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SURVEY

Toward UAV Path Planning Problem Optimization Considering the Internet of Drones

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ABSTRACT The use of Unmanned Aerial Vehicles (UAVs) has become popular in recent years, especially for their potential in various practical applications, but for their use to become a reality in this context, it is necessary to study about it. One of the main problems involving UAVs, regardless of the application to which it will be used, is path planning, which is crucial to ensure safety, economy, and effectiveness. In this study we present a literature review on the path planning optimization problem and the methods used to solve it. To this end, we seek to explore the existing papers in literature on this topic, identifying mathematical models, analyzing characteristics of the objective function, types of obstacles, number of UAVs considered, the nature of the solution adopted and deployments and integration in the Internet of Drones (IoD). A comparative analysis of the works analyzed was presented in the form of tables for each path planning technique considered. In addition, some advantages and safety of the methods were also listed. We furthermore present a set of open research challenges, high-level insights, and future research directions related to the UAV path planning problem in the context of IoD. This study contributes deeply with the advancement of state of art regarding the path planning strategies on the Internet of Drones since we provide a thorough analysis of characteristics of the mathematical models used in the UAV path planning problem reviewing papers published in relevant journals and conferences in the last 4 years (2018 to 2022), highlighting the advantages and disadvantages of each method as well as the possibilities of implementation and integration with IoD.

INDEX TERMS Internet of Drones, IoD architecture, optimization, path planning techniques, unmanned aerial vehicles (UAV).

I. INTRODUCTION

Drones, as known as UAVs, are the most usual way to refer to an aircraft that does not carry a crew. Several terms are used to refer to "drones". Besides UAV, the most common are unmanned aircraft systems (UAS), remotely piloted vehicles (RPVs)and remotely piloted aircraft (RPAs). In recent years, we have observed the increasing popularity and use of UAVs in different handy applications, such as delivery, transportation, agriculture, monitoring, medical assistance, image capturing, among others [1], [2], [3], [4], [5], [6], [7], [8], [9]. In the past, UAVs were mainly used in military applications where one or more drones were used for weather monitoring, soldier recognition, search and rescue. These applications persist and as listed above, several others have emerged, bringing new challenges and the need for more research about them.

Currently, there are several studies related to delivery applications with UAVs. Large and well-known companies such as Amazon [10], Google, iFood [11], are investing in research and possibilities to make their deliveries via drones. However, for such implementation to be possible and feasible in the future, it is necessary to organize and coordinate the airspace and drones, since several implementations will use it.

The IoD derives its name from IoT by putting "Drones" in place of "Things" [12]. Thus, IoD have similar properties to IoT. Gharibi et al. [13] defined IoD as a layered network control architecture that helps coordinate drones. To aid in the organization of airspace, the IoD is composed of airways.

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The node responsible for coordinating the drones is the Zone Service Provider (ZSP). In IoD, the ZSP is responsible for controlling the airspace. IoD provides generic services for various drone applications such as package delivery, traffic surveillance, search and rescue, and more. A robust airspace allocation architecture will be required, as using UAVs for more routine activities, such as package delivery, will result in thousands of daily flights in the same area. This will lead, for example, to many conflicts between UAVs navigating similar or intersecting routes [13].

In the context of IoD, and simply in applications involving UAVs, different factors can be discussed, among them safety, battery consumption, integration with other vehicular networks, traffic control, path coverage, Path Planning. The UAV Path Planning problem is widely studied, some works in the literatures [14], [15], [16], [17], and [18] address this problem in different contexts, factors, techniques, and applications; however, there is still much to be studied and explored regarding this problem in the IoD context. Therefore, this work intends to search and explore the existing knowledge about the UAV Path Planning problem, identify gaps in the literature, characterize the identified studies as to the characteristics of the objective function, types of experiments, number of UAVs considered, and nature of the solution. Opportunities for new research in the area are also highlighted. It is worth noting that, given the number of works that address the Path Planning problem in the context of IoD, in this review we consider works that deal with the UAV Path Planning problem in a general context. In the IoD context there is still a lot of open research: collision and interference, energy consumption, Path Planning considering various information such as management, security among others [19]. In this context, there are works that deal with IoD but not with Path Planning. For example, in [20] the authors propose a network architecture for IoD with scalability for UAVs in an urban environment addressing Path Planning issues, security, privacy, and network connectivity. The paper does not discuss methods or implementations for Path Planning, but proposes an architecture, framework, and guidelines for implementing Path Planning systems. In [2], the authors address possible applications involving UAVs in future smart cities. In [21], an energy-efficient strategy to avoid collisions with minimum energy required for drones reach the destination safely in the contexto of IoD.

From these considerations, we note the need for a comprehensive and informative study on the possibilities and challenges of UAV Path Planning in the context of IoD.

A. ABBREVIATIONS AND ACRONYMS

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

II. MOTIVATION AND ORGANIZATION

In recent years, studies related to UAVs have seen significant growth, given their substantial potential for applications in

TABLE 1. List of abbreviations.

