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Review

Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges

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ABSTRACT

Path planning is one of the most important problems to be explored in unmanned aerial vehicles (UAVs) for finding an optimal path between source and destination. Although, in literature, a lot of research proposals exist on the path planning problems of UAVs but still issues of target location and identification persist keeping in view of the high mobility of UAVs. To solve these issues in UAVs path planning, optimal decisions need to be taken for various mission-critical operations performed by UAVs. These decisions require a map or graph of the mission environment so that UAVs are aware of their locations with respect to the map or graph. Keeping focus on the aforementioned points, this paper analyzes various UAVs path planning techniques used over the past many years. The aim of path planning techniques is not only to find an optimal and shortest path but also to provide the collision-free environment to the UAVs. It is important to have path planning techniques to compute a safe path in the shortest possible time to the final destination. In this paper, various path planning techniques for UAVs are classified into three broad categories, i.e., representative techniques, cooperative techniques, and non-cooperative techniques. With these techniques, coverage and connectivity of the UAVs network communication are discussed and analyzed. Based on each category of UAVs path planning, a critical analysis of the existing proposals has also been done. For better understanding, various comparison tables using parameters such as-path length, optimality, completeness, cost-efficiency, time efficiency, energy-efficiency, robustness and collision avoidance are also included in the text. In addition, a number of open research problems based on UAVs path planning and UAVs network communication are explored to provide deep insights to the readers.

Contents

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List of Abbreviations

The list of abbreviations and definitions used throughout the paper are shown in Tables 1, 2.

1. Introduction

In the last few years, we have witnessed the popularity and usage of unmanned aerial vehicles (UAVs) in a wide range of applications. Also, during this time, various communication standards and technologies evolve (e.g, grid and cloud computing, big data analytics, and software-defined networking). These communication standards and technologies have been widely used by various generations starting from the first generation (1G) to fifth generation (5G) for providing data sharing among UAVs and other smart objects. From the past few years, we have witnessed changes in different generations starting from the pure analog with no data capabilities (1G), digital circuit system for full-duplex communication and for voice telephony (2G), broadband and multimedia (video signals) systems (3G), high speed and enhanced 3G (4G), and IP networking and end-to-end connectivity (5G) as shown in Fig. 1. These communication standard technologies have been developed for new generation of cellular wireless communication in UAVs. The thousand of billions of inter-connected wireless devices need high-reliability, low-latency, battery lifetime in UAVs communication in next generation cellular networks. Particularly, 5G cellular networks are considered as important components of UAV-aided enhanced mobile broadband [1]. In such an environment, UAVs are used as flying base-stations to provide communication services to ground stations and are referred as UAVs-assisted communication [2–5]. Similarly, UAVs used for a multitude of applications from cargo delivery to surveillance referred to as cellular-connected UAVs [6,7].

However, this revolution does not happen in a day rather its foundation stone has been laid down long back in the history. For example, in the year 1965, a new revolutionary invention of the Internet changed the world. In the 1970s, ARPANET [8] was reformed from the military *securenet* to a civilian secure Internet which becomes an integral part of human lives. Nowadays, Internet creates a new market place which turns into a big business which never happens. Some of the big corporations (Gmail, google, yahoo, Amazon, Flipkart) do their business from different offices using Internet irrespective of their geographical locations. Internet is a worldwide network in which billion of users/things are inter-connected using the transmission control protocol/Internet protocol (TCP/IP)-based set of network protocols. It serves as a local and global data communication standard that connects million of public, private, academic and business networks. This type of environment where billions of things are inter-connected with each other for data sharing and communication is also called as the *'Internet of Things'* (IoT) [9]. It is defined as the inter-connection of physical objects or smart devices such as-smart meter, smart vehicles, drones, and sensor devices which allows these devices to communicate and data exchange with each other using the Internet [10].

From the above-mentioned smart devices, drones are widely used for air and ground operations (navigation, surveillance and reconnaissance). These are also known as UAVs. They are defined as the type of aircrafts which operate without human pilot interaction. Some of the components of an unmanned aircraft system are ground-based controller, UAVs and a platform that provides communication between the two. UAVs may use a wide variety of cameras or sensors to capture heterogeneous data such as-thermal images, audio, and videos for

Table 1
List of abbreviations.

List of abbreviations	Meaning
AC	Alternate Current
ACO	Ant Colony Optimization
AI	Artificial Intelligence
A*	A- Star
APF	Artificial Potential Field
ANN	Artificial Neural Networks
AMUAV	Adaptive MAC Protocol for UAVs
CMOMMT	Cooperative Multi-robots Observating Multiple Moving Targets
CPU	Central Processing Unit
DC	Direct Current
DMPC	Decentralized Model Predictive Control
DEM	Digital Elevation Map
DoS	Denial-of-Service
ESC	Electronic Speed Controller
ECD-PRM	Exact Cell Decomposition-Probabilistic Road Maps
EPF-RRT	Environment Potential Field-Rapid-exploring Random Trees
ESN	Echo State Network
E-Spiral	Energy-aware Spiral
EBF	Energy-aware Back and Forth
1G	First Generation
4G	Fourth Generation
5G	Fifth Generation
FSA*	Fringe Saving A- Star
FH	Fixed Horizon
GPSR	Greedy Perimeter Stateless Routing
GB	Gigabytes
GHz	Gigahertz
GA-GA	Genetic Algorithm–Genetic Algorithm
GA–GH	Genetic Algorithm–Genetic Heuristic
GPU	Graphical Processing Unit
GAA*	Generalized Adaptive A- Star
GPS	Global Positioning System
TUAV	Hunter and Shadow Tactical UAV
HFLC	Hierarchical Fuzzy Logic Controller
ISR	Intelligence, Surveillance and Reconnaissance
IGA	Improved Genetic Algorithm
INF	In-Fly-Awareness
IBVs	Image Based Visual Servoing
IMC	Inter-Module Communication
IPv6	Internet Protocol version 6
IETF	Internet Engineering Task Force
KB	Kilobytes
LIDAR	Light Detection and Ranging
LASER	Light Amplification by Stimulated Emission of Radiation
LiPo	Lithium Polymer
LoWPAN	Low Power Personal Area Networks
MB	Megabytes
MUFT	Most Uncovered First
MPC	Model Predictive Control
MDP	Markov Decision Process
MACD	Modified Adaptive Cell Decomposition
NBO	Nominal Belief Optimization
PRM	Probabilistic Road Maps
PSO	Particle Swarm Optimization
PFM	Potential Field Method
POMDP	Partially Observable Markov Decision Process
PSA-ACO	Particle Swarm Algorithm-Ant Colony Optimization
PFIH	Push Forward Insertion Heuristic

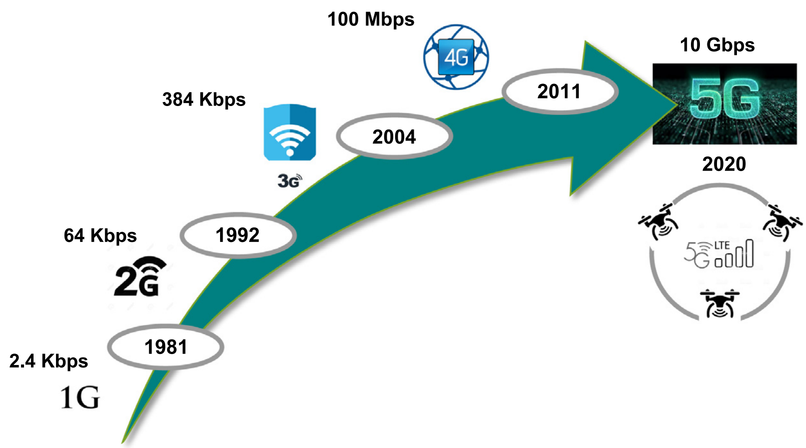

Fig. 1. Evolution of technologies in UAVs communication.

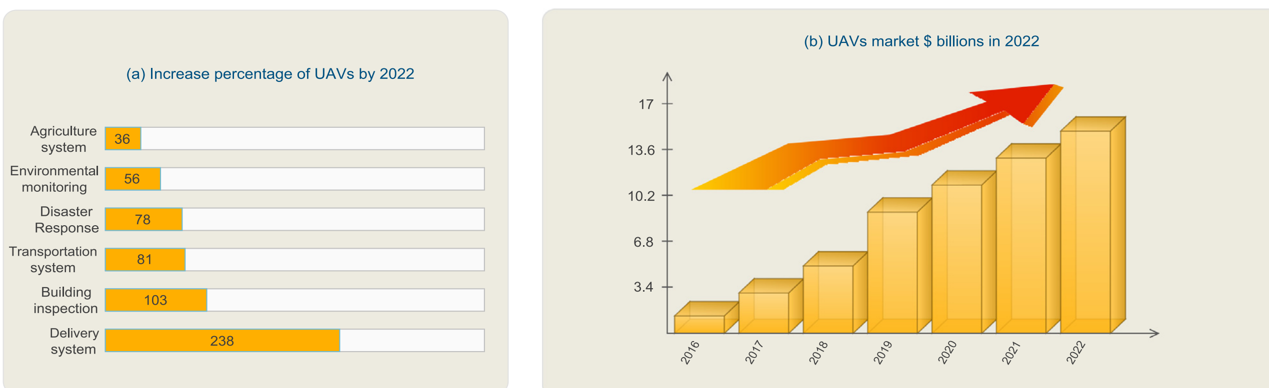

Fig. 2. (a) Percentage increase of UAVs by 2022 in different applications (b) UAVs market by 2022 in $ billions [11].

Table 2
List of abbreviations.

List of abbreviations	Meaning
QoE	Quality-of-Experience
QT	Quality Threshold
RH	Receding Horizon
RRT	Rapid-exploring Random Trees
RRT*	Rapid-exploring Random Trees- Star
RRT*-FN	Rapid-exploring Random Trees- Star-Fixed Node
RRT*-AR	Rapid-exploring Random Trees- Star-Alternate Routes
RHO	Receding Horizon Optimization
SARSA	State–Action–Reward–State–Action
2G	Second Generation
TSP	Traveling Salesman Problem
3G	Third Generation
TCP/IP	Transmission Control Protocol/Internet Protocol
IoT	Internet of Things
3-D	Three-Dimensional
2-D	Two-Dimensional
UAVs	Unmanned Aerial Vehicles
UGVs	Unmanned Ground Vehicles
UKF	Unscented Kalman Filter
USMP	UAVs Search Mission Protocol
UCAV-N	Unmanned Combat Air Vehicles for Navy
UCAV-AF	Unmanned Combat Air Vehicles for Air Force
VTAL	Vertical Take Off Landing
VD	Voronoi Diagram
VRF	Vehicle Routing Problem

various applications such as-precision agriculture, smart transportation, crowd management to name a few. But, this heterogeneous type of data may not be handled by the traditional technologies. So, the new upcoming technologies (edge computing, big data, software-defined networking) are widely used for the development and deployment of UAVs in various applications such as-navigation, localization, mapping, and searching. It has been found in the literature that the percentage increase of UAVs in various applications for target missions by the year 2022 would be increased as shown in Fig. 2(a). Also, from the report of Interact Analysis [11], the UAVs market will be increased to $15 billion by the year 2022 as shown in Fig. 2(b).

UAVs are widely used for military and civilian applications such as-climate monitoring, environmental research, rescue and search operations, and weather forecasting. [12,13]. They have high mobility, portability, scalability and flexibility to give better performance in terms of short path length, maximum roll angle, minimum turning angle, fast speed. In addition to this, they also have the capabilities to hold and escape from the enemy's attack in an emergency situation.

1.1. Need of autonomy for path planning in UAVs

In a dynamic environment, there may exist obstacles during the execution of various operations by UAVs. The existing technologies (big data, cloud computing) are incapable to solve the problems of finding the path and locating the objects because UAVs are not able to find solutions by themselves [15]. So, there is a requirement of autonomy in UAVs for performing various operations. It is a mechanism in which

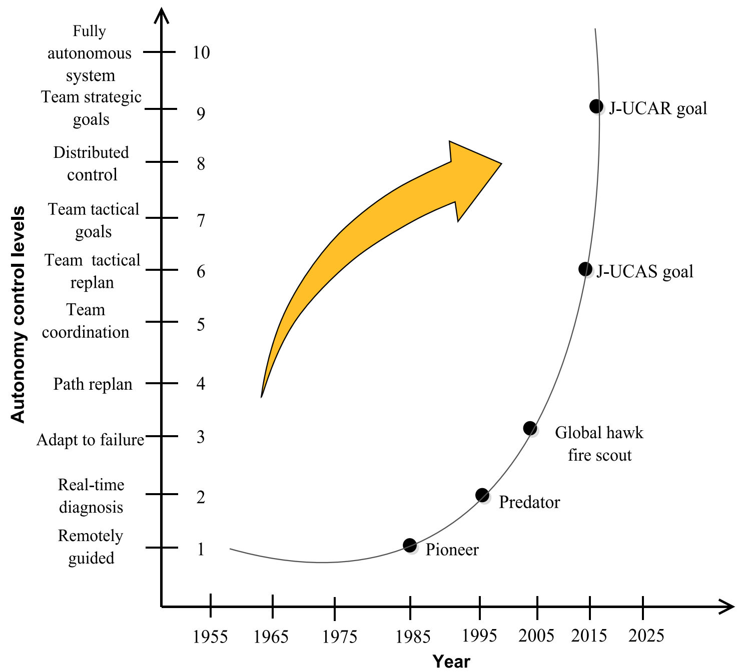

Fig. 3. UAVs autonomy control levels in the years to come [14].

UAVs have the capabilities to make decisions by themselves using available information. This information can be captured by sensors, cameras or by global positioning system (GPS). It increases the performance and efficiency of the UAVs because all the decisions are explored by the UAVs themselves except critical decisions such as-launching a missile [16].

Autonomy in UAVs is used in various areas such as-path planning, task scheduling, trajectory planning, task allocation, and communication [17]. There are ten levels in the autonomous system which are called as autonomy control levels. These levels are used to define the autonomy as a metric in UAVs. These levels are also used for representing the UAVs path planning techniques. For example, authors in [14] described the autonomy control levels using which UAVs are used to make the control decisions. The autonomy control levels of the UAVs over the years are shown in Fig. 3.

UAVs have the capabilities of vertical take-off and landing (VTAL) with high mobility that generally used for various issues such as-path planning, data dissemination in a real-time environment. But, for executing the operations like sensing and computation in UAVs communication system, path planning is critical.

1.2. Overview of path planning

Path planning is a problem of determining a path for the UAVs from an initial point to the goal point. The path determination for the UAVs should be free from all collisions from the surrounding obstacles. Their planned motion satisfies the UAVs physical/kinematic constraints such as-electrical energy and kinetic energy [18]. UAVs path planning consists of following key terms which are discussed below [19].

- **Motion planning:** Motion planning is concerned with robotics. This planning satisfies the constraints such as-flight path, turning a crank. in path planning motion. It optimizes the path in terms of short path length and minimum turning angle.
- **Trajectory planning:** Trajectory planning is about the motion planning. It encloses the path planning having velocity, time, and kinematics of UAVs motion.
- **Navigation:** Navigation is a part of motion planning, trajectory planning, collision avoidance, and localization. It is a general term in which controlling and monitoring of the UAVs movement is from one place to another.

Fig. 4. 3-D environment scenario for UAVs.

For path planning, there is a requirement of 3-D (three-dimensional) view in complex environments. The simple 2-D (two-dimensional) path planning methods are not able to find the obstacles and objects in comparison to the complex 3-D environment. So, 3-D path planning techniques are on demand for UAVs surveillance and navigation in a cluttered and complex environment. The scenario of a 3-D environment is as shown in Fig. 4.

A path planning for 3-D (D^3) environment with stationary obstacles $O = \{O_1, O_2, \ldots..O_n\} \subset D^3$, from P_s to P_t is as shown in Fig. 4. Assume that the free workspace without obstacles/ problems is represented by W_{free}. Then, the path planning problem for D^3 environment is (P_s, P_t, W_{free}) for which various functions is defined as follows.

Let a function $\delta[0,T] \rightarrow D^3$ is defined in the bounded region where, T is represented as a time. Then, following holds.

$\delta(0) = P_s \rightarrow$ at starting time

$\delta(T) = P_t \rightarrow$ at target time

there exists, $\emptyset = \delta(\beta) \in W_{free}$

for all, β in [0,T]

Then, ∅ is called path planning of UAVs.

For an optimal path planning, cost (c), time (t), energy (e) should be minimized. So, it can be defined as follows.

$$\delta'(c,t,e) = \text{minimum of } \delta(c,t,e)$$

where, δ is the function of all set of feasible path and δ' is an optimal path computation function. The communication energy of UAVs base-station can be reduced by minimizing the transmission power. Similarly, minimizing the mechanical energy of UAVs, there is a need for consumption model in UAVs communication system [20]. The energy-efficiency in UAVs communication system can be modeled as follows.

$$E = (P_{min} + \alpha \text{h})\text{t} + (P_{max}) \text{ (h/s)}$$

where as, t represents the operating time, h represents the height, and s represents the speed of the UAVs. P_{min} and α depends on weight and motor characteristics. We can say that, P_{min} is the minimum power needed to start the UAVs with α as the motor speed multiplier.

Hence, the total communication cost (T_{com}) to minimize the time and cost in UAVs communication system is as follows.

$$T_{com} = t_s + (t_o + t_h)l$$

where as, t_s represents the startup time of UAVs, t_o represents the overhead time, t_h represents per-hop time of the UAVs, and l represents the communication links between the source and destination.

With these parameters, robustness, completeness and collision avoidance factors have also been considered in the existing proposals for finding the optimality of UAVs path planning.

