and became more frequent. Nowadays, we can see that UAVs are used in many fields such as security and surveillance [2, 3], agriculture [4, 5], meteorology [6, 7], archaeology [8, 9], etc. They serve especially for reaching inaccessible areas and in emergency cases (disaster rescue) [10, 11]. With more automation, UAVs are considered as autonomous vehicles able to make appropriate decisions according to their autonomy level.

UAV Path planning is one of the most important problems in the navigation and control of UAVs [12]. Its main objective is to find the optimal and collision-free trajectory to reach the desired destination by satisfying some criteria such as length (distance), smoothness, cost, computational time, and energy. To achieve these objectives, path planning needs to face with some constraints related to the UAV's physical characteristics such as energy, velocity, and UAV's axes. The path planning is conditioned by the work-space depending on whether it is urban, rural, or authorized. In Europe and some partner countries, the EUROCONTROL organization manages and coordinates the exploitation of UAVs with Air Navigation Service Providers (ANSPs) by defining a set of regulations [13] and prohibited flying areas [14]. The urban environment is a challenging area, it is characterized by cluttered areas that are complicated and complex. Particularly,

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to improve the efficiency of UAV's operations in urban, sub-urban, and inter-city areas, The Single European Sky ATM Research (SESAR) launched a two years project called CORUS-XUAM [15]. The main objective of this project is to establish new technologies, concepts, and rules for the deployment of airspace systems in these areas [16]. In fact, buildings and moving vehicles present a large risk to the movement of UAVs. They are considered as obstacles that may lead UAVs to make dangerous maneuvers and rotations that can cause physical damages. Nevertheless, rural zones are characterized by a less density of obstacles. Therefore, UAVs are less vulnerable to damages. On the other side, in high-level altitude, UAVs suffer less from the obstacles as the number of threats decreases but it makes them greedy in energy consumption. To overcome that, the energy sources of UAVs are multiplied. Actually, UAVs can be powered by fuel, battery, chemical substances, and solar cells [17].

Path planning is an NP-hard problem. Several research works have been presented to solve it with classical techniques, heuristics, meta-heuristics, and machine learning approaches. In the past couple of years, some surveys overview the different approaches. Each of them brings a contribution as it is summarized in Table 1. In fact, in [18], authors focused on the UAV path planning using classical algorithms using velocity and acceleration as criteria of classification. Yang et al. [19] presented a survey of UAV path planning approaches categorized into five classes including sampling-based, node-based, mathematical-based, bio-inspired-based, and multi-fusion-based approaches. Pandey et al. [20] reviewed the UAV path planning optimization based on meta-heuristic algorithms. Zhao et al. [21] surveyed meta-heuristics and machine learning algorithms used for optimizing the UAV path planning. Radmanesh et al. [22] introduced some UAV path planning objectives and presented UAV path planning approaches classified into classical and heuristic techniques. Aggarwal and Kumar [23] presented UAV path planning techniques classified into three categories including representative techniques, coordinate techniques, and non-coordinate techniques. Despite that, to the best of our knowledge, no previous work classified the path planning techniques according to the approaches they used. To address this, we propose through this paper a comprehensive review of researches related to UAV path planning by distinguishing five families: classical methods, heuristics, meta-heuristics, machine learning, and hybrid approaches.

This paper gathers publications from several credible databases such as IEEE, Springer, Taylor and Francis, World Scientific, and Elsevier as shown in Table 2. Fig. 1 presents the number of UAV path planning publications by database and by publication type. We can see that most of the conferences targeted IEEE database, while we notice a balance in journal publications between Elsevier, IEEE, and Springer. The names of the concerned journals are detailed in the top 10 ranking given in Table 3. Fig. 2 illustrates the number of UAV path planning publications by year. In the last four years, this field recorded a great rise with a peak reached in 2018. Fig. 4 represents the distribution of publication we

Table 1 Summary of survey works on UAV path planning

Authors (Refs.)	Year	Environment	Summary
Goerzen et al. [18]	2010	Static and dynamic	Classical algorithms for UAV path planning Analyses based on problem's type, dimensions of the environment, completeness, optimality, and time efficiency. The main constraints are velocity and acceleration
Yang et al. [19]	2014	Static and dynamic	Sampling based, node based, mathematical based, bio-inspired, and multi-fusion for UAV path planning. Analyses based on real-time planning, the environment, and time efficiency
Pandey et al. [20]	2017	Static and dynamic	UAV path planning based on Meta-heuristic algorithms Future research directions in UAV path planning based on meta-heuristics
Zhao et al. [21]	2018	Static and dynamic	Meta-heuristic and machine-learning algorithms for UAV path planning Analyses based on time (online and offline planning) and space
Radmanesh et al. [22]	2018	Static and dynamic	Classical and heuristic algorithms for UAV path planning Some UAV path planning objectives Analyses based on computational and error rate
Aggrawal and Kumar [23]	2020	Static and dynamic	Representative techniques, cooperative techniques, and non cooperative techniques for UAV path planning UAV path planning objectives Analyses based on path length, optimality, completeness, cost efficient, time efficient, energy efficient, robustness, and collision avoidance Coverage and connectivity in UAV networks Security in UAV networks Future research directions for UAV path planning

Table 2 Selected databases

Database	URL
ACM	https://dl.acm.org/
IEEE	https://ieeexplore.ieee.org/
ELSEVIER	https://www.elsevier.com/
Sage Publications	https://us.sagepub.com/
Springer	https://link.springer.com/
Taylor & Francis	https://www.tandfonline.com
World Scientific	https://www.worldscientific.com/
Hindawi	https://www.hindawi.com/

surveyed based on the countries UAV path planning where China and USA are the most active countries in this area ahead of India, Korea, Italy, Australia, Singapore, Canada, Brazil, and Germany.

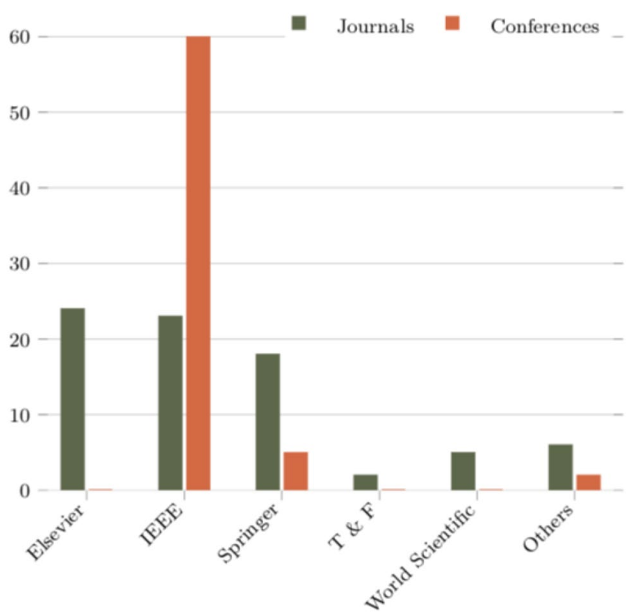

Fig. 1 Number of UAV path planning publications by database

As presented in Fig. 3, the remainder of this paper is organized as follows. Section 2 describes the process of research methodology. Section 3 presents objectives and constraints related to UAV path planning. Section 4 summarizes and analyses previous methods used for solving the UAV path planning problem. Section 5 draws results analysis of UAV path planning approaches. Finally, section 6 concludes this paper and gives perspectives.

2 Research Methodology

In the process of the literature review on UAV path planning using optimization approaches, we adopt the systematic literature review methodology. At first, we start by searching papers providing a review or survey on this area. In order to find survey articles related to our subject, the following set of keywords was used in Google Scholar:

- UAV path planning survey
- UAV path planning review
- UAV path planning overview

Some interesting survey papers are presented in Table 1.

Secondly, for finding new proposals and research papers in the UAV path planning context, we use the following search strings in google scholar:

- Artificial intelligence for UAV path planning
- Cooperative UAV path planning
- Dynamic UAV path planning
- Classical approaches for UAV path planning
- Heuristics for UAV path planning
- Meta-heuristics for UAV path planning
- Multi-UAV path planning
- Machine learning for UAV path planning
- Optimal UAV path planning
- UAV path planning algorithms
- UAV path planning optimization

Table 3 Top 10 Journals ranked by the number of UAV path planning publications

Journals	Database	Rank	Number of publications
IEEE access	IEEE	1	12
Journal of intelligent & robotic systems	Springer	2	8
Applied soft computing	Elsevier	3	5
Neurocomputing	Elsevier	3	4
Aerospace science and technology	Elsevier	4	3
Applied intelligence	Springer	5	2
Knowledge-based systems	Elsevier	5	2
Unmanned systems	World scientific	5	2

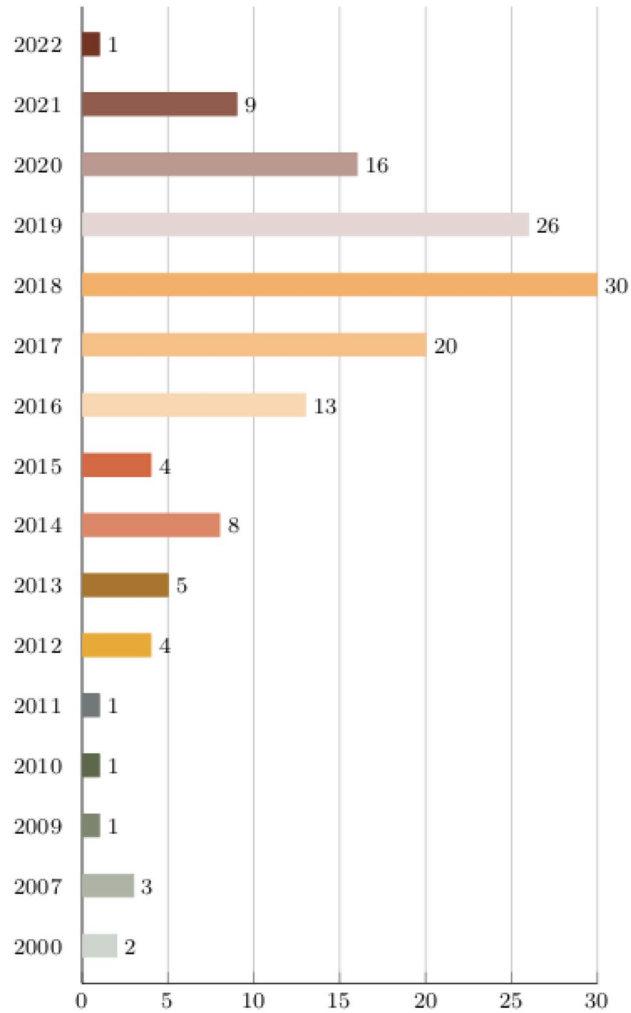

Fig. 2 Number of UAV path planning publications per year

To screen the large number of resulted papers, the criteria for paper inclusion/exclusion were considered as summarized in Table 4

Finally, we give a set of research questions, which are helpful to identify the lack of research in the field of UAV path planning. Therefore, the present paper tries to answer five main questions presented in Table 5.

3 Path Planning: Objectives and Constraints

Various objectives and constraints are involved in the resolution of the UAV path planning problem. In the following, we give the definition of the most studied ones:

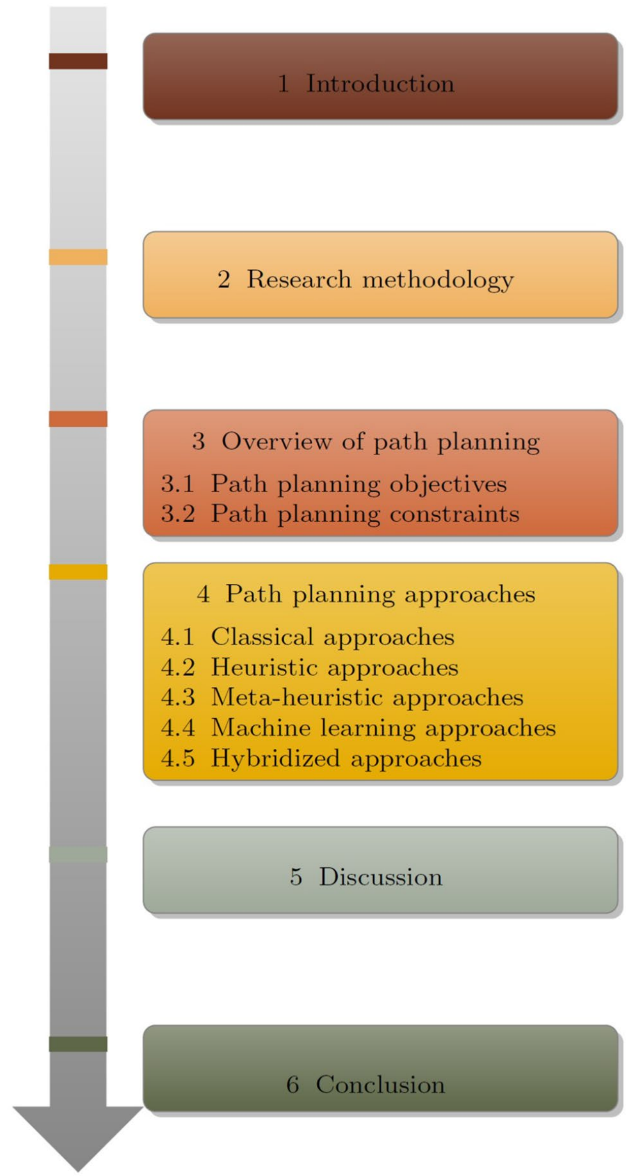

Fig. 3 The organization of this survey

3.1 Path Planning Objectives

3.1.1 Path Optimization

This objective includes the path length and its smoothness. The path length is the traveling distance between the source and destination nodes. Smoothness in fact that the path ensures continuity as long as possible by avoiding turns and obstacles.

3.1.2 Time-Efficiency

Time efficiency, often called planning time, is the required time for UAVs to generate the full and optimal path between source and destination points.

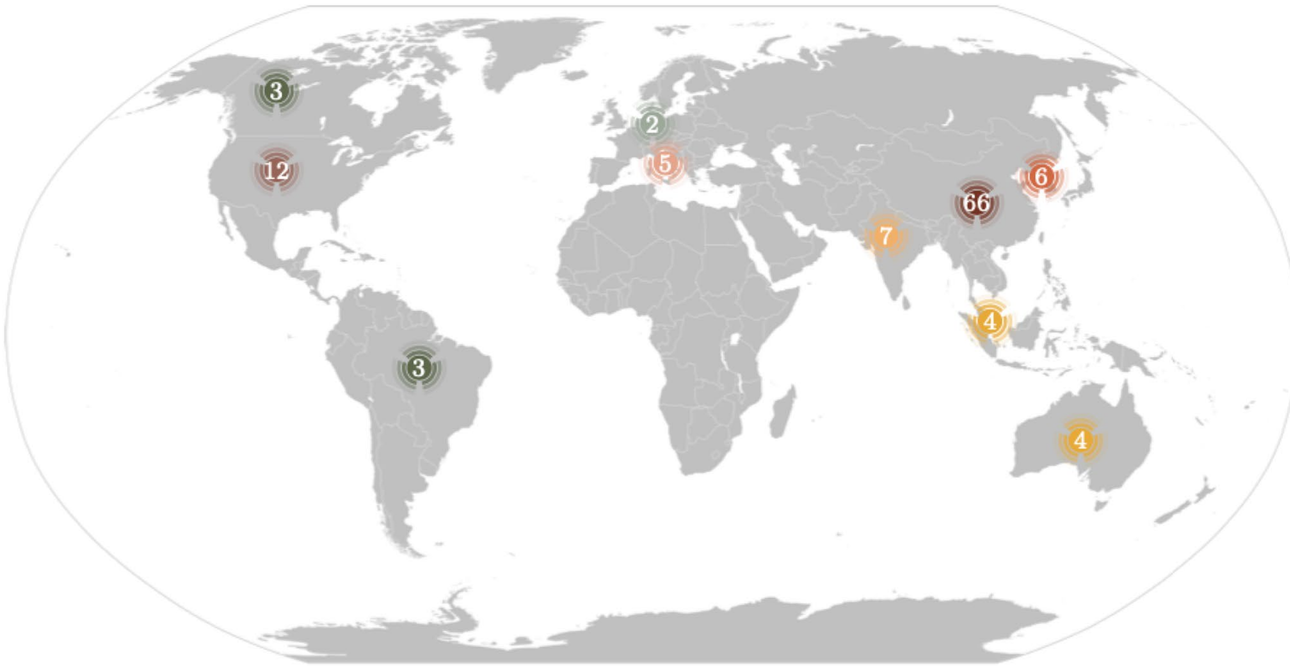

Fig. 4 Top 10 countries ranked by number of publications on UAV path planning

Table 4 Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Articles published in legitimate journals and conferences	Articles published in predatory journals and conferences
Articles published in English	Articles written in an other language other than English
Articles having more than 4 pages	Articles published in the form of abstract, keynote, tutorial, and posters
Articles dated from 2000 to January, 2022	Articles that do not provide any details for solving UAV path planning
Articles that brought a significant contribution to UAV path planning	Uncompleted articles
Articles representing a complete version when several versions of the article exist	

Table 5 Research questions

Question	Purpose
What was the main algorithm used?	Identify the algorithm and its classification
Which parameters were taking account?	Determinate the main contributions, the objective function and if the method took in consideration UAV constraints
Which simulator was used?	Verify the requirements of algorithm simulations and applications
Were the experiences tested in dynamic or static environment?	Affirm whether the proposed approach is adaptive to real tasks
Which algorithms were used in the comparison?	Validate the the effectiveness of the used method

3.1.3 Collision Avoidance

Collision avoidance is the ability of UAVs to detect and avoid any obstacle in order to move without any physical damage.

3.1.4 Cost-Efficiency

This objective represents the sum of multiple computation costs of UAVs such as hardware and software cost, fuel cost, memory cost, battery charging cost, and CPU cost.

3.2 Path Planning Constraints

3.2.1 Altitude

Altitude is directly related to the safety of UAVs. In fact, when UAVs fly at a low level of altitude, then the number of obstacles increases. Consequently, collisions probability increases. On the other hand, flying at a high level of altitude increases the energy consumption of UAVs. The altitude is given in meters.

3.2.2 Climb/Descend Angles

Climb and descend angles are presented as necessary angles of UAVs for taking off, landing, and moving between multiple heights. They are measured in degrees. Climb and descend angles influence energy consumption, especially for fixed-wings.

3.2.3 Energy Consumption

Energy consumption is represented as the power consumed by UAVs in terms of fuel, battery, chemical substances, or solar panels. It depends on traveling time, distance, altitude, and also the nature of the served environment. The energy consumption is given in Watts

3.2.4 Obstacles and Threats

Obstacles are defined as any objects that interrupt UAVs path. Obstacles can be static (such as buildings, mountains, trees...) or dynamic like moving objects and vehicles. Radars and missiles are considered as real threats since the radar can detect UAVs and missile damages them by their attacks.

3.2.5 UAV's Axes

UAV in motion performs multiple rotations in three dimensions. These rotations revolve around three main axes, which are pitch, roll, and yaw angle axes.

3.2.6 Velocity

Velocity is a constraint for UAVs in the context of path planning. It affects directly the fuel consumption and the safety of UAVs during the path planning process. It is preferred to take into consideration a rational velocity to preserve energy.

4 Path Planning Approaches Classification

In the literature, several path planning approaches were proposed in the UAV area. We propose in the following a classification based on the type of the used Algorithm. As shown in Fig. 5, we distinguish five categories: methods based on classical approaches, methods using heuristics, methods using meta-heuristics, those applying machine learning, and hybrid methods (Tables 6 and 7).

4.1 Classical Approaches

Various classical approaches were developed for solving the UAV path planning problem including Rapid-exploring Random Trees (RRT) [61], Voronoi Diagram (VD) [62], Artificial Potential Field (APF) [63], Visibility Graph (VG) algorithm [64], Dijkstra algorithm [65], and Probabilistic Road Map (PRM) algorithm [66]. They are summarized in Fig. 6 and Table 8.

4.1.1 Rapid-Exploring Random Trees Algorithm

Yang et al. [24] developed a novel approach, called Gaussian Process-based RRT (GP-RRT), based on the integration of Gaussian Process (GP) map-building model into RRT algorithm for tackling the UAV path planning problem. The effectiveness of GP-RRT algorithm was evaluated in two test areas (urban and 3D cluttered environments) using Rotary UAV. Simulation results showed that GP-RRT provides a safe and collision-free path in the most complex 3D environment.

In the work of Kothari and Postlethwaite [25], an enhanced RTT algorithm, called Chance Constraint-RRT (CC-RRT), based on the introduction of Chance Constraint approach [67] into RRT algorithm for solving the real-time UAV path planning problem. The performance of CC-RRT was validated using two scenarios. In the first one, experiments were performed with the presence of 4, 20, and 25 obstacles. In the second one, 4 static obstacles and one dynamic obstacle were used. Experimental results proved that CC-RRT is more efficient compared to the standard RRT on real-time detection, cost optimization, and avoidance of dynamic obstacles.