Abbreviations	Meaning
UAV	Unmanned Aerial Vehicle
IoD	Internet of Drones
RPV	Remotely Piloted Vehicle
TSP	Traveling Salesman Problem
VRP	Vehicle Routing Problem
VANET	Vehicle Ad hoc Network
PSO	Particle Swarm Optimization
DE	Diferential Evolution
ABC	Artificial Bee Colony
TLBO	Teaching Learning-Based Optimization
GWO	Gray Wolf Optimization
LSA	Lightning Search Algorithm
MTSP	Multi-objective Traveling Salesman Problem
FO	Objective Function
PP	Path Planning
GA	Genetic Algorithm
EVNS	Energy-aware Variable Neighbor Search
IoT	Internet of Things
EDTP	Energy and Delay Optimized Trajectory Planning
ARMA	Auto-Regressive Moving Average
MILP	Mixed Integer Linear Programming
JSC	Job-Shop Centric
VRC	Vehicle Routing Centric
2D	Two-dimensional
ACO	Ant Colony Optimization
CNNs	Convolutional Neural Networks
SSO	Simplified conventional Swarm Optimization
SOCP	Second Order Conic Programming
DBSCAN	Density Based Spatial Clustering with Noise
MAVs	Manned Aerial Vehicles
NSGA-II	Non-dominated Sorting Genetic Algorithm II
QoS	Quality of Service
HR-MAGA	Recursive Hierachical Multi-Agent Genetic Algorithm
CFSDP	Clustering by Fast Search and Find of Density Peaks
GSA	Gravitational Search Algorithm
MSGSA	Mixed Strategy based Gravitational Search Algorithm
SA	Simulated Annealing
UGV	Unmanned Ground Vehicle
3D	Three-dimensional
GENERAL	searchinG timE allocatioN undEr coopeRative pAth pLanning
GRASP	Greedy Randomized Adaptive Search Procedure
EKF-SLAM	Extended simultaneous Kalman Filter Localization and Mapping
YOLO	You Only Look Once
GPM	Guassian Path Method
SPEA	Strength Pareto Evolutionary Algorithm
ADAS	Ant Colony algorithm based on elitist Strategy
DP	Dynamic Programming
I-GWO	Incremental Gray Wolf Optimization
Ex-GWO	Expanded Gray Wolf Optimization
S-PSO	Particle Swarm Optimization based on adaptive weight Sets
ANN	Adaptive Neural Network
centIPA	Centrifuge Immunne Plasm Algorithm
EDA-CostA*	Hybrid Distribution Estimation Algorithm
TA	Task Assignment
TO	Trajectory Optimization

TABLE 2. List of abbreviations.

Abbreviations	Meaning
RPA	Remotely Piloted Aircraft
ZSP	Zone Service Provider
ITS	Intelligent Transportation System
FANET	Flying Ad-hoc Network
IoFT	Internet of Flying Thing
MANET	Mobile Ad-hoc Network
UANET	UAV Ad-hoc Network
DO	Drone Operation
DTCO	Drone-truck Combined Operation
UC	Urban Computing
VD	Voronoi Diagram
IDA	Improved Dandelion Algorithm
NEH	Nawaz-Enscore-Ham
LKH	Lin-Kernighan Heuristic
NBGA	Neighborhood Based Genetic Algorithm
GBPSO	Global Best Particle Swarm Optimization
IBA	Intelligent Bug Algorithm
GWO	Gray Wolf Optimization
WOA	Whale Optimization Algorithm
SCA	Sine Cosine Algorithm
D3QN	Dueling Double Deep Q-networks
oHJB	Opportunistic Hamilton-Jacobi-Bellman
PDE	Partial Differential Equation
QT	Quality Threshold
PIOFOA	Improved Pigeon-inspired Optimization Algorithm
RLGWO	Reinforcement Learning-based Grey Wolf Optimizer Algorithm
DAA	Detect and Avoid
UTM	Unmanned Aircraft System Traffic Management
MTOW	Maximum Take-Off Weight
NP	Non-deterministic Polynomial time
memEAPF	Membrane Evolutionary Artificial Potential Field Method
APF	Artificial Potential Field
QAPF	Q-learning and Artificial Potential Field.
DA-APF	Deterministic annealing (DA) and Artificial Potential Field
ECoVG	Elliptical Concave Visibility Graph
VG	Visibility Graph
IVG	Improved Visibility Graph
EVG	Essential Visibility Graph
GVD	Generalized Voronoi Diagram
NSPP	Navigation Strategy with Path Priority
PRM	Probabilistic Roadmap
DEP	Dynamic Exploration Planner
ACPRM	Avoidance Critical Probabilistic Roadmaps
r-PRM	Recursive Probabilistic Roadmap
GLS	Generalized Laser Simulator
RRT	Rapidly Exploring Random Tree
M2M-DW	Decomposition-based Constrained Multi-objective Evolutionary Algorithm
GEO-DLS	Golden eagle Optimizer with Double Learning Strategies
MSEL-ABC	Multi-strategy Evolutionary Learning Artificial Bee Colony
MSFDE	Multi-Strategy Fusion Differential Evolution Algorithm
DRL	Deep Reinforcement Learning
DQN	Deep Q-Networks
DDQN	Double Deep Q-Networks
RL	Reinforcement Learning
BBO	Biogeography-Based Optimization
MVO	Multiverse optimizer
MHS	Modified Harmony Search

various fields. However, they also pose considerable challenges that must be addressed for practical implementation. One extensively studied problem in this context is the Path Planning problem.