1.3. Steps in the path planning

Path planning of the UAVs is represented as 'U' consists of two phases as follows. The first phase is the pre-processing phase. In this phase, nodes (points) and edges (lines) are drawn on the workspace 'W' with obstacles 'O'. Then, the concept of the configuration space (c-space) to describe U and O on W is applied [19,21]. Next, representation techniques are applied for generating the graph maps. Each path planning technique defines the path for UAVs having points and lines in a different way. The second phase is the query phase in which search and rescue operations are performed from the starting point of the path to the target point. For the query phase, the graph search-based algorithms such as-ant colony algorithm, flood-fill algorithm, Floyd algorithm are used. There are a number of path planning methods such as-probabilistic models, mixed integer linear programming [22–25], bio-inspired models, evolutionary models [26–28] which can also be used for an optimal UAVs path planning.

There are a number of proposals to represent the c-space on W in the path planning such as-potential fields [29–32], cell decomposition [33–36], roadmaps [37–40]. C-space is configured by the fields which are generated from the starting point (P_s), target point (P_t) and the O. The repulsive forces are generated from O and P_s and attractive forces are generated from P_t. The path is computed on the basis of resultant forces from P_s to P_t with O. In c-space, a U configuration is a point specification of all the positions relative to a fixed coordinate system. It is expressed as the *'vector'* of the position parameters as shown in Fig. 5.

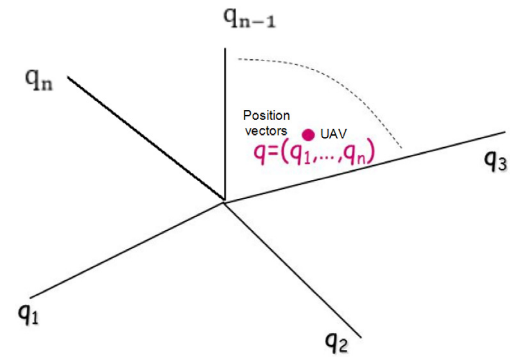

Fig. 5. Position vector of UAVs in a c-space.

1.4. Challenges in path planning

Many research proposals have been discussed in the past to solve the path planning problems on UAVs [21,41–43]. They have explored the path planning in UAVs communication system in terms of different shapes and complexities. For example, authors in [44,45] described their regions by different sweep direction to find an optimal path. Also, Torres et al. [46] explored the back and forth pattern to minimize the distance between sub-areas. The collisions and banned flight zones have been considered in [47]. Similarly, authors in [48–51] proposed the hybrid decomposition technique and approximate cellular decomposition technique used to divide the coverage area into the exact shape (triangle). In a similar way, Acevedo et al. [52] presented the spiral-like pattern to perform path planning in complex coverage areas.

The main objective of path planning techniques is to have less computational cost and time for an optimal path planning. The path generated from these techniques should be optimal so that it consumes minimum energy, takes less time, and reduces the effect of collision between the UAVs.

On the other hand, it needs to satisfy the robustness and completeness criterion during path planning techniques. The major challenges for an optimal path planning of UAVs are as follows.

- **Path length:** The path length is defined as the total distance covered by the UAVs from the starting point to the final point of the target.
- **Optimality:** Optimality defines that the system should be time efficient, cost efficient and energy-efficient. It can be defined in following three ways, i.e., optimal, sub-optimal and non-optimal.
- **Completeness:** Completeness is defined as the criterion used in path planning for finding the path if it exists. It provides the platform to the UAVs and provides the solution if the path planning technique is able to search an optimal path.
- **Cost-efficiency:** Cost-efficiency depends upon the total computation cost of the UAVs network communication. It consists of various factors such as-cost between two nodes, fuel cost, battery charging cost, memory space cost, software and hardware cost of the UAVs.
- **Time-efficiency:** Time-efficiency means that UAVs cover the target operation from initial to goal point with obstacles in the minimum time. This can be possible if and only if UAVs use an optimal and shortest path for completing the target operation.
- **Energy-efficiency:** Energy-efficiency is defined as the minimum energy consumption by UAVs in terms of fuel, battery power energy, energy used for smoothing the trajectory during target operations.
- **Robustness:** Robustness is defined such that the UAVs have the capabilities to tolerate the position sensitive device errors, the rotation driving errors, linear driving errors during path planning.
- **Collision avoidance:** Collision avoidance is defined as the mechanism in which UAVs have the power to detect the collisions so that there is no physical damage to UAVs.

These parameters are considered for the detailed analysis of UAVs path planning techniques in the existing proposals.

1.5. Motivation

UAVs are widely used for analyzing risks and endangered missions in an obstacle environment without hazardous to human life. UAVs

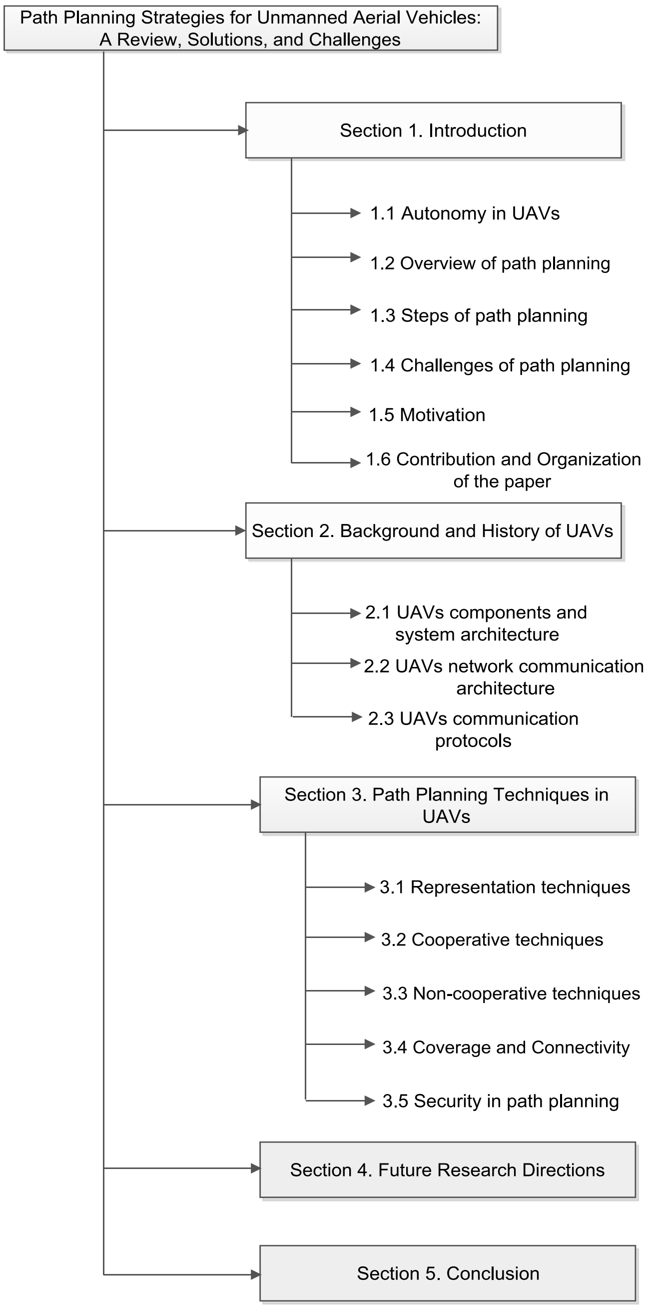

Fig. 6. The organization of this paper.

require no human intervention, so there is no loss to humans if it gets attacked by the enemies. But now, many UAVs need human interaction to oversee, control and monitor the various operations. With the involvement of human operators' decisions, UAVs are unable to execute a target mission as desired. Thus, there is a requirement that UAVs have the capabilities to make decisions of the safe path by themselves. In order to take self-decisions, UAVs need to refer path planning techniques.

Path planning of UAVs in a 3-D environment have many problems and uncertainties. So, to get a realistic path for UAVs, all factors (path length, optimality, and completeness) should be taken into consideration. By using the techniques of path planning, not only an optimal and collision-free path can be discovered but also it minimizes the path length, travel time and energy consumption. So, to gain knowledge of various path planning techniques for UAVs, we presented a comprehensive survey by exploring the existing articles from different angles. It enhances the usage of UAVs path planning techniques for various applications. So, this paper mainly represents the existing proposals based on UAVs path planning techniques.

A number of existing surveys based on UAVs network communication exists in the literature [53–56] having characteristics of UAVs network, communication issues, path planning, charging techniques, and requirements of UAVs. For example, Hayat et al. [53] described the communication of UAVs network applied in civilian applications with their network characteristics. Gupta et al. [55] analyzed the UAVs networks in detail and elaborated on the issues for providing stability and reliability to the UAVs network. Motlagh et al. [57] provided the IoT-services such as-delivery system from the low altitude sky-based UAVs. They also presented a detailed survey of UAVs communication. Li et al. [58] provided an extensive review of various fifth generation (5G) techniques. These techniques are based on UAVs network communication which includes physical and network layers. Authors in [59] discussed the detailed analysis of path planning techniques and related survey articles on UAVs path planning in [60]. The security attacks on the communication network of UAVs have been discussed in [61]. After analysis of the existing proposals, it has been observed that most of the literature articles have considered UAVs network communication. But, none of these articles have considered the UAVs path planning techniques used in various applications. Moreover, the existing survey proposals have not analyzed the benefits of path planning techniques for UAVs communication. Therefore, in this paper, a comprehensive survey based on UAVs path planning techniques is presented for various applications. The existing surveys related to UAVs communication are summarized in Table 3.

1.6. *Contribution and organization of the paper*

The significant contributions provided in this survey paper are as follows.

- We discuss the path planning techniques in UAVs network communication for various mission-critical operations performed by UAVs.
- We represent the path planning techniques into three broad categories, i.e., representative techniques, coordinate techniques, and non-coordinate techniques and discuss in the form of existing proposals.
- We present the coverage and connectivity and security of the UAVs in UAVs network communication.
- We compare the proposed survey with the existing proposals based on path planning in UAVs network communication.

The main aim of this survey paper is to represent the path planning techniques used in UAVs network communication. The purpose of path planning techniques in UAVs is not only to find an optimal solution but also to provide the collision-free path to the UAVs. We explore the path planning techniques by doing critical analysis of the existing proposals in the tabular form. We use various parameters such as—path length, optimality, completeness, cost-efficiency, time efficiency, energy-efficiency, robustness, and collision avoidance.

Rest of the paper is organized as follows. Section 2 represents the history and background of the UAVs. In Section 3, a detail analysis of various path planning techniques is provided. This section also represents the coverage and connectivity of UAVs based on path planning techniques. Also this section represents the security mechanisms used in UAVs path planning. Section 4 describes the open problems in the UAVs network communication for future research directions. Finally, Section 5 concludes the article. The organization of this paper is as shown in Fig. 6.

Table 3
Existing surveys related to the UAVs communication.

References	Brief summary	1	2	3	4	5	6	7	8	9	10
Hayat et al. [53]	A survey on the requirements and characteristics of UAV communication networks	✓	x	x	x	x	x	x	x	✓	✓
Mozaffari et al. [54]	An extensive survey in wireless networks using UAV communication	✓	x	x	x	x	x	x	x	✓	x
Gupta et al. [55]	A comprehensive survey on the issues of UAV networks	x	x	x	x	x	x	x	x	✓	✓
Cao et al. [56]	Analysis of airborne communication networks	✓	x	x	x	x	x	x	x	✓	x
Motlagh et al. [57]	A detailed survey based on IoT-services by UAV communication networks	✓	✓	x	✓	x	✓	✓	x	✓	✓
Li et al. [58]	Advances and future trends of UAV communication in 5G and beyond	✓	x	x	x	x	x	x	x	✓	✓
Krishna and Murphy [61]	A survey on the cybersecurity of UAVs	✓	x	x	x	x	x	x	x	✓	x
Valente et al. [59]	Aerial coverage optimization technique in agriculture system	✓	x	x	x	x	x	x	x	x	x
Miller et al. [60]	Path planning strategy in a threat environment	✓	✓	✓	✓	✓	✓	✓	x	✓	✓

1: Path planning; 2: Sampling-based techniques; 3: AI techniques; 4: Mathematical models; 5: Machine learning models; 6: Bio-inspired models; 7: Multi-objective models; 8: Graph search-based techniques; 9: Coverage and connectivity; 10: Security; ✓: considered; x: not considered.

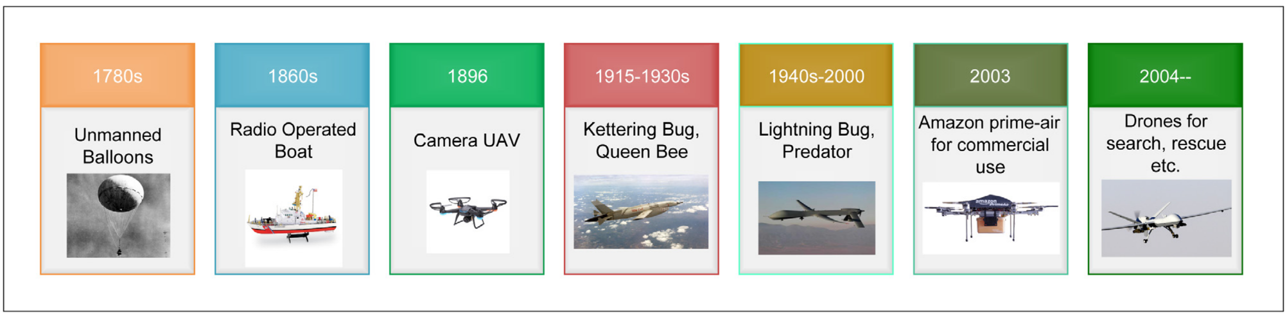

Fig. 7. Evolution of UAVs.

2. Background and history of UAVs

The evolution of UAVs started from the 1780s and still, it is one of the most emerging technologies in a real-world environment [62,63]. From the year 1780s to 1840s, the bomb-filled unmanned balloons were used by Montgolfier French brothers and Austrians. In the year 1860s, camera-based UAVs were developed for the surveillance purpose which was a big revolution in the UAVs network communication. After this, from the 1910s to 1930s, various bomb-filled balloons were discovered such as-Kettering bug and Queen bee. In the 1940s, the first remote control based UAVs were developed against enemy attackers named as operation *'Aphrodite'*. As time passes, various remote-controlled UAVs were developed such as-Ryan fire bee, Pioneer, Predator which is used for the monitoring and execution of various applications [64].

A new and exciting innovation in UAVs was done in 2003 which is called as amazon prime air by Amazon CEO 'Jef Bezos' which is used for commercial purpose. From 2003 to till date, the creation and development of UAVs gain popularity day by day and is discussed in [65,66]. Now, this technology can be used in various applications such as-agriculture system, disaster response etc. The history of UAVs from the 1780s to now is as shown in Fig. 7. From the report of cloudtweaks, the rise of UAVs usage in different countries by the year 2022 is as shown in Fig. 8 [67].

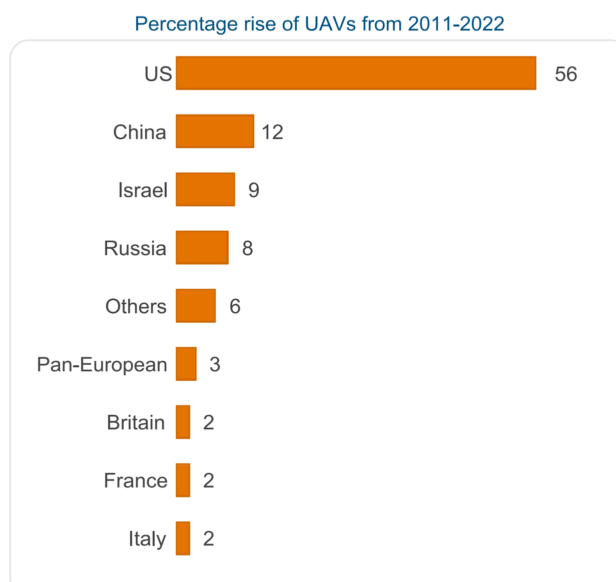

Fig. 8. Rise of UAVs usage in different countries.

2.1. UAVs components and system architecture

Fig. 9 shows the main high-level functional components of the UAVs path planning. The layered structure consists of data collection, data processing, and actuation. The data collection layer having hardware components such as-on-board sensors, light detection and ranging (LIDAR) path planning track, back and front cameras and communication smart devices, i.e., transceivers. The data is collected by these hardware components of the UAVs and is processed by the UAV's central control system, which is then used in mapping, localization, and decision-making system. The central control system actuates the UAVs and is used for the real-world environment.

Fig. 10 depicts the area covered by the above-mentioned hardware components. For instance, front and rear UAVs collision is avoided by the infrared devices by detecting the obstacles during UAVs path planning. These infrared devices provide the solution from avoiding collisions such as—path change warning by detecting the extra object and traffic view in the path. UAVs are equipped with a series of video and photograph cameras to locate the surrounding and back view of the path. LIDAR is used for avoiding collisions in UAVs path planning. UAVs consist of major components such as—electronic speed controller (ESC), GPS module, sensors, gimbal, flight control, battery. All the aforementioned components are inter-connected and work closely with each other as shown in Fig. 10. The detail description of the components of the UAVs is as follows.