Lin and Saripalli [26] proposed an improved RTT algorithm based on the integration of Dubins curves strategy into RTT algorithm for optimizing the UAV path planning in an indoor environment. The robustness of the improved RRT algorithm was tested in a 3D environment using Parrot ARDrone with the presence of 6 static obstacles, 24 virtual moving obstacles, and 20 real dynamic obstacles.

Table 6 The objectives and constraints considered in classic Approaches

Algorithms	References	Objectives				Constraints					
		Path optimiza-tion	Time efficiency	Collision avoidance	Cost efficiency	Altitude	Climb/descend angle	Energy	Threats	UAV's axes	Velocity
GP-RRT	Yang et al. [24]			✓					✓	✓	
CC-RRT	Kothari and Postlethwaite [25]		✓	✓	✓			✓	✓	✓	✓
Improved RRT	Lin and Saripalli [26]	✓		✓		✓			✓	✓	✓
VPB-RRT	Xinggang et al. [27]	✓	✓	✓					✓	✓	
EPF-RRT	Yang et al. [28]	✓		✓					✓		
IRRT	Zu et al. [29]	✓		✓					✓	✓	✓
Im-RRT	Sun et al. [30]	✓	✓	✓					✓	✓	
Improved RRT	Meng et al. [31]			✓	✓	✓			✓	✓	
HDDRRT	Wen et al. [32]	✓		✓	✓	✓		✓	✓	✓	✓
Bidirection-al Spline RRT*	Lee et al. [33]	✓		✓		✓			✓	✓	✓
RRT*GL	Aguilar et al. [34]		✓	✓	✓			✓	✓		
IRRT*	Meng et al. [35]	✓		✓					✓		
Rectified RRT*	Mechali et al. [36]	✓		✓	✓			✓	✓		
VD	Bortoff et al. [37]	✓		✓		✓		✓	✓	✓	
Improved VD	Chen et al. [38]	✓		✓	✓			✓	✓	✓	✓
MVD	Baek and Han [39]			✓	✓	✓		✓	✓		✓
Heteroge-neous VD	Feng and Murray [40]	✓	✓	✓					✓	✓	
V-diagram	Chen and Zhao [41]	✓	✓	✓					✓	✓	✓
Improved APF	Moon et al. [42]	✓		✓					✓	✓	✓
APF-IRP	Qian et al. [43]	✓	✓	✓		✓	✓		✓		✓
Modified APF	Budiyanto et al. [44]	✓	✓	✓		✓			✓		✓
Improved APF	Chen et al. [45]	✓		✓	✓	✓		✓	✓		✓
Modified APF	Liu and Zhao [46]			✓					✓		
MPFM	Mac et al. [47]			✓		✓			✓	✓	
Improved APF	Abeywick-rama et al. [48]	✓	✓	✓	✓			✓	✓	✓	
Modified APF	Sun et al. [49]			✓					✓		
ePFC	Woods and Hung [50]	✓	✓	✓					✓	✓	✓
Improved APF	Zhiyang and Tao [51]	✓		✓					✓	✓	
HPF	Dai et al. [52]	✓		✓	✓			✓	✓		
Improved APF	Bai et al. [53]	✓		✓					✓	✓	
Improved APF	Feng et al. [54]			✓					✓	✓	✓

Table 6 (continued)

Algorithms	References	Objectives				Constraints					
		Path optimization	Time efficiency	Collision avoidance	Cost efficiency	Altitude	Climb/descend angle	Energy	Threats	UAV's rotation	Velocity
Improved APF	Yingkun [55]	✓		✓	✓			✓	✓	✓	
Novel APF	Abeywick-rama et al. [56]	✓	✓	✓		✓			✓		✓
RGV	D'amato et al. [57]	✓		✓		✓	✓		✓	✓	✓
LEVG	D'amato et al. [58]	✓		✓		✓	✓		✓	✓	
Modified DIJKSTRA	Maini and Sujit [59]	✓		✓					✓	✓	
OGCA and OGSA	Wang et al. [60]	✓	✓	✓			✓		✓	✓	

Experimental results demonstrated the efficiency of the proposed algorithm in avoiding both static and dynamic obstacles in real-time.

Xinggang et al. [27] suggested a Variable Probability-based Bidirectional RRT (VPB-RRT) algorithm for solving the UAV path planning problem. The performance of the VPB-RRT algorithm was evaluated in a 3D environment with two experiences. In the first experience, 6 static obstacles were used in a simple study area. In the second one, 7 static obstacles and one complex barrier were distributed randomly in the area. The superiority of VPB-RRT was demonstrated in terms of path length and planning time compared to A*, RRT, and RRT-Connect [68].

Yang et al. [28] proposed a novel model, called EPF-RRT, based on the integration of Potential Field into the original RTT for solving the UAV path planning problem. The performance of EPF-RRT was validated using simple and complex obstacles taking into account path length and time cost metrics. Experimental results demonstrated that EPF-RRT provides good performance compared to the traditional RRT in terms of path length and execution time.

Zu et al. [29] suggested an improved RRT (IRRT) algorithm for solving the multi-UAVs trajectory planning problem. The IRRT algorithm was tested using three experiences in a 2D study area. In the first experience, 2 UAVs were used and their paths were generated in a way that conflict occurred. The second experience used 5 UAVs and 7 circular obstacles with trajectory conflict. In the last one, 5 UAVs and 15 circular obstacles were distributed without conflict. Experimental results demonstrated the efficiency of improved RRT in the cooperation of multiple UAVs under conflict circumstances. Improved RRT algorithm reached the target in an acceptable time in case of unpredictable threats presence.

Sun et al. [30] developed an Improved RRT (Im-RRT) algorithm based on the integration of dynamic p_g value and dynamic step length in RRT algorithm for optimizing the UAV path planning. The effectiveness of Im-RRT was assessed in a 2D area with the presence of 25, 75, and 100 static obstacles. Experimental results demonstrated that Im-RRT outperforms Bi-RRT [69] and RRT of path length generation and execution time.

Meng et al. [31] proposed a novel approach based on RRT algorithm for optimizing the UAV path planning. The proposed algorithm was evaluated in a real 3D complex topography containing mountains taking into account three constraints such as altitude, pitch angles, and range of UAV in flying missions. It was demonstrated that the improved RRT algorithm is appropriate for the 3D environment since it ensures a safe and collision-free path with a wider range.

Wen et al. [32] proposed Heuristic Dynamic Domain RTT (HDDRRT) algorithm based on the hybridization of Dynamic Domain RTT [70] and an extension of RTT

Table 7 Advantages and disadvantages of classical algorithms used in UAV path planning

Algorithm	Advantages	Disadvantages
APF	Low time complexity Fast convergence Easy implementation	Not suitable for dynamic environment Poor performance in the presence of multiples obstacles Low computational efficiency
RRT	Suitable for simple and static environments Solution with completeness guaranteed Easy implementation	Path's quality not considered Non optimal path
PRM	Suitable for static and complex environment Suitable in path re-planning scenarios Short path generation	Long processing due to continuous check collision
Dijkstra	Short path generation Easy implementation Suitable for complex environment	High time complexity Not efficient for long distances Not suitable for dynamic environment
VG	Suitable for simple cases Suitable for static environment	Non efficient in 3D environments Not suitable for complex obstacles' shapes Efficiency decreases when the number of obstacles increases Unsafe path generation
VD	Safe path generation Suitable for real-time path planning	Long path length Non optimal path Convergence not guaranteed

(RRT*) [71] algorithms for enhancing the online UAV path planning. The robustness of HDDRRT was tested in both 2D and 3D static environments with the presence of complex obstacles. Simulation results validated the strength of HDDRTT in terms of selecting safe paths and avoiding obstacles in dangerous environments.

Lee et al. [33] presented a Bidirectional Spline-RRT* (BS-RRT*) algorithm based on the integration of the spline method [72] into RRT algorithm for solving the UAV path planning problem. The performance of the BS-RRT* algorithm was validated in two study cases using small RC aircraft. In the first case, UAV has a fixed altitude and the flight is in 2D. In the second case, UAV is free to move in three directions. Experimental results proved that the Bidirectional spline-RRT* algorithm provides a safe and smooth path for fixed-wing UAVs by satisfying the constraints related to fixed-wing flight.

Aguilar et al. [34] suggested a novel approach based on the combination of RRT* Goal [34] and RTT* Limit [34] algorithms for UAV path planning problem. The effectiveness of RRT*GL was assessed in a 3D environment using RGB-D sensors to collect the work-space environment. Simulation results showed that RRT*GL provides better performance compared to original RRT, RRT*, RRT* Goal, and RTT* Limit in terms of optimal path, execution time, and energy efficiency.

Meng et al. [35] developed an Informed RRT* (IRRT*) algorithm based on the integration of the oblique cylinder subset method into RRT* algorithm for optimizing the UAV path planning. The performance of IRRT* was evaluated in a 3D cubic area test using 1, 3, and 6 ground cylindrical obstacles. Experimental results proved the superiority of IRRT* algorithm compared to the traditional RRT* algorithm in terms of path length optimization and safe flying in larger search areas.

Mechali et al. [36] suggested a Rectified RRT* algorithm based on integrating the smoothing method into RRT* algorithm for solving the UAV path planning problem. The effectiveness of Rectified RRT* was validated in a 3D real environment using 3 parallel piped and parallel segment obstacles separately with the presence of 1, 2, and 3 static obstacles. According to the simulation, Rectified RRT* provided a smooth and short trajectory compared to RRT* algorithm. Moreover, Rectified RRT* optimizes energy consumption.

4.1.2 Voronoi Diagram

Bortoff [37] introduced the Voronoi Diagram algorithm for solving the UAV path planning problem. The author evaluated the Voronoi Diagram algorithm in two cases with 10 known obstacles and 2 random radars. In both cases, simulation results demonstrated that the Voronoi Diagram algorithm generates optimal path length while keeping a safe distance from threats.

In another work, Chen et al. [38] developed an improved Voronoi Diagram algorithm based on the integration of Consistence theory [73] into Voronoi Diagram for solving the multiple UAVs path planning problem. The effectiveness of the improved Voronoi Diagram algorithm was experienced in a static environment with 3 moving UAVs in a square area. Simulation results proved the robustness of the presented method in terms of collision-avoidance and path length optimization.

Fig. 5 Classification of UAV path planning approaches

Baek and Han [39] suggested a modified Voronoi Diagram algorithm (mVD) for solving the UAV path planning problem. The performance of mVD was estimated using 1 UAV and 15 sensors distributed randomly in a square area of 300×300 [m^2]. Experimental results showed that mVD performs better traditional VD, CSS [74], and exhaustive search [75] algorithms in terms of computation complexity and energy consumption optimization.

Feng and Murray [40] proposed a heterogeneous Voronoi Diagram algorithm for solving the UAV path planning problem. The performance of the heterogeneous Voronoi Diagram was examined in a windy study area in two scenarios, with and without obstacles including 322 serving hospitals/EMS stations and 282 spatial units. Simulation results validated the effectiveness of the heterogeneous Voronoi Diagram algorithm compared to the traditional Homogeneous Voronoi Diagram technique in terms of time response and space allocation.

Chen and Zhao [41] developed a modified Voronoi Diagram algorithm based on the integration of cubic

Table 8 Summary of classic approaches for UAV path planning

Algorithm	Authors (Refs.)	Year	Environment	Multi-UAVs	Results
GP-RRT	Yang et al. [24]	2013	Static	No	GP-RRT gives good performance by obtaining a safe and collision-free path in a complex 3D environment
CC-RRT	Kothari and Postlethwaite [25]	2013	Dynamic	No	CC-RRT gives competitive results compared to RRT in terms of real time planning and cost efficiency.
Improved RRT	Lin and Saripalli [26]	2014	Dynamic	No	Improved RRT achieves better results in terms of optimal path generation in case of dynamic environment.
VPB-RRT	Xinggang et al. [27]	2014	Static	No	Superiority of VPB-RRT compared to A*, RRT, and RRT-Connect in terms of planning time and path length.
EPF-RRT	Yang et al. [28]	2018	Static	No	Superiority of EPF-RRT compared to RRT in terms of path length.
IRRT	Zu et al. [29]	2018	Dynamic	Yes	IRRT gives better performance in terms of smooth path generation in case of dynamic and multi-UAVs environment.
Im-RRT	Sun et al. [30]	2018	Static	No	Robustness of Im-RRT compared to Bi-RRT and RRT in terms of execution time and path length.
Improved RRT	Meng et al. [31]	2019	Static	No	Improved RRT achieves competitive results in terms of path cost and constraints handling.
HDDRRT	Wen et al. [32]	2015	Static	No	Robustness of HDDRRT in comparison with NFZ-DDRRT, TADDRRT, and TARRT* in terms of path cost and path length.
Bidirectional Spline-RRT*	Lee et al. [33]	2016	Static	No	Bidirectional Spline-RRT* gives better performance in terms of optimal path generation.
RRT*GL	Aguilar et al. [34]	2017	Static	No	Superiority of RRT*GL compared to RRT, RRT*, RRT*G, and RRT*L in terms of energy consumption, execution time, and path cost.
IRRT*	Meng et al. [35]	2018	Dynamic	No	IRRT* achieves better performance compared to RTT* by providing the shortest path length.
Rectified RRT*	Mechali et al. [36]	2019	Static	No	Robustness of Rectified RRT* compared to RRT* by obtaining the shortest and least cost path.
VD	Bortoff et al. [37]	2000	Static	No	VD gives better performance in terms of optimal path generation.
Improved VD	Chen et al. [38]	2017	Dynamic	Yes	Superiority of Improved VD by obtaining the shortest and least cost path.
MVD	Baek and Han [39]	2019	Dynamic	Yes	Efficiency of MVD compared to Exhaustive search in terms of energy consumption and path cost.
Heterogeneous VD	Feng and Murray [40]	2018	Static	No	Heterogeneous VD gives better performance compared to Homogeneous VD in terms of short path length and response time.
V-diagram	Chen and Zhao [41]	2019	Dynamic	Yes	Effectiveness of V-diagram in terms of path length and planning time.
Improved APF	Moon et al. [42]	2013	Dynamic	Yes	Robustness of Improved APF compared to RRT in terms of path length.
APF-IRP	Qian et al. [43]	2015	Dynamic	No	APF-IRP gives competitive results compared to Rolling Plan in terms of path length and execution time
Modified APF	Budiyanto et al. [44]	2015	Dynamic	Yes	Modified APF outperforms other optimization approaches in terms of execution time and path length.
Improved APF	Chen et al. [45]	2016	Static	No	Efficiency of Improved APF compared to APF in terms of path length and energy optimization.
Algorithm	Authors (Refs.)	Year	Environment	Multi-UAVs	Results
Modified APF	Liu and Zhao [46]	2016	Static	No	Modified APF achieves competitive results in terms of safe path generation and avoiding concave threats.
MPFM	Mac et al. [47]	2016	Static	No	MPFM gives better performance compared to APF.

Table 8 (continued)

Algorithm	Authors (Refs.)	Year	Environment	Multi-UAVs	Results
Improved APF	Abeywickrama et al. [48]	2017	Dynamic	Yes	Superiority of Improved APF compared to APF and random selection APF in terms of energy consumption, planning time, and path length.
Modified APF	Sun et al. [49]	2017	Dynamic	Yes	Modified APF gives better results compared to APF in a dynamic environment.
ePFC	Woods and Hung [50]	2017	Dynamic	Yes	Robustness of ePFC compared to PFC in terms of path length and execution time.
Improved APF	Zhiyang and Tao [51]	2017	Static	No	Improved APF gives better performance in terms of optimal path generation.
HPF	Dai et al. [52]	2018	Dynamic	Yes	Efficiency of HPF compared to APF and IPF in terms of path cost and path length.
Improved APF	Bai et al. [53]	2018	Dynamic	Yes	Superiority of Improved APF compared to APF in terms of path length.
Improved APF	Feng et al. [54]	2018	Dynamic	Yes	Improved APF gives competitive results compared to APF in a dynamic environment.
Improved APF	Yingkun [55]	2018	Static	No	Improved APF obtains better results in terms of path length and cost optimization.
Novel APF	Abeywickrama et al. [56]	2018	Dynamic	Yes	Novel APF outperforms compared to APF in terms of path length and computational time.
RGV	D'amato et al. [57]	2019	Dynamic	Yes	RGV achieves competitive results compared to RGV without RVW by obtaining the shortest path length.
LEVG	D'amato et al. [58]	2019	Static	No	LEVG gives better performance compared to other existing algorithms in terms of path optimization.
Modified DIJKSTRA	Maini and Sujit [59]	2016	Static	No	Modified DIJKSTRA achieves better results in comparison with DIJKSTRA by obtaining the shortest path length
OGCA and OGSA	Wang et al. [60]	2015	Static	No	Efficiency of OGCA and OGSA in comparison with PRM* and A* in terms of path length and execution time.

spline and crowding mechanisms into Voronoi Diagram algorithm for optimizing multi-UAVs path planning in a 2D dynamic environment. The effectiveness of the proposed algorithm was evaluated using 3 UAVs and 2 dynamic ground targets. Experimental results proved that the modified Voronoi Diagram algorithm can successfully generate a safe path for multiple UAVs in a reasonable execution time with the presence of sudden threats.

4.1.3 Artificial Potential Field

An improved APF was proposed by Moon et al. [42], which is the hybrid of APF and A* for solving the multi-UAV path planning problem in a 3D dynamic environment. The performance of the improved APF was validated using 3 fixed-wing UAVs and results showed that UAVs achieve optimal path and maintain mission accomplishment without collision.

Qian et al. [43] suggested a novel approach, called APF-Improved Rolling Plan (APF-IRP), for UAVs real-time path planning optimization. The effectiveness of APF-IRP algorithm was assessed in 2D and 3D complex study areas with the presence of static and dynamic threats distributed randomly. Simulation results proved that APF-IRP outperforms the traditional Rolling Plan algorithm by obtaining a safe path with collision detection and avoidance.

Budiyanto et al. [44] proposed a modified APF algorithm for optimizing the Quad-Copter UAV path planning in static and dynamic environments. The efficiency of the modified APF algorithm was validated in 3 scenarios using 2 square obstacles with 1, 2, and 5 Parrot AR Drones in each scenario, respectively. Experimental results demonstrated that the modified APF gives good results in both static and dynamic threats avoidance, and can ensure optimal path with short execution time.

Chen et al. [45] developed an enhanced APF approach based on the integration of optimal control method into APF for solving the UAV path planning problem. The effectiveness of the enhanced APF algorithm was assessed in a 3D study zone using Quad-rotor Helicopter with the presence of 7 convex and non-convex threats. Experimental results proved that the enhanced APF algorithm

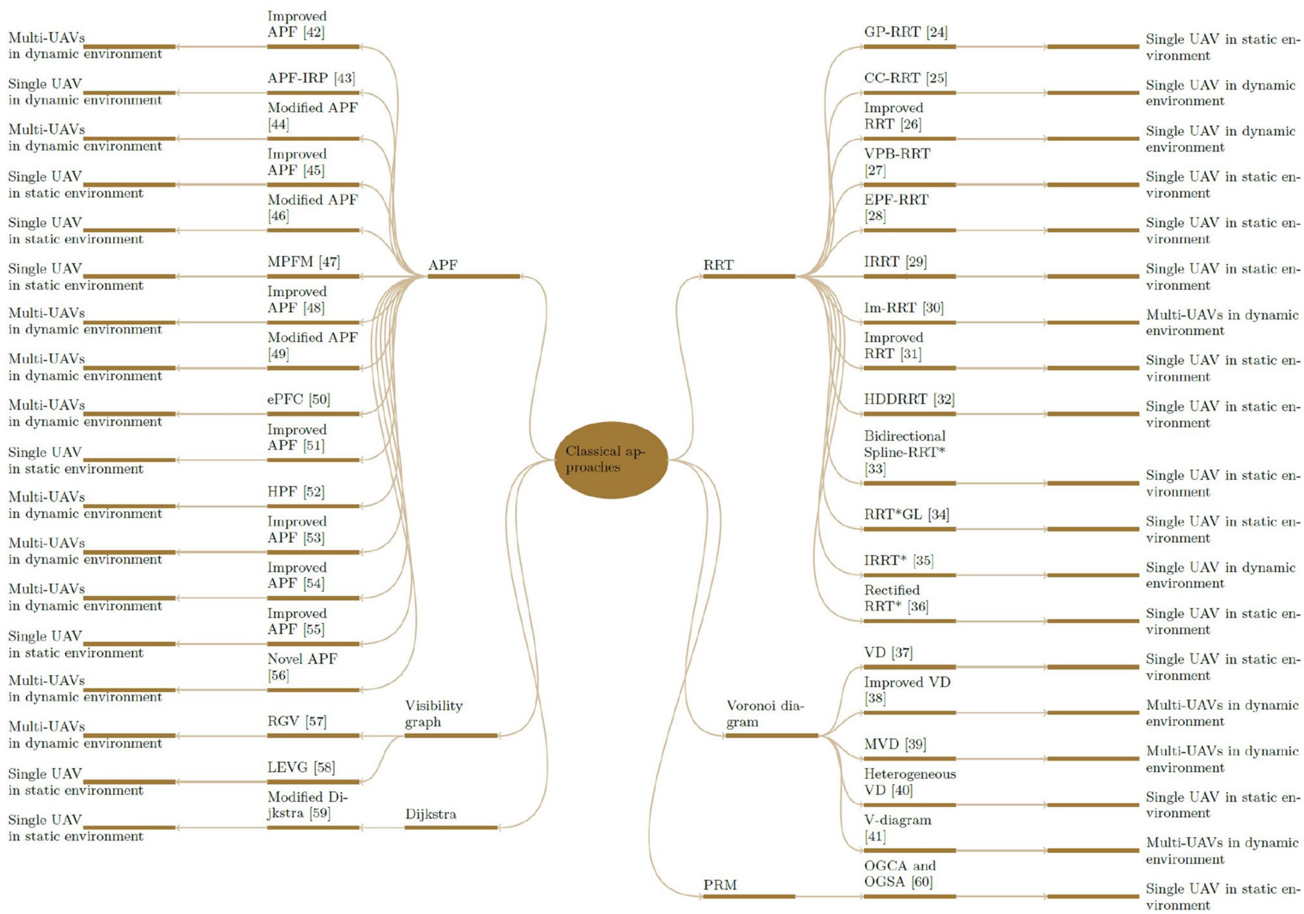

Fig. 6 Classical approaches for UAV path planning

provides optimal path length and handles dead point situations better than the classical APF algorithm.