The primary goal of this problem is to design a path from a source point to a destination point, attempting to minimize costs (which may involve various factors) while considering critical constraints such as battery consumption, obstacle avoidance, and safety.

Despite its seemingly simple concept, planning routes for UAVs remains challenging in real-world scenarios. This is due to the complex nature of airspace, where considerations must be made for the presence of other UAVs and airplanes simultaneously. Similar to ground route planning, airspace planning faces restrictions and limitations.

Therefore, to facilitate the planning of deliveries via UAVs across diverse sectors, it is essential to coordinate airspace, taking into account communication, interconnection, and, in essence, considering the architecture of the IoD. While some works in the literature [22] address Path Planning (PP) in the IoD context, there is still much to be studied concerning real-world applications and the coordination of airspace as a whole.

The UAV Path Planning problem has been extensively studied across various applications and contexts, employing diverse methods, simulations, and, in essence, considering several aspects by the global research community.

Given the significance of this topic, the objective of this paper is to provide a comprehensive review of recent literature (from 2018 to 2022). The focus will be on papers published in journals or event proceedings that address the UAV Path Planning problem, specifically with regard to:

1) Objective function: what is considered in the objective function, whether it comprises only a single objective or is multi-objective.
2) Quantity of UAVs considered.
3) Environment, time domain (2D or 3D) and mode (offline or online).
4) Types of obstacles.
5) Path Planning Techniques.
6) Possibility of deployment and integration in IoD.

Thus, the main contributions of this work are:

1) Comparative Analysis: providing a thorough comparative analysis of methods employed for solving UAV Path Planning. The considered methods encompass classic, heuristic, meta-heuristic, machine learning, mathematical models, and hybrid approaches.
2) Literature Review: presenting the fundamental characteristics of the UAV Path Planning problem as considered in over 200 recent works published between 2018 and 2022 in the literature.
3) Deployment and Integration in IoD: offering insights into the possibilities of deploying and integrating UAV Path Planning within the IoD. This includes a detailed

discussion of the main challenges associated with this integration and proposing potential avenues for future research.

This study is organized as described below.

- Section III: Overview of Related Works - presentation of relevant studies and literature related to the UAV Path Planning problem.
- Section IV: Methodology - description of the methodology adopted to conduct and structure this literature review.
- Section V: Characteristics, Definitions, and Challenges of IoD - discussion of the main characteristics, definitions, and challenges associated with the IoD.
- Section VI: UAV Path Planning - overview of UAV Path Planning, including a summary of techniques and the compilation of analyses presented in tabular form.
- Section VII: Mission Planning - presentation of an overview of mission planning for UAVs.
- Section VIII: Implantation and Integration in IoD - exploration of possibilities for the implementation and integration of the studied Path Planning techniques within the context of IoD.
- Section IX: Future Works - discussion of potential directions for future research in the field.
- Section X: Conclusions - presentation of the conclusions drawn from the findings and discussions presented throughout the article.

III. RELATED WORKS

In recent years, some studies have investigated problems involving drones in different contexts and applications.

This study differs from the works listed in the Table 3 in terms of the content addressed contributing deeply with the advancement of state of art regarding the UAV Path Planning strategies on the IoD since we provide a thorough analysis of characteristics of the mathematical models used in the UAV Path Planning problem reviewing papers published in relevant journals and conferences in the last 4 years (2018 to 2022), highlighting the advantages and disadvantages of each method as well as the possibilities of implementation and integration with IoD. Therefore, in addition to analyzing the techniques used for Path Planning, we analyze and list how they can be incorporated in the context of the IoD.

Table 3 summarizes the information regarding similar work and the focus of this paper.

IV. METHODOLOGY

For this study, we selected papers using the following approach:

1) Database Searches: Conducted searches in the IEEE and Science Direct databases using the keywords "UAV Path Planning problem." Due to the large number of papers listed, search refinements were implemented. In the refinement process, we considered papers (journal articles or papers published in event proceedings) from the period 2018-2022 containing keywords such as "UAV Path Planning problem," "mathematical modeling," "optimization," and "Internet of Drones (IoD)."
2) Citation Analysis: Examined articles cited in the papers identified during the database searches. After searching the databases and downloading the papers, we analyzed their references and included relevant papers that addressed drone Path Planning problems, particularly those considering optimization aspects.