- **Electronic speed controller:** ESC is an electronic circuit which is an essential part of the UAVs that offers high frequency and power

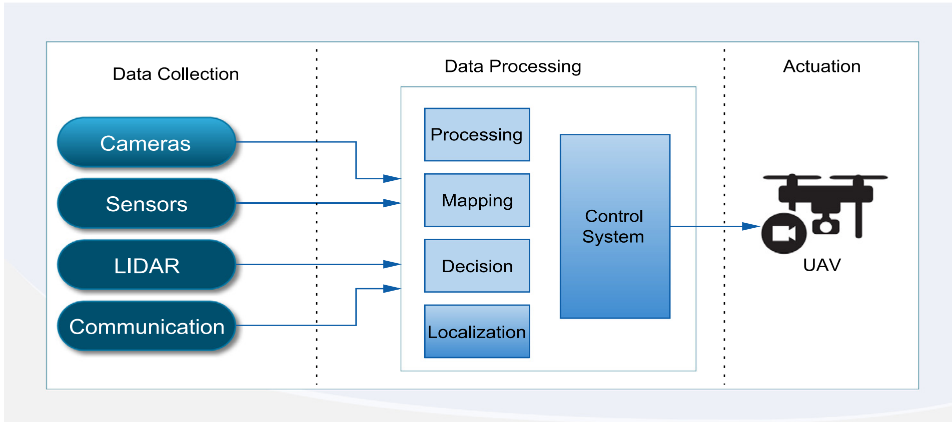

Fig. 9. Functional components of UAVs system.

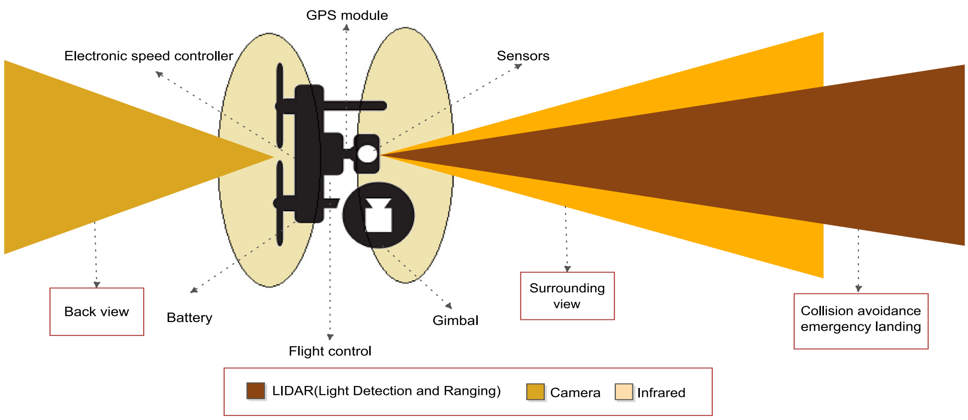

Fig. 10. Components of UAVs.

to the UAVs motors. It is used for varying the electronics's motor speed and to convert the direct current (DC) power to 3-phase alternate current (AC) power.

- **Global positioning system module:** GPS module is used for computing the time and location information of UAVs. It also provides the longitude, latitude, elevation and compass information of the UAVs. It is important for the requirement of navigation and autonomous flight system.
- **Flight controller:** Flight controller takes input from the GPS module, light amplification by stimulated emission of radiation (LASER) monitors and other sensors. It is the central part of the UAVs and controls the whole functioning of the UAVs network communication.
- **Battery:** The battery in UAVs is made from the lithium polymer (LiPo) for power, energy and lifetime density of the UAVs. They always carry an extra battery for the emergence of long duration target operations.
- **Gimbal:** Gimbal is the pivoting point of the UAVs that rotates about *x*, *y*, and *z-axis*. It provides stabilization to the UAVs. It is important for clicking good photographs and videos.
- **Sensors:** There are two type of sensors in the UAVs. The first one is used for creating 3-D images using LIDAR and thermal vision cameras. LIDAR is used to achieve high accuracy digital terrain models based on UAVs remote sensing. The LIDAR-based UAVs are widely used in several applications using high-resolution images by collecting data from various sources [68,69]. Thermal vision cameras are used in UAVs communication system for potential imaging. These cameras used in agriculture and ecological research for disease detection and high-throughput phenotype in plant breeding [70,71]. The second type of sensors is used to detect and avoid collisions using ultrasonic, infrared, time-of-flight vision. These sensors have been used to make accurate decisions on 3D-positioning in UAVs communication system. These can also be used to keep track for real-time UAVs collision detection and avoidance [72].

With the civilian UAVs, military UAVs are also widely used in a real-time environment for hazardous missions. From 1985 to 2015, the different type of military UAVs are used in various fields like a navy, army, and air force as shown in Fig. 11. The different UAVs have different specifications in terms of turning angle, rotation angle, sensors, vision cameras, version and tolerance power. The military UAVs which are used for the three above-mentioned cases are: (i) pioneer, fire scour vertical take-off and landing tactical UAV and unmanned combat air vehicle for navy (UCAV-N), (ii) hunter and shadow tactical UAV (TUAV) and (iii) predator, global hawk and UCAV for air force (UCAV-AF) respectively. These UAVs are still used for the military applications by upgrading the communication and range for multi-purpose. These military UAVs are small in size, have system stability, payloads, platform, communications and information processing units. These are also named as a killer drone, spy drone, attack drone, and surveillance drone. These are very low in cost with respect to fuel, purchase, and maintenance but expensive in terms of production and keeps up.

The main importance of these military UAVs is that they can be used at any place or time to avoid the risks of harming human resources and human lives by detecting and tracking enemy actions.

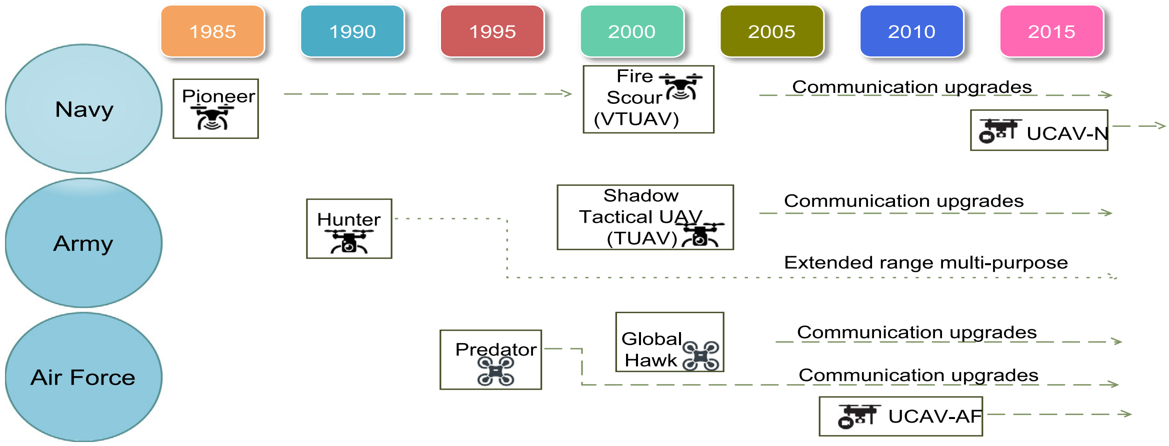

Fig. 11. UAVs used for military purposes over the years.

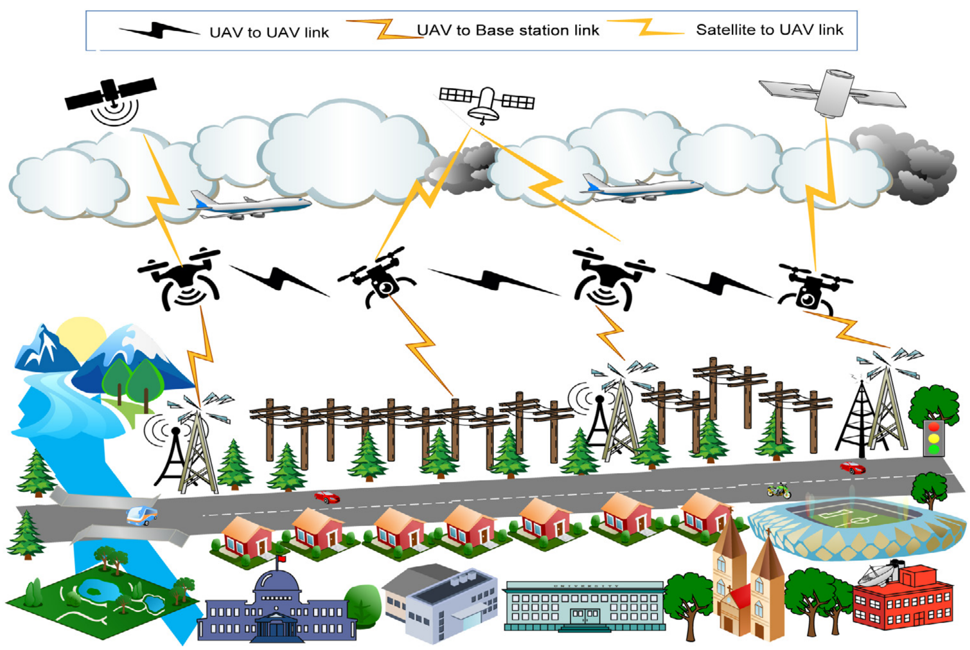

Fig. 12. UAVs network communication architecture.

2.2. UAVs network communication architecture

UAVs need to perform path planning when they are moving from one place to another. They identify the surrounding environment using sensors to plan, navigate and control movements in the air. The UAVs path planning steps need to be followed for the execution of operations by UAVs are (i) weather and climate monitoring, (ii) navigation, (iii) mobility control of the UAVs. The above-mentioned steps are applied until the UAVs have reached the destination point. In the first step, weather and climate monitoring of the surroundings give environmental awareness. In the second step, the path planning techniques and navigation are applied to find an optimal path. In the third step, the mobility and speed of the UAVs are controlled by the control system for collision avoidance. In addition to environmental awareness, the UAVs communicate with other UAVs for the infrastructure management during target operation.

Fig. 12 shows that the UAVs communicate with the satellites, infrastructure, and its neighboring UAVs. There is a number of links such as-satellite to UAVs, UAVs-to-UAVs and UAVs to base stations used in UAVs network communication. Each link represents a different type of communication information and data [73]. The network shown in Fig. 12 has three types of links based on the communication coverage and connectivity. These are (i) UAVs to base station link which is used for recording and transmitting the readings of an instrument such as audio and video. This is known as radio communication. (ii) In the addition of radio, satellite to UAVs link carries weather, climate, GPS information which is known as satellite communication, and (iii) UAVs-to-UAVs link share their information with the other UAVs using a wireless communication.

In this paper, path planning techniques of UAVs in various applications have been discussed. To reduce the communication delay between the UAVs, there is a need for close inter-connection with the other UAVs. Sometimes, it is not possible for the UAVs to maintain a path link with the served users. As a consequence, to find an optimal path link for UAVs, there is a need for UAVs path planning techniques. The representation and mapping of UAVs path planning techniques are discussed in the following sections.

2.3. UAVs communication protocols

The wireless communication system is used to control the devices and to analyze the data. It is widely used in remote systems (UAVs)

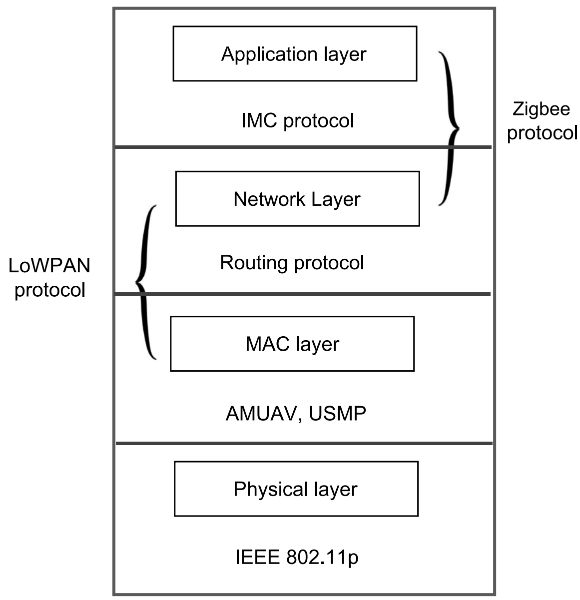

Fig. 13. UAVs communication protocols.

to reach the areas where humans cannot reach itself easily. In this paper, we have discussed wireless communication between UAVs to base-stations, UAVs-to-UAVs, and UAVs-to-satellites. It may also act as a mobile access point during satellite communication to have multi-hop transmissions [74]. The communication protocols used in UAVs communication system are described as follows. The pictorial representation of UAVs communication protocols is as shown in Fig. 13.

1. **MAC layer:** The medium access control layer is one of two sublayers that make up data link layer. It is used to send data packets to and from the network interface card to another shared channel over the communication. The current MAC protocol is omnidirectional which is not suitable for UAV s communication due to long distance between the UAVs. So, the authors in [75] provided an adaptive MAC protocol for UAVs is called*AMUAV* protocol. It has the capability to deal with bidirectional antennas and tolerates the UAV s altitude. It also provides better end-to-end delay, throughput, and low-interference. Similarly, authors in [76] proposed the UAVs search mission protocol (USMP) to improve search efficiency in terms of the distance between UAVs and change in the direction of UAVs. The routing protocol, *i.e.,* geographic greedy perimeter stateless routing (GPSR) with USMP is used to send the forward packets at their most specific search decision.
2. **Physical layer:** This layer deals with the physical connectivity between two entities. It includes hardware equipment, cabling, wiring, pulses, and frequencies used to represent the signals in binary. The IEEE 802.11 physical layer protocol is used for UAVs communication system. It applies to wireless LANs and provides 1 or 2 Mbps transmission with 2.4 GHz band. The improved version of IEEE 802.11 is IEEE 802.11p by adding wireless access in the vehicular environment. In this direction, authors in [77] used the protocol for the connectivity of UAVs in vehicular environments. This protocol is capable to perform handover without any loss of data. But, it does not address any network mobility issues.
3. **Network layer:** In this layer, data is transmitted in the form of packets through routers in an ordered format. In this direction, Tuna et al. [78] proposed a routing protocol used for UAVs communication system in case of emergency for post-disaster solutions. In [78], each UAV has an onboard computer responsible to give information on end-to-end communication, autonomous navigation, and formation control.
4. **Application layer:** It is an abstraction layer to share communication protocols used by the end-users for the communication network. In this context, the authors in [79] proposed the inter-module communication (IMC) protocol for UAVs communication in underwater systems and technology laboratory. They have provided the inter-connection between vehicles, sensors, and human operators to search the real-time data information. This also abstracts the communication and hardware heterogeneity via shared messages over the communication channel.

Like layered protocols, Zigbee, LoWPAN and MAVLink are the protocols used for UAVs communication which are described as follows.

1. **Zigbee protocol:** This protocol is used for telemetry communication between UAVs. It is widely used for UAVs wireless communication system because of ultra-low power consumption, low-cost, and ease of design [80]. It is also used to achieve high-integration, portability, and applicability [81]. It consists of a geographical control station to communicate with UAVs. It can also display all the parameters of UAVs as well as data recorded by GPS [82].
2. **LoWPAN protocol:** Low power personal area network protocol was created by the Internet Engineering Task Force (IETF). It is used for low power wireless sensor networks over IPv6. It is used in factory automation to monitor tasks such as—machine assessment for failure prevention or energy consumption monitoring. The main benefits of LoWPAN are reliability, transparency, scalability, and services to the data flow at end-to-end. It provides dual communication approach for reliable communication between the UAVs and the base-stations as shown in Fig. 14 [83]. It introduces the adaptation layer between the MAC layer and network layer.
3. **MAVLink protocol:** The Micro Air Vehicle Link is a protocol used for bidirectional communication between the UAVs and ground base-stations [84]. It is a point-to-point communication which allows information exchange between UAVs and UGVs. It is a part of DroneCode Project, governed by Linux Foundation [85]. Its message is sent by bitwise through the communication channel, followed by a checksum. If the checksum does not match with the message then, it discards by the communication channel.

From the aforementioned discussion on UAVs communication protocols, we have observed that UAVs require high-mobility and location awareness during communication. The connection between the UAVs using aforementioned protocols improve safety, traffic management, mobility and enhances the development in accident prevention, pre-emptive maintenance, vehicular social networking and many more. Each UAVs should have the information of other UAVs present in the communication network to cope with emergency situations. The control management in intermittent connectivity of UAVs communication using wireless communication protocols provides high mobility to the UAVs.

3. Path planning techniques in UAVs

Currently, a lot of research work has been done on the UAVs path planning techniques in various applications. The two important steps for UAVs path planning process are: (i) representation of the UAVs in a 3-D environment for the objects and obstacles identification in the free workspace, and (ii) creation of a map or graph that consider the configurations and specifications of the UAVs in a 3-D environment.

The UAVs path planning techniques are categorized into two categories. The first representation technique is based on c-space which depends on cell decomposition [86], roadmaps [87,88], potential fields

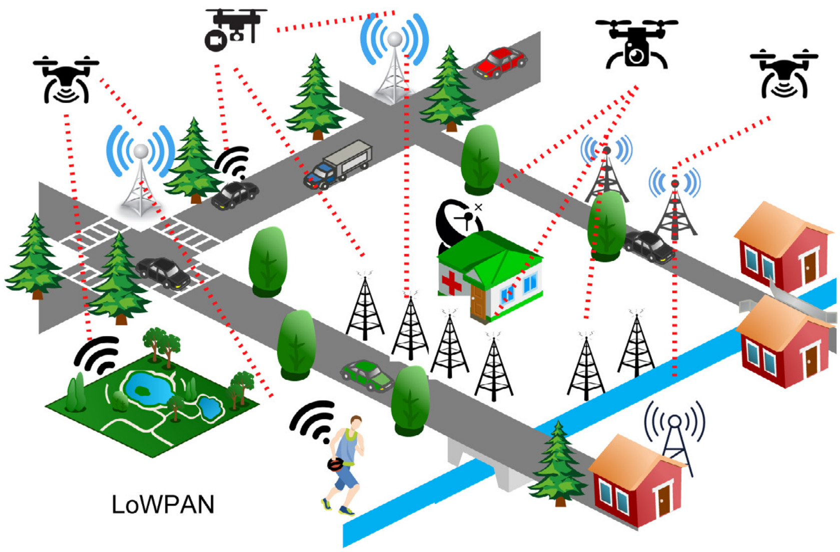

Fig. 14. LoWPAN protocol used in UAVs communication.