In their proposal, Liu and Zhao [46] suggested a modified APF technique based on the integration of virtual waypoint into APF algorithm for solving the UAV path planning problem. The performance of the modified APF algorithm was evaluated in a 2D square area using random positioned circular obstacles. Simulation results showed the effectiveness of the modified APF in terms of safe path generation and avoiding concave threats.

Mac et al. [47] proposed a Modified Potential Field Method (MPFM) for solving the UAV path planning problem. The effectiveness of MPFM algorithm was assessed using AR-Drone 2.0 Quad-rotor UAV flying under known and unknown threats. Experimental results demonstrated that MPFM guarantees the safety of the path to reach the target destination in a complex environment, while APF fails.

Authors in [48] suggested an improved APF algorithm based on the integration of selective avoidance strategy into APF algorithm for optimizing the multi-UAV path planning. The robustness of the improved APF was evaluated in a 2D dynamic environment using 3 flying UAVs. Simulation results demonstrated that the improved APF algorithm outperforms traditional APF in terms of path length generation and energy consumption efficiency. Sun et al. [49] proposed an enhanced APF algorithm for solving the multi-UAVs path planning problem. Distance factor and Jump strategy approaches were integrated into APF algorithm to avoid the local minimum point. The effectiveness of the enhanced APF was validated in a 3D urban environment using 6 UAVs flying close to 30 horizontal and vertical obstacles. According to the test results, the enhanced APF algorithm is effective compared to the traditional APF algorithm in handling multiple-UAV path planning without damages.

Woods and Hung [50] suggested an extended APF Controller (ePFC) for optimizing the UAV tracking mission in a 3D dynamic real environment. The performance of ePFC was evaluated using ARDrone 2.0 UAV with virtual obstacles in case of static and dynamic targets. Experimental results proved that ePFC outperforms the ordinary PFC in terms of computational time and collision avoidance on both static and dynamic targets.

Zhiyang and Tao [51] developed an improved APF algorithm based on the introduction of the advanced search method in APF algorithm for solving the UAV path planning problem. The robustness of the improved APF algorithm was assessed in a 2D environment using 4 static circular obstacles with different radius. Simulation results showed the merits of the improved APF algorithm in terms of safe path generation and smooth optimal trajectory.

Dai et al. [52] proposed a Hierarchical Potential Field (HPF) approach for optimizing the multi-UAVs path planning. The effectiveness of HPF algorithm was validated in a 3D environment using 4 UAVs and 6 types of geometric threats (sphere, Regular tetrahedral, cube, Cylindrical, and random shape). Simulation results showed the merits of HPF algorithm compared to APF and Improved APF [52] in terms of path length optimization, path cost, and threat avoiding.

Authors in [53] developed an improved approach based on the integration of B-spline Interpolation strategy [76] into APF algorithm for multi-UAVs path planning problem. The performance of the improved APF approach was evaluated in a 2D dynamic environment based on 2 cases. 2 UAVs and 11 obstacles were deployed in the first case. In the second one, 4 UAVs with 11 obstacles were used. According to the results, the improved APF outperforms APF in terms of path length optimization and error rate.

Feng et al. [54] proposed an Improved APF based on the introduction of the Formation Control method into the standard APF algorithm for UAV tracking mission and collision avoidance. The effectiveness of the improved APF was validated in a 3D environment using 3 UAVs and 3 static obstacles. Simulation results demonstrated that the Improved APF algorithm ensures safe tracking mission and distance between multiple UAVs by satisfying fixed-wing constraints.

In the proposal of Yingkun [55], the author presented an enhanced APF algorithm for solving the Agriculture UAV path planning problem. The robustness of the enhanced APF algorithm was validated in a 2D environment using 4 and 9 obstacles of different shapes. Simulation results showed that the enhanced APF algorithm can easily reach successfully the final destination in a simple and complex environment with a shorter path.

Abeywickrama et al. [56] proposed a modified APF algorithm for handling the multiple UAVs path planning problem. A virtual target point is created to increase attractive force which pushes UAVs in altitude to avoid the obstacles in 3D flight. The performance of the modified APF algorithm was evaluated in 3 cases using 3, 5, and 10 UAVs, respectively. Compared to the traditional APF method, modified APF provides better results in terms of flight time optimization and threat avoidance.

4.1.4 Visibility Graph Algorithm

D'Amato et al. [57] developed a Bi-level optimization algorithm based on the Visibility graph algorithm for solving the cooperative UAV path planning problem in a 2D dynamic environment. The robustness of the proposed algorithm was assessed in 4 study cases. In the first case, 4 UAVs were deployed with 12 obstacles. The second case used 13 UAVs with 12 obstacles. In the third study case, 5 UAVs and 27 obstacles were used. In the last one, 9 UAVs were deployed with the presence of 24 obstacles. Simulation results showed that the proposed algorithm provided the optimal and collision-free trajectory. In terms of computation cost, it is shown that the proposed algorithm is efficient for less than 6 UAVs.

In their work, D'Amato et al. [58] proposed a Layered Essential Visibility Graph (LEVG) algorithm based on the integration of Dubins curves into Visibility graph algorithm for solving the fixed-wing UAV path planning problem in a 3D environment. The performance of LEVG algorithm was evaluated in a 3D environment in 2 experiences. In the first one, 5 geometrical obstacles were used in the first experience. In the second experience, obstacles were replaced by a mountain. According to the results, LEVG algorithm is efficient in terms of path cost optimization, path efficiency, and obstacle avoidance.

4.1.5 Dijkstra Algorithm

Maini and Sujit [59] applied a novel approach based on Dijkstra algorithm for enhancing the UAV path planning in a complex environment. The performance of the proposed approach was evaluated using 12 dynamic obstacles taking into account the turning angle constraint. Experimental results showed that the proposed approach gives good performance compared to Dijkstra in terms of path length and collision avoidance.

4.1.6 Probabilistic Road Map Algorithm

Wang et al. [60] proposed Obstacle-free graph construction algorithm (OGCA) and Obstacle-free graph search algorithm (OGSA) for solving the UAV path planning problem. The two algorithms are improved versions of PRM* [71] and A* [77] algorithms respectively. The performance of OGCA and OGSA was validated in a 3D environment with 2 experiences. In the first one, multiple climbs were used as threats. In the second one, a cuboid obstacle was added inside the map. It was demonstrated that OGCA provides good performance compared to PRM* algorithm in terms of execution time. It was also revealed that OGSA and A* have approximately the same time complexity.

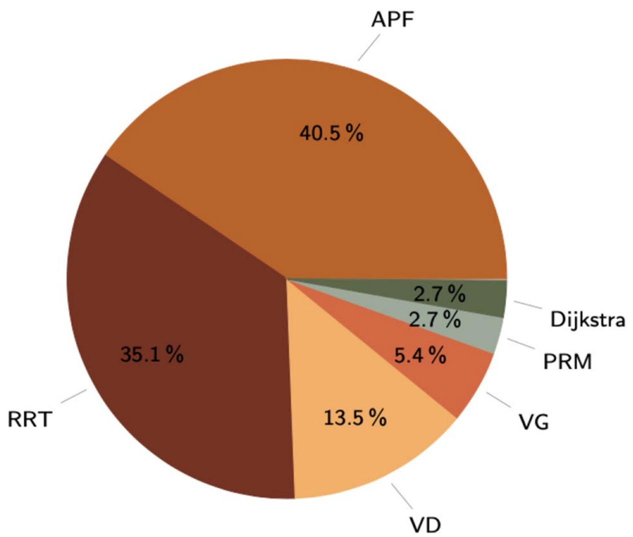

Fig. 7 Classical approaches for UAV path planning

4.1.7 Analysis

As presented in the subsection above, several classical approaches such as RRT, VD, APF, VG, Dijkstra, and PRM are proposed for solving the UAV path planning problem. The main reason of their success is their easy implementation while giving good results in terms of Path optimization, fast solution generation, and efficiency for static environments with simple obstacles. The pros and cons of each of them are provided in Table 7.

We can see clearly from Fig. 7 that APF algorithm is the most applied approach thanks to its easy implementation, fast convergence, and low time complexity. However, it has some weaknesses such as poor performance, low efficiency, and failure in case of the presence of multiple obstacles, especially, when they are close to each other. In this case, it is RRT that performs well and gives good solutions with completeness guaranteed. Nevertheless, RRT does not take into account the length of the path. To overcome this issue, PRM and Dijkstra algorithms were applied to provide an optimal path length and manage the complexity of obstacles. VG and VD are two famous classical algorithms that are both able to solve the real-time UAV path planning problem. Therefore, VG is not suitable for complex obstacles' shapes and its efficiency decreases when the number of obstacles increases. VD overcomes this issue by ensuring more safety, but no optimal paths are guaranteed in terms of length.

4.2 Heuristic Approaches

For solving the UAV path planning, many heuristic-based algorithms were proposed as shown in Fig. 8. The summary of heuristic approaches is given in Table 9. Hereafter, we present some of them.

4.2.1 A-Star Algorithm

In path planning, A-Star (A*) algorithm is a popular heuristic algorithm, it was firstly introduced by Hart et al. [97].

Dong et al. [78] proposed a Virtual Force A* (HVFA) algorithm based on the introduction of virtual force method [98] into A* algorithm for solving the UAV path re-planning problem. The performance of HVFA algorithm was assessed in 4 experiences. In the first and second experiences, HVFA was performed in a 2D environment using 10 circle obstacles in comparison with A* algorithm. In the 2 last experiences, the level of threats was increased and HFVA algorithm was performed in comparison to Fuzzy virtual Force (FVF) [98]. It was demonstrated that HVFA provides better performance compared to A* and FVF in terms of path cost and execution time (Table 10).

Geng et al. [77] suggested A* algorithm for solving multi-UAVs path planning problem. The effectiveness of A* was evaluated in a 3D environment in 2 cases. In the first case, one cubic obstacle with mountains was used in the simulation. In the second case, only the mountains were used. According to experimental results, A* algorithm provides an optimal path compared to other path planning approaches. However, computation time is a little higher due to supplementary processing when stealth is considered.

Wang et al. [79] proposed an improved A* algorithm, called Dubins-Sparse A-Star (Dubins-SAS) algorithm, based on the integration Dubins curve into SAS algorithm [99] for optimizing the UAV path planning. The effectiveness of Dubins-SAS algorithm was assessed in a 2D environment using 3 obstacles. Experimental results demonstrated that Dubins-SAS outperforms SAS algorithm in terms of planning time and the number of nodes needed to find the optimal path.

In their proposal, Tianzhu et al. [80] suggested an improved A* algorithm for optimizing the UAV path planning in a 3D environment. The performance of the Improved A* algorithm was evaluated in a 3D simulation map using 3 different experiences. In the first one, eight static obstacles and one flying UAV at high altitude were used. In the second one, the number of obstacles was reduced to 2. In the last experience, radar was added to test the behavior of the UAV under dangerous threats. Simulation results showed that improved A* provides better performance compared to ACO and APF in terms of cost-efficiency and path length optimization.

Zhang and Meng [81] developed Sparse A* Search (SAS) algorithm for solving the UAV path planning problem. The effectiveness of SAS algorithm was validated in a 3D environment with the presence of multiple mountains

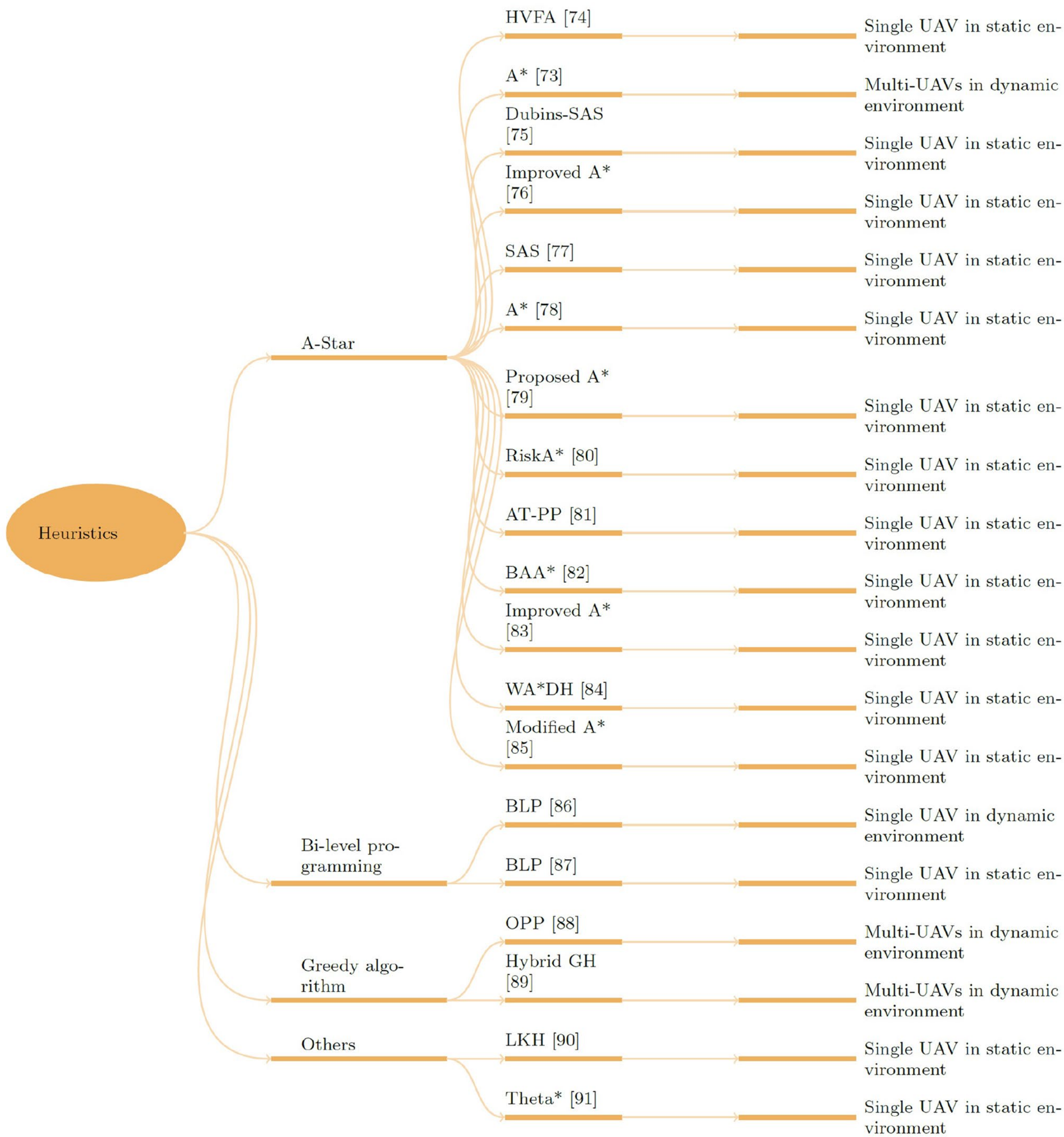

Fig. 8 Heuristic approaches for UAV path planning

distributed randomly. According to experimental results, SAS algorithm guarantees better performance by obtaining a collision-free optimal path that satisfies turning angles and flight height constraints.

Chen et al. [82] proposed A* algorithm for optimizing the UAV path planning. The effectiveness of A* algorithm was assessed in a 2D grid map environment taking into account the fuel cost and barrier complexity metrics. Simulation results demonstrated that A* algorithm gives good performance in terms of cost optimization and path length.

Zhang and Hsu [83] developed an improved path planning algorithm based on the integration of GNSS error

Table 9 Summary of Heuristic approaches for UAV path planning

Algorithm	Authors (Refs.)	Year	Environment	Multi-UAVs	Results
HVFA	Dong et al. [78]	2011	Static	No	Effectiveness of HVFA compared to A and FVF in terms of path length and execution time.
A*	Geng et al. [77]	2014	Dynamic	Yes	A* achieves competitive results in term of path length.
Dubins-SAS	Wang et al. [79]	2014	Static	No	Robustness of Dubins-SAS compared to SAS in terms of execution time.
Improved A*	Tianzhu et al. [80]	2016	Static	No	Superiority of Improved A* compared to ACO and APF in terms of path length and execution time.
SAS	Zhang and Meng [81]	2017	Static	No	SAS gives better performance in term of path cost and path length.
A*	Chen et al. [82]	2018	Static	No	A* achieves better results in terms of path cost and path length.
Proposed A*	Zhang and Hsu [83]	2019	Static	No	Effectiveness of the improved A* compared to A* in terms of path length.
RiskA*	Primatesta et al. [84]	2019	Static	No	Robustness of RiskA* compared to A* in terms of path length.
AT-PP, MT-PP and IPS	Madrani et al. [85]	2019	Static	No	Effectiveness of AT-PP, MT-PP and IPS compared to SP in terms of path length and execution time.
BAA*	Wu et al. [86]	2020	Static	No	BAA* achieves competitive results compared to CA* and SA* in terms of path length and execution time.
Improved A*	Zhang et al. [87]	2020	Static	No	Superiority of Improved A* compared to D* and SAS in terms of path length and execution time.
Weighted A* with Deviate Heuristic (WA*DH)	Lim et al. [88]	2021	Static	No	WA*DH gives competitive results compared to Weighted A* [89] in terms of path length.
Modified A*	Zhang et al. [90]	2022	Static	No	Modified A* outperforms BLM A* [90] and A* in terms of path length and execution time
BLP	Liu et al. [91]	2013	Dynamic	No	Robustness of BLP compared to A_{2d}, FBCRI, MILP, and RRT in terms of execution time and path length
BLP	Kang et al. [92]	2017	Static	No	BLP gives better performance compared to A*, PSO, and RRT in a complex environment.
OPP	Ahmed et al. [93]	2016	Dynamic	Yes	Superiority of OPP algorithm compared to FDFR and GLC in terms of energy consumption.
GH	Silva et al. [94]	2017	Dynamic	Yes	Efficiency of Hybrid GH compared to GA, and MPGA in terms of execution time.
LKH	Freitas et al. [95]	2020	Static	No	Robustness of LKH compared to ACO and GLS in terms of execution time, path cost, and path length.
Theta*	De Filippis et al. [96]	2012	Static	No	Theta* achieves competitive results compared to A* by obtaining the shortest path length.

distribution into A* algorithm for solving Global Navigation Satellite System localization map error for UAVs. The effectiveness of the improved A* was tested in a real environment of an urban area using Quad-copter at different height positions. Experimental results showed that the improved A* provides a safe path according to position error prediction with minimum cost compared to A* and APF.

Primatesta et al. [84] proposed RiskA* algorithm for optimizing the UAV path planning in an urban environment. The effectiveness of RiskA* algorithm was validated in 2D urban zones. It was demonstrated that the RiskA* algorithm is able to provide better performance compared to A* and RA* [100] in terms of safe path searching, path cost, and risk avoidance.

Madrani et al. [85] developed three approaches based on A* algorithm for optimizing Quality of Service (QoS) in the UAV path planning. Average Throughput-Path Planning (AT-PP) and Maximum Throughput-PP (MT-PP) algorithms were designed for QoS processing, while Improved Path Smoothing (IPS) was used for path planning optimization. The performance of enhanced A* algorithms was evaluated in a 2D environment in cases of present and absent winds. Compared to Shortest Path (SP) algorithm, AT-PP/IPS, and MT-PP/IPS provides better results in communication throughput. However, MT-PP/IPS and AT-PP/IPS algorithms engender more energy consumption.