After selecting the articles, the subsequent step involved dedicated reading of the title, abstract, and keywords to verify that the chosen articles indeed address the characteristics under analysis. Subsequently, in Section VI, the works are analyzed and compared in the form of tables, focusing on the following aspects: objective function, number of UAVs, environment, mode, obstacles, and method. Additionally, tables are used to list some advantages and disadvantages of each technique for UAV Path Planning.

It is essential to highlight that the UAV Path Planning problem is addressed in the literature from two perspectives: 1. the Path Planning itself and, 2. the path coverage. Given the substantial volume of papers on both perspectives, this work specifically focuses on analyzing papers that address only the UAV Path Planning problem. Works related to path coverage were not considered in this study.

The primary distinction in the methodology employed for this study, as opposed to similar reviews, lies in our comprehensive consideration of Path Planning techniques. We analyze these techniques in a broad sense, emphasizing their potential integration into the context of the IoD. This approach allows us to explore not only the intricacies of Path Planning but also the broader implications and possibilities that arise when considering the intersection of Path Planning techniques with IoD.

V. INTERNET OF DRONES

The IoD is a network architecture designed specifically to facilitate communication between drones and various ground-based network entities [13], [27]. Encompassing the envisioned Intelligent Transportation System (ITS) scenario, this concept is tasked with addressing a range of requirements. These include the management of self-organized aerial traffic flow, ensuring fair access to a shared wireless communication channel, and implementing all levels of security and privacy [53].

Gharibi et al. [13] devised a cross-layered network architecture for IoD management to address these requirements, wherein drones are required to navigate along well-defined airways. In a similar vein, Svaigen et al. [53] proposed an IoD structure composed of airways that resemble terrestrial roads. Intersections are formed by the convergence of two or more airways, nodes are defined as reachable Points of Interest through an alternating sequence of airways and intersections, and ZSP serve as infrastructure components akin to base stations. ZSPs provide navigation information

TABLE 3. Overview of some similar surveys.

Year	Reference	Highlight	Comparision of current research work in relation to	Domain
2023	This work	Review of UAV Path Planning problem analyzing the objective function, quantity of drones, environment, type of domain, mode optimization techniques used. Furthermore, we discusses the possibility of deployment and integration in IoD.	Aspects of UAV Path Planning: objective function, quantity of drones, environment, type of domanin, mode, optimization techniques. Deployment and integration in IoD.	Path Planning and IoD
2022	Shahid et al [23]	Comprehensive study of UAV Path Planning, discussing: environment, dimensions, obstacles, type and number of UAVs and optimization techniques used.	Metaheuristics methods. Cost, time, energy efficient Path Planning, environment, dimensions, obstacles, mode and number of UAVs.	Path Planning
2021	Viloria et al [24]	Systematic literature review of the different models studied for the routing problems using UAVs, regarding to the optimized objectives, solution methods, applications, and type of vehicles.	Objective Function. Constraints. Logistics application. Types models. Type of solution method.	Drones routing problems
2021	Vashisth et al [25]	Systematic review of Path Planning models and their corresponding techniques in UAVs Communication network.	Cooperative Techniques. Representation Techniques. Non-cooperative techniques. coverage & Connectivity. Security & Privacy.	Path Planning
2021	Abdelmaboud [26]	Comprehensive study covering requirements, taxonomy, recent advances, and challenges of future research trends in IoD.	Drone applications. Commercial case studies. Recent advances in IoD.	IoD
2021	Boccadoro et al [27]	Detailed study of multifaceted aspects of IoD, at a macroscopic level and finer level focusing in the drone adoption for the economy and society.	Drone Applications.	IoD
2021	Zaidi et al [19]	State-of-the-art of IoFT.	IoT, FANET, and IoFT MANET, VANET, UANET and FANET UAV system, multi-UAV system.	IoFT
2021	Yahuza et al [12]	Deals with recent trends in the security and privacy issues that affect the IoD network.	IoD architecture. Drones Classifications. Security and privacy.	IoD
2021	Khan et al [28]	State-of-the-art UAV Path Planning algorithms and obstacle avoidance techniques	UAV Path Planning with obstacle avoidance and without obstacle avoidance. UAV Path Planning tecniques.	Path Planning
2020	Chung et al [29]	State-of-the-art optimization approaches in the civil application of drone operations (DO) and Drone-truck combined operations (DTCO).	Drone operations. drone-truck combined operations. Application areas.	Drones
2020	Aggarwal et al [30]	Review of UAV Path Planning techniques, classifying as: representative, cooperative and non-cooperative techniques.	Representative techniques, cooperative techniques, and non-cooperative techniques. Security, coverage and connectivity.	Path Planning
2019	Koufi et al [32]	Survey of variants of the Traveling Salesman and Vehicle Routing Problems for UAVs and applications.	TSP. VRP. Resolution techniques. Quantity of vehicles. UAV's Applications.	UAV path optimization problems
2019	Xu & Che [33]	Brief review of different meta heuristic algorithms and hybrid meta-heuristic algorithms through TSP in UAV route planning.	TSP. MTSP. Metaheuristic methods for TSP. TSP with Neural Network and Fuzzy Neural Network.	Drones Route Planning
2019	Song et al [34]	Survey on representative approaches to the 3D UAV Path Planning problem.	Path Planning algorithms: graph-based algorithms, the heuristic search algorithms, the field-based algorithms, and the intelligent optimization algorithms.	Path Planning
2019	Allaire et al [35]	Review of UAVs real-time trajectory planning.	Flyability, real-time, and embedded criteria. World representation, path generation, and trajectory generation.	Trajectory planning
2018	Otto et al [36]	Survey of optimization problems arising in the operations planning of drones in civil applications.	Drone's operations: area coverage, search operations, routing for a set of locations, Data gathering and wireless sensor network, communication links, operational aspects of network of drones.	Drones
2018	Chandra et al [37]	Prototype survey on Path Planning and obstacle avoidance with drones.	Path planning techniques.	Path Planning
2018	Radmanesh et al [38]	Comprehensive and comparative study of UAV Path Planning and obstacle avoidance algorithms.	Heuristic and non-heuristic techniques. Exact techniques.	Path Planning
2018	Coutinho et al [39]	Comprehensive review of UAV routing and trajectory optimization Problem.	Trajectory optimization problem. vehicle routing problem. Path planning. Task assignment	UAV's routing problems
2018	Zhao et al [40]	Overview of computational intelligence methods for the UAV Path Planning problem.	Computational intelligence algorithms. Types of time domain. Types of environment models.	Path Planning