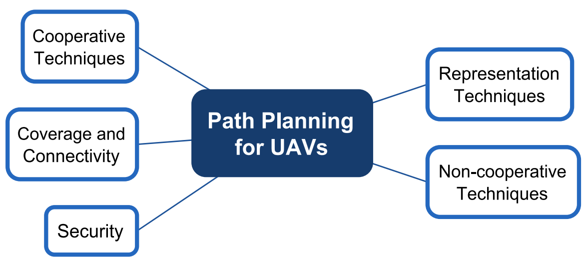

Fig. 15. Taxonomy of UAVs path planning techniques.

[89,90] and Voronoi diagram. The second category is based on coordinate and non-coordinate technique to represent the algorithms such as-genetic algorithm, evolutionary models [91,92], simulated annealing method, ant colony optimization (ACO) to name a few. Authors in [59], discussed the detailed analysis of path planning techniques and related survey articles based on UAVs path planning in [60,93].

The path planning problem for UAVs is implemented as an optimization problem such that it gains an optimal solution among all the possible ones. There is no exact algorithm that defines an optimal path for the UAVs. The methods and algorithms for these path planning techniques are used to find the exact behavior of the UAVs for finding an optimal solution. The main taxonomy of the UAVs path planning techniques is as shown in Fig. 15.

3.1. Representation techniques

The first step of UAVs path planning process is how to represent the UAVs in a 3-D environment. In this mechanism, the two most important representation techniques, i.e., sampling-based and artificial intelligence (AI) based are explored as follows. The main taxonomy of the representation techniques is as shown in Fig. 16.

3.1.1. Sampling-based techniques

The sampling-based techniques need the pre-defined information of the workspace configuration with respect to the 3-D environment. It divides the environment into a different set of nodes and then maps the nodes on the workspace configuration using optimal path planning algorithms. The different type of sampling-based techniques in UAVs path planning are rapid-exploring random trees (RRT), RRT-star (RRT*), A-star (A*), probabilistic roadmaps (PRM), particle swarm optimization (PSO) which are explained in the next sections.

3.1.1.1. Cell decomposition. In a cell decomposition, firstly the free c-space is divided into a different set of cells or regions so that a safe path between two points in the same cell or the adjacent cells can be computed easily. Once the cell decomposition of the free space is computed then, the organization of the cells in a sequential manner is done. For UAVs path planning in c-space, different methods and algorithms can be used depending on the type of cells. For example, authors [94] presented a survey in sampling-based UAVs path planning techniques. They have compared the RRT and PRM algorithms using computational cost and time. They have introduced the two new algorithms, i.e., ***exact cell decomposition*** on the probabilistic road map (ECD-PRM) and the ***modified adaptive cell decomposition*** (MACD) in a c-space as shown in Fig. 17 [95]. These algorithms reduce the impact of cell decomposition in the UAVs path planning. Similarly, authors in [96] discussed the A*, RRT and PSO algorithms and compared the results using robustness. They have evaluated the results that RRT algorithm behaves better than A* and PSO algorithms. They have also demonstrated that RRT algorithm performs better in simple cases and A* and PSO algorithms perform better in low variance cases.

3.1.1.2. Roadmaps. The roadmaps method consist of two phases (i) construction and (ii) query. In the construction phase, the connectivity of the free c-space is computed by defining the network curves in the 3-D environment. After the construction of roadmaps, an initial and final configuration points is solved in the query phase. By the concatenation of curves, the searching queries of UAVs path planning queries between these points can be answered. These answers are used in the query phase by classical AI algorithms such as-genetic algorithm and dynamic programming. Additionally, the smoothing of the UAVs resulting path is done in the third phase.

Roadmaps technique is used for solving the UAVs path planning queries moving in a static environment. The computation time of the queries is finished during processing time and their queries is solved in a real-time. The smoothing of the final path of the UAVs is done by roadmaps algorithms such as-RRT, A*, RRT*. For example, Jang et al. [97] proposed these algorithms for optimal-control based UAVs path planning. They have solved the traveling salesman problem (TSP) using roadmaps. They have also computed the minimum flight time with the coverage of all remote sensing areas so as to execute all communication tasks of the UAVs. The simulation results show that the computation time for path refinement and solving the TSP is less than 1% of the roadmaps construction time. The flight time of the UAVs reduce by approx 10% as compared to the other proposals. The various roadmaps algorithms are discussed as follows.

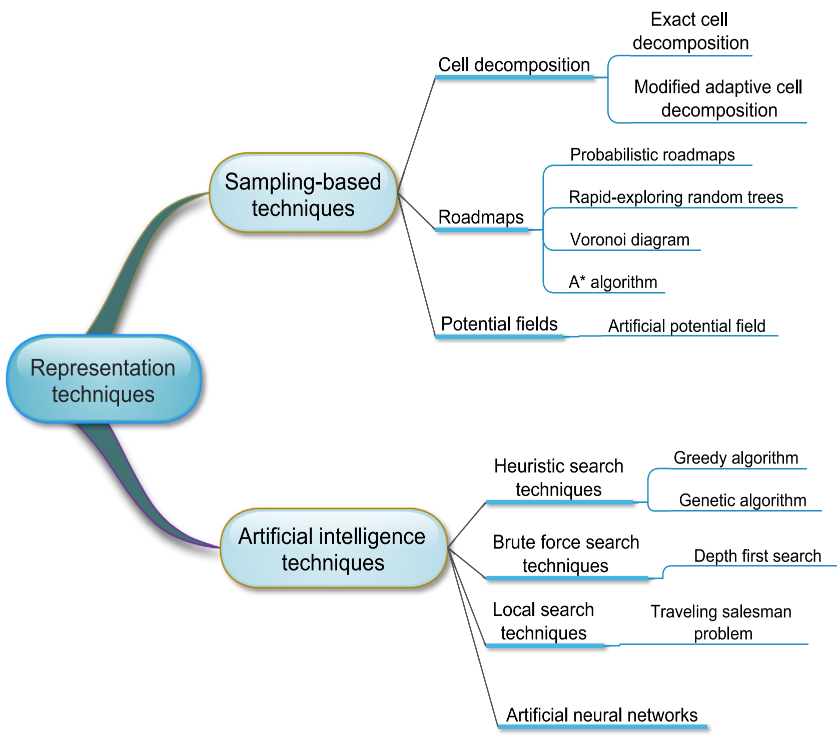

Fig. 16. Taxonomy of the representation techniques.

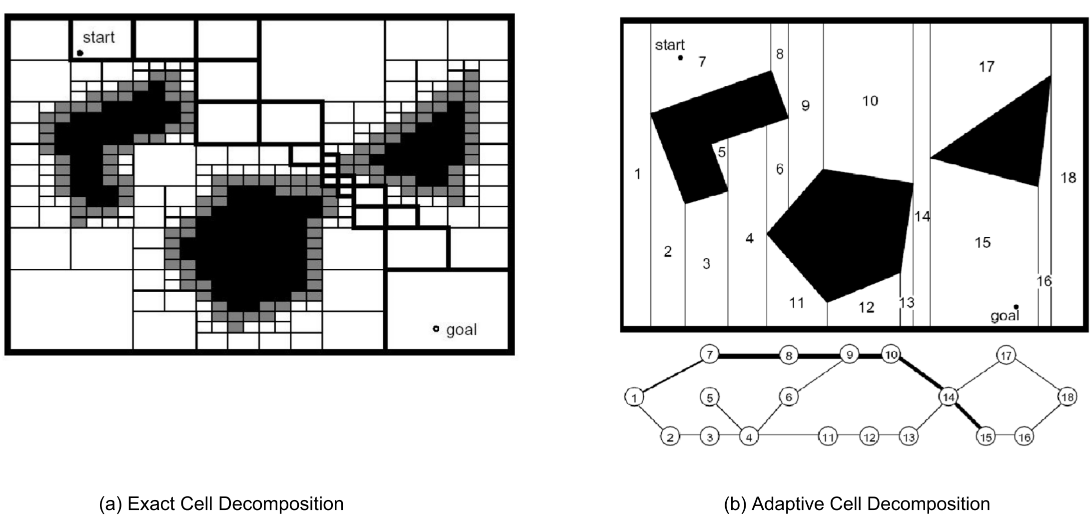

Fig. 17. (a) Exact cell decomposition (b) Adaptive cell decomposition [95].

A. Probabilistic roadmaps-

PRM, a roadmaps algorithm for UAVs path planning, was designed by Stanford and Utrecht simultaneously [98–101]. It consists of random nodes connected by the straight edges. The thick line in Fig. 18 shows that the shortest path from the source to the target point on the roadmaps and is called the PRM [102]. For example, Mansard et al. [103] proposed the kinodynamic PRM with non-linear predictive control model. PRM has been used for optimal path trajectories in UAVs path planning. Then, they used the non-linear predictive control to initialize and to monitor the state trajectories. Similarly, Meng et al. [104] proposed this roadmap algorithm for tracking and searching the path in an urban environment. They have investigated that this technique can also be used for collision avoidance and to find communication gap failures in the UAVs.

B. Rapid-exploring random trees-

RRT, a roadmaps algorithm became the most popular in sampling-based techniques for a single motion planner [105]. It is used to design a high-dimensional spaces by randomly building a space-filling tree as shown in Fig. 19. In the basic RRT algorithm, a single step of fixed distance is computed but the extension of RRT, i.e., RRT-Connect [106] became a more greedy variant which is used for collision avoidance between the UAVs. For example, Zhang et al. [107] proposed RRT-Connect and combines it with an artificial potential field that gives an optimal UAVs path planning. The simulation results for RRT and RRT-Connect in case of distance is 197.9240 meters (m) and 188.6642 m and in case of time is 0.7475 s and 0.0363 s respectively. Similarly, Wen et al. [108] proposed a RRT algorithm to solve the problem of a feasible and safe path between UAVs. They have used this algorithm to predict the dynamic threats and receding horizon (RH) to solve the online path planning. They have also used the RRT* algorithm to optimize the

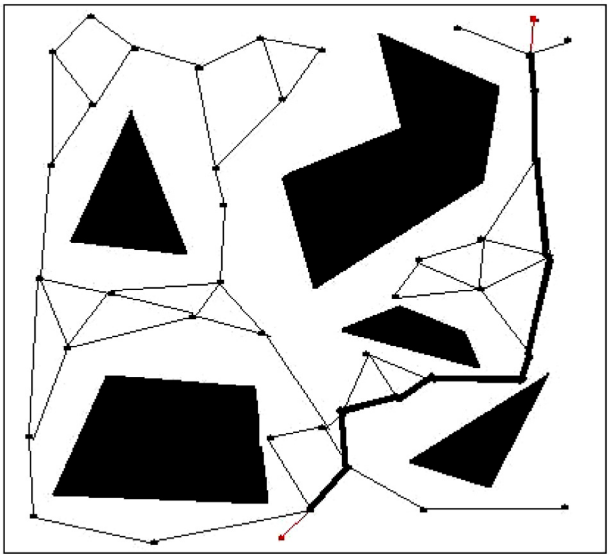

Fig. 18. Probabilistic roadmaps [102].

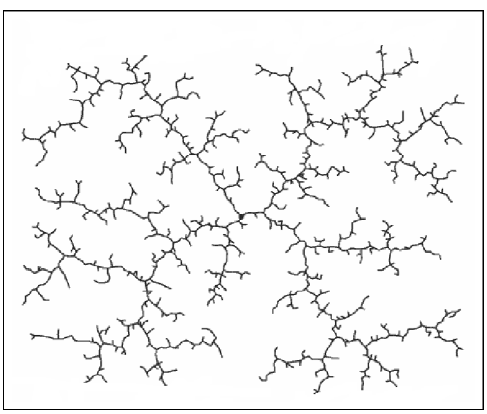

Fig. 19. Rapid-exploring random trees.

UAVs path. Similarly, Lin et al. [109] discussed the three variations of this algorithm (i) to generate the trajectory planning for UAVs, (ii) to find the intermediate path and utilize the way-points and (iii) to predict an optimal solution for UAVs in an obstacle environment.

RRT algorithm is used to design an efficient path for UAVs by the dense covering of free c-space. For example, Yang et al. [110] proposed the environmental potential field based RRT (EPF-RRT) algorithm to solve the problem of UAVs path planning. The simulation results for RRT and EPF-RRT in case of average time cost is 0.295861 s and 0.351792 s and in case of average path length is 180.7879 m and 144.3313 m respectively. They demonstrated that this model has high efficiency and to performs well for the convergence problems. Authors in [111] discussed the benefits of UAVs by creating a map or graph of the unmanned ground vehicles (UGVs) using RRT. They have described that UAVs give better results for UGVs path searching because it has a better field view. Zu et al. [112] described this algorithm for the safe path between two end-points in the presence of obstacles. They have also discussed that if UAVs suddenly detect a new obstacle then this algorithm finds the new path quickly which is free from all obstacles. Levin et al. [113] presented an approach in an aircraft system which involves knife-edge maneuver. In this proposal, roadmaps has been used to construct the planar graphs and algorithm has been used to design a safe, smooth and straight-line path for UAVs.

RRT algorithm finds the path for UAVs only in non-convex high dimensional spaces. So, for the improvement of this algorithm, authors

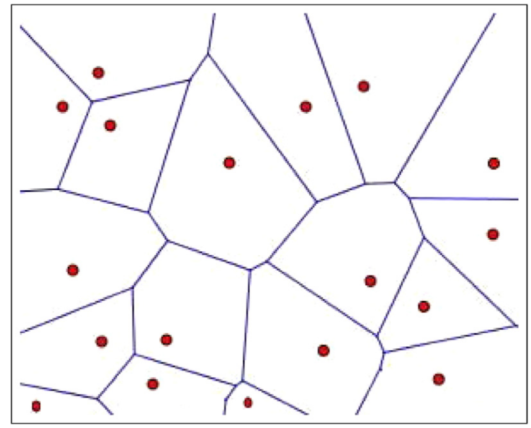

Fig. 20. Structure of voronoi diagram.

proposed new enhancements such as-bidirectional-RRT, dynamic value and dynamic length [114]. The simulation results show that an improved version of RRT gives a high success rate and efficiency in motion planning, time and path length of UAVs. Similarly, Li et al. [115] proposed the improved version RRT* algorithm with model predictive image-based visual servoing (IBVS) for the quadrotor. In this proposal, the RRT* algorithm has been used for optimal path trajectories and model predictive IBVS used for optimizing the cost function with respect to the velocity and visibility of UAVs. In the same way Li et al. [116] proposed an algorithm used to control the UAVs path planning strategies in an obstacle environment. Nurimbetov et al. [117] proposed a sparse-based RRT* algorithm for hybrid UAVs in a dense urban environment. These UAVs are capable of vertical take-off landing called VTOL with high mobility, speed, and efficiency in UAVs path planning. The evaluation results show that the distance between the two end-points is 3 kilometers (km) and completed by the UAVs in 262 s.

From the analysis, we found that the improved version of the RRT algorithm gives an efficient and optimal UAVs path planning. But still, there is a number of improved version of RRT algorithms, i.e., RRT*-smart, RRT*-fixed node (RRT*FN), RRT*-alternate routes (RRT*AN) which have not been used yet for UAVs path planning.

C. Voronoi diagram

Voronoi diagram (VD) are used for roadmaps. In a specific plane, it is used for dividing the surface into regions on the basis of the distance to the way-points as shown in Fig. 20. The nodes and edges to build roadmaps are defined differently for each method. VD defines nodes which are at equal distance from all the points surrounding by the obstacles. The path generated as a graph from the VD is highly safe because the obstacles are so far from all the edges of the path [19]. For example, Chen et al. [118] proposed the consistency theory for the optimality of the UAVs. They used the VD to design the roadmaps and finding the obstacles. Then, they have used the cooperative control method to attack the multiple obstacles. The consistency theory in VD has been used for an optimal path and compute the total flight cost. They have considered three UAVs and finding the starting and target points of the path using VD (i) (1900, 10) and (3200, 8600), (ii) (5400, 10) and (5000, 8000), and (iii) (7800, 10) and (7000, 8000) respectively.

VD are related to various geometric shapes like medial axis and zone diagrams. Shen et al. [119] proposed an improved version of VD to divide the low-altitude sharing space into multiple areas. They have developed an automatic dependent surveillance-broadcast (ADS-B) track method used to control and monitor the UAVs in VD space. In this proposal, authors also found that the proposed method reduces the collision probability and ensures safety between manned and unmanned aircraft systems.

D. A-star algorithm

A* algorithm [120,121] is commonly used for UAVs path planning to compute the path based on the cost from the current node to both starting and goal points. It addresses the problem on a map grid for finding an optimal and shortest path. In this proposal, Chen et al. [122] discussed the advantages and disadvantages of this algorithm and compared it with the genetic and ACO algorithms. They also build the model to plan a safe path and to reduce the consumption of fuel in UAVs. Similarly, He et al. [123] discussed the comparative study of path planning algorithms such as-Floyd algorithm, ACO algorithm, and Dijkstra algorithm. They have considered only real-time path abilities of these algorithms and found that Dijkstra which is equivalent to A* algorithm performs better among all algorithms for finding an optimal path for UAVs.