Wu et al. [86] proposed a Bi-directional Adaptive A* (BAA*) algorithm for solving the UAV path planning

Table 10 The objectives and constraints considered in heuristic approaches

Algorithms	References	Objectives				Constraints					
		Path optimization	Time efficiency	Collision avoidance	Cost efficiency	Altitude	Climb/ Descend angle	Energy	Threats	UAV's axes	Velocity
HVFA	Dong et al. [78]	✓	✓	✓					✓	✓	✓
A*	Geng et al. [77]	✓		✓		✓	✓		✓	✓	
Dubins-SAS	Wang et al. [79]		✓	✓					✓	✓	✓
Improved A*	Tianzhu et al. [80]	✓	✓	✓		✓	✓		✓	✓	
SAS	Zhang and Meng [81]	✓		✓	✓	✓	✓	✓	✓	✓	
A*	Chen et al. [82]	✓		✓	✓			*	✓		
Proposed A*	Zhang and Hsu [83]	✓		✓		✓			✓		
RiskA*	Primatesta et al. [84]	✓		✓					✓	✓	
AT-PP, MT-PP and IPS	Madrani et al. [85]	✓	✓	✓					✓	✓	✓
BAA*	Wu et al. [86]	✓	✓	✓		✓			✓	✓	
Improved A*	Zhang et al. [87]	✓	✓	✓		✓			✓	✓	✓
WA*DH	Lim et al. [88]	✓		✓					✓		
Modified A*	Zhang et al. [90]	✓	✓	✓			✓		✓	✓	
BLP	Liu et al. [91]	✓	✓	✓		✓			✓	✓	✓
BLP	Kang et al. [92]			✓					✓	✓	
OPP	Ahmed et al. [93]			✓	✓	✓		✓	✓	✓	
Hybrid GH	Silva et al. [94]		✓	✓					✓	✓	✓
LKH	Freitas et al. [95]	✓	✓	✓	✓				✓		
Theta*	De Filippis et al. [96]	✓		✓		✓			✓	✓	✓

problem. Directional, adaptive step, and adaptive weight search strategies were introduced to improve the expansion process, path smoothness, and exploration speed. The performance of BAA* algorithm was validated in a 3D complex environment using 4 static obstacles in 3 different study cases. Simulation results demonstrated that BAA* algorithm outperforms A* and SA* [101] by generating the best path cost with minimum nodes and less execution time.

Zhang et al. [87] proposed an Improved A* algorithm, called Learning Real-Time A-star algorithm (LRTA-Star) based on the combination of Model-based predictive control [102] and A* algorithm for real-time penetration path planning. The performance of LRTA-Star algorithm was assessed in a 3D environment in 3 cases with the presence of 4, 8, and 13 obstacles respectively in each study case. Simulation results showed the robustness of LRTA-Star in comparison with SAS and D* algorithms [103] in terms of time-efficiency and path length optimization.

4.2.2 Bi-Level Programming Algorithm

In the work of Liu et al. [91], authors proposed an improved Bi-Level Programming (BLP) algorithm based on the integration of multiple optimization strategies into BLP algorithm [104] for solving the real-time UAV path planning problem. The performance of the improved BLP algorithm was evaluated in 10 scenarios inside a 3D complex environment using multiple Surface to Air Missiles (SAMs) as threats. It was demonstrated that BLP algorithm provides better performance compared to A_{2d} [105], FBCRI[106], MILP [107], and RRT in terms of smooth path length, planning time, and minimum peak error.

Kang et al. [92] proposed BLP algorithm for solving the UAV path planning problem. The performance of BLP algorithm was validated in a 2D environment based on 10 experiences compared to RRT, A*, and PSO. At each experience, the number of obstacles is increased by one starting from one obstacle. Experimental results showed that BLP and RRT algorithms give better performances compared to A* and PSO. BLP is appropriate in complex situations and low variance, while RRT is appropriate in simple cases and large variance.

4.2.3 Greedy Algorithm

Ahmed et al. [93] proposed an Optimal Path Planning (OPP) algorithm based on the hybridization of two variants of greedy algorithm, called, Greedy Least Cost (GLC) and First Detect Fist Reserve (FDFR) to enhance the energy consumption for the UAV path planning. The robustness of OPP algorithm was evaluated in a 3D environment using multiple flying Parrot AR drones. Experimental results demonstrated that OPP algorithm outperforms original GLC and FDFR heuristics in terms of energy efficiency.

In the work of Silva et al. [94], Greedy heuristic (GH) algorithm was proposed for solving the UAV path planning problem. The performance of GH algorithm was validated in a 2D environment under critical situations in comparison with GA and Multi-Population GA (MPGA). Experimental results demonstrated that GH outperforms GA and MPGA of path length and execution time.

4.2.4 Others

Fritas et al. [95] proposed Lin–Kernighan heuristic (LKH) algorithm for improving the UAV path planning in biological pest control applications. Authors evaluated LKH algorithm in 3 non-convex areas in comparison with Ant Colony Optimization (ACO) [108] and Guided Local Search (GLS) [109] algorithms. Experimental results proved that LKH algorithm outperforms ACO and GLS algorithms in terms of path length optimization, cost-efficiency, and time-execution.

In their proposal, De Filippis et al. [96] developed a novel heuristic approach as an extension of A* algorithm, called Theta* algorithm, for optimizing the UAV path planning problem in a 3D environment. The effectiveness of Theta* algorithm was evaluated in both urban and highlands areas with different shapes of obstacles. Compared to A* algorithm, experimental results proved the superiority of Theta* algorithm in terms of path length optimization and constraints handling.

4.2.5 Analysis

Several heuristic algorithms were proposed to overcome the drawbacks of classical approaches and bring some improvements for solving the UAV path planning problem. The strengths and weaknesses of each of them are summarized in Table 11.

A* algorithm is the popular and the most widely used heuristic algorithm for solving the UAV path planning (as shown in Fig. 9). It takes into account the path quality in terms of length and reduces the time complexity of the UAV path planning problem. Moreover, it provides the optimal path with fast convergence. However, this approach presents some weaknesses in handling multi-objective UAV path planning, especially in dynamic environments. To address this issue, BLP approach is applied. It can successfully solve the multi-objective UAV path planning by assigning to each level a single objective. Nevertheless, it is limited in case of multi-UAVs path planning. LKH and GH are two effective heuristic algorithms applied for handling the UAV path planning problem thanks to their simple and easy implementation. Despite that, both algorithms suffer from high

Table 11 Advantages and shortcoming of Heuristic algorithms used in UAV path planning

Algorithm	Advantages	Shortcoming
A*	Short path generation Low time complexity Near-optimal solutions Fast convergence	Not appropriate for multi-objective UAV path planning optimization Inefficient in dynamic environments
BLP	Optimal approach Appropriate for multi-objective UAV path planning problem	No suitable in multi-UAVs environments
GH	Simple and easy implementation Fast convergence	Optimal solution not guaranteed High computational time
LKH	Intelligent optimization approach Near-optimal solutions	High computational time
Theta*	Short path generation Low time complexity in static environments Low computational time	Not appropriate for dynamic environment and sudden obstacles

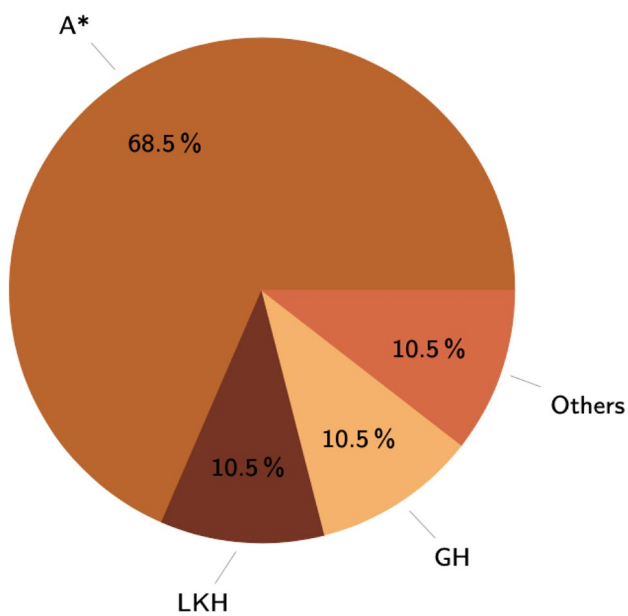

Fig. 9 Heuristic approaches for UAV path planning

computational time. To reduce it, Theta* algorithm is introduced. This algorithm provides the shortest path, even if it presents some lacks in dynamic environments.

4.3 Meta-heuristics

Meta-heuristic algorithms are widely used for optimizing the UAV path planning as shown in Fig. 10 and Table 12. They are divided into two main categories: single-based and population-based approaches. In the single-based category, only Tabu Search algorithm [110] was explored on the studied area. However, several approaches from the population-based category were applied as we can see below.

4.3.1 Single-Based Approaches

Du et al. [111] presented a modified Tabu search algorithm based on the integration of Nawaz-Enscore-Ham (NEH) method [190] into Tabu Search for solving the multiple UAVs path planning problem. This algorithm did undergo three different scenarios using 2, 4, and 8 UAVs for each scenario, respectively. Simulation results proved the superiority of the proposed algorithm compared to ABC [191], ACO [192], ASTS [193], Greedy [194], POMDP [195], PSO-GA [196] , and RHC [197] in terms of time efficiency.

4.3.2 Population-Based Approaches

(A) Evolutionary based

In their proposal, Brintaki and Nikolos [112] suggested Differential Evolution algorithm (DE) [198] for solving the multi-UAVs path planning problem. The efficiency of DE algorithm was assessed in a maritime environment with the presence of 3 flying UAVs and multiple islands. Simulation results demonstrated that DE algorithm provides an optimal and safe path in a reasonable traveling time.

An improved Non-dominated Sorting Genetic Algorithm (NSGA-II) based on the introduction of B-spline method into NSGA-II [199] for solving the UAV path planning problem was proposed by Mittal and Deb [113]. The robustness of the improved NSGA-II algorithm was validated in a complex environment using mountains as obstacles. Simulation results demonstrated the superiority of the improved NSGA-II algorithm compared to NSGA-II in terms of path length optimization and collision avoidance.

Roberge et al. [114] used GA for solving the fixed-wing UAV path planning problem. The effectiveness of GA was validated in 2 fictive and 6 real complex maps and results

Table 12 Summary of meta-heuristic approaches for UAV path planning

Algorithm	Authors	Year	Environment	Multi-UAVs	Results
Modified Tabu Search	Du et al. [111]	2019	Dynamic	Yes	Efficiency of Modified Tabu Search compared to ABC, ACO, ASTS, Greedy, POMDP, PSO-GA, and RHC in terms of detection time.
DE	Brintaki and Nikolos [112]	2005	Dynamic	Yes	DE algorithm achieves better results in terms of path length and travelling time.
NSGA-II	Mittal and deb [113]	2007	Static	No	Effectiveness of NSGA-II algorithm in terms of short and safe path generation.
GA	Roberge et al. [114]	2012	Static	No	GA algorithm achieves better results compared to PSO algorithm in terms of path optimization, computational time, and cost-efficiency.
mDELC	Zhang et al.[115]	2015	Static	No	mDELC outperforms ABC, CPSO, DELC, SADE, and ϵDE by providing the shortest path.
GA-LRO	Li et al. [116]	2016	Static	No	Superiority of GA-LRO compared to A* and GA by obtaining the Shortest path.
FA-DE	Adhikari et al. [117]	2017	Static	No	Efficiency of FA-DE algorithm compared to DE in term of path cost.
Modified GA	Fu et al. [118]	2018	Static	No	Superiority of Modified GA compared to GA and PSO in terms of energy consumption, cost optimization, and path length.
GA+MILP	Dai et al. [119]	2018	Dynamic	Yes	GA+MILP gives better performance compared to ACO in terms of energy consumption and path cost.
NBGA	Xiao et al. [120]	2019	Dynamic	Yes	Efficiency of NBGA compared to CBGA by giving the shortest path.
HR-MAGA	Yang et al. [121]	2020	Static	No	Robustness of HR-MAGA compared to GA and P-MAGA in terms of path length and execution time.
Multi-objective GA SICQ SIC+	Hayat et al. [122]	2020	Dynamic	Yes	SICQ and SIC+ give best results compared to SH and SHC in terms of coverage, connectivity, and missing time.
DE	Chawra and Gupta [123]	2020	Static	No	DE provides competitive results compared to GA and NSGA-II in terms of path length and travelling time.
PSO	Sujit and beard [124]	2009	Dynamic	Yes	PSO provides an optimal path in short execution time
ACO	Zhang et al. [125]	2010	Static	No	ACO gives an optimal and safe path
θ-QPSO	Fu et al. [126]	2011	Static	No	Efficiency of θ-QPSO compated to DE, GA, θ-PSO, PSO, and QPSO in terms of path length and execution time.
Improved PSO	Liu et al. [127]	2016	Static	No	Superiority of Improved PSO compared to FA, GA and PSO in terms of path length.
Multi-colony ACO	Cekmez et al. [128]	2016	Static	No	Effectiveness of Multi-colony ACO compared to ACO algorithm in terms of path optimization.
DAALO	Yao and wang [129]	2017	Static	No	Efficiency of DAALO compared to ABC, ALO, GA, and PSO in terms of path length.
Hybrid PSO	Wu et al. [130]	2017	Static	No	Superiority of hybrid PSO by obtaining shortest and smooth path.
MWPS	Yongbo et al. [131]	2017	Static	No	Efficiency of MWPS compared to GA, RS and WPS in terms of path length and path cost.
GBPSO	Huang and Fei [132]	2018	Static	No	GBPSO gives competitive performance compared to CPSO, DE, QPSO, PSO and PSOPC by providing low execution time, low path cost, and shortest path.
IABC	Tian et al. [133]	2018	Dynamic	Yes	Robustness of IABC compared to ACO by obtaining Low execution time, Low path cost, and shortest path.
IWOA	Wu el al. [134]	2018	Static	No	IWOA achieves better performance in terms of path cost and energy consumption.
θ-MAFOA	Zhang et al. [135]	2018	Static	No	Robustness of θ-MAFOA compared to ABC, FOA, ICA, IFFO, MFOA, and PSO in terms of path length and path cost.

Table 12 (continued)

Algorithm	Authors	Year	Environment	Multi-UAVs	Results
GSO	Pandey et al. [136]	2018	Static	No	Robustness of GSO compared to BBO, DIJIKSTRA, IBA and PSO in terms of path length, path cost, and energy optimization.
GSO	Goal et al. [137]	2018	Dynamic	No	GSO gives competitive results in terms of execution time and path cost.
SCPIO	Zhang et al. [138]	2018	Dynamic	Yes	The superiority of SCPIO compared to PIO and PSO by obtaining the shortest path in less execution time.
IIWD	Sun et al. [139]	2018	Static	No	IIWD has better performance compared to IWD in term of optimal path length
Modified PSO	Muliawan et al. [140]	2019	Dynamic	No	Modified PSO gives competitive results in terms of path length.
GWO	Dewangan et al. [141]	2019	Dynamic	Yes	Superiority of GWO algorithm compared to A*,BBO, Dijikstra, D*, GSO, IBA, PSO, SCA, and WOA in terms of path length, cost efficiency, and execution time.
TLP-COA	Cai et al. [142]	2019	Dynamic	No	Effectiveness of TLP-COA compared to PSO and RRT in terms of path length and execution time.
SHA	Zhang et al. [143]	2019	Static	No	Robustness of SHA compared to ACO in terms of path length and execution time.
GEDGWO	Wang et al. [144]	2019	Dynamic	Yes	GEDGWO achieves better performance compared to HBBOG [145], LGWO [146], RWGWO [147], MC-SHADE [148], BLPSO [149], IABC [150], and CETMS [151] in terms of path length and path cost.
AS-N	Yue and chen [152]	2019	Dynamic	Yes	Efficiency of AS-N compared to GA, MMAS, and PSO in terms of path length and execution time.
MACO	Li et al. [153]	2019	Dynamic	Yes	MACO gives competitive results compared to improved ACO [154] algorithm in terms of path length and path cost.
CIPSO	Shao et al. [155]	2020	Dynamic	Yes	Efficiency of CIPSO compared to CBPSO [156], LCPSO [156], LVPSO [156], MGA [157], PMPSO [127] and PSO in terms of path length and execution time.
Improved PSO	Liu et al. [158]	2019	Dynamic	Yes	Robustness of Improved PSO compared to A*, AO* [159], and Tau [160] in terms of path length, execution time and cost optimization .
MP-CGWO	Yang et al. [161]	2020	Dynamic	Yes	MP-CGWO has better performance compared to DE, GWO, and PSO in term of path length, execution time and cost optimization.
SPSO	Phung and Ha [162]	2021	Static	No	SPSO outperforms GA, DE, ABC, PSO, QPSO [163] and θ-PSO [164] in terms of path length, path cost, and execution time.
IBA	Zhou et al. [165]	2021	Static	No	IBA gives competitive results compared to ABC, BA, BA-ABC [166], BAM [167], GFACO [168] and IABC [169] in terms of short path length and execution time
MCFO	Chen et al. [170]	2016	Static	No	Robustness of MCFO compared to CFO [171], FA, GA, PSO, and RS [172] in terms of path cost and path length.
MVO	Kumar et al. [173]	2018	Dynamic	Yes	MVO achieves better performance compared to ALO, DA [174], GWO, MFO [175] and WOA in terms of execution time and path length.
Modified MVO	Jain et al. [176]	2019	Dynamic	Yes	Superiority of Modified MVO compared to BBO and GSO in term of path length and path cost.
Plant Grow algorithm (PGA)	Zhou et al. [177]	2021	Static	No	MHS gives better results in terms of execution time compared to A* and RRT. For path length, it is similar to the one generated by A*
Neighborhood global learning based Flower Pollination Algorithm	Chen et al. [178]	2021	Static	No	NGFPA outperforms others algorithms [61, 63, 97] in terms of path cost and smoothness

Table 12 (continued)

Algorithm	Authors	Year	Environment	Multi-UAVs	Results
Mixed-Strategy Based Gravitational Search Algorithm (MSGSA)	Xie et al. [181]	2021	Static	No	Effectiveness of MSGSA compared to GSA [182], GGSA [183], and PSOGSA [184] in terms of path length
Modified FWA	Alihodzic et al [185]	2016	Static	No	Modified FWA achieves better performance compared to BA [186], CS [187], DE, and PSO in terms of execution time and path cost.
MHS	Wu et al. [188]	2017	Dynamic	Yes	MHS gives competitive results in terms of path length.
MHS	Binol et al. [189]	2018	Dynamic	Yes	Effectiveness of MHS compared to GA in terms of path length, path cost, and execution time.

showed that GA provides better performance compared to PSO algorithm in terms of path length and fuel consumption.

Authors in [115], presented a novel approach, called improved Differential Evolution (mDELC), based on the integration of improved Level Comparison strategy into Differential Evolution algorithm. The robustness of mDELC algorithm was validated in a 3D environment using as threats different non-flying zones including Anti-aircraft gun, forbidden cubic, radars cylindrical, and missiles cylindrical zones.

Li et al. [116] proposed a path planning technique, called Genetic Algorithm-Local Rolling Optimization (GA-LRO), based on the introduction of Local rolling mechanism into GA and for optimizing the UAV path planning. GA-LRO used GA for global path planning and Local rolling Optimization for cost optimization. The performance of GA-LRO algorithm was tested in a complex environment using multiple static obstacles with different shapes. Test results demonstrated the effectiveness of GA-LRO algorithm compared to GA and A* in terms of vertexes and overall distance.

Adhikari et al. [117] suggested a Fuzzy Adaptive Differential Evolution algorithm (FA-DE) based on the integration of Fuzzy logic mechanism [200] into Differential Evolution for solving the UAV path planning problem. The performance of FA-DE was evaluated in a 3D complex environment using 8 different obstacles. Simulation results proved the efficiency of FA-DE algorithm compared to two modified DE algorithms presented in [117] in terms of cost optimization and convergence rate.

Authors in [118] developed an improved GA algorithm for optimizing the UAV path planning. The robustness of the improved GA was evaluated using DJI GO M100 UAV inside a 2D static area with multiple obstacles. Experimental results showed that the improved algorithm outperforms PSO and GA algorithms in terms of cost optimization, path length, energy consumption, and handling of turning angles.

A novel approach based on the integration of Mixed Integer Linear Programming (MILP) into GA algorithm for improving the UAV path planning in a complex environment was proposed by Dai et al. [119]. The effectiveness of the proposed method was validated in a 3D urban and mountain area using 2, 5, and 7 UAVs respectively. Experimental results demonstrated the superiority of the proposed method compared to ACO and GA in terms of cost efficiency and energy optimization environment.