to drones through a fairness policy, adhering to governing laws related to airways, intersections, and nodes to ensure a safe and reliable flow of drone traffic. It's noteworthy that a ZSP must maintain independence from drone companies and, consequently, cannot access application contextual information unless permitted by the drone. Figure 1 illustrates an IoD environment based on these considerations.

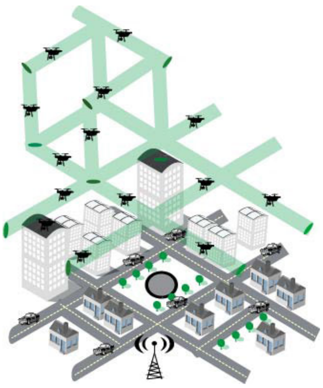

FIGURE 1. IoD environment in an urban cenario. Source: Bine et al. [52].

The IoD presents a practical solution to address challenges in Flying Ad-hoc Networks (FANET) and the Internet of Things (IoT), capitalizing on the advantages offered by UAVs. UAVs bring flexibility, maneuverability, efficient mobile data dissemination, rapid deployment, and cost-effectiveness to the IoD framework [26]. Within the IoD architecture, UAVs function as networked objects capable of communication among themselves, exchanging data, particularly related to flight coordination capabilities. Additionally, UAVs establish communication with a designated ground infrastructure responsible for storing and processing data. This infrastructure enables services and provides updated information to remote users connected to dedicated application servers [27].

The IoD has garnered significant attention in recent literature, attributed to the flexibility and adaptability of drone networks across diverse scenarios and applications. The appeal of IoD lies in its capacity to enhance the performance of various network architectures. UAVs, driven by technological advancements and practical advantages such as high mobility, real-time monitoring, coordination capabilities (dependent on system architectures and communication technologies), load transport, and access to hard-to-reach locations, are becoming increasingly popular. The broad range of functionalities associated with UAVs opens up numerous applications through IoD, including smart agriculture, goods delivery, search and rescue, surveillance systems, and data and image collection, as well as telecommunications [27], [54].

The relationship between IoT, IoD, and Urban Computing (UC) is depicted in Figure 2. Figure 3 illustrates some IoD applications in different environments. Consequently, the IoD architecture, along with its functionalities and applications, significantly contributes to and enhances scenarios related to smart cities and UC [19], [54], [57].

Given the complexity of the IoD scenarios, several issues necessitate thorough investigation. To explore potential solutions involving the use of drones in the IoT, numerous survey

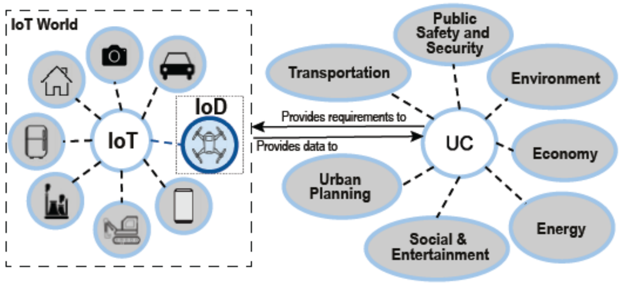

FIGURE 2. IoT, IoD and UC. Source: Bine et al [54].

studies have been published in the literatures [12], [13], [19], [26], [27], [57], [58], [59], [60], and [61]. These surveys aim to provide insights, analyze challenges, and present advancements in IoD, contributing to the understanding and development of effective solutions for diverse applications.