The analysis of the existing proposals based on A* algorithm is as follows. Benders et al. [124] proposed this algorithm to plan a collision-free path with the varying wind and flight performance conditions. They have also presented a line graph-based method for performance control of UAVs in a windy environment. In this proposal [125], authors used this algorithm in modeling scheme for the effectiveness and efficiency of UAVs. They have also represented an environmental modeling method to reduce the height dimension and to ignore the problems below the height of flying UAVs. Similarly, Li et al. [126] discussed the path coordination between UAVs and UGVs. They used this algorithm to find an optimal path between UAVs and UGVs using local rolling optimization method. Gupta et al. [127] represented this algorithm for multiple UAVs. They demonstrated the fact that multiple UAVs can compensate the problem of single UAV failure during the surveillance and reconnaissance. The simulation results show that as the number of UAVs increases from one to four then the computation time to complete the task decreased from 13.59 to 3.89 s. Similarly, Kwak et al. [128] represented this method for flight surveillance of UAVs. In this proposal [128], firstly the flight-related data has been collected then it is analyzed. Secondly, the path between imaging points are joined for an optimal flight of UAVs. The results show that the proposed method is used for 100 nodes and the flight length of 764.27 m. Sun et al. [129] used this algorithm to predict the path for the real-time operations of UAVs. They have also used the triple-stage path prediction algorithm for the task assignment and B-spline curve to smooth the predicted path for UAVs. For target planning, target matching, and parametric analysis, Zhang et al. [130] designed a heuristic method. They used the A* algorithm for target planning, Hungarian algorithm for target matching, and parametric analysis has been done using the parameters like step-size, turning angle, a proportion of heuristic function. In the same way, Li et al. [131] used this algorithm to find an optimal route between the base station to the supplier and from the client to the desired location in the delivery system.

In the improved version of A* algorithm, there is a number of algorithms like Block A*, D*, field D*, fringe saving A* (FSA*), generalized adaptive A* (GAA*) which is used for UAVs path planning. These algorithms are commonly used for path finding and graph traversal in UAVs path planning. For example, Chengjun et al. [132] described the improved A* algorithm for UAVs path planning. They have considered various parameters such as-target, requirements of the mission, consumption of fuel, area and obstacles for an optimal routing of UAVs. Similarly, Song et al. [133] and Bo et al. [134] proposed the modified version of A* algorithm. In this proposal [133], the path is considered on the basis of weighted graph by graph traversing method. Then, modified A* algorithm has been applied on the graph for optimality and efficiency of the path. The evaluation results show that the modified A* algorithm reduces the path length from 71.1 m to 68.58 m. In [134], authors proposed the algorithm with decentralized model predictive control (DMPC) for the better optimization of UAVs.

A* algorithm has also been used to route a high-level planning in UAVs path planning. Ma et al. [135] proposed a coordination method based on Lyapunov function provides a low-level trajectory planning with A* algorithm. The simulation results provide efficiency, shortest path and minimum time to UAVs path planning. Penin et al. [136] presented the bidirectional A* algorithm for the trajectory planning under the intermittent measurements. The planning algorithm managed the two tasks (i) minimum time and (ii) acceptable measurement to reach the target. They also provide the feasibility and continuity in path planning of UAVs by the convex hull and B-spline curves. In the same way, Liang et al. [137] proposed this algorithm based on a digital elevation map (DEM) in military and civilian applications. They have used the Bresenham line-drawing algorithm to line the initial path and bezier curve for smoothing this line path. From the literature survey on this algorithm, we found the path comparison results based on the different versions of A* algorithm as shown in Fig. 21 [137].

Mengying et al. [138] compared the improved version of this algorithm with APF and PSO on the basis of advantages, disadvantages, potential improvements, and fundamental theories. They have concluded the results that improved A* algorithm are widely used for collision avoidance. But from the deep analysis on this algorithm and to make better UAVs path planning, researchers can use this algorithm. We also found that the improved version and variations of A* algorithm has not been widely used in UAVs path planning.

3.1.1.3. Potential field method. Potential field method (PFM) is a simple and light method for dynamic path planning [139]. It represents the environment to design an object as a particle. It is moving under the control of potential fields around the c-space. The UAVs path is calculated on the basis of the resultant fields from the initial point to the target point. However, the conventional PFM suffers from the local minima causing the UAVs to stuck before it reaches the target. For example, Dai et al. [140] proposed the hierarchical PFM to solve the problem of unreachable destinations. They have added some rotational force between the UAVs that reduces the local minima and collision problems between the UAVs. To improve the PFM for multi-UAVs, Bai et al. [141] introduced the longitudinal factor in PFM that also solves the local minima problem between UAVs. They have described the B-spline interpolation method for satisfying the performance of the UAVs.

Authors in [139,142,143] indicate that there are many ways to overcome the limitations of PFM and used for collision avoidance in UAVs path planning. For example, Abeywickrama et al. [144] proposed a technique that reduces the collision between the UAVs. They showed that the proposed PFM model was time efficient with respect to the traditional PFM model. It is used for the UAVs navigation. The improved version of PFM, i.e., APF is used to design the path and to attract the UAVs for the desired goal configurations. It repels the UAVs from c-space obstacles and collisions. It gained popularity in obstacle and collision avoidance applications for UAVs path planning. For example, Chen et al. [145] introduced this method by adding the coordination force in it to solve the local minima problem of UAVs. The simulation results show that the proposed method is optimal, safe and collision-free for UAVs path planning. This method gives the probability of 98% by successfully avoiding collisions which is 15% more than the original method. Similarly, Yingkun et al. [146] designed a threat model based on improved APF method in an agricultural system. This method has been used for finding the local minimum points and generated the random goal points. From the analysis of the existing proposals, this method has several advantages and is suitable for real-time applications. The generated path from this method is optimal as well as smooth for UAVs path planning.

The detailed analysis of the existing proposals in sampling-based techniques of UAVs path planning are shown in Table 4.

3.1.2. Artificial intelligence techniques

Artificial intelligence (AI) is an approach to make the computer, a robot which can be automatically controlled by the software and thinks intelligently in the same way an intelligent human thinks. AI is a way to use and organize the knowledge efficiently and effectively so that it can

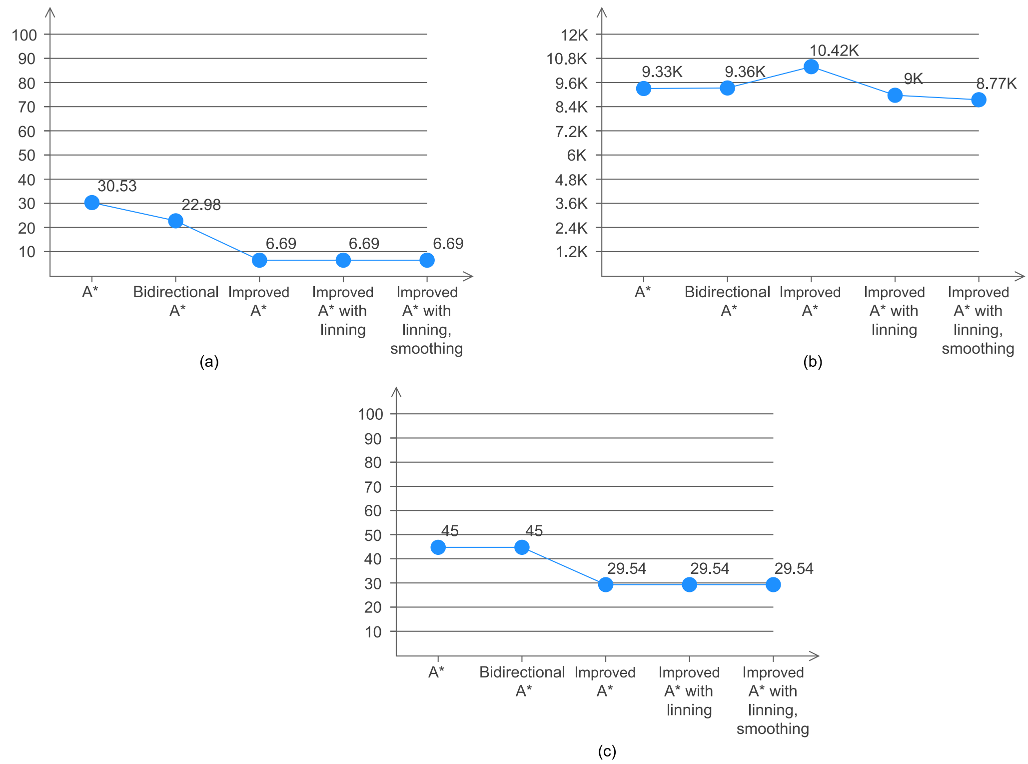

Fig. 21. (a) Computation time (seconds) (b) Path length (m) (c) Maximum pitch angle (degrees) [137].

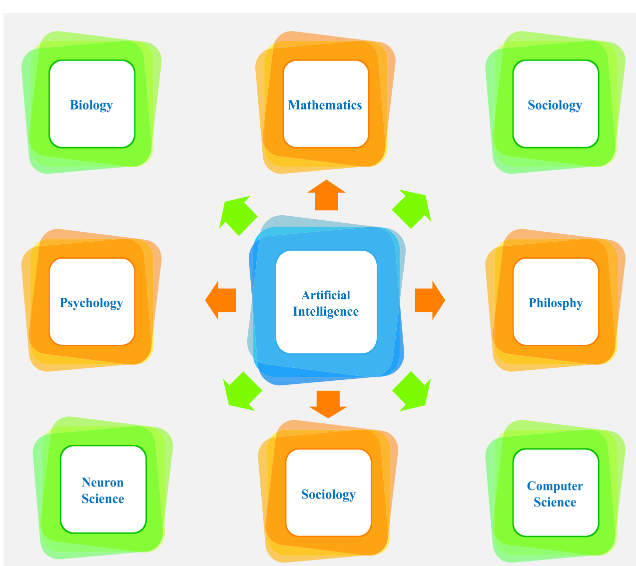

Fig. 22. Areas that develop artificial intelligence.

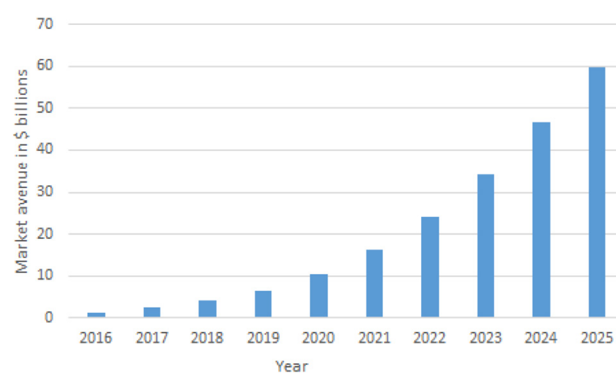

Fig. 23. Revenues from AI market worldwide.

be used in many situations. It is a technology based on the development of mathematics, engineering, and biology. There are one or more areas that can be used to develop and build an intelligent system as shown in Fig. 22. From the market intelligence Tractica firm reports that the annual worldwide AI revenue increases from $1.38 billion in 2016 to $59.75 billion in 2025 as shown in Fig. 23 [147]. There are three types of techniques used in AI for UAVs path planning which are discussed below. The detailed analysis of the existing proposals in AI techniques of UAVs path planning is shown in Table 5.

3.1.2.1. Heuristic-search techniques. Heuristic-search techniques are used for an optimal UAVs path planning by cost estimation method from the starting point to the goal point. In this section, a greedy and genetic algorithm based path planning methods of UAVs are discussed. For example, Park et al. [148] proposed the DroneNetX framework for network reconstruction over the relay deployment and connectivity probing in ad-hoc networks. They have used the heuristic-search technique for an optimal path planning of UAVs. They have explored the deployment points which can be used for the improvement in data delivery to the destination points. Similarly, Pan et al. [149] proposed the most uncovered first (MUFT) technique based on a ***greedy algorithm*** that overcomes the problem of 'cooperative multi-robots observation of multiple moving targets' (CMOMMT) [150,151] using multiple-UAVs. The simulation results show that other algorithms save the aircraft system from collisions only 12.5% whereas genetic algorithm with genetic algorithm (GA-GA) reports the best success rate of 71.3%–75% in collision avoidance. Arantes et al. [152] proposed the GA–GH method called genetic algorithm with greedy heuristic to evaluate the hardware problems and path re-planning of UAVs. They have used in-fly awareness (INF) security system for the emergency landing of UAVs in such cases like overheating, engine failure etc.

Table 4
Relative comparison of the existing proposals in sampling-based techniques.

Reference	1	2	3	4	5	6	7	8
Samaniego et al. [94]	–	Optimal	–	✓	✓	x	x	✓
Kang et al. [96]	–	Optimal	–	x	x	x	✓	x
Jang et al. [97]	–	Optimal	–	✓	✓	x	x	x
Masehian et al. [102]	–	Optimal	–	x	✓	✓	✓	✓
Mansard et al. [103]	–	Optimal	–	✓	✓	x	x	x
Meng et al. [104]	–	Optimal	–	x	✓	x	x	✓
Kuffber et al. [106]	–	–	Probabilistic completeness	x	✓	x	x	✓
Zhang et al. [107]	–	Optimal	Probabilistic completeness	✓	✓	x	x	x
Wen et al. [108]	–	Non-optimal	Probabilistic completeness	✓	x	x	✓	✓
Lin et al. [109]	–	–	Probabilistic completeness	x	x	x	✓	✓
Yang et al. [110]	136.9996 m	Optimal	–	✓	✓	✓	x	✓
Fedorenko et al. [111]	–	Non-optimal	–	x	✓	x	x	x
Zu et al. [112]	–	Optimal	–	✓	✓	x	x	✓
Levin et al. [113]	–	Optimal	–	✓	✓	x	✓	x
Qinpeng et al. [114]	–	Optimal	Probabilistic completeness	✓	✓	x	x	x
Li et al. [115]	–	–	–	✓	✓	x	x	✓
Li et al. [116]	–	Optimal	–	✓	x	x	x	✓
Nurimbetov et al. [117]	3 km	Probabilistic optimal	–	✓	x	x	x	✓
Chen et al. [118]	max-91245 m, min-9292 m	Optimal	–	✓	✓	✓	x	x
Shen et al. [119]	–	Optimal	–	x	✓	x	x	✓
Hart et al. [121]	–	Optimal	–	✓	✓	✓	✓	✓
Chen et al. [122]	–	Optimal	–	✓	x	x	x	x
Benders et al. [124]	120 m	Sub-optimal	Completeness	✓	✓	x	x	✓
Lv et al. [125]	287.99 m	Optimal	–	✓	✓	x	x	x
Li et al. [126]	–	Optimal		✓	x	x	x	x
Gupta et al. [127]	avg 2122.625 m	Optimal	–	✓	✓	x	x	x
Kwak et al. [128]	764.27 m	Optimal	Completeness	x	✓	x	x	x
Sun et al. [129]	–	Optimal	–	x	x	x	x	x
Zhang et al. [130]	–	Optimal	–	✓	✓	x	x	x
Li et al. [131]	–	Optimal	–	✓	✓	x	x	x
Chengjun et al. [132]	–	Optimal	–	✓	✓	✓	✓	x
Song et al. [133]	68.58 m	Optimal	–	✓	x	x	x	x
Bo et al. [134]	156.0343–169.5740 m	–	–	✓	✓	x	✓	✓
Ma et al. [135]	max-2481.8 m, min-792.1 m	Sub-optimal	–	✓	✓	x	x	✓
Penin et al. [136]	–	Asymptotic optimal	Probabilistic completeness	✓	✓	✓	✓	✓
Liang et al. [137]	–	Non-optimal	–	x	x	x	x	x
Mengying et al. [138]	–	Optimal	–	✓	x	x	✓	x
Budiyanto et al. [139]	min avg-10.75 m	Optimal	–	x	x	x	x	✓
Dai et al. [140]	784.62 km	Optimal	–	x	x	x	x	✓
Bai et al. [141]	165.1251 km	Non-optimal	–	x	x	x	x	x
Guang et al. [142]	–	–	–	x	✓	x	✓	x
Mac et al. [143]	–	–	–	✓	x	x	x	✓
Abeywickrama et al. [144]	–	Optimal	–	✓	x	x	x	✓
Yingkun et al. [146]	max-689 m	Optimal	–	✓	x	x	x	x
Chen et al. [145]	–	Optimal	–	x	x	x	x	✓

1: Path length; 2: Optimality; 3: Completeness; 4: Cost efficient; 5: Time efficient; 6: Energy-efficient; 7: Robustness; 8: Collision avoidance; –: not-mentioned; ✓: considered; x: not considered.

Genetic algorithm is used to generate solutions for search problems based on the operations like mutation, crossover and selection. It is also used to minimize the completion time of the tour that includes terrain coverage and network connectivity of UAVs. For example, Li et al. [153] presented a search and rescue method based on the genetic algorithm. They have used this algorithm to optimize the working trajectory and improve the performance of UAVs. Similarly, Hayat et al. [154] proposed an optimization method based on this algorithm to assign tasks and plans a path for UAVs. Roberge et al. [155] presented a parallel genetic algorithm using embedded graphical processing unit (GPU) system for an optimal path planning. They have used this algorithm to minimize the average altitude of UAVs that protects from the enemy radars. It also reduces the fuel consumption of UAVs. Authors in [156] presented the cellular decomposition technique to minimize the path length and to maximize the coverage area in an agriculture system. They have used the genetic algorithm for TSP to find the shortest path in UAVs path planning. The simulation results show that the area coverage by UAVs during operations is up to 97.9%. In [157], Zhou et al. proposed the energy efficient system for path planning and task assignment. Path planning of UAVs has been done by a genetic algorithm and task assignment problem has been solved by a Gale–Shapely algorithm. Similarly, Liu et al. [158] used the genetic algorithm for the age-optimal trajectory planning of UAVs. They have used the Hamiltonian path to find the shortest path for the collection of data from ground nodes.

3.1.2.2. Brute-force search techniques. Brute-force techniques are the effective and can be used for UAVs path planning. They do not need any specific knowledge of the problem and work under the small number of possible states. Some basic requirements needed at the time of brute-force techniques are an initial state, description of a goal state, and valid operators. The important brute-force techniques are breadth first search and depth-first search. Sharma et al. [159] constructed a ***depth-first search*** algorithm for aerial mobile robots. They have also proposed an efficient greedy backtracking approach that minimizes the effect of backtracking in civilian and military applications.