A novel approach, called Neighborhood Based Genetic Algorithm (NBGA), was proposed by Xiao et al. [120] for solving multi-UAVs dynamic path planning and UAV/UGV coordination. The performance of NBGA was validated in a 2D study area with 1 flying UAV, 2 target points, and 2 UGVs moving at each point. Experimental results demonstrated that NBGA provides an optimal path length in comparison with Center Based Genetic Algorithm [201].

Yang et al. [121] developed a Hierarchical Recursive-Multi Agent Genetic Algorithm (HR-MAGA) for solving the UAV path planning problem. The performance of HR-MAGA algorithm was validated in a 3D complex environment using 4 maps with 3 obstacles at each map. Simulation results showed that HR-MAGA outperforms GA and PSO-GA [114] in terms of convergence speed, path generation, stability, and time-efficiency.

In the work of Hayat et al. [122], authors proposed two approaches, called Simultaneous Inform and Connect with QoS (SICQ) and SIC following QoS (SIC+) algorithms, for optimizing the UAV path planning. The performance of SICQ and SIC+ strategies was evaluated in a simple environment using one base station with different flying UAVs. Test results proved that SIC+ outperforms SICQ in terms of informative time and coverage.

Chawra and Gupta [123] suggested DE algorithm for optimizing multi-UAVs path planning for data collection in cluster-based Wireless Sensor Network. The effectiveness of DE algorithm was validated in 4 regions with the presence of one Base Station (BS) and one flying UAV at each region. Experimental results demonstrated that DE algorithm outperforms GA and NSGA-II algorithms in terms of traveling time and path length optimization.

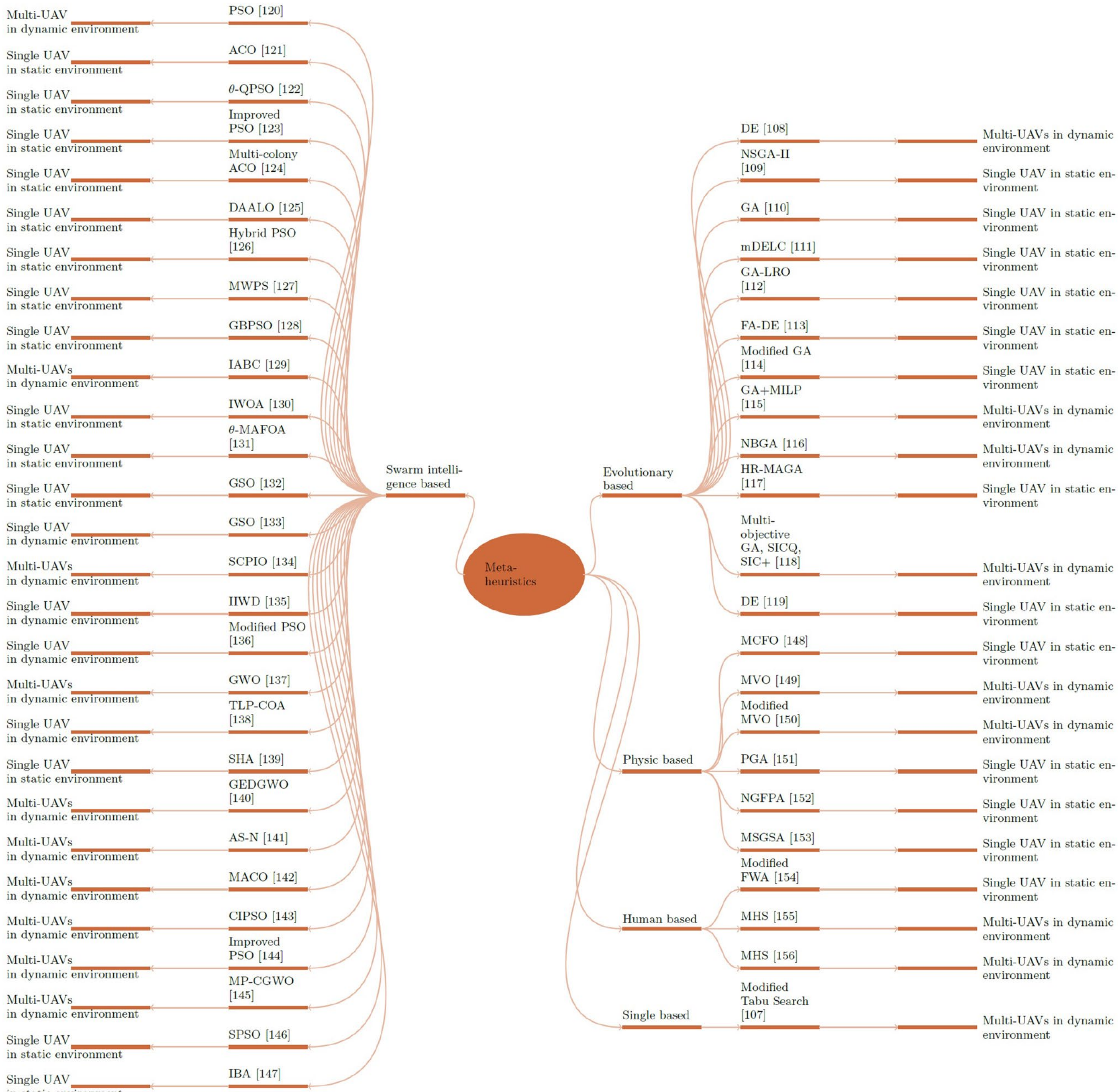

Fig. 10 Meta-heuristics for UAV path planning

(B) Swarm Intelligence based

Fu et al. [126] presented a novel variant of Particle Swarm Optimization called Phase-encoded Quantum Particle Swarm Optimization algorithm (θ-QPSO) based on the combination of Phase-encoded PSO (θ-PSO) [164] and Quantum PSO (QPSO) [202] for solving the UAV path planning problem. The performance of θ-QPSO was running in a 3D static environment and validated in 2 different experiences using 4 and 5 spherical obstacles in each experience. Simulation results proved the efficiency of θ-QPSO compared to DE, GA, θ-PSO, PSO, and QPSO in terms of path optimization and execution time.

In the work of Liu et al. [127], authors proposed an improved Particle Swarm Optimization (PSO) algorithm based on the introduction of Adaptive Sensitive Decision into PSO algorithm for solving the UAV path planning problem in a 3D static environment. The effectiveness of the improved PSO algorithm was evaluated in 2 study experiences. In the first one, Experiments were performed using 5 cylindrical obstacles and 4 mountains. in the second one, 9 obstacles and 4 mountains were distributed on the map.

Simulation results demonstrated that the improved PSO algorithm outperforms GA, PSO, and FA [203] algorithms in terms of path cost and path generation.

Cekmez et al. [128] suggested a Multi-Colony Ant Colony Optimization (Multi-colony ACO) algorithm, for solving the UAV path planning problem. The effectiveness of Multi-colony ACO algorithm was evaluated in a static environment with 4 circular threats. Experimental results demonstrated that Multi-colony ACO algorithm outperforms the traditional ACO algorithm in terms of optimized path selection and collision-free path.

Yao and wang [129] proposed an improved Ant Lion Optimizer, called, Dynamic Adaptive Ant Lion Optimizer (DAALO), for solving the UAV path planning problem. The robustness of DAALO algorithm was assessed in a 2D environment based on 2 experiences with 9 circles obstacles and 14 rectangular obstacles, respectively. Simulation results showed the effectiveness of DAALO algorithm compared to GA, PSO, ABC [204], and ALO [205] in terms of convergence speed, path length optimization, and path cost efficiency.

Wu et al. [130] proposed a modified PSO algorithm based on PSO and Bezier curves model for optimizing the real-time UAV path planning. The effectiveness of the modified PSO was evaluated in a 3D complex urban area using Firefly Hexacopter without any previous awareness of the environment. Simulation results showed that the modified PSO algorithm provides a collision-free and smooth path in a reasonable computational time.

Yongbo et al. [131] proposed a Modified Wolf Pack Search (MWPS) algorithm for solving the 3D UAV path planning problem. The performance of MWPS was validated in 3D fake and real environments using fixed-wing and rotor wings UAV flying. Experimental results showed that MWPS algorithm outperforms GA, RS [172] and WPS [131] in terms of cost-efficiency and computational time.

Huang and Fei [132] developed a Global Best Particle Swarm Optimization (GBPSO) algorithm for solving the fixed-wing UAV path planning problem. The performance of GBPSO algorithm was evaluated in a 3D complex environment based on 2 experiences using 7 obstacles in the first experience and 18 obstacles in the second one. In comparison with PSO, modified versions of PSO [149–207], and DE, GBPSO gives better results in terms of convergence speed, cost-efficiency, execution time, and path length optimization.

Tian et al. [133] suggested an Improved Artificial Bee Colony (IABC) algorithm for Multi-UAVs dynamic tracking planning. The performance of IABC algorithm was tested in a 2D environment using Quad-Rotor UAVs with static and dynamic obstacles. Test results showed that IABC algorithm outperforms ACO algorithm in terms of path length optimization, execution time, and path cost-efficiency.

Wu el al. [134] suggested an Improved Whale Optimization Algorithm (IWOA) and Restrained Interfered Fluid Dynamic System (RIFDS) for solving the UAV path planning problem. The performance of IWAO was evaluated in a 3D static urban environment using 5 cubic and 6 cylindrical static obstacles. Simulation results showed that IWOA algorithm outperforms WOA [208], GWO, GSA [182], and PSO in terms of path generation and energy consumption.

An approach called, θ-Mutation Adaptation Fruit Fly Optimization Algorithm (θ-MAFOA) was proposed by Zhang et al. [135], which is based on the integration of mutation adaptation mechanism and phase angle-based encoded strategy into Fruit Fly Optimization Algorithm (FOA) for solving the UAV path planning problem. The effectiveness of θ-MAFOA was validated in a 3D static environment taking into account 3 constraints including the climbing/Descend angle, UAV's axes, and obstacles.

In [136], Pandey et al. proposed a path planning approach based on Glowworm Swarm Optimization (GSO) [209] solving the UAV path planning problem. The performance of GSO algorithm was evaluated in 2D and 3D environments using 3 space areas.

Goal et al. [137] developed a path planning technique based on GSO algorithm for solving the UAV path planning in a 3D dynamic environment. The performance of the proposed GSO was tested using 3D static obstacles, 3D random static obstacles, and 3D dynamic moving obstacles. Simulation results demonstrated the effectiveness of GSO algorithm in terms of cost and time efficiency in a 3D dynamic environment.

Zhang et al. [138] presented a novel bio-inspired technique, called Social-Class Pigeon Inspired Optimization (SCPIO) algorithm, for optimizing multi-UAVs coordination and path planning. The robustness of SCPIO was validated in a 3D dynamic study area with the presence of 5 UAVs and 8 static threats. In another work, Sun et al. [139] proposed an Improved Intelligent Water Drop Algorithm (IIWD) for solving the UAV path planning problem. The performance of IIWD algorithm was evaluated in a 2D simulation environment using 4 different grid maps with complex obstacles. Simulation results proved the effectiveness of IIWD algorithm compared to the traditional IWD [210] algorithm in terms of path cost optimization and processing stability.

In the work of Muliawan et al. [140], an improved PSO algorithm was proposed for optimizing the UAV path planning in autonomous Spraying Task application. The robustness of the improved PSO was tested in a 2D environment in 3 experiences with 8, 10, and 12 areas, respectively. Simulation results showed the performance of the improved PSO algorithm in terms of path length and cost-efficiency.

Dewangan et al. [141] used Grey Wolf Optimizer (GWO) algorithm for solving the multiple UAVs path planning problem in a 3D complex environment. The performance of GWO algorithm was tested using 3 different maps, with the presence of 7 obstacles in the first map, 8 obstacles in the second map, and 16 obstacles in the last map. Simulation results demonstrated that GWO algorithm outperforms Dijkstra, A*,D*, PSO, IBA [211], SCA [212],BBO, GSO, and WOA algorithms in terms of computation time and trajectory cost.

Cai et al. [142] proposed a Tri Level Programming-Cognitive behavior Optimization Algorithm (TLP-COA) hybridizing COA [213] and TLP solution for solving the real-time UAV path planning problem. The effectiveness of TLP-COA algorithm was assessed in a 3D complex environment using 10 static obstacles and one emergent threat. Experimental results proved the superiority of TLP-COA compared to RRT and PSO in terms of trajectory path and planning time. In another work, a Self-Heuristic Ant was proposed by Zhang et al. [143], which is based on Ant-Colony Optimization for solving the UAV path planning problem. The performance of the presented SHA algorithm was assessed in a 3D environment using U-type static obstacles in 3 different maps.

In another work, Wang et al. [144] suggested an improved Grey Wolf Optimization (GWO), called Gaussian Estimation of Distribution Grey Wolf Optimizer (GEDGWO), based on the integration of Gaussian Estimation of Distribution (GED) strategy into GWO for solving the multi-UAV multi-target urban tracking problem. The performance of GEDGWO algorithm was validated in tracking mission 3D environment using 7 cylindrical obstacles and 4 flying UAVs.

Yue and chen [152] proposed a hybrid approach, called ant colony algorithm with punitive measures (AS-N) based on the integration of penalty strategy on Ant Colony Optimization Algorithm for optimizing the UAV path planning. The efficacy of AS-N algorithm was evaluated in a 2D environment with the presence of static and dynamic obstacles. Simulation results demonstrated that AS-N algorithm outperforms Min Max Ant System (MMAS) [152], GA, and PSO in terms of path generation and time optimization. In a similar work, Li et al. [153] developed a novel approach, termed Modified Ant Colony Optimization (MACO), which joined metropolis criterion to ACO algorithm for multi-UAVs path planning. The robustness of MACO was assessed in a 2D grid map with the presence of 7 static obstacles and 3 UAVs.

Shao et al. [155] suggested a Comprehensively Improved PSO (CIPSO) algorithm for solving Multi-UAVs path planning problem. The robustness of CIPSO algorithm was tested in a 3D dynamic environment using 10 UAVs and 3 static obstacles. In another work, Liu et al. [158] presented a modified PSO algorithm based on the introduction of Spatial Refined Voting Mechanism into PSO for solving multi-UAVs path planning problem. The performance of the modified PSO was evaluated in a 3D environment based on 4 experiences. In the first one, 2 UAVs and 5 static obstacles were used. The second experience deployed 4 UAVs with 5 obstacles. In the third one, 7 obstacles were randomly distributed with the presence of 2 UAVs. In the last one, 4 UAVs and 7 obstacles were used. Experimental results demonstrated the superiority of the modified PSO algorithm compared to A*, AND/OR star algorithm, and Tau [160] in terms of path generation, execution time, and dynamic threat avoidance.

Yang et al. [161] proposed an improved GWO algorithm, called Multi Population-Chaotic GWO (MP-CGWO), for solving the multi-UAVs path planning problem. The effectiveness of MP-CGWO was tested in a 3D environment based on 2 experiences. In the first experience, 3 moving UAVs and 6 mountains were used. In the second one, 6 UAVs and 6 mountains were used. Experimental results showed that MP-CGWO outperforms PSO, DE, and GWO algorithms in terms of convergence speed and path cost efficiency.

(III) Physic-based techniques

Chen et al. [170] developed a Modified Central Force Optimization (MCFO) algorithm for solving the UAV path planning problem. The performance of the MCFO algorithm was simulated in 3D static and complex environments using 6 obstacles. Similarly, Kumar et al. [173] proposed a Multi-Verse Optimizer (MVO) algorithm for enhancing the Quality of Service (QoS) in the UAV path planning. The performance of MVO algorithm was assessed in 6 different cases, inside a 2D grid map, in the first case, 2 moving UAVs having the same priority were presented, in the second case, the two UAVs had different priorities, in the third case, a circular obstacle was added to the first case, in the fourth case, 2 circular obstacle and 2 UAVs with different priorities were presented, in the fifth case, 3 UAVs with different priorities were flying without obstacles in the area, in the last case, the area had 2 UAVs with the same priority, another UAV with different priority, and 2 obstacles. Simulation results proved that MVO outperforms GWO, WOA, DA [174], ALO, and MFO [175] algorithms in terms of running time, convergence speed, and path length.

In their proposal, Jain et al. [176] proposed a modified MVO algorithm for solving the UAV path planning problem. The performance of the modified MVO algorithm was tested in a complex environment in cases of single UAV and multiple UAVs. Test results showed that the modified MVO algorithm gives better performance compared to Glowworm Swarm Optimization (GSO) and Bio-geography-based optimization (BBO) in terms of path length and path cost. It is also shown that the time-execution of the modified MVO is higher compared to BBO in the case of a single UAV, and closer in the case of multiple UAVs.

(IV) Human based

Authors in [185] proposed a Modified Firework Algorithm (FWA) based on the introduction of new feasibility rules into FWA for solving the UAV path planning problem. The performance of the modified FWA was tested in a 2D environment with 8 distributed obstacles. Simulation results demonstrated the superiority of the modified FWA compared to a number of BA [186], CS [187], DE, and PSO in terms of path cost optimization and execution time.

Wu et al. [188] developed an improved path planning algorithm, called Modified Harmony Search algorithm (MHS), based on the integration of Pythagorean Hodograph (PH) curve into Harmony Search algorithm for optimizing the multiple UAVs path planning. The performance of MHS was tested in a 3D urban area with 6 complex obstacles and 2 UAVs. Simulation results demonstrated the robustness of MHS algorithm in terms of collision avoidance and path length optimization.

In the work of Binol et al. [189], authors presented a modified Harmony Search algorithm for solving multi-UAVs path planning problem. The performance of the modified Harmony Search algorithm was validated using 2 experiences. The first one used 2 UAVs and 5 Road-Site Unit (RSU), while the second one used 3 UAVs and 28 RSU. Experimental results showed that the modified HS performs better than GA in terms of path cost, execution time, and convergence rate (Table 13).

4.3.3 Analysis

As presented in this section, several meta-heuristics are proposed for solving the UAV path planning problem. Each of them present some strengths and weaknesses as shown in Table 14.

Single solution meta-heuristic algorithms are easy and simple to implement in the UAV path planning. They provide good results in terms of time optimization in both static and dynamic environments. Despite that, these algorithms are not widely used, because the optimal path is not guaranteed due to their stagnation in local optima. On the other hand, several classes of population-based meta-heuristics are proposed including evolutionary-based, Swarm-based, physic-based, and human-based. Swarm-based algorithms are the most applied methods in UAV path planning as shown in Fig. 11. They are characterized by their fast convergence and solution generation providing optimal paths in both static and dynamic environments. Human and physic-based algorithms are two other classes of population-based meta-heuristics which are not widely used in the UAV path planning due to their high time complexity.

4.4 Machine Learning Techniques

Various machine learning-based techniques were applied for solving the UAV path planning problem as illustrated in Fig. 12 and summarized in Table 15. These techniques are presented in the following.

4.4.1 Neural Network

Nikolos et al. [214] proposed a Radial Basis Functions Artificial Neural Network (RBF-ANN) algorithm for optimizing the UAV path planning. The robustness of RBF-ANN was evaluated in 4 different scenarios where 3 UAVs were flying near multiple mountains. Simulation results demonstrated that RBF-ANN gives better performance compared to the ordinary DE algorithm in terms of path length, collision avoidance, and execution time.

In the proposal of Wu et al. [215], authors presented an improved Deep Q-Network (DQN) model based on the integration of Lazy training method into the deep Q-network [240] technique for optimizing the UAV path planning. The effectiveness of the improved DQN model was validated in a 2D environment based on 3 scenarios using 9, 27, and 52 obstacles, respectively. Experimental results demonstrated that the improved DQN model outperforms traditional DQN in terms of path length, execution time, and stability.

Yan et al. [216] proposed an improved technique, called Dueling Double Deep Q-networks (D3QN) algorithm, based on deep Q-networks algorithm for optimizing the UAV path planning. The performance of D3QN algorithm was evaluated in a 3D environment based on 3 experiences. In the first experience, 1 UAV and 3 static defense entities were used. In the second and third experiences, 1 UAV and 2 dynamic obstacles were used. Experimental results showed the superiority of D3QN algorithm compared to DDQN and DQN in terms of stability, safe path generation, and threats avoidance.

Shiri et al. [217] proposed a neural network-based Opportunistic Hamilton-Jacobi-Bellman (oHJB) approach for solving the remote UAV online path planning problem. The performance of oHJB was assessed using one base station and one UAV flying at a fixed altitude under wind constraints. Experimental results showed that oHJB gives better performance compared to aHJB and mHJB in terms of path length, traveling time, and energy consumption.