In the realm of the IoD, several crucial features demand thorough investigation. These features include: connectivity and coverage, reliability, data processing and storage, energy consumption and supply, cooperation and collaboration real-time communication, effective cost, security and privacy.

These aspects are fundamental to the successful development and deployment of IoD applications, as highlighted in the literature [19]. Understanding and addressing these features are pivotal in overcoming challenges and ensuring the effective functioning of drone networks within the broader IoT context.

In the context of the IoD, there are still challenges to overcome, particularly to ensure that practical applications can fully benefit from the IoD framework, ultimately contributing to the development of smart and connected cities and enhancing the quality of life for the population. These challenges include:

1) Regulation and coordination of airspace: ensuring safe and smooth flights, especially for UAVs.
2) Efficient communication networks: guaranteeing effective connectivity among all the elements constituting the IoD.
3) Data security and privacy: addressing concerns related to the security and privacy of data for all parties involved.
4) Security of application scenarios involving UAVs: ensuring the security of various application scenarios that involve the use of UAVs.

Furthermore, considering the IoD architecture, additional challenges persist [19], [35], [60], [61], [62]: collision and interference, drone control and management, security and privacy, data rate and coverage, drone power consumption, scalability, stability, communication networks.

Addressing these challenges is crucial for the successful development and implementation of IoD, fostering its potential to revolutionize various aspects of urban life and infrastructure.

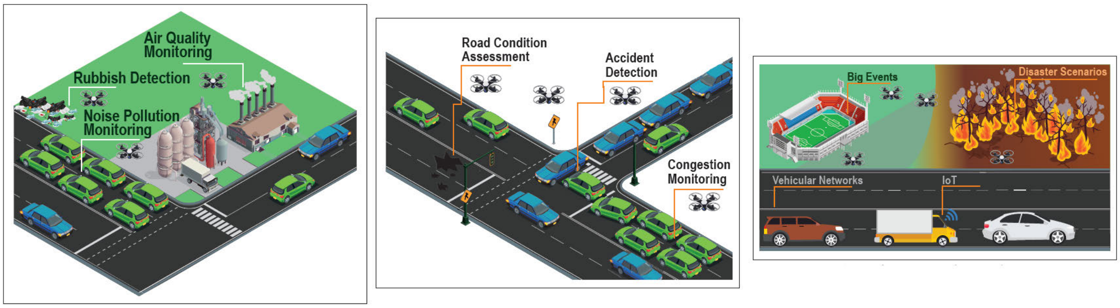

FIGURE 3. Some IoD applications. Source: Bine et al [54].

Given the diverse characteristics, requirements, and applications encompassed by the IoD architecture, a key concern in this context is Path Planning, briefly described in the previous section. The challenges associated with Path Planning in IoD primarily revolve around:

1) Obtaining safe, obstacle-free, and viable paths: ensuring that paths generated are safe, devoid of obstacles, and feasible for drone navigation.
2) Implementation of paths in IoD architecture: determining how to implement paths within the IoD architecture. One potential approach involves the use of airways organized in layers, as illustrated in Figure 4.
3) Selection of suitable Path Planning techniques for IoD: identifying which among the existing techniques for Path Planning are best suited for the IoD scenario.

Addressing these challenges is essential to enable efficient and reliable Path Planning within the IoD framework, contributing to the successful deployment of drone networks in various applications and scenarios.

In view of the different characteristics, requirements and applications that IoD architecture encompasses, one of the key issues in this context is Path Planning, which was briefly described in the previous section. The challenges of Path Planning in IoD mainly involve: obtaining safe, obstacle-free and viable paths, how to implement the paths in the IoD architecture (one possibility is the of airways in layers, as shown in the Figure 4) and which of the existing techniques for Path Planning are better suited for the IoD scenario.

VI. UAV PATH PLANNING TECHNIQUES

Indeed, UAV Path Planning techniques can be categorized into four main groups: optimization-based methods, searching-based methods, sampling-based methods, and learning-based methods.

Each category has its strengths and weaknesses, and the choice of method often depends on the specific characteristics of the environment, the complexity of the Path Planning task, and the available data. The optimal Path Planning technique for a given scenario may vary based on the application requirements and the constraints of the IoD architecture.

Absolutely, Path Planning for UAVs involves determining a trajectory from a starting point to a target point while ensuring that the path is collision-free. This is a critical aspect of UAV navigation, ensuring the safe and efficient movement of drones through their environment. Various Path Planning techniques, as mentioned earlier, are employed to address this challenge and generate collision-free paths for UAVs in diverse scenarios and applications [30].