3.1.2.3. Local search techniques. Local search techniques are used to solve computationally hard problems. These techniques are used to find an accurate and optimal solution by applying local changes. It always return a solution even the path is interrupted by many obstacles during the processing time of search operations. The main techniques under local search are hill climbing, local beam search, TSP. For example, Huang et al. [160] represented the deployment scheme based on TSP to ensure the shortest path for UAVs path planning. In this proposal [160], target points are clustered using clustering analysis based on the load bandwidth and scanning bandwidth. They have also used the PSO

Table 5
Relative comparison of the existing proposals in AI techniques.

Reference	1	2	3	4	5	6	7	8
Park et al. [148]	–	Optimal	–	✓	✓	x	x	✓
Pan et al. [149]	–	Optimal	–	x	x	x	x	x
Da Silva Arantes et al. [152]	4150 m	–	–	x	✓	x	x	x
Li et al. [153]	–	–	–	✓	✓	✓	x	x
Hayat et al. [154]	–	Optimal	–	x	x	x	x	x
Roberge et al. [155]	–	–	–	✓	x	x	✓	x
Pham et al. [156]	–	Optimal	–	x	✓	x	x	x
Zhou et al. [157]	–	Optimal	–	✓	✓	✓	x	x
Liu et al. [158]	–	Optimal	–	✓	✓	x	x	x
Sharma et al. [159]	1.06 km	Approximate optimal	Completeness	✓	✓	✓	x	x
Huang et al. [160]	–	Optimal	–	x	✓	x	✓	x
Scherer et al. [161]	–	–	–	x	✓	x	✓	x
Wang et al. [162]	–	Approximate optimal	–	x	✓	✓	x	x
Perazzo et al. [163]	–	Approximate optimal	–	x	✓	✓	x	x
Kurdi et al. [164]	–	Optimal	–	x	x	x	x	✓
Zhang et al. [165]	–	–	–	x	✓	x	x	x

1: Path length; 2: Optimality; 3: Completeness; 4: Cost efficient; 5: Time efficient; 6: Energy-efficient; 7: Robustness; 8: Collision avoidance; –: not-mentioned; ✓: considered; x: not considered.

algorithm to optimize the path for UAVs. The evaluation results show that the average scanning range of UAVs are 1020.17 km, and average flight time is 5.1 h.

Local search techniques are used to mitigate the problem of small coverage of the area by UAVs. For example, Scherer et al. [161] proposed two algorithms named as half horizon cooperative and full horizon based on TSP for solving the small coverage area problem. Half horizon cooperative has been used to solve the limited communication range problem and full horizon algorithm has been used to find all the locations, the UAVs have to reach. Similarly, Wang et al. [162] proposed the 2-tie search algorithm for making communication links between n-UAVs and coverage large area during search operations. They have used this algorithm for tracking the missing animals using multi-UAVs in a lost pet recovery system. Perazzo et al. [163] proposed the three algorithms based on TSP for the secure positioning and verification of the UAVs path. They have used the LocalizerBee algorithm for finding the set of devices, VerifierBee algorithm to verify the device position and PreciseVerifierBee algorithm to guarantee the position of the devices in UAVs path planning.

From the analysis of existing proposals in AI algorithms, we concluded that heuristic-search, brute-force search, and local search techniques are used by the authors in UAVs path planning. These techniques are used for finding an optimal path to the destination in multi-UAVs environment. But, among these three techniques, the heuristic-search based genetic algorithm is widely used in UAVs path planning.

3.1.2.4. Artificial neural networks. Artificial neural network (ANN) is defined as a system in which highly inter-connected processing elements are combined together to form a network. In this network, three layers exist (i) the first input layer processes the input elements, (ii) the second hidden layer performs operations on the input data, and (iii) the third output layer gives back a response results and outputs as shown in Fig. 24. It is used to find an optimal path planning solutions for UAVs. For example, Kurdi et al. [164] proposed a neural network-based algorithm to solve the navigation and position problems of UAVs. In this proposal [164], ANN takes input from the GPS, robot vision system and quad-copter vision system and gives output in the form of localization to the UAVs. Similarly, Zhang et al. [165] used the neural networks to learn and regulate the line-of-sight path control of UAVs so that UAVs can act precisely in adverse conditions. They have also presented the path planning control method to find an optimal path for UAVs.

3.2. Cooperative techniques

Cooperative techniques are important to recognize many learning methods which can be analyzed to fit within multiple categories like problem solving and graphic organizers. They consists of mathematical models, bio-inspired models, machine learning models, control theory models used for the UAVs path planning. The taxonomy of the cooperative techniques is shown in Fig. 25.

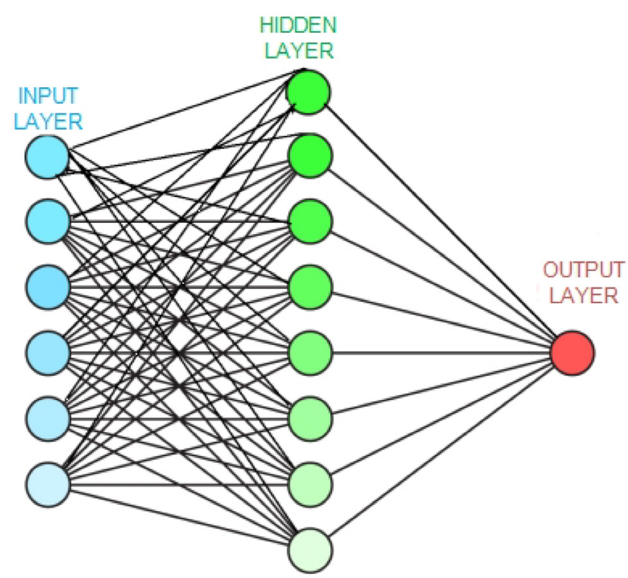

Fig. 24. Artificial neural networks.

3.2.1. Mathematical models

Mathematical models use mathematical equations and functions like Lyapunov function, Bezier curve which are used for solving the problems of UAVs path planning. They consists of various algorithms having linear programming, control theory [60], probabilistic models [166], meta-heuristic models [167], multi-objective optimization models [168] for UAVs path planning. These mathematical models consider all the factors such as-cost, time, and energy. and are used to find an optimal path for UAVs. A mathematical model based path planning problem is shown in Fig. 26.

3.2.1.1. Linear programming. Linear programming used in UAVs path planning for converting the non-linear complex problems to linear programming models. It consists of mixed integer linear programming [93], binary linear programming [169], non-linear programming [170,171] which is used for UAVs path planning. For example, Mathew et al. [172] solved the TSP by ***integer linear programming*** using multiple charging robots. The goal is to have the minimum cost

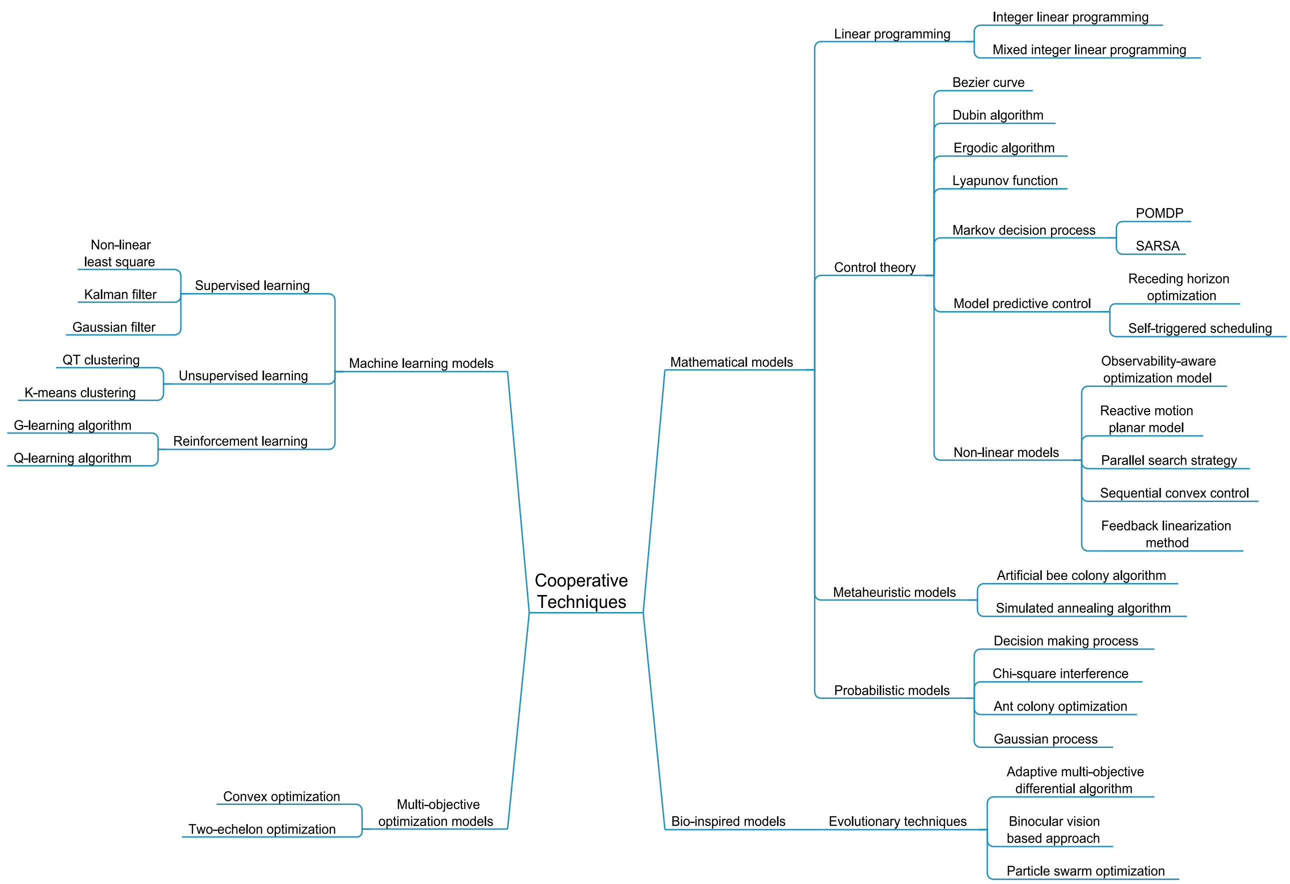

Fig. 25. Taxonomy of cooperative techniques in UAVs path planning.

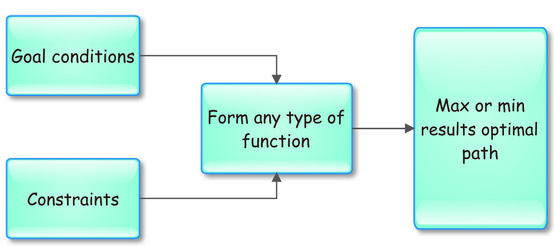

Fig. 26. Mathematical model-based path planning problem.

for designing an optimal path using the fixed horizon (FH) and RH. The simulation results show that RH produces the solution of total path cost within 20% of the optimal FH solution. Similarly, De Waen et al. [173] used the ***mixed integer linear programming*** for making the UAVs trajectory planning more powerful. They have also improved the scalability and consistency by solving obstacles between the initial and final positions.

3.2.1.2. Control theory. Control theory contains non-linear predictive models, Lyapunov function [174], Dubin algorithm [175], model predictive control (MPC) method [176] used for UAVs path planning. For example, John and Dutta [177] proposed the literature survey on UAVs problems like task assignment, path planning and collision avoidance of UAVs. They have discussed the various algorithms based on plume wrapping problem and provide a cooperative approach for good intercommunication between UAVs.

Bezier curve are used to model the smooth curves which can be scaled indefinitely. This curve has been used to plan the UAVs path to smooth the path between the way-points [178,179]. In [178], authors used the RRT* algorithm with PSO for planning the collision-free path for UAVs. They have also used an optimal path using path selection strategy which is used to smooth the optimal path. Similarly, In this proposal [179], authors used this curve in photo-voltaic farm to improve the efficiency and reliability in an agriculture system.

Dubin algorithm is used to find the path for UAVs which is based on the algebraic solutions. For example, Shi et al. [180] proposed this algorithm for fixed-wing UAVs. This algorithm provides safety, privacy and minimum distance between goal states. The simulation results show that the decreased turning length reduces the curve reduction rate by more than 50%. They have also demonstrated that less turning time of the UAVs reduces the impact of adverse conditions like crosswind. Wu et al. [181] proposed the same algorithm by considering the positions such as-angular rate loop, flight path loop, position loop and angle loop in a wind disturbance environment. For angular rate loop and angle loop, authors used the back-stepping linear active control model and for flight path loop and position loop, authors used the inverse dynamic method. Using these, UAVs can fly persistently along the target points in a cluttered environment.

Ergodic algorithm is used in path planning having soft-wing UAVs and is irreducible in nature. Soft-wing UAVs are different types of UAVs used in the path planning. These UAVs are simple in structure having low cost [220]. For example, Huang et al. [182] proposed this algorithm to control of soft-wing UAVs. The simulation results show that the difference in actual trajectory and the expected trajectory is less than 0.5% for removal of haze.

Lyapunov is a control theory function which is used to control the stability of the UAVs in a dynamic environment [183,184,221]. In this proposal [183], Dai et al. proposed the APF and sliding mode [185] based control theory for the cooperativeness of multi-UAVs. The simulation results show that the cross track error reduces from 500 m to 10 m in 19 s. They have also concluded that the maximum roll angle is 35

Table 6
Relative comparison of the existing proposals in mathematical models.

Reference	1	2	3	4	5	6	7	8
Miller et al. [60]	–	Optimal	–	✓	x	x	x	x
Schumacher and Chandler [93]	–	Optimal	–	✓	✓	x	x	x
Masehian and Habibi [169]	–	Optimal	–	✓	x	x	✓	x
Chamseddine et al. [170]	–	Optimal	–	x	✓	✓	✓	x
Borrelli et al. [171]	–	Optimal	–	✓	✓	x	x	✓
Mathew et al. [172]	–	Optimal	Completeness	✓	✓	✓	✓	x
De Waen et al. [173]	88–3041 m	Optimal	–	x	x	x	x	✓
John and Dutta [177]	–	–	Completeness	x	✓	x	x	✓
Wu et al. [178]	–	Optimal	–	x	✓	x	x	✓
Luo et al. [179]	–	Optimal	–	✓	✓	✓	x	x
Shi et al. [180]	1634.70 m–3236.80 m	Optimal	–	x	✓	x	x	x
Wu et al. [181]	–	–	–	x	x	x	x	x
Huang et al. [182]	–	–	–	✓	✓	x	x	x
Dai et al. [183]	–	–	–	x	x	x	x	✓
Zhang et al. [184]	–	Optimal	–	x	✓	x	✓	✓
Shah et al. [185]	–	Optimal	–	✓	✓	x	✓	x
Oliveira et al. [186]	–	–	–	x	✓	x	x	x
Darbari et al. [187]	–	Optimal	–	x	✓	x	x	✓
Yu et al. [188]	–	Sub-optimal	–	x	✓	x	x	x
Eaton et al. [189]	–	Optimal	–	✓	x	x	✓	✓
Yang et al. [190]	–	Optimal	–	✓	x	x	x	X
Speck and Bucci [191]	–	Optimal	–	x	X	x	x	✓
Schlotfeldt et al. [192]	–	Sub-optimal	–	✓	x	x	✓	✓
Yao et al. [193]	–	Optimal	–	x	x	x	x	✓
Alessandretti and Aguiar [194]	–	Optimal	–	✓	x	x	x	x
Wang and Zhang [195]	–	–	–	x	x	x	x	x
Sun et al. [196]	–	–	–	x	x	x	x	x
Zhang et al. [197]	–	Optimal	–	✓	x	x	x	✓
Zhou et al. [198]	–	Optimal	–	x	✓	x	x	✓
Koohifar et al. [199]	–	Optimal	–	x	✓	x	x	✓
Yel et al. [200]	–	Optimal	–	x	x	x	x	✓
Hausman et al. [201]	–	Optimal	–	✓	✓	x	✓	x
Wallar et al. [202]	–	Optimal	–	✓	✓	✓	✓	✓
Li et al. [203]	–	Optimal	–	✓	x	✓	x	x
Zhang et al. [204]	–	Optimal	–	✓	✓	x	x	x
Farid et al. [205]	–	–	–	x	✓	x	x	x
Kyriakis and Moustris et al. [206]	–	–	–	x	x	x	x	x
Cabecinhas et al. [207]	–	–	–	x	✓	x	✓	x
Tian et al. [208]	1090.57–1177.82 m	Optimal	–	✓	✓	x	x	✓
Cheng et al. [209]	–	Optimal	–	✓	✓	x	✓	x
Wei et al. [210]	–	Optimal	–	✓	✓	x	x	x
Popovic et al. [211]	–	–	–	x	x	✓	x	x
Li and Chen [212]	–	–	–	✓	✓	x	✓	x
Mostafa et al. [213]	–	–	–	✓	x	x	x	x
Ji et al. [214]	429.9885 m, 662.0707 m	Optimal	–	x	x	✓	x	x
Yang and Yoo [215]	–	Optimal	–	✓	✓	✓	x	x
Ladosz et al. [216]	–	Optimal	–	✓	✓	x	x	x
Tokekar et al. [217]	–	Optimal	–	✓	✓	✓	x	x
Popovic et al. [218]	–	Optimal	–	✓	✓	x	x	x
Yang et al. [219]	–	Optimal	–	x	✓	x	x	x

1: Path length; 2: Optimality; 3: Completeness; 4: Cost efficient; 5: Time efficient; 6: Energy-efficient; 7: Robustness; 8: Collision avoidance; –: not-mentioned; ✓: considered; x: not considered.

degrees at 1214 s, when the track error is approx 55 m. Chamseddine et al. [221] proposed the navigation law to develop the communication relay between ground units and UAVs. In this proposal [221], UAVs used the signal strength and angle of arrival information of ground units for finding an optimal path. Zhang et al. [184] proposed the Lyapunov function for the formation of UAVs tracking. They have also used the feedback control for heading the convergence of UAVs, variable airspeed controller for angular spacing and graph theory for tracking the moving targets. Similarly, Oliveira et al. [186] proposed the path generation algorithm having this function to solve the path problems. They have used the parameters such as-path's calculation, the linear and angular velocity of UAVs.