4.4.2 Supervised Learning

Chen et al. [218] presented a novel approach based on Support Vector Machine (SVM) for solving the UAV path

Table 13 The objectives and constraints considered in meta-heuristic approaches

Algorithms	References	Objectives				Constraints					
		Path optimiza-tion	Time efficiency	Collision avoidance	Cost efficiency	Alti-tude	Climb/ Descend angle	Ener-gy	Thre-ats	UAV's axes	Velo-city
Modified Tabu Search	Du et al. [111]		✓	✓		✓			✓	✓	
DE	Brintaki and Nikolos [112]	✓	✓	✓					✓	✓	✓
NSGA-II	Mittal and deb [113]	✓		✓		✓			✓	✓	
GA	Roberge et al. [114]	✓	✓	✓		✓		✓	✓		
mDELC	Zhang et al.[115]	✓		✓		✓	✓		✓	✓	✓
GA-LRO	Li et al. [116]	✓		✓					✓		
FA-DE	Adhikari et al. [117]			✓	✓			✓	✓		
Modified GA	Fu et al. [118]	✓		✓	✓			✓	✓	✓	
GA+MILP	Dai et al. [119]			✓	✓	✓		✓	✓		✓
NBGA	Xiao et al. [120]	✓		✓					✓	✓	✓
HR-MAGA	Yang et al. [121]	✓	✓	✓		✓			✓	✓	
Multi-objective GA SICQ SIC+	Hayat et al. [122]	✓	✓	✓					✓		
DE	Chawra and Gupta [123]	✓	✓	✓					✓		
PSO	Sujit and beard [124]	✓		✓	✓		✓	✓	✓	✓	
ACO	Zhang et al. [125]	✓		✓	✓			✓	✓	✓	
θ-QPSO	Fu et al. [126]	✓	✓	✓		✓	✓		✓	✓	
Improved PSO	Liu et al. [127]	✓		✓					✓	✓	✓
Multi-colony ACO	Cekmez et al. [128]	✓		✓					✓		
DAALO	Yao and wang [129]	✓		✓					✓	✓	
Hybrid PSO	Wu et al. [130]	✓		✓					✓	✓	
MWPS	Yongbo et al. [131]	✓		✓	✓	✓		✓	✓	✓	✓
GBPSO	Huang and Fei [132]	✓	✓	✓	✓			✓	✓		
IABC	Tian et al. [133]	✓	✓	✓	✓			✓	✓		
IWOA	Wu el al. [134]			✓	✓	✓		✓	✓	✓	✓
θ-MAFOA	Zhang et al. [135]	✓		✓	✓	✓	✓		✓	✓	✓
GSO	Pandey et al. [136]	✓		✓	✓	✓		✓	✓	✓	
GSO	Goal et al. [137]		✓	✓	✓	✓		✓	✓		
SCPIO	Zhang et al. [138]	✓	✓	✓					✓	✓	✓
IIWD	Sun et al. [139]	✓		✓	✓				✓	✓	
Modified PSO	Muliawan et al. [140]	✓		✓					✓		

Table 13 (continued)

Algorithms	References	Objectives				Constraints					
		Path optimiza-tion	Time efficiency	Collision avoidance	Cost efficiency	Alti-tude	Climb/ Descend angle	Ener-gy	Thre-ats	UAV's Rotation	Velo-city
GWO	Dewangan et al. [141]	✓	✓	✓	✓				✓		✓
TLP-COA	Cai et al. [142]	✓	✓	✓		✓			✓	✓	
SHA	Zhang et al. [143]	✓	✓	✓		✓	✓		✓	✓	
GEDGWO	Wang et al. [144]	✓		✓					✓	✓	✓
AS-N	Yue and chen [152]	✓	✓	✓					✓		
MACO	Li et al. [153]	✓		✓	✓			✓	✓	✓	
CIPSO	Shao et al. [155]	✓	✓	✓					✓		
Improved PSO	Liu et al. [158]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
MP-CGWO	Yang et al. [161]	✓	✓	✓	✓	✓	✓	✓	✓		✓
SPSO	Phung and Ha [162]	✓	✓	✓	✓	✓	✓	✓	✓	✓	
IBA	Zhou et al. [165]	✓	✓	✓	✓	✓	✓	✓	✓	✓	
MCFO	Chen et al. [170]	✓		✓	✓	✓		✓	✓	✓	✓
MVO	Kumar et al. [173]	✓	✓	✓					✓	✓	✓
Modified MVO	Jain et al. [176]	✓		✓	✓			✓	✓	✓	
Plant Grow algorithm	Zhou et al. [177]	✓	✓	✓				✓	✓		
NGFPA	Chen et al. [178]			✓	✓			✓	✓	✓	
MSGSA	Xie et al. [181]	✓		✓		✓			✓	✓	
Modified FWA	Alihodzic et al. [185]		✓	✓	✓			✓	✓	✓	
MHS	Wu et al. [188]	✓		✓					✓	✓	
MHS	Binol et al. [189]	✓	✓	✓	✓			✓	✓		

Table 14 Advantages and disadvantages of Meta-heuristic algorithms used in UAV path planning

Algorithm	Advantages	Disadvantages
Single based	Efficient in dynamic environment High time efficiency	Optimal path not guaranteed Stagnation in local optima
Evolutionary based	Optimal path Fast convergence High computational efficiency	High time complexity Not appropriate for real time path planning
Swarm Intelligence Based	Speed convergence Fast solution generation High path efficiency	Optimal path not guaranteed Low time efficiency Easy trap to local optima
Human based	Easy implementation Suitable in complex and dynamic environment	High time complexity Easy trap to local optimum
Physic based	Ability to escape local optimum solution Optimal path generation	High time complexity Not appropriate for real time path planning

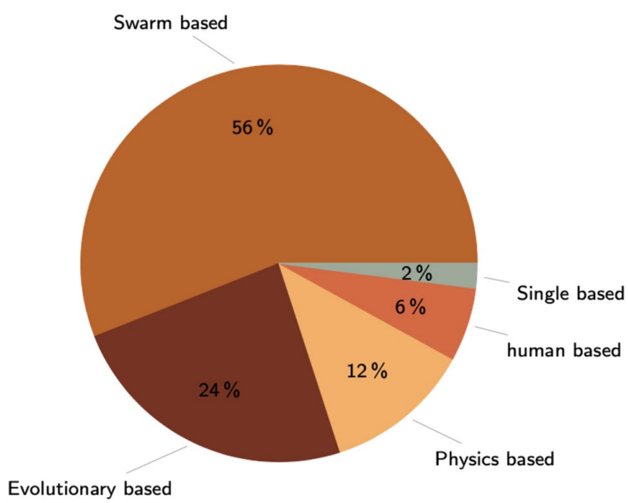

Fig. 11 Meta-heuristic approaches for UAV path planning

planning problem. The robustness of SVM model was evaluated in a 3D complex environment containing multiple mountains and one flying Aircraft UAV. Simulation results demonstrated that SVM generates smooth trajectory and safe path while flying closer to obstacles.

Yoo et al. [219] suggested Gaussian Process (GP) regression for optimizing the UAV path planning. The performance of GP regression algorithm was validated in a 2D environment using 2 UAVs. Experimental results demonstrated that GP regression algorithm gives better performance compared to Kalman Filter model [220] in terms of path length and execution time.

In their proposal, Koo et al. [221] applied the polynomial regression model for optimizing the UAV path planning in data collection mission. The effectiveness of the polynomial regression model was evaluated in a 3D environment with the presence of multiple sensors. According to experimental results, the polynomial regression approach outperforms GE algorithm in terms of path generation with maximum data collection from sensors.

Radmanesh et al. [222] suggested a high-dimensional regression technique with Partial Differential Equation (PDE) for optimizing the multiple UAVs path planning. The proposed technique adopted 3 models for multi-UAVs control including centralized, decentralized, and sequential models. The effectiveness of the proposed technique was evaluated in a dynamic environment based on 3 experiences. In the first experience, 3 UAVs were tested in a 2D-free area. In the second experience, 8 UAVs were distributed in a 2D area with 1 static threat. In the last one, 3 UAVs were used in a 3D complex area. Test results proved that the high-dimensional regression technique gives good performance compared to Mixed Linear Programming (MILP) in terms of path length and execution time.

4.4.3 Reinforcement Learning

Ragi and Chong [223] suggested an improved Partially Observable Markov Decision Process (POMDP) based on the integration of Nominal Belief-state Optimization strategy (NBO) into POMDP approach for optimizing the UAV path planning in a dynamic environment. The performance of the improved POMDP approach was evaluated using multiple UAVs, static targets, moving targets, and obstacles. Experimental results demonstrated that the improved POMDP algorithm provides an optimal path in tracking both static and moving targets in a complex environment.

Zhang et al. [224] developed a novel approach, called Cooperative and Geometric Learning Algorithm (CGLA), for optimizing multiple UAV path planning. The robustness of CGLA algorithm was evaluated in 4 experiences. In the first experience, 1 UAV with 10 obstacles were used. The second one used 2 UAVs and 2 obstacles. In the third experience, 2 UAVs with virtual obstacles were used. The last one used 3 UAVs, and 7 obstacles. Simulation results

Table 15 Summary of machine learning approaches for UAV path planning

Algorithm	Authors (Refs.)	Year	Environment	Multi-UAVs	Results
RBF-ANN	Nikolos et al. [214]	2007	Static	No	Efficiency of RBF-ANN algorithm compared to DE algorithm in terms of path length generation and execution time
Improved DQN	Wu et al. [215]	2017	Static	No	Improved DQN achieves better results compared to DQN in small time
D3QN	Yan et al. [216]	2019	Dynamic	No	Superiority of D3QN compared to DDQN and DQN in optimal path
oHJB	Shiri et al. [217]	2020	Static	No	Robustness of oHJB compared to aHJB and mHJB [217] in terms of path length, energy optimization, and traveling time efficiency
SVM	Chen et al. [218]	2014	Static	No	Effectiveness of SVM in terms of path optimization
GP	Yoo et al. [219]	2017	Dynamic	Yes	GP achieves best communication delay in comparison with Kalman filter [220]
Polynomial Regression	Koo et al. [221]	2018	Static	No	Efficiency of Polynomial Regression compared to GE in terms of data collection and short path length
PDE	Radmanesh et al. [222]	2020	Dynamic	Yes	PDE gives best results compared to MILP in terms of path length and execution time
POMDP	Ragi and Chong [223]	2013	Dynamic	Yes	POMDP achieves best results in terms of path length
CGLA	Zhang et al. [224]	2014	Dynamic	Yes	Effectiveness of CGLA compared to A_{2D} [105], BCV [225] and Q-learning [226] in terms of path length and execution time
ARE	Yijing et al. [227]	2017	Static	No	Superiority of ARE compared to Q-learning in terms of execution time
Deep RL ESN	Challita et al. [228]	2018	Dynamic	Yes	Robustness of Deep RL ESN comparing to SP in terms of time-efficiency and energy optimization
Deep-Sarsa	Luo et al. [229]	2018	Dynamic	Yes	Deep-Sarsa gives good results in terms of safe path generation under dynamic environment
Improved Q-learning	Yan and Xiang [230]	2018	Static	No	Efficiency of Improved Q-learning compared to Q-learning in terms of path length
Q-learning	Zhang et al. [231]	2018	Static	No	Q-learning gives better performance in terms of execution time
MARER Q-learning	Xie et al. [232]	2020	Static	No	Robustness of MARER Q-learning compared to Q-learning in terms of path length and path cost
RQ-ADSA-DRQN	Xie et al. [233]	2021	Dynamic	No	Robustness of RQ-ADSA-DRQN compared to DQN [234] and DRQN [235] in terms of path length, path cost and execution time
MLQN	Cui and Wang [236]	2021	Dynamic	Yes	Superiority of MLQN compared to Q-Learning in terms of path length
Modified SOM	Pierre et al. [237]	2020	Static	No	Modified SOM achieves competitive results in terms of optimal path generation
DBSCAN	Choi et al. [238]	2017	Dynamic	No	Superiority of DBSCAN compared to one-layer DBSCAN [239] in terms of energy efficiency and execution time

demonstrated that CGLA outperforms to A_{2D} [105], BCV [225] and Q-learning [226] in terms of path length optimization, execution time, and collision risks.

Yijing et al. [227] proposed an Adaptive and Random Exploration (ARE) approach based on Q-learning algorithm for optimizing the UAV path planning. The effectiveness of ARE algorithm was evaluated in 4 different experiences. The first one contained multi-obstacle arrays. Collateral walls were used in the second experience. In the third experience, multi-wall traps were used. In the last one, mixed obstacles were distributed in a 2D environment. Simulation results showed that ARE algorithm generates an optimal path in real-time planning compared to the traditional Q-learning algorithm.

Authors in [228] presented a Deep Reinforcement Learning Echo State Network (Deep-RL-ESN) model based on the integration of Deep ESN (DESN) into RL algorithm for solving the multi-UAVs online path planning. The performance of Deep-RL-ESN model was validated in a 2D environment using 5 UAVs and 15 Base Stations. Experimental

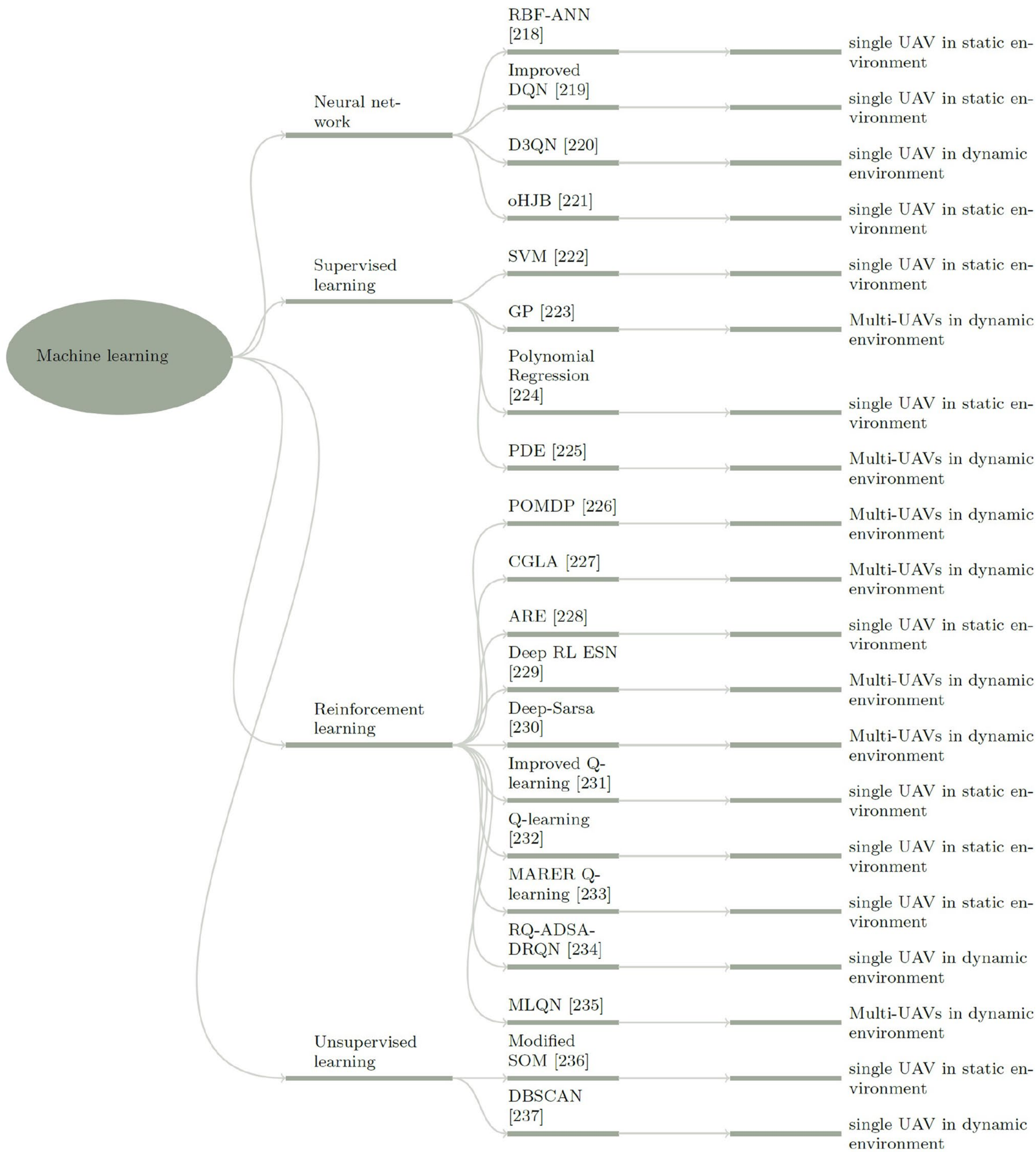

Fig. 12 Machine learning approaches for UAV path planning

results demonstrated that Deep-RL-ESN model outperforms the shortest path algorithm in terms of path, length, and energy consumption.

Luo et al. [229] suggested Deep-State action reward state action (Deep-Sarsa) algorithm based on the reinforcement Deep-Sarsa learning approach for optimizing the UAV path planning. The effectiveness of Deep-Sarsa algorithm was assessed in a 3D dynamic environment using 4 UAVs and 1 static obstacle. Simulation results proved that Deep-Sarsa algorithm provides a collision-free path in the case of multiple UAVs cooperation.

Yan and Xiang [230] proposed an enhanced Q-learning algorithm based on the integration of ε-greedy and Boltzmann approaches into the Q-learning algorithm for solving the UAV path planning problem. The performance of the improved Q-learning algorithm was evaluated in a 2D environment with the presence of 3 circular obstacles. Experimental results demonstrated that the improved Q-learning algorithm provides the shortest path and generates minimum steps to reach the target compared to the original Q-learning technique.

In their proposal, Zhang et al. [231] suggested a novel approach based on the integration of state machine and differential-equation models into Q-learning algorithm for optimizing the QuadRotor UAV path planning. The robustness of the proposed algorithm was validated in a 2D complex environment where the UAV hovered at a fixed height. Simulation results revealed that the proposed algorithm ensures a collision-free path and optimizes the iteration number to join the target point.

In the work of Xie et al. [232], authors developed an improved Q-learning algorithm, called MARER Q-learning, based on the integration of Experience Relay function into the Q-learning algorithm for solving the UAV path planning problem. The effectiveness of MARER Q-learning algorithm was validated in a 3D environment using mountains with different heights as obstacles. Simulation results proved that MARER Q-learning algorithm outperforms the ordinary Q-learning algorithm in terms of path generation, computational cost, and convergence speed.

4.4.4 Unsupervised Learning

In the proposal of Pierre et al. [237], authors proposed an improved Kohenen's Self-Organizing Map (SOM) technique based on the hybridization of competitive learning and particle physics for optimizing the UAV path planning. The performance of the improved SOM algorithm was assessed in a 3D study environment in 3 scenarios. In the first one, one UAV was used in a free area. In the second one, 4 obstacles were distributed randomly on the map. In the last one, 5 obstacles were used with different characteristics. Experimental results demonstrated that the improved SOM can successfully avoid obstacles and overcomes local minimum problems.

Choi et al. [238] presented Two-layer approaches based on clustering and Predictive Control models for optimizing the fixed-wing UAV path planning. The performance of Two-layer approaches was assessed in a 3D environment using 1 aircraft UAV and 3 obstacles. Test results showed that Two-layer approaches provide better results compared to one-layer approach [239] in terms of optimal path, execution time, energy efficiency, and dynamic obstacle avoidance (Table 16).

4.4.5 Analysis

As presented before, several approaches based on machine learning were proposed for UAV path planning. The advantages and disadvantages of each of them are summarized in Table 17.

Neural Network is one of the first machine learning techniques used for solving the UAV path planning problem. It is suitable for dynamic environments and demonstrates its ability to handle multi-objective path planning while providing good solutions with fast convergence. However, it suffers from high computational complexity that increases as long as the complexity of the environment increases. To overcome this issue, the supervised learning algorithm is introduced. It reduces the complexity of the UAV path planning problem and offers better solutions. However, its efficiency is low for large datasets with long processing time. On the other hand, as we can see in Fig. 13 that reinforcement learning-based techniques are the widely used for optimizing the UAV path planning under multiple constraints, especially UAV's axes. Nevertheless, they are greedy in terms of memory and energy consumption. One of the solutions to deal with that is the use of unsupervised learning-based techniques. In fact, they are more efficient in optimizing the energy consumption in uncertain environments. Though, like all machine learning algorithms, they also suffer from long processing time, especially in real-time path planning.

4.5 Hybrid Approaches

In addition to the previously defined approaches, some algorithms are based on the hybridization of several methods. In general, several ways of hybridization are possible. However, in the UAV path planning problem, we found only 4 combination types: combining two classical methods, combining a classical approach with heuristic, combining a classical method with meta-heuristic, and combining two meta-heuristics. The concerned approaches are summarized in Fig. 14 and Table 18 below with the specification of the obtained performance.

4.5.1 Classical with Classical Approaches

Authors in [241] proposed a dynamic improved Voronoi Diagram algorithm based on the combination of Voronoi Diagram and Dijkstra algorithm for solving the UAV path planning problem. The performance of the improved Voronoi Diagram algorithm was simulated in a radar threat region of 8x8 Km and results demonstrated that the improved Voronoi Diagram algorithm provides better results in terms of time-efficiency and path optimization.