The UAV Path Planning problem is often formulated and solved as an optimization problem, where the goal is to design a path for the UAV that either minimizes costs or maximizes the UAVs' utility. While the specifics of the Path Planning problem may vary based on the objective, certain requirements remain crucial. These include factors such as the path to be traversed by the UAV and the energy consumption, which are integral considerations in any application involving UAVs [38]. When delving into the Path Planning problem, several key terms and concepts emerge [30]:

1) Movement: considers factors such as turning angle, path length, and the flight path of the UAV.
2) Trajectory: encompasses parameters like speed, time, and the kinematics of UAV movement.
3) Navigation: comprises elements of motion planning, trajectory planning, collision avoidance, and location determination.

Furthermore, according to [40], the UAV Path Planning problem is characterized by several essential attributes:

1) Security: this aspect is concerned with ensuring the safety of UAVs, particularly in environments where tasks are performed in potentially threatening conditions. Minimizing the probability of detection by hostile radars and other UAVs is a key consideration.
2) Physical Viability: refers to the physical constraints and limitations associated with the use of UAVs. This includes considerations such as the maximum path distance and the minimum path length.
3) Performance of the mission: relates to the ability of a path to satisfy the specific requirements of a given mission. Designing a path to complete a mission involves meeting various requirements, including maximal turning angles, maximum climbing/diving angles, and minimal flying heights.

4) Real-time implementation: pertains to the efficiency of the Path Planning algorithm, particularly in the context of real-time implementation. The dynamic nature of UAV flight environments necessitates computationally efficient path-planning algorithms to respond promptly to changing conditions.

These attributes collectively contribute to the complexity of the UAV Path Planning problem, requiring a comprehensive and adaptive approach to address the diverse challenges posed by different mission scenarios.

Certainly, planning a path for UAVs involves consideration of various crucial aspects, as highlighted in [23]: environment (static, urban, uncertain, complex, wind fields, threat, etc), dimensions (2D, 3D), obstacles (static, dynamic), mode (offline, online), number of UAVs (single, multiple).

The UAV Path Planning problem is recognized as a complex optimization problem and is generally classified as NP-hard [23]. Regarding the mathematical model for UAV Path Planning, it typically involves an objective function aimed at cost minimization subject to certain constraints that vary based on the specific application requirements.

The objective function may consider one or multiple attributes, and in the latter case, it is referred to as a multi-objective function. An example of a mathematical formulation for UAV Path Planning using an exact approach is provided in [22]. The authors consider a scenario with a single UAV and multiple regions conforme (1). The path to be traversed by the drone is represented as $P = p_{i,j}|i \in [1, m], j \in [1, m]$, where each element $p_{i,j}$ is a boolean variable indicating whether the UAV can fly from region i to region j. This binary representation helps define the feasible paths for the UAV in the optimization model.

$$
\begin{aligned}
&\min \quad T = \sum_{i=1}^{m}\sum_{j=1}^{m} p_{i,j} \\
&\text{s.t.} \begin{cases}
\forall i, j \in [1, m], \text{ if } p_{i,j} = 1, \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \leq 1 \\
\forall i \in [1, m], \text{ if } B_i = 1, \sum_{j=1}^{m} p_{i,j} = \sum_{j=1}^{m} p_{j,i} = 0 \\
\sum_{i=1}^{m} p_{0,i} = \sum_{j=1}^{m} p_{j,m} = 1 \\
\forall j \in [1, m], \text{ if } \sum_{i=1}^{m} p_{i,j} = 1, \sum_{k=1}^{m} p_{j,k} = 1 \\
p_{i,j} \in \{0, 1\}
\end{cases}
\end{aligned}
\tag{1}
$$

The first constraint em (1) guarantees that the UAV can only fly over adjacent regions, restricting its movement to neighboring areas. The second Constraint guarantees that the UAV can only fly over adjacent regions, restricting its movement to neighboring areas. The third constraint ensures that the initial position and the target position are within the defined flight path, aligning with the specified mission requirements. The four constraint represents that the UAV cannot stop during the flight path, emphasizing continuous movement from the initial position to the target position.

These constraints collectively define the conditions that the solution must satisfy to be considered a valid and feasible path for the UAV. The inclusion of such constraints is essential for addressing practical considerations and ensuring the optimization problem aligns with real-world scenarios and requirements.

Another example of mathematical formulation for the PP proposed by Ren et al. [41]. The authors presents a multi-objective Path Planning approach considering two objectives: distance and safety. V is a set of points in space, denoted by $\{v_1, v_2, \cdots, v_N\}$. E is a set of edges connecting two points in V, denoted by $\{e_1, e_2, \cdots, e_M\}$. A path p is a sequence of points $\{v_1, v_2, \cdots v_h\}$ from the source point v_1 to the destination point v_h. $c_{i,j}$ is the non-negative cost of the j^{th} objective assigned for the i^{th} edge ($i \in [1, M]$) and $j \in [1, K]$, K is the number of objectives. K equals to 2 and $c_{i,1}$ and $c_{i,2}$ are costs of the i^{th} edge for distance and safety index respectively. Let $f_j(p)$ be the total cost of all edges in path p for the j^{th} ($j \in [1, K]$) objective. Then, $f(p)$ is the objective vector for path p: $f(p) : \{f_1(p), f_2(p), \cdots, f_K(p)\}$. In this case, the authors mades a trade-off among all objectives and try to obtain Pareto optimal solutions.