Markov decision process (MDP) is based on the mathematical and control models used in situations where outputs are randomly generated or under the control of decision-maker. MDP has been used in [187] for an optimal control of UAVs path planning with the decision process. For example, Yu et al. [188] solved the obstacles present in UAVs path planning using a Bayesian filter and MDP. Partially observable Markov decision process (POMDP) is a method based on the generalization of a MDP. It is an agent decision process of MDP. In this method, dynamics of the system are determined by MDP because the agent cannot pay attention to the underlying states. This process has been used efficiently in [189,190] for fixed tracking and for moving targets. Eaton et al. [189] proposed the POMDP with nominal belief state optimization (NBO) for UAVs. The simulation results show robustness and computationally efficient algorithm in a dynamic environment. The optimality of the UAVs path can be achieved by combining the POMDP and unscented Kalman filter (UKF) in [190]. Speck and Bucci [191] proposed the novel state–action–reward–state–action (SARSA) approach for decentralized control problems of UAVs and Schlotfeldt et al. [192] proposed the decentralized approach to improve the robustness and scalability of the centralized system.

Model predictive control is a model used to control the UAVs path planning process while satisfying a set of constraints. For example, Yao et al. [193] proposed the distributed MPC to optimize the path of the UAVs. They have also used the sensor detection model, point-mass model, and target probability map to search a target. Similarly, Alessandretti and Aguiar [194] addressed the MPC to design the flight path and generated a linear and angular velocities of UAVs using kinematic model. MPC has been used to design and plan the path for UAVs in [195,196]. Wang and Zhang [195] used the threat gain fuzzy controller with MPC to make the UAVs path safe and secure from the threat attacks. The simulation results show that the average time consumption of rolling optimization is 82 milliseconds (ms). In [196], authors used MPC in express transportation, data collection, and rescue operations for UAVs. Authors used MPC based receding horizon optimization (RHO) which is used to control the optimality of UAVs and ensures efficiency [197,198]. To optimize the trajectory, zhou et al. [198] used this optimization. Similarly, Koohifar et al. [199] used this optimization to localize the moving radio frequency sources in civil and military operations. In the same way, Yel et al. [200] proposed this optimization approach using self-triggered scheduling, risk analysis, reachability program and re-planning strategy for UAVs path planning. The results concluded that the central processing unit (CPU) utilization decreases by 2.7% to the use of self-triggered scheduling.

Non-linear model is a combination of the model parameters which depends on one or more independent variables. It is a system in which change of output is not proportional to the change of input. For example, Hausman et al. [201] developed the non-linear system based on observability-aware optimization model for self-calibration applications. This model has been used for motion planning, path planning, calibration and identification of UAVs. Similarly, Wallar et al. [202] proposed the reactive motion planner to check the risk-sensitive areas of UAVs. The objective is to cover the maximum area, high data quality, persistent surveillance and collision avoidance for the efficiency and scalability of UAVs. Li et al. [203] proposed the parallel search strategy model for an optimal path planning in plateaus and mountain environment. In this proposal [204], an optimal method has been used by sequential convex program model for non-linear system problems. Farid et al. [205] proposed the computationally fast algorithm to design a smooth and feasible trajectory for UAVs. The control design and modeling of UAVs have been done using feedback linearization method in [206]. Similarly, Cabecinhas et al. [207] proposed the adaptive state feedback controller to guarantee the convergence of path for UAVs. This method also ensures the position and speed error of UAVs in a wind disturbance environment.

3.2.1.3. Meta-heuristic algorithms. UAVs can do their work efficiently in the air, ground as well as underwater search operations. The main problems for UAVs are to do an optimal path planning for tracking and completing the operations. For example, in [222], authors reviewed the new enhancements for an optimal path planning of UAVs based on meta-heuristic algorithms. The meta-heuristic model contains ***artificial bee colony algorithm*** [223], ***simulated annealing algorithm*** [224] for UAVs path planning. For example, Tian et al. [208] proposed the improved artificial bee colony algorithm for the track planning of UAVs. This algorithm has fewer parameters and faster convergence which helps to avoid dynamic threats in a real-time environment. Cheng and Li [209] proposed a genetic algorithm having simulated annealing which is called as GASA algorithm used to improve the UAVs track planning. This algorithm provides least cost, robustness, best route, the speed of convergence and precise optimization to the UAVs path planning.

3.2.1.4. Probabilistic models. Probabilistic models having ***decision making process*** [225], ***chi-square method*** [226], ***ACO, Gaussian filter*** [227] have been used as reliability models for UAVs tracking and path planning. For example, Wei et al. [210] developed the testbed and optimal path plan from source UAVs to the destination UGVs. They have used the probabilistic model to find the next target of the UAVs. Similarly, Popovic et al. [211] used this model to plan the UAVs path in an adaptive way. They have used the evolutionary optimization to detect the weeds in an agriculture system. Li and Chen [212] proposed the various adaptive models to focus on a real-time search planning instead of using pre-defined path planning. They have introduced the decision-making mechanism to reduce the wrong predictions and to improve the UAVs path planning. Mostafa et al. [213] proposed the performance visualized assessment model to check the performance of UAVs in the indoor environment. They used the chi-square interference module for trajectory and localization method for UAVs navigation mission. The simulation results show that the average completion time of the mission is 4.08 min. Similarly, Ji et al. [214] proposed the 2-opt algorithm to optimize the search and rescue operations of UAVs. They focused on the disaster environment like trapped persons in fire and earthquake with improved efficiency and shorten flight time. The results show that ACO based path length is 459.091 m and 2-opt algorithm based path length is 437.4242 m. The network acquisition of UAVs path planning in the disaster operations is as shown in Fig. 27. Similarly, Yang and Yoo [215] proposed ACO with a genetic algorithm to obtain an optimal path with energy, time, sensing and risk efficiency.

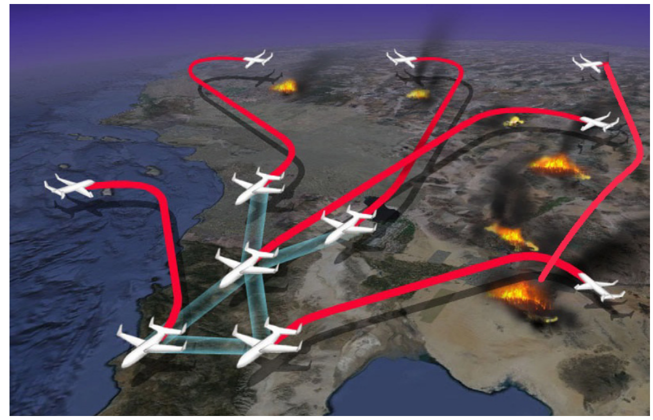

Fig. 27. Network acquisition in the disaster environment.

Gaussian Process based on the probabilistic model has been used in [216–218] to improve the air to ground communication links. In [216], authors used this process to improve the efficiency of relay trajectory between UAVs and UGVs in an urban environment. In [217], authors solved the sampling TSP and symbiotic UAV–UGV problem by the accuracy of maps in a precision agriculture system. In [218], authors used the multi-resolution mapping and information path planning in area monitoring of UAVs. Similarly, Yang et al. [219] proposed this process to complete the cargo drop mission with a minimum flight-time and landing errors of UAVs. The simulation results show that the flight time is 15.2 s and actual landing errors is 36.68 m.

The relative comparison of the existing proposals in mathematical models of UAVs path planning is shown in Table 6.

3.2.2. Bio-inspired models

Bio-inspired model deals with the problems which come from biological behavior like behavioral neuroscience and physiological biology [228]. The path planning techniques in this model are used for managing and constructing a possible solution for a complex environment of UAVs. It proposes a stable method that converges to the goal stability. This model consists of various algorithms having evolutionary techniques and neural networks for describing the path planning techniques of UAVs. In [229], authors described an interactive and learning environment. It is used for the students to process of bio-inspired optimization which is used in UAVs path planning. It includes four steps: (i) introduction, (ii) recognition, (iii) practice and (iv) collaboration that enhances the learning efficiency of the students towards the bio-inspired models.

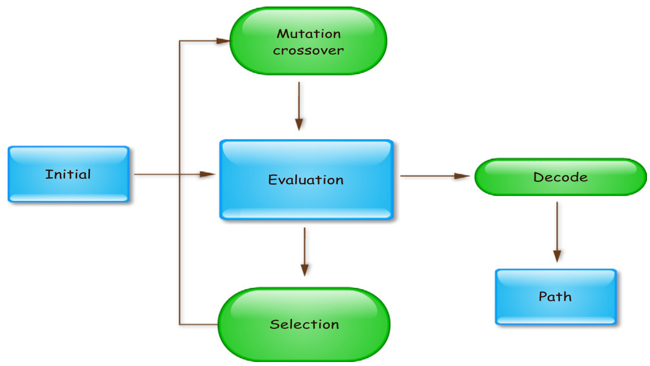

Fig. 28. Evolutionary process used for UAVs path planning.

3.2.2.1. Evolutionary techniques. Evolutionary techniques [230] having memetic algorithm [231], PSO used for UAVs path planning. In this technique, a randomly selected solution is used from all the possible paths of UAVs path planning and then other constraints are taken into consideration such as-environment, the capacity of robots, and goal specifications. According to the fitness of the solutions, the moving path is selected as a parent path. This parent path is then used for generating the next new paths, i.e., small and discrete moving paths. After, the results are analyzed. In the end, the best moving path is selected for the UAVs optimal path as shown in Fig. 28.

Adaptive-multi-objective-differential-evolution algorithm has been proposed in [232,233] for solving the multi-objective problems in UAVs for the selection of the way-points for the exploration of UAVs. In [232], authors used the geosynchronous (GEO-UAVs) to identify an optimal path and to guarantee the safety of UAVs. The simulation results show that the total time spend for multi-objective problems is 520 s. Similarly, Liu et al. [234] presented the ***binocular vision-based*** technique for UAVs in an outdoor environment. These sensors have been used to obtain the local paths and to analyze the obstacles in UAVs path planning.

PSO algorithm has been used in [235–238] for trajectory planning and path planning of UAVs in a minimum time to reach to the destination. This algorithm is used to derive the expression to optimize the flight path and to avoid the collision between the UAVs. In [236], authors used hierarchical fuzzy logic controller (HFLC) to assign the tasks to UAVs during path planning. In [237], authors proposed a mathematical model with an optimization algorithm between UAVs and UGVs for the marsupial system. The total completion time to complete the tasks between UAVs and UGVs is 6.5472 h. Similarly, Chen et al. [238] proposed the improved genetic algorithm (IGA) and PSO based ant colony optimization (PSO-ACO) algorithm to solve the TSP in UAVs. They have discussed that IGA based on the evolutionary model solves the TSP with great convergence and PSO-ACO based on swarm intelligence adjusts an optimal solution for UAVs.

The comparative analysis of the existing proposals in bio-inspired models of UAVs path planning as shown in Table 7.

3.2.3. Machine learning models

Machine learning is a part of AI that enables computer to response without being explicitly programmed. The machine learning-based algorithms are divided into three categories like supervised learning, unsupervised learning and reinforcement learning. These categories are divided into various algorithms like clustering, classification, linear regression which is used for UAVs path planning. The steps used in the machine learning techniques for UAVs path planning are shown in Fig. 29. The first step is to identify and gathering the data from various resources. Then, data cleaning is used for the selection of machine learning algorithm. The next step is to build the model based on the selection of an machine learning algorithm. The last step is to train the model on different data sets and results path prediction and data visualization.

Table 7
Relative comparison of the existing proposals in bio-inspired techniques.

Reference	1	2	3	4	5	6	7	8
Foo et al. [228]	–	Optimal	–	✓	x	x	✓	✓
Duan et al. [229]	–	Optimal	Completeness	✓	x	x	✓	x
Hasircioglu et al. [230]	–	–	–	✓	x	x	x	✓
Shahidi et al. [231]	–	Optimal	–	✓	x	x	x	✓
Sun et al. [232]	–	Optimal	–	✓	✓	x	x	x
Yang et al. [233]	–	Optimal	–	✓	✓	x	x	✓
Liu et al. [234]	–	Optimal	–	✓	x	x	x	✓
Zhang et al. [235]	–	Optimal	–	x	✓	x	x	x
Hafez et al. [236]	–	Optimal	–	✓	✓	x	x	✓
Ren et al. [237]	–	Optimal	–	✓	✓	✓	x	x
Chen et al. [238]	–	Optimal	–	x	x	x	x	x

1: Path length; 2: Optimality; 3: Completeness; 4: Cost efficient; 5: Time efficient; 6: Energy-efficient; 7: Robustness; 8: Collision avoidance; –: not-mentioned; ✓: considered; x: not considered.

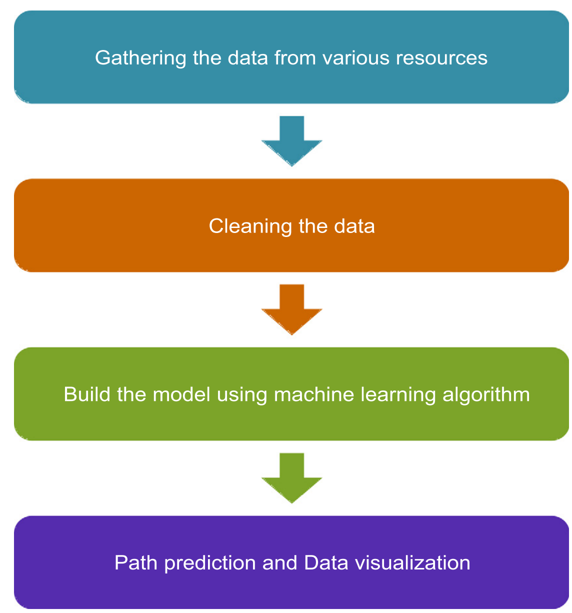

Fig. 29. Machine learning process in UAVs path planning.

3.2.3.1. Supervised learning. In supervised learning [251], we only trained an algorithm for path planning process but cannot able to figure out the exact function. It is used to build the model where dependencies exist between the input elements and predicted target value. The perception of the learning algorithm is to correct the prediction for having an output. It consists of various algorithms like Gaussian filter and Kalman filter used for UAVs path planning. These learning algorithms are based upon various assumptions. For example, Jiang and Liang [239] proposed the ***nonlinear least-square*** method for the estimation of the targets during UAVs path planning in a threat environment. A case-based guidance method has also been used to complete the standoff multi-target operation. Similarly, Kang et al. [240] proposed the ***Kalman filter*** used to solve the problem of noise and provides the secure flight space to UAVs in a complex environment. Similarly, Wu et al. [241] proposed this filter to solve the various problems such as-noise in the air, collision probability, cluster state prediction and track planning of UAVs. The simulation results show that the collision probability between the UAVs is only 0.2% using this filter but the error rate is high. So, to decrease the error rate of this filter, Yoo et al. [242] proposed the ***Gaussian filter*** with reduced time delays and less packet loss in UAVs. They have concluded that the mean is 2.5 and variance is 0.2 with Gaussian distribution in UAVs path planning.

Table 8
Relative comparison of the existing proposals in machine learning techniques.

Reference	1	2	3	4	5	6	7	8
Jiang et al. [239]	–	Optimal	–	✓	✓	✓	x	✓
Kang et al. [240]	–	–	–	x	✓	x	x	✓
Wu et al. [241]	–	–	–	x	✓	x	x	✓
Yoo et al. [242]	–	Optimal	–	✓	✓	x	x	x
Faigl and Vana [243]	–	Optimal	–	x	✓	x	x	x
Farmani et al. [244]	–	Optimal	Completeness	✓	✓	x	x	x
Tartaglione and Ariole [245]	–	–	–	✓	✓	x	x	✓
Teuliere et al. [246]	–	–	–	✓	x	x	✓	x
Yue and Zhang [247]	–	Optimal	–	✓	✓	✓	✓	x
Luan et al. [248]	1.3564–1.7787 m	Optimal	–	x	✓	x	x	x
Zhang et al. [249]	–	Optimal	–	x	x	x	x	✓
Yijing et al. [250]	–	Optimal	–	x	x	x	x	x

1: Path length; 2: Optimality; 3: Completeness; 4: Cost efficient; 5: Time efficient; 6: Energy-efficient; 7: Robustness; 8: Collision avoidance; –: not-mentioned; ✓: considered; x: not considered.

3.2.3.2. Unsupervised learning. Unsupervised learning is a family of machine learning algorithms used for descriptive modeling and pattern detection. It consists of various clustering algorithms such as-quality threshold (QT) clustering [252], k-mean clustering used in the path planning of UAVs [243]. These learning techniques are used on the input elements to detect the patterns, data points, and mining rules to help in better understanding of UAVs path planning. For example, Farmani et al. [244] proposed an optimal path planner and sensor manager which is called as clustering algorithm for tracking the multiple targets. In this proposal, each UAV used the Kalman filter to know the exact location of the target. By using this method, the computational complexity of the path planning reduces from O(n^m) to O(mn). Similarly, Tartaglione and Ariola [245] presented an obstacle avoidance strategy based on ***QT clustering*** for searching landmarks. They have also used the leader–follower technique to solve the optimization and coordination problems of UAVs. With this clustering, ***K-means clustering*** has also been used in UAVs path planning [246,247]. This clustering method is used to cluster the target points which solves the scheduling problem of UAVs. For example, in [246], authors used this clustering method to capture the potential poses from the images of the camera. They have also used the particle filtering [253] to integrate all the poses and propagated through a classic condensation scheme [254]. Similarly, in [247], authors used the simulated annealing method with clustering to solve the problem of multi-UAVs in disaster conditions to increase the coverage area of the UAVs. The results concluded that the coverage area of the cruise is more than 92% by UAVs during cruise time.