An Improved RRT-Connect (IRRTC) algorithm was proposed by Zhang et al. [242], which is based on the

Table 16 The objectives and constraints considered in machine learning approaches

Algorithms	References	Objectives				Constraints					
		Path opti-mization	Time efficiency	Collision avoidance	Cost efficiency	Alti-tude	Climb/ Descend angle	Ener-gy	Thre-ats	UAV's axes	Velo-city
RBF-ANN	Nikolos et al. [214]	✓		✓	✓				✓	✓	✓
Improved DQN	Wu et al. [215]		✓	✓					✓		
D3QN	Yan et al. [216]	✓		✓		✓			✓		
oHJB	Shiri et al. [217]	✓	✓	✓	✓			✓	✓		✓
SVM	Chen et al. [218]	✓		✓		✓	✓		✓	✓	✓
GP	Yoo et al. [219]	✓	✓	✓					✓	✓	
Polynomial Regression	Koo et al. [221]	✓		✓				✓	✓		
PDE	Radmanesh et al. [222]	✓	✓	✓					✓	✓	✓
POMDP	Ragi and Chong [223]	✓		✓					✓	✓	✓
CGLA	Zhang et al. [224]	✓	✓	✓					✓		
ARE	Yijing et al. [227]		✓	✓					✓		
Deep RL ESN	Challita et al. [228]		✓	✓	✓			✓	✓	✓	✓
Deep-Sarsa	Luo et al. [229]			✓					✓		
Improved Q-learning	Yan and Xiang [230]	✓		✓		✓			✓	✓	
Q-learning	Zhang et al. [231]		✓	✓					✓	✓	✓
MARER Q-learning	Xie et al. [232]	✓		✓	✓	✓		✓	✓	✓	
RQ-ADSA-DRQN	Xie et al. [233]	✓	✓	✓	✓	✓	✓	✓	✓	✓	
MLQN	Cui and Wang [236]	✓		✓					✓	✓	
Modified SOM	Pierre et al. [237]	✓		✓				✓			
DBSCAN	Choi et al. [238]		✓	✓	✓	✓	✓		✓		✓

Table 17 Advantages and disadvantages of machine learning algorithms used in UAV path planning

Algorithm	Advantages	Disadvantages
Neural Network	Suitable for dynamic environment Ability for solving multi-objective UAV path planning Fast convergence	Long time consuming Not appropriate for real-time UAV path planning Optimal solutions not guaranteed High learning cost High computational complexity
Supervised Learning	Near-optimal solutions Reduce the complexity of UAV path planning Suitable for complex environments	Long processing time Less efficient in large datasets training
Reinforcement Learning	Efficient in handling UAV's manoeuvrability Efficient for multi-UAV path planning	Long processing time Not appropriate for real-time UAV path planning More resources requirements in terms of UAV's memory and energy Solutions often not optimal
Unsupervised Learning	Fast convergence Convergence to near optimal solutions High energy efficiency Efficient in uncertain environments	Long processing time Inefficient in real-time UAV path planning

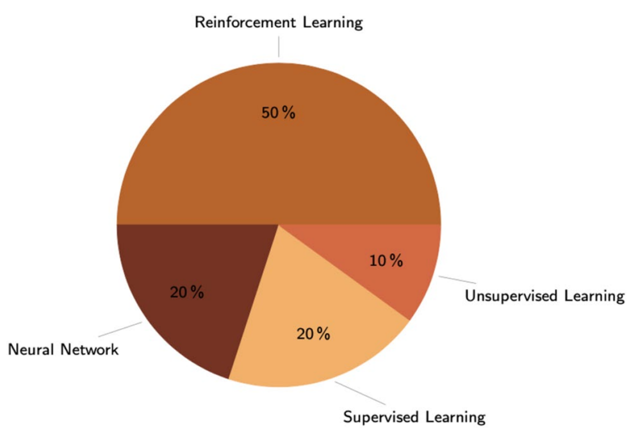

Fig. 13 Machine learning approaches for UAV path planning

hybridization of RRT-Connect with Artificial Potential Field algorithm for optimizing the UAV path planning in a 2D static environment. The performance of IRRTC algorithm was validated using one large obstacle, 2 large obstacles, 3 large obstacles, 23 small obstacles, 25 small obstacles, and 100 small obstacles. Simulation results showed that IRRTC algorithm outperforms the traditional RRT, RRT-Connect , and APF algorithms in terms of optimal path length and execution time.

Wang et al. [243] proposed an improved RTT (i-RRT) algorithm based on the combination of RRT with APF and curve smoothing method for optimizing the UAV path planning in a 3D environment. The effectiveness of i-RRT algorithm was evaluated in a 3D simulation environment with the presence of 6 mountains with different altitudes. Experimental results proved that i-RRT algorithm outperforms the classical RRT algorithm in terms of path length and computational time.

In their work, Shen and Li [244] developed an improved APF algorithm based on the combination of APF and RRT algorithms for solving the UAV path planning problem. The robustness of the improved APF algorithm was validated in a 2D environment with 6 circular obstacles. According to simulation results, improved APF outperforms APF in terms of path length. Similarly, Debnath et al. [245] proposed an Elliptical Concave Visibility Graph (EC*o*VG) model based on the combination of VG and Dijkstra algorithms for solving the UAV path planning problem. The effectiveness of EC*o*VG was validated in a 2D complex environment with the presence of 20, 30, 100, 150, and 200 static obstacles. Simulation results proved the superiority of EC*o*VG algorithm compared to Equilateral-Space Oriented VG (ESOVG) [246] technique in terms of path length generation, execution time, and safe flying.

4.5.2 Heuristics with Classical Approaches

Chandler et al. [247] developed an improved Voronoi Diagram algorithm by combining the Voronoi Diagram algorithm with A* and Rendezvous approach for optimizing the Multi-UAVs path planning. The effectiveness of the proposed Voronoi Diagram algorithm was evaluated in a 3D environment with 3 flying UAVs and 10 static obstacles. Experimental results proved that the proposed VD algorithm gives good performance by obtaining optimal path length. It is also shown that the improved Voronoi Diagram coordinates and ensures communications between multiple UAVs about threats locations.

In their proposal, Yan et al. [248] developed an improved PRM algorithm aggregating original PRM with octree and A* algorithms for solving the UAV path planning problem in a 3D environment. The effectiveness of the improved PRM

Table 18 Summary of hybrid approaches for UAV path planning

Algorithm	Authors (Refs.)	Year	Environment	Multi-UAVs	Results
Modified VD	Chen et al. [241]	2014	Dynamic	No	Modified VD outperforms other path planning approaches in terms of energy consumption and path length.
IRRTC	Zhang et al. [242]	2018	Static	No	Effectiveness of IRRTC compared to APF, RRT, and RRT-Connect [68] in terms of execution time and path length
i-RRT	Wang et al. [243]	2019	Static	No	Efficiency of i-RRT compared to RRT in terms of execution time and path length.
Improved APF	Shen and Li [244]	2020	Static	No	Robustness of Improved APF compared to APF in terms of optimal path length.
EC*o*VG	Debnath et al. [245]	2020	Static	No	Efficiency of EC*o*VG compared to ESOVG [246] in terms of execution time and path length.
Optimal VD	Chandler et al. [247]	2000	Dynamic	Yes	Optimal VD achieves better results in terms of path length
Improved PRM	Yan et al. [248]	2013	Static	No	Improved PRM achieves better results compared to other existing approaches by providing the shortest path length in real-time planning.
D* lite-IPRM	Xue et al. [249]	2014	Static	No	Superiority of D* lite-IPRM compared to PRM in terms of computational time and path length.
Visibility roadmap	Ahmad et al. [250]	2017	Static	No	Effectiveness of Visibility roadmap compared to Grid map in terms of energy consumption, planning time, and path length.
Improved VG	Naazare et al. [251]	2019	Dynamic	No	Superiority of Improved VG in terms of collision-free path.
Hybrid Dijkstra	Qu et al. [252]	2018	Static	No	Efficiency of Hybrid Dijkstra algorithm in terms of path length.
mVGA^{v}	Pehlivanog [253]	2012	Static	No	Robustness of mVGA^{v} algorithm compared to mVGA [253], VGA [254], and RGA [255] by obtaining optimal path with a low computational time
HGA	Arantes et al. [256]	2016	Static	No	HGA gives better results compared to CSA [257] and CPLEX [258] in terms of shortest path length.
PSO-APF	Girija and ashok [259]	2019	Dynamic	Yes	Effectiveness of PSO-APF compared to PSO in terms of path length, path cost, and execution time.
PSO-GA	Roberge et al. [260]	2014	Static	No	Robustness of PSO-GA compared to GA and PSO in terms of execution time and path cost.
TLBO*	Ghambari et al. [261]	2019	Static	No	Robustness of TLBO* compared to TLBO [262] in terms of path length and planning time.
MMACO-DE	Ali et al. [263]	2020	Dynamic	Yes	Efficiency of MMACO-DE compared to ACO in shortest path length
PIOFOA	Ge et al. [264]	2020	Dynamic	Yes	Effectiveness of PIOFOA compared to AGASA [265], DPSO [266], GWO [141], IBA [267], MWPS [131], PPPIO [268], PSOGSA [269], and SDPIO [270] in terms of short path length, low execution time, and path cost
HSGWO-MSOS	Qu et al. [271]	2020	Static	No	Superiority of HSGWO-MSOS compared to GWO, SA [272] and SOS [273] in terms of path length and path cost.
RLGWO	Qu et al. [274]	2020	Static	No	RLGWO achieves better performance compared to EEGWO [275], GWO, IGWO [276] and MGWO [277] in terms of path length and path cost.
DL-GA	Pan et al. [278]	2021	Dynamic	Yes	DL-GA outperforms GA and Random choosing in terms of path length and execution time

algorithm was evaluated in 2 different cases. In the first case, the UAV was flying inside a simple environment with the presence of 3 levels of sparse trees. In the second case, cubic obstacles were added to the environment. Experimental results demonstrated that the improved PRM algorithm generates a short and collision-free path in the case of real-time planning compared to traditional PRM.

Xue et al. [249] suggested a hybrid approach, called D* lite-IPRM, hybridizing PRM with D* lite algorithm for optimizing the UAV path planning in both 2D and 3D environments. The robustness of D* lite-IPRM algorithm was assessed in 3 scenarios. In the first scenario, Experiments were performed using 5 and 10 circular obstacles. In the second scenario, 2 radars were introduced. In the last one, UAV was flying in a 3D environment with the presence of multiple mountains. Simulation results proved that D* lite-IPRM outperforms original PRM in terms of path length and execution time.

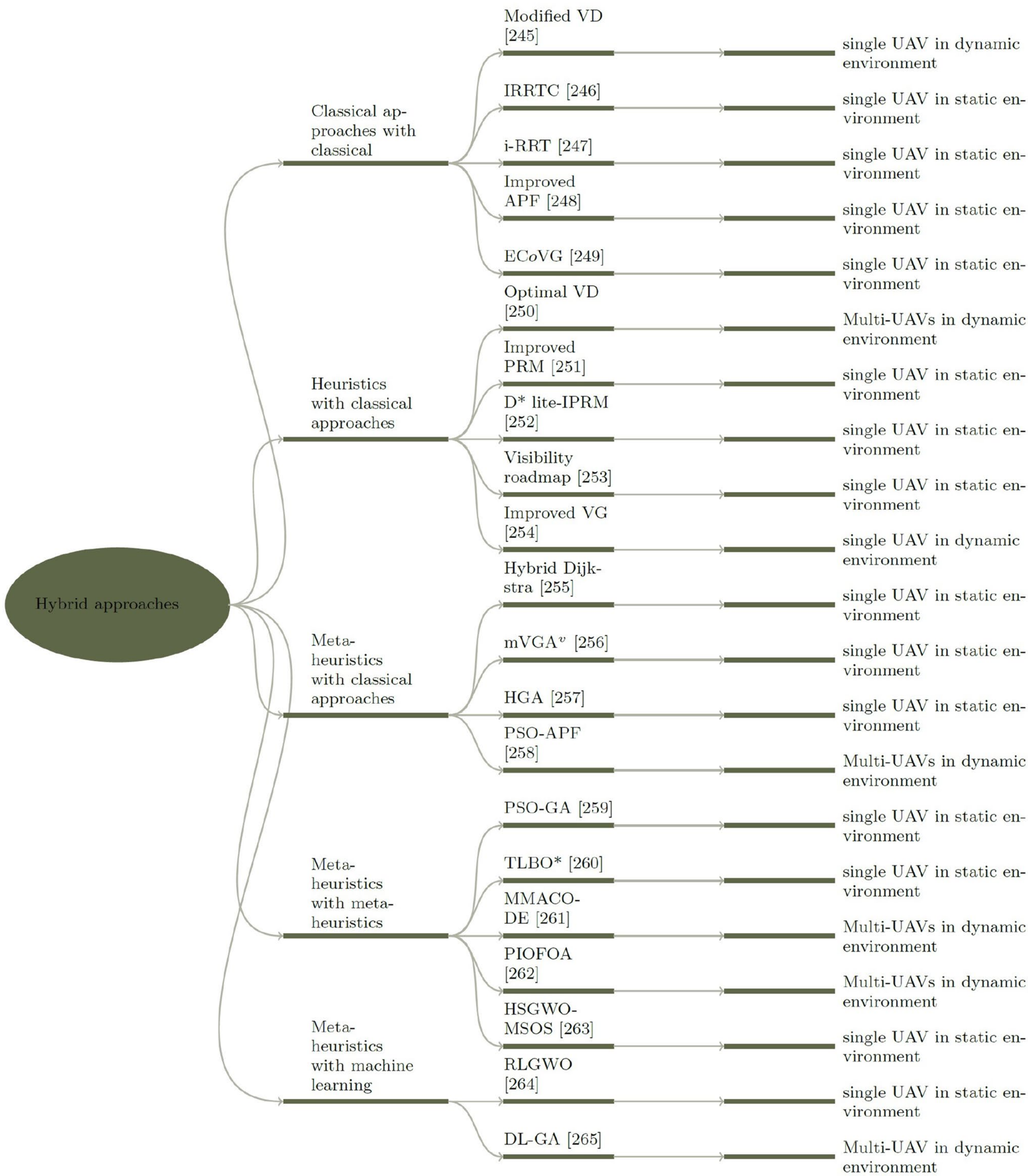

Fig. 14 Hybrid approaches for UAV path planning

Ahmad et al. [250] proposed a Visibility road-map algorithm based on the combination of visibility Graph algorithm with A* heuristic for optimizing the path planning for Small UAVs (SUAVs). The effectiveness of the visibility road-map algorithm was evaluated in a 3D static environment with the presence of 5, 10, 15, 20, and 25 distributed obstacles. Experimental results showed that the Visibility road-map algorithm outperforms the ordinary grid map algorithm in terms of computation time, traveling path length, and energy consumption optimization. In a similar work, Naazare et al. [251] suggested a hybrid approach based on the Visibility Graph algorithm and A* algorithm. The effectiveness of the proposed algorithm was evaluated using AirRobot AR200 in both simulation and real area. Experimental results showed that the proposed algorithm provides an optimal path.

4.5.3 Meta-heuristics with Classical Approaches

Qu et al. [252] hybridized Dijkstra, APF, and GA algorithms for solving the fixed-wing UAV path planning problem. The hybrid method used Dijkstra algorithm to seek the shortest path, APF algorithm aimed to find the feasible path by guiding UAV toward smoothness area with avoiding threats, the purposed of GA algorithm is to enhance the path. The performance of the hybrid method was validated in both 2D and 3D environments using 20 obstacles. Simulation results showed the robustness of the hybrid algorithm by obtaining a short and safe trajectory.

Pehlivanog [253] developed a modified Multi-frequency Vibrational Genetic Algorithm (mVGA^v) based on the hybridization of multi-frequency Genetic Algorithm and Voronoi Diagram model for solving the UAV path planning problem. The effectiveness of mVGA^v was assessed in a 3D sinusoidal area and urban environment. Experimental results demonstrated that mVGA^v outperforms other variants of GA algorithm existing in the literature [253–255] in terms of computational time and local minimum avoidance (Table 19).

A hybrid technique, called Hybrid Genetic Algorithm (HGA), was introduced by Arantes et al. [256], which is based on the combination of GA and Visibility Graph for solving the UAV path planning problem. The effectiveness of HGA was evaluated in a 2D non-convex environment using static obstacles distributed in 50 maps. Simulation results showed the efficacy of HGA compared to CSA [257] and CPLEX [258] in terms of path length efficiency and running time optimization.

Girija and ashok [259] proposed a novel algorithm, called PSO-APF, based on the combination of PSO and APF algorithms for optimizing the UAV path planning. The effectiveness of PSO-APF algorithm was validated in a 3D dynamic cubic area with complex obstacles and 3 moving UAVs. Test results showed that PSO-APF algorithm outperforms the original PSO algorithm in terms of time-efficiency, path cost optimization, and collision-free path generation.

4.5.4 Meta-heuristics with Meta-heuristics

In [260], a hybrid PSO-GA was proposed in an attempt to do real-time UAV path planning problems. The effectiveness of PSO-GA was evaluated in a 3D complex environment using 18 scenarios with 6 different locations. In the work of Ghambari et al. [261], authors developed a novel approach, called TLBO* based on the combination of Teaching Learning-based Optimization (TLBO) with Genetic Algorithm for solving the UAV path planning problem. The performance of TLBO* was validated in both 2D and 3D areas with the presence of obstacles randomly distributed. Simulation results showed the superiority of the proposed TLBO* compared to the original TLBO algorithm in terms of best path generation, time efficiency, and collision avoidance.

Authors in [263] proposed a hybrid approach, called Maximum-Minimum Ant Colony Optimization-DE algorithm (MMACO-DE), based on the combination of ACO and DE for solving the multi-UAVs path planning problem in a dynamic environment. The effectiveness of MMACO-DE algorithm was evaluated in a 3D environment in the case of single UAV and 3 UAVs. Simulation results showed the performance of MMACO-DE compared to the original ACO algorithm in terms of path and cost optimization.

Ge et al. [264] presented a modified Pigeon-Inspired Optimization, called, Pigeon Inspired optimization Fruit fly optimization algorithm (PIOFOA) based on the combination of Pigeon-inspired optimization (PIO) and Fruit fly optimization algorithm(FOA) for solving the UAV path planning problem in a 3D dynamic environment. The robustness of PIOFOA algorithm was validated in 3 experiences using six moving obstacles. In another work, Qu et al. [271] proposed a hybrid path planning algorithm (HSGWO-MSOS) based on the hybridization of Simplified GWO with Modified Symbiotic Organism Search for solving the UAV path planning problem. The performance of HSGWO-MSOS was validated in both 2D and 3D complex environments with 8 static obstacles.

4.5.5 Meta-heuristics with Machine Learning

Qu et al. [274] hybridized GWO and Reinforcement Learning model for solving the UAV path planning problem. The performance of RLGWO was simulated in 3 case studies inside a 3D area with the presence of 8 static obstacles.The robustness of RLGWO compared to EEGWO [275], GWO [279], IGWO [276], and MGWO [277] in terms of convergence time, path cost computation, and collision avoidance were demonstrated.

4.5.6 Analysis

The present section addresses several hybrid approaches as shown in Fig. 15, which bring significant improvements by taking advantages from strengths of the methods they are composed of and overcome their limitations.