3.2.3.3. Reinforcement learning. Reinforcement learning is widely used to solve the path planning techniques of the UAVs. It is a continuous process and always learn from the environment in an iterative manner. In the literature, authors mainly used the reinforcement learning [255], deep reinforcement learning [256] and deep Q-network [257] for the path planning of UAVs. For example, in [248], authors proposed the ***G-learning*** method to solve the problems of path planning in a 3-D based UAVs scenario. This algorithm is used to compute the cost matrix based on a geometric distance for UAVs path planning. Then, the updated information is broadcasted to the other UAVs for collision avoidance. The simulation results of the proposed method based on computational time for two UAVs is 156.7 s and 1030.6 s with respect to the original computational time is 3616.9 s and 7515.2 s respectively. Zhang et al. [249] proposed the ***Q-learning*** algorithm for UAVs path planning. Similarly, Yijing et al. [250] proposed this algorithm to interact with the environment without any knowledge of training samples. They have used the adaptive and random exploration technique for UAVs navigation and collision avoidance.

The detailed analysis of the existing proposals in machine learning models of UAVs path planning is shown in Table 8.

3.2.4. Multi-objective optimization models

Multi-objective optimization model includes convex optimization [258], two-echelon optimization [259] used for UAVs path planning. These optimization models have been used in [260,261] to improve the search problems in a cluttered environment. In [260], authors proposed an optimization framework for on-line and off-line search operations. In the off-line system, UAVs capture the static obstacles and in on-line system, UAVs capture the dynamic obstacles during cruise time. In this proposal [261], authors optimize the search and survival strategies to localize a large number of target points for the UAVs. The simulation results show that there is an improvement in the detection of errors approx by 10%. Koohifar et al. [262] proposed the steepest descent to track the radio frequency sources using UAVs. They have also compared the mathematical and bio-inspired algorithms to estimate the target position and to plan the future trajectory for UAVs. They have found the mean and standard deviation of processing time using steepest descent are 41.3 and 9.8 s. Ti and Li [263] solved the problems such as-joint task, resource allocation, computation offloading and path planning in a fog cloud-based mobile system. They have converted the non-convex integer non-linear programming to integer linear programming by ***convex optimization*** method. Similarly, Zeng et al. [264] used this optimization and designed the way-points for UAVs path planning in the minimum completion time. In this proposal, the simulation results show that the completion time of the UAVs path planning is reduced by 50%. Jeong et al. [265] also proposed this optimization to optimize the path planning between the mobile users and UAVs. In this proposal, UAVs provide computation offloading opportunities to the mobile users with minimum energy consumption. Lee and Yu [266] proposed the optimization process based on the gravitational potential energy. They discussed that the solar-powered UAVs are effective for energy efficiency and to increase the tolerance power. Luo et al. [267] proposed the ***two-echelon optimization*** algorithm for UGVs and UAVs. The algorithm has been used to minimize the intelligence, surveillance, and reconnaissance (ISR) mission time.

From the analysis of these algorithms, we concluded that these cooperative algorithms are widely used for UAVs path planning. A lot of research work has been done using these techniques for UAVs path planning in various applications. From the literature study on these techniques, we found that the mathematical, bio-inspired, machine learning and multi-objective based algorithms provide an optimal, safe and shortest path to the UAVs in UAVs path planning. The detailed analysis of the existing proposals in multi-objective optimization techniques of UAVs path planning is shown in Table 9.

3.3. Non-cooperative techniques

Non-cooperative techniques are those in which path planning methods and algorithms act independently and must aware of each other's rule and regulations to find the path for UAVs. There is a number

Table 9
Relative comparison of the existing proposals in multi-objective optimization.

Reference	1	2	3	4	5	6	7	8
Yin et al. [260]	–	Optimal	–	✓	✓	✓	x	✓
Angley et al. [261]	–	Optimal	–	✓	x	x	x	x
Ti and Li [263]	–	Optimal	–	x	x	✓	x	x
Zeng et al. [264]	–	Optimal	–	✓	✓	✓	x	✓
Jeong et al. [265]	–	Optimal	–	✓	✓	✓	x	x
Lee and Yu [266]	–	Optimal	–	x	x	✓	x	x
Luo et al. [267]	–	Optimal	–	✓	✓	x	x	x

1: Path length; 2: Optimality; 3: Completeness; 4: Cost efficient; 5: Time efficient; 6: Energy-efficient; 7: Robustness; 8: Collision avoidance; –: not-mentioned; ✓: considered; x: not considered.

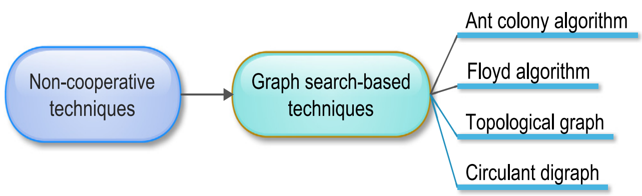

Fig. 30. Taxonomy of non-cooperative techniques.

of algorithm exists such as-graph search-based algorithms like circular digraph, Floyd algorithm, flood-fill algorithm used for UAVs path planning (see Fig. 30).

Chen et al. [268] used the ***ACO*** algorithm to solve the reconnaissance path for UAVs. They have discussed the operation of 68 fixed locations and divided the goal into 19 sub-goals. These sub-goals have been inspected by the four UAVs in the minimum flight time. Similarly, Li [269] proposed this algorithm to solve the communication problems between multiple communication targets for UAVs. They have planned a route between communication targets using raster map. This map has been used to create a good communication link between communicating targets. The simulation results show that the optimal objective function value is 85.6 m. Morita et al. [270] developed an efficient path planning technique for radiation dose mapping. They have compared the proposed algorithm with flood-fill and greedy 2-opt algorithms to extract the sub-routes from the void areas. The simulation shows that the proposed algorithm gives better results in case of turns, path length and elapsed time which is 8, 406 m and 325 s respectively. Yang et al. [271] proposed the method of cooperative patrol route for multi-base multi-UAVs. They have used the ***Floyd algorithm*** to predict the starting path and then optimizes the path using improved push forward insertion heuristic (PFIH) algorithm. Razzaq et al. [272] proposed the graph-based routing algorithm that provides route planning and collision avoidance of UAVs with the other moving objects. Du and Cowlagi [273] proposed the incremental repair of constant-altitude seed path for UAVs. They have used the ***topological graph*** on a grid map to find the shortest path for UAVs. The results show that the repaired path length in two cases is 4.09 m and 11.7 m which is 38.8% cost reduction. Bogdanowicz et al. [274] proposed the ***circular digraph*** for military engagement, surveillance and monitoring the different set of areas. This method provides collision-free, persistently flying of UAVs, and obstacle-free path for UAVs which results the maximum coverage area during search operations.

The detailed analysis of the existing proposals in non-cooperative techniques of UAVs path planning is shown in Table 10.

3.4. Coverage and connectivity

From the past few years, the coverage and connectivity problem in UAVs path planning has attracted a big attention from the researchers among the globe. The main challenge is to construct a reliable and scalable network infrastructure in the troposphere or underwater environments. The underwater sensor networks have been discussed

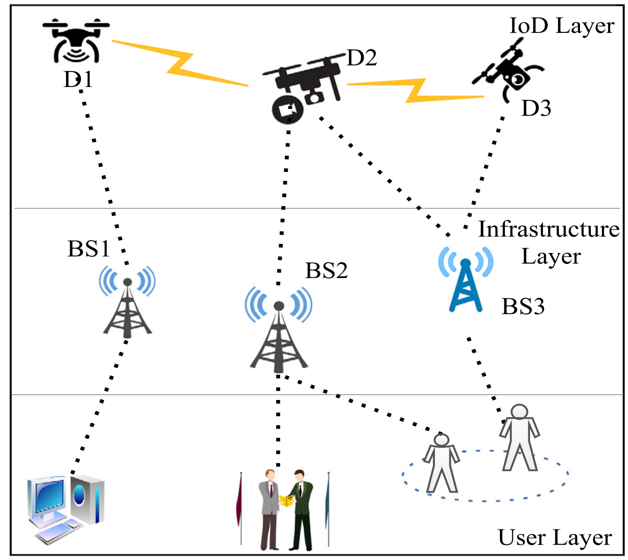

Fig. 31. Coverage and connectivity of UAVs path planning.

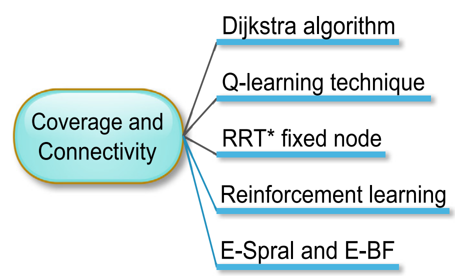

Fig. 32. Taxonomy of coverage and connectivity.

in [275] whereas weather forecasting and climate monitoring problems have been studied and solved in [276,277] using UAVs. UAVs are used to track the information of various scenarios such as-parking system, office work, or walking distance of person for surveillance and reconnaissance. The network connection exists among the UAVs, ground devices, and base stations using wireless communication. Then, this information is delivered to the ground devices through base stations using coverage and connectivity linkage is shown in Fig. 31.

Fig. 32 shows the taxonomy of coverage and connectivity in UAVs path planning. For example, authors in [278], presented the full-coverage connectivity of ad-hoc networks to maximize the coverage area and to minimize the use of number of UAVs in an urban environment. They have reconstructed the network in an isolated regions with an outside environment. In this proposal, they have used ***Dijkstra's algorithm*** that provides an optimal and collision-free path for UAVs. The simulation results show that only 30 UAVs have been used for the coverage area of 98% in UAVs path planning. Colonnese et al. [279] proposed the quality of experience (QoE) based UAVs path planning for mobile video streaming in heterogeneous network. They have used the ***Q-learning*** approach in UAVs path planning algorithm which improves QoE. Bouzid et al. [280] proposed the ***RRT* fixed node*** (RRT*FN) to find an optimal coverage of UAVs in a cluttered environment. They have used the genetic algorithm to solve the TSP by computing the complete path. They have also used the heuristic approach to solve the vehicle routing problem (VRP) due to the limited battery power of UAVs. The simulation results show that the UAVs covering all map with a coverage rate of 94%. Challita et al. [281] proposed the ***reinforcement learning*** echo state network (ESN) based algorithm that determines an optimal path and allocation of resources to the UAVs. They concluded that the proposed scheme decreases the rate in wireless

Table 10
Relative comparison of the existing proposals in non-cooperative techniques.

Reference	1	2	3	4	5	6	7	8
Chen et al. [268]	–	Optimal	–	x	✓	x	x	x
Li [269]	1 km	Optimal	–	✓	✓	✓	x	x
Morita et al. [270]	406 m	–	–	✓	✓	x	x	x
Yang et al. [271]	–	Optimal	–	✓	✓	x	x	x
Razzaq et al. [272]	100 km	Optimal	–	✓	✓	x	x	✓
Du and Cowlagi et al. [273]	4.09 m and 11.7 m	–	Completeness	✓	x	x	x	x
Bogdanowicz et al. [274]	–	–	–	x	✓	x	✓	✓

1: Path length; 2: Optimality; 3: Completeness; 4: Cost efficient; 5: Time efficient; 6: Energy-efficient; 7: Robustness; 8: Collision avoidance; –: not-mentioned; ✓: considered; x: not considered.

Table 11
Relative comparison of the existing proposals in coverage and connectivity.

Reference	1	2	3	4	5	6	7	8
Akyildiz et al. [275]	–	Sub-optimal	–	✓	x	✓	✓	✓
Alam et al. [276]	–	Optimal	–	x	x	x	x	x
Ammari et al. [277]	Cube side length-1000 m	–	–	x	x	✓	x	x
Batsoyol et al. [278]	–	Optimal	–	x	✓	x	x	✓
Colonnese et al. [279]	–	Optimal	–	x	✓	x	✓	x
Bouzid et al. [280]	10.69 m	Optimal	–	✓	x	✓	x	x
Challita et al. [281]	–	Optimal	–	x	✓	✓	x	x
Cabreira et al. [282]	–	Optimal	–	✓	✓	✓	x	x

1: Path Length; 2: Optimality; 3: Completeness; 4: Cost Efficient; 5: Time Efficient; 6: Energy-Efficient; 7: Robustness; 8: Collision Avoidance; –: not-mentioned; ✓: considered; x: not considered.

latency by 62% and increases the rate in energy-efficiency by 14%. Cabreira et al. [282] proposed the ***energy-aware spiral coverage and back and forth*** (E-spiral and E-BF) algorithms for exact photometry to success and to guarantee of the UAVs operation. These algorithms reduce the energy consumption of UAVs by predicting the overall energy usage during flight time. The detailed analysis of the existing proposals in coverage and connectivity of UAVs path planning is shown in Table 11.

3.5. Security in UAVs path planning

Security and privacy is a major concern in UAVs path planning. Most of the research proposals are based on UAVs network communication based on the security threats in UAVs. Authors are mainly focused on the vulnerabilities of UAVs network communication. They found the solutions that how the UAVs network can be prevented from the security threats. For example, Lin et al. [283] discussed the UAVs network architecture and study the security and privacy requirements in UAVs. They have also addressed the flexibility, data confidentiality, and privacy leakage of the UAVs which provides security to the UAVs. Similarly, Javaid et al. [284] analyzed the security threats in the UAVs network. They have also described the causes of loss of control of UAVs and provide the mitigation methods to secure them. Kharchenko and Torianyk [285] used the intrusion modes and effects criticality analysis for cybersecurity in the UAVs network. They have managed and audit the critical infrastructure control of UAVs from vulnerabilities and security threats. Sanjab et al. [286] proposed the network interdiction game based mathematical framework for enhancing the security of the drone delivery system. The network game has been used to compute the minimum time between the producer, consumer, and the drone delivery system. The simulation results show that the shortest path probability increases from 0.51% to 0.81%. Similarly, Zahariadis et al. [287] proposed the preventive maintenance of the critical infrastructure of 5G and UAVs network in an energy transmission and distribution process. It provides zero delays, enhanced security, optimal usage of UAVs and privacy to the UAVs network. Liang et al. [288] proposed the public blockchain framework for secure data collection and communication in UAVs network. The simulation results show that the average response time increases with an increase of size of data transmission that provides scalability and capability. Akram et al. [289] proposed the effective, independent and localized fleet control methods to manage the large number of UAVs simultaneously. They have focused on flight control management, collision avoidance and physical privacy, safety, and security of UAVs in the UAVs network communication.

From the security analysis of the existing proposals in UAVs network communication, we concluded that UAVs communication may face malicious attacks like denial-of-service (DoS), eavesdropping etc. A lot of research proposals has been discussed about the security threats and problems in the UAVs network communication. But, in UAVs path planning, a less number of research proposals that provide security and privacy protection to the UAVs.

4. Future research directions

Although, a lot of research work has been done on UAVs network communication. They have discussed the various algorithms and techniques used in UAVs network communication. But still, there are so many issues and constraints that need to be further investigated. In the following section, we provide new opportunities in an emerging communication network and highlight the interesting topics for future research directions.

- **Efficient path planning:** Although there are many research proposals exist in the literature on UAVs path planning but still, there are many obstacles and issues exist. So, there is a need for an efficient path planning in the air-to-ground UAVs network communication.
- **Energy-efficiency:** Energy consumption is the bottleneck of the UAVs network communication. LiPo-based batteries are used for target operations and hydrogen fuel cells are used for extending the flight times in UAVs. So, the charging efficiency of the UAVs is lower because of the long duration and random operations. To enhance the energy-efficiency of the UAVs network communication, the use of green energy resources (solar energy, wind energy) is required to charge the battery of the UAVs.
- **UAVs communication:** The traditional routing protocols used in the UAVs network communication cannot work properly due to close communication with other UAVs, fast speed, and high mobility. So, there is a need for a wireless communication network which can control the flight of UAVs and provides a good communication service among UAVs, satellites, and base-stations.
- **Security and Privacy:** UAVs network communication may face malicious attacks (DoS, man-in-the-middle, eavesdropping) due

to open links and topologies among UAVs, satellites, and base-stations. So, in the UAVs network communication, security and privacy is the major concern. To avoid this, there is a need for a secure mechanism in the UAVs communication.

- **Integration of different segments:** There are major problems and issues in the integration of air, ground, and space UAVs network communication, i.e., how to take advantage and how to ensure link reliability. To integrate this network using UAVs, there is a need to design a dedicated and incentive-based cross-layer protocol that can provide scalability and reliability to the UAVs communication.
- **Union of UAVs and IoT system:** Gharibi et al. [290] were the first who described the integration of UAVs and IoT system in UAVs network communication called as *'Internet of Drones'*. Due to the unique characteristics (fast deployment, high mobility, scalability) of this integration, it is the promising solution for realizing the framework of future IoT system with UAVs in the network communication.

5. Conclusion

This paper represents a comprehensive survey of UAVs path planning techniques. Broadly, path planning for UAVs is classified into three main categories, *i.e.*, representative techniques, coordinate techniques, and non-coordinate techniques. With these techniques, coverage and connectivity of the UAVs communication system has been discussed. In the end, the security mechanisms used in UAVs communication system have also been explored. Based on each category of path planning, critical analysis of existing proposals has been done with a comparison table using various parameters such as-path length, optimality, completeness, cost efficiency, time efficiency, energy efficiency, robustness and collision avoidance has been discussed. Finally, some open issues and suggestions are highlighted for the readers to work on.

Declaration of competing interest

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

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