Table 19 The objectives and constraints considered in hybrid approaches

Algorithms	References	Objectives				Constraints					
		Path opti-mization	Time efficiency	Collision avoidance	Cost efficiency	Alti-tude	Climb/ descend angle	Ener-gy	Thre-ats	UAV's axes	Velo-city
Modified VD	Chen et al. [241]	✓		✓	✓			✓	✓		
IRRTC	Zhang et al. [242]	✓	✓	✓					✓		
i-RRT	Wang et al. [243]	✓	✓	✓					✓		
Improved APF	Shen and Li [244]	✓		✓					✓	✓	
EC*o*VG	Debnath et al. [245]	✓	✓	✓					✓		
Optimal VD	Chandler et al. [247]	✓		✓					✓	✓	✓
Improved PRM	Yan et al. [248]	✓	✓	✓					✓		
D* lite-IPRM	Xue et al. [249]	✓	✓	✓		✓			✓		
Visibility roadmap	Ahmad et al. [250]	✓	✓	✓	✓	✓		✓	✓	✓	✓
Improved VG	Naazare et al. [251]	✓		✓					✓		
Hybrid DIJIKSTRA	Qu et al. [252]	✓		✓		✓			✓		
mVGA^{v}	Pehlivanog [253]	✓	✓	✓		✓			✓	✓	✓
HGA	Arantes et al. [256]	✓	✓	✓					✓		
PSO-APF	Girija and ashok [259]	✓	✓	✓	✓		✓	✓	✓		✓
PSO-GA	Roberge et al. [260]		✓	✓	✓	✓		✓	✓		
TLBO*	Ghambari et al. [261]	✓	✓	✓		✓			✓		
MMACO-DE	Ali et al. [263]	✓		✓		✓			✓		
PIOFOA	Ge et al. [264]	✓	✓	✓	✓	✓		✓	✓		✓
HSGWO-MSOS	Qu et al. [271]	✓		✓	✓			✓	✓	✓	
RLGWO	Qu et al. [274]	✓		✓	✓			✓	✓	✓	
DL-GA	Pan et al.[278]	✓	✓		✓			✓			

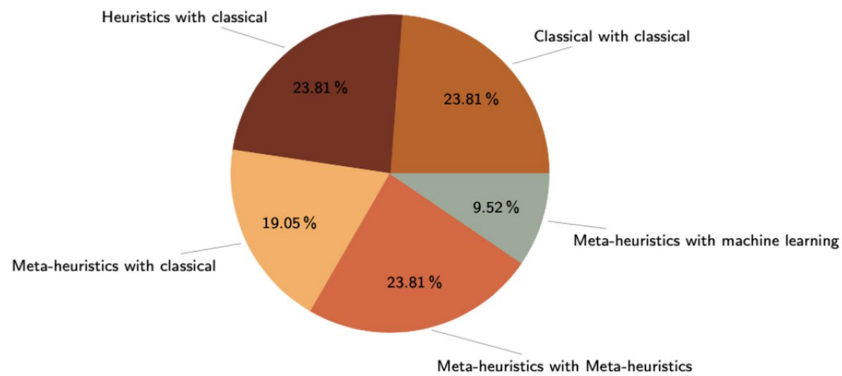

Fig. 15 Hybrid approaches for UAV path planning

As previously mentioned, some classical algorithms such as APF and VG are more sensitive to complex obstacles and their effectiveness depends on them. To address this shortcoming, hybridization with other classical approaches that succeeded in face of obstacles as RRT are proposed. This kind of hybridization provides more safety to the UAV by better managing the collisions. As shown in Table 7, Dijkstra algorithm generates the shortest path. To benefit from this advantage, several combinations with other classical algorithms are introduced. These hybridizations offer better quality of the path in terms of length. However, they still require all the information about the environment which takes long processing time. To overcome this lack, hybrid classical approaches with heuristics are proposed. These hybridizations provide optimal paths by reducing the required processing time. However, they are not appropriate for dynamic environments with sudden obstacles. Thus, hybridizing meta-heuristics with classical approaches improves this limitation and can be used in real-time cases. The hybridization of meta-heuristics between them is another way used to further enhance the quality of the provided path and reach the optimal solution. Also, combining meta-heuristics with machine learning reduces the time and cost compared to techniques using only machine learning algorithms.

5 Discussion

From this study, important points can be summarized as follow:

Figures 16, 17 and 18 give respectively a synthesis about the addressed environments, the evaluated metrics as well as the proportions at which the different approaches are used.

We can see that the static environment is the one that is mostly taken into account. This is expected because of the regularity it offers. The use of dynamic and multi-UAVs environments are not negligible either and many propositions consider them.

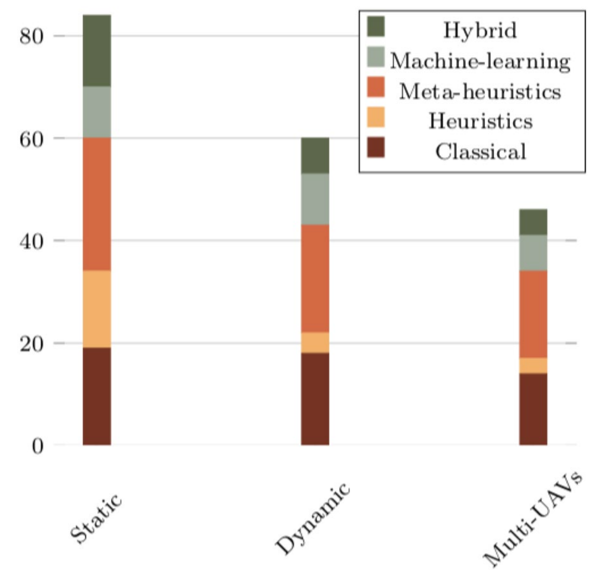

Fig. 16 Experimented environment of UAV path planning

Regarding the metrics, it seems that in the UAV path planning problem the path quality is more priority than the cost it could generate. In fact, as shown in Fig. 17, the most evaluated measures are path optimization and collision avoidance.

Various approaches were used for solving the UAV path planning problem since 2000. As shown in Fig. 18, 34.3% of them are based on Meta-heuristics, 25.3% used classical techniques, whereas hybrid approaches, machine learning, and heuristics are used in only 14.5% and 13% of cases, respectively. The strengths and weaknesses of each approach are given in Table 20 where we can notice the following results:

Several classical approaches were applied for solving the UAV path planning problem such as RRT, VD, APF, VG, Dijkstra, and PRM. The main reason of their success is their easy implementation while giving good results (Path optimization, fast solution generation, and time-efficiency) for static environments with simple obstacles. This makes them suitable

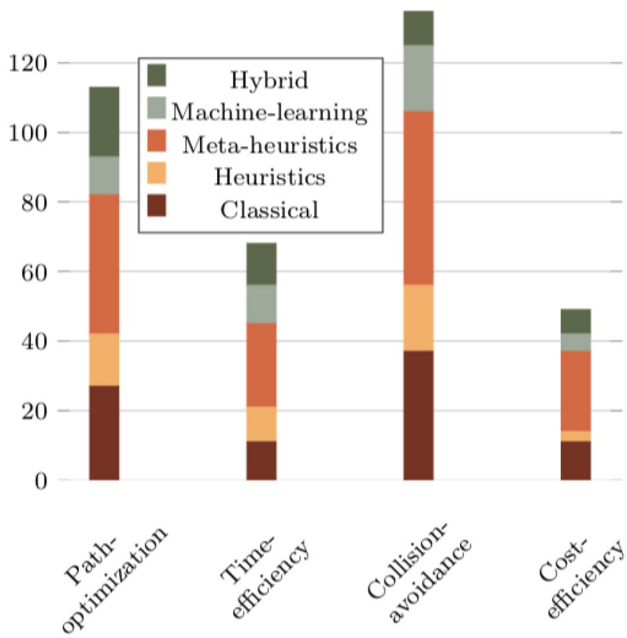

Fig. 17 Optimization results of UAV path planning

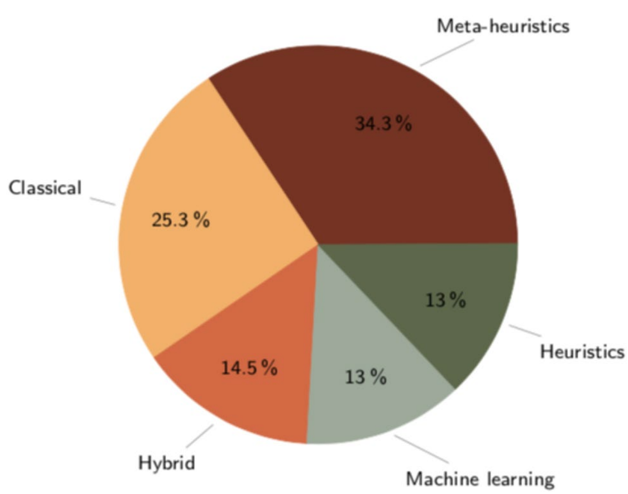

Fig. 18 The optimization approaches for UAV path planning

and reliable for real-time planning. However, no theoretical guarantee is provided about the optimality of the given solutions due to the presence of constraints. Moreover, classical algorithms require full information about the environment to be performed. They provide poor performance in complex and dynamic environments with different threats and obstacles.

Heuristic algorithms appeared to overcome the drawbacks of classical approaches. They are partially intelligent and require only some information about the environment to be performed. Heuristics generate a short and safe path for UAV path planning with a reasonable computational time. Heuristics are more optimal in static and simple environments. Nevertheless, they do not respond well in the case of dynamic and complex environments. Moreover, heuristics return generally bad solutions for UAV path planning problem in the case of multi-objective resolutions. To deal with the heuristic limits faced in multi-objective cases, meta-heuristics are the alternative which is widely used in UAV path planning. They are known to present many advantages as they are intelligent approaches which makes them appropriate for dynamic and complex environments. In UAV path planning problem, meta-heuristics give good quality solutions (path optimization: length, smoothness, cost, energy, and computational time) for complex and dynamic environments while handling UAV's constraints. Despite their advantages, meta-heuristics remain not suitable for real-time path planning.

Machine learning algorithms are also appropriate for complex and dynamic environments since they are intelligent approaches and their behavior are near to human one. Although, machine learning algorithms present several advantages, they have some weaknesses. Firstly, the time required for processing is higher, so it is not appropriate for real-time planning. Secondly, high execution time requires high resources consumption which impacts the cost of the applied approach. Thirdly, Machine learning approaches require large datasets of the environment to provide optimal solutions, especially with supervised learning.

6 Conclusion

The UAV path planning is an important research issue in the field of aerial robotics and automation which has attracted increasing interest from several academics and researchers. In this paper, we presented a comprehensive review of more than 150 articles related to UAVs path planning approaches published from January 2000 to January 2022. We categorized them into five classes: classical methods, heuristics, meta-heuristics, machine learning, and hybrid algorithms. We highlighted various objectives and constraints on which we provide a comparative analysis. The latter is done according to path length, time efficiency, collision avoidance, and cost efficiency as objectives to satisfy under energy, threats, velocity, altitude, UAV's axes and the climb/descend angle constraints. We drew a number of discussions showing mainly the most used approaches in each class. This study allowed us to become aware of some new challenges and needs for future research directions in this context, such as:

- Introducing the Quality of Service in the UAV path planning;
- Multiple path selection in the process of UAV path planning;
- Handling multiple targeted destinations in path planning;
- Hybridizing meta-heuristics with more classical approaches and/or machine learning algorithms for optimizing the UAV path planning in dynamic environments;
- Applying recent meta-heuristics for solving the UAV path planning problem;
- Parallel implementation of meta-heuristics for optimizing UAV path planning results;
- Incorporating uncertainty in the UAV path planning problem;
- Addressing UAV path planning in high dimensional environments.

A: Appendix

In the present appendix, we gather in a table the set of acronyms used in this paper and their meanings.

Acronym	Explanation
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
AGASA	Self Adaptive Genetic Simulated Annealing algorithm
APF	Artificial Potential Field
APF-IRP	Artificial Potential Field Improved Rolling Plan
AGOA	Adaptive Grasshopper Optimization Algorithm
aHJB	Hamilton Jacobi Bellman
ALO	Ant Lion Optimizer
ARE	Adaptive and Random Exploration
A*	A-Star
AS-N	Ant Colony Optimization with punitive measures
AT-PP	Average Throughput Path planning
ASTS	Ant System Tabu Search
BA	Bat Algorithm
BAA*	Bidirectional Adaptive A-star
BBO	Biogeography Based Optimization
BLP	Bi-Level Programming
BS	Base Station
CBGA	Center Based Genetic Algorithm
CBPSO	Chaos Based initialization Particle Swarm Optimization
CC-RRT	Chance Constraint Rapidly-exploring Random Tree
CFO	Central Force Optimization
CGLA	Cooperative and Geometric Learning Algorithm
CIPSO	Comprehensively Particle Swarm Optimization
CPSO	Constrained Particle Swarm Optimization
CS	Cuckoo Search
DA	Dragonfly Algorithm
DAALO	Dynamic Adaptive Ant Lion Optimizer
DBSCAN	Density Based Spatial Clustering of Application with Noise
DDRRT	Dynamic Domain Rapidly-exploring Random Tree
DE	Differential Evolution
Deep RL ESN	Deep Reinforcement Learning Echo State Network
Deep Sarsa	Deep State action reward state action
DELC	Differential Evolution with Level Comparison
DPSO	Discrete Particle Swarm Optimization
DQN	Deep Q Network
DRL	Deep Reinforcement Learning
D3QN	Dueling Double Deep Q Networks
Dubins SAS	Dubins Sparse A-Star
ECoVG	Elliptical Concave Visibility Graph
ϵDE	Constrained Differential Evolution
EEGWO	Exploration Enhanced Grey Wolf Optimizer
ESOVG	Equilateral Space Oriented Visibility Graph
ePFC	Extended Potential Field Controller

Table 20 Strengths and Weaknesses of UAV path planning approaches

Approach	Strengths	Weaknesses
Classical	Good results (Path optimization, fast solution generation, and time-efficiency) for static environments with simple obstacles Easy implementation for various static environments Low resources requirements and low computational cost	Failing in local minima problems No guarantee about the optimality of results due to the presence of constraints Poor performance in complex and dynamic environments with different threats and obstacles Requiring the full information about the environment to be performed
Heuristics	Good solutions for UAV path planning with mono-objective resolutions Appropriate for static environments under different constraints Partially intelligent Reasonable response time	Not always reaching optimal solutions Bad solutions for UAV path planning with multi-objective resolutions Stuck in local optima Not suitable for dynamic and complex environments
Meta-heuristics	Good results for UAV path planning with multi-objective resolutions Reasonable execution time Intelligent approaches with easy implementation Good quality solutions (path optimization: length, smoothness, cost, energy , and computational time) for complex and dynamic environments	Optimal solutions not guaranteed Not suitable and reliable for real time planning Control parameters tuning More resources requirements No theoretical converging property
Machine learning	Optimal results (path length, smoothness, time efficiency, and collision avoidance) Intelligent approaches Suitable for dynamic environments and sudden changes	Requirement of large datasets of the environment to provide optimal solutions, especially with supervised learning Requirement of several training before providing an accurate final model. High computational time High computational cost

Acronym	Explanation
EPF-RRT	Environmental Potential Field Rapidly-exploring Random Tree
FA	Firefly Algorithm
FA-DE	Fuzzy Adaptive Differential Evolution
FBCRI	Feedback Based CRI
FDFR	First Detect First Reserve
FOA	Fruit fly Optimization Algorithm
FVF	Fuzzy Virtual Force
FWA	Firework Algorithm
GA	Genetic Algorithm
GA-LRO	Genetic Algorithm-Local Rolling Optimization
GBPSO	Global Best Particle Swarm Optimization
GEDGWO	Gaussian Estimation of Distribution Grey Wolf Optimizer
GH	Greedy Heuristic
GLS	Guided Local Search
GNSS	Global Navigation Satellite System
GP	Gaussian Process
GP-RRT	Gaussian Process Rapidly-exploring Random Tree
GSO	Glowworm Swarm Optimization
GTSP	Generalized Traveling Salesman Problem
GWO	Grey Wolf Optimizer
HDDRRT	Heuristic Dynamic Domain Rapidly-exploring Random Tree
HGA	Hybrid Genetic Algorithm
HPF	Hierarchical Potential Field
HR-MAGA	Hierarchical Recursive Multi Agent Genetic Algorithm
HSGWO-MSOS	Hybrid Simplified Grey Wolf Optimizer-Modified Symbiotic Organism Search
HVFA	Hybrid Virtual Force A* search
IABC	Improved Artificial Bee Colony
IBA	Intelligent BAT Algorithm
ICA	Imperialist Competitive Algorithm
IFFO	Improved Fruit fly Optimization
IGWO	Improved Grey Wolf Optimizer
IITD	Improved Intelligent Water Drop algorithm
ITD	Intelligent Water Drop algorithm
IPS	Improved Path Smoothing
IRRT	Improved Rapidly-exploring Random Tree

Acronym	Explanation
IRRT*	Informed Rapidly-exploring Random Tree-Star
IWOA	Improved Whale Optimization Algorithm
IRRTC	Improved Rapidly-exploring Random Tree Connect
LCPSO	Linear varying Coefficient Particle Swarm Optimization
LEVG	Layered Essential Visibility Graph
LKH	Lin Kernighan
LRTA-Star	Learning Real Time A-star
LVPSO	Linear varying maximum Velocity Particle Swarm Optimization
MACO	Modified Ant Colony Optimization
MCFO	Modified Central Force Optimization
mDELC	improved Differential Evolution with Level Comparison
MFO	Moth Flame Optimization
MFOA	Multi-swarm Fruit fly Optimization Algorithm
MGA	Modified Genetic Algorithm
MGOA	Modified Grey Wolf Algorithm
mHJB	Opportunistic Hamilton Jacobi Bellman
MHS	Modified Harmony Search
MILP	Mixed Integer Linear Programming
MMACO-DE	Maximum Minimum Ant Colony Optimization Differential Evolution
MMAS	Maximum Minimum Ant System
MPC	Model Predictive Control
MP-CGWO	Multi Population-Chaotic Grey Wolf Optimizer
MPFM	Modified Potential Field Method
MPGA	Multi-Population Genetic Algorithm
MT-PP	Maximum Throughput Path planning
mVD	Modified Voronoi Diagram
mVGA	Multi-frequency Vibrational Genetic Algorithm
mVGA^{v}	Multi-frequency Vibrational Genetic Algorithm with voronoi
MVO	Multi-Verse Optimizer
MWPS	Modified Wolf Packet Search
NBO	Nominal Belief-state Optimization
NFZ-DDRRT	No-Fly Zone Dynamic Domain Rapidly-exploring Random Tree
NSGA	Non-dominated Sorting Genetic Algorithm
NBGA	Neighborhood Based Genetic Algorithm

Acronym	Explanation
OGCA	Obstacle-free Graph Construction Algorithm
OGSA	Obstacle-free Graph Search Algorithm
oHJB	Opportunistic Hamilton Jacobi Bellman
OPP	Optimal Path Planning
PDE	Partial Differential Equation
PH	Pythagorean Hodograph
PIO	Pigeon Inspired Optimization
PIOFOA	Pigeon Inspired Optimization Fruit fly Optimization Algorithm
P-MAGA	Path planning Multi-Agent Genetic Algorithm
PMPSO	Position Mutation Particle Swarm Optimization
POMDP	Partially Observable Markov Decision Process
PPPIO	Predator Prey Pigeon Inspired Optimization
PRM	Probabilistic Road Map
PSO	Particle Swarm Optimization
PSO-APF	Particle Swarm Optimization-Artificial Potential Field
PSO-GA	Particle Swarm Optimization -Genetic Algorithm
PSOGSA	Particle Swarm Optimization Gravitational Search Algorithm
PSOPC	Particle Swarm Optimizer with Passive Congregation
QoS	Quality of Service
QPSO	Quantum Particle Swarm Optimization
RBF-ANN	Radial Basis Functions Artificial Neural Networks
RGA	Regular Genetic Algorithm
RGV	Reduced Visibility Graph
RHC	Receding Horizon Control
RLGWO	Reinforcement learning Grey Wolf Optimizer
RRT	Rapidly-exploring Random Tree
RRTC	Rapidly-exploring Random Tree Connect
RRT*	Rapidly-exploring Random Tree-Star
RRT* G	Rapidly-exploring Random Tree-Star Goal
RRT* GL	RRT Goal Limit
RRT* L	Rapidly-exploring Random Tree-Star Limit
RS	Random Search
RSU	Road Site Unit
RVW	Rendez-Vous Waypoints

Acronym	Explanation
Sarsa	State action reward state action
SA	Simulated Annealing algorithm
SADE	Self Adaptive Differential Evolution
SAS	Sparse A* Search
SCA	Sine Cosine Algorithm
SCPIO	Social Class Pigeon Inspired Optimization
SDPIO	Slow Diving Pigeon Inspired Optimization
SH	Short Horizon algorithm
SHA	Self Heuristic Ant
SHC	Short Horizon Cooperative algorithm
SICQ	Simultaneous Inform and Connect with Quality of service
SIC+	Simultaneous Inform and Connect following Quality of service
SOM	Self Organisation Map
SOMR	Surface Of Minimum Risk
SOS	Symbiotic Organism Search
SVM	Support Vector Machine
TADDRRT	Threat Assessment based Dynamic Domain Rapidly-exploring Random Tree
TARRT*	Threat Assessment based RRT* Rapidly-exploring Random Tree-Star
θ-MAFOA	θ-Mutation Adaptation Fruit Fly Optimization Algorithm
θ-QPSO	Phase-encoded Quantum Particle Swarm Optimization algorithm
θ-PSO	Phase-encoded Particle Swarm Optimization algorithm
TLBO	Teaching Learning Based Optimization
TLP-COA	Tri Level Programming Cognitive behavior Optimization Algorithm
TSP	Traveling Salesman Problem
UAV	Unmanned Aerial Vehicle
UGV	Unmanned Ground Vehicle
VD	Voronoi Diagram
VGA	Vibrational Genetic Algorithm
VPB-RRT	Variable Probability based bidirectional Rapidly-exploring Random Tree
WOA	Whale Optimization Algorithm
WPS	Wolf Packet Search

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Declarations

Conflict of interest The authors declare that there is no conflict of interest with any person(s) or Organization(s).

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