The multi-objective modeling proposed by Ren et al. [41] is a way to solve the PP, but there are several others in the literature that consider other objective functions, constructed according to the problem to be solved. Given the complexity and the different aspects that can be considered in the PP, there are different works in the literature that consider different attributes and characteristics, as well as different solution methods for it [42], [43], [44], [45], [46], [47], [48], [49], [50], [51].

To satisfy the attributes, the key terms and the optimization problem related to UAV Path Planning problem, there are several traditional methods, such as RRT, PRM, APF methods and computational intelligence methods. These methods have their strengths and drawbacks, and in the literature several hybrid methods that combine one or more methods have emerged with the aim of overcoming the disadvantages.

The UAV Path Planning within the context of the IoD indeed presents significant challenges. The primary objective is to devise effective flight paths for drones, allowing them to reach their destinations while navigating through obstacles and minimizing energy consumption. Moreover, the coordination of multiple drones sharing the same airspace adds complexity to the problem. The key characteristics of the UAV Path Planning problem in the IoD context include:

1) 3D Space: the problem involves planning paths in 3D space, considering the altitude along with the horizontal dimensions. This adds an extra layer of complexity compared to 2D Path Planning.
2) Offline and online planning: the time domain categorization distinguishes between offline and online planning. In the offline case, information about the environment is known beforehand and used for path

construction. In contrast, the online case involves planning paths on the fly, utilizing real-time sensor data.

3) Information Availability: offline planning requires a priori knowledge of the environment, including the locations of obstacles. Online planning, on the other hand, relies on sensor data collected during the flight.
4) Multi-drone coordination: the IoD scenario involves multiple drones sharing the same airspace. Coordinating their movements to avoid collisions and optimize the use of airspace is a crucial aspect.
5) Obstacle avoidance: effectively avoiding obstacles is a primary concern to ensure the safety and success of drone missions.

The illustration in Figure 4 visualizes a scenario depicting the complexity of UAV Path Planning in the IoD context. This complexity highlights the need for advanced planning algorithms, real-time decision-making capabilities, and efficient coordination mechanisms.

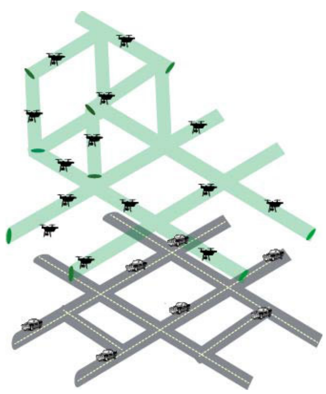

FIGURE 4. UAV path planning in IoD. Adapted by Bine et al. [52].

In this section, we analyze the works regarding: objective function; quantity of UAVs considered; environment, time of domain (2D or 3D) and mode (offline or online); obstacles and Path Planning methods. Furthermore, we discuss the possibility of deployment and integration in IoD scenario.

The state-of-the-art researches are compared in tabular form based on the parameters including objective function, single or multiple UAVs, environment of UAV operations, types of domain and mode. The advantages and limitations of the Path Planning approaches are also presented in tables.

In view of the vast existing literature on UAV Path Planning techniques, it is clearly impossible to consider all the works published in the period considered (2018 to 2022), so we consider a representative and sufficient number of works to provide relevant information on the topic addressed in this article.

A. CLASSICAL METHODS

The classical methods for Path Planning problem includes the sampling-based methods: cell decomposition, roadmaps, potential field. Furthermore, the methods Rapid-exploring Random Tree (RRT), Voronoi Diagram (VD), Visibility Graph (VG), Dijkstra algorithm and Probabilistic Road Map (PRM) are considered classical methods for the UAV Path Planning.

1) CELL DECOMPOSITION

It consists of decomposing the free space of the drone into simple regions called cells, so that a path between two configurations in different cells can be easily generated. An undirected graph representing the adjacency relation between the cells is then constructed, and over this graph the path search is performed [63]. The nodes of this graph are the cells extracted from free space: two nodes are connected by an edge if and only if two corresponding cells are adjacent. Then, the result of the search is a sequence of cells called a channel. Hence, a free path can then be computed from this sequence.

This technique is categorized into two types: exact cell decomposition and approximate cell decomposition. In exact cell decomposition, the free space is divided into cells whose union exactly matches the free space. In approximate cell decomposition, cells have predetermined shapes, and their union is strictly contained within the free space. Generally, these methods are not exhaustive because, depending on the chosen accuracy, they may not identify a path between two configurations even if one exists. However, the accuracy of these methods is typically adjustable. Figure 5 illustrates both exact and approximate cell decomposition.

After cell division is performed, different methods can be used in the case of UAV Path Planning: Probabilistic Roadmap Method (PRM), Rapidly-exploring Random Tree (RRT), A* algorithm [30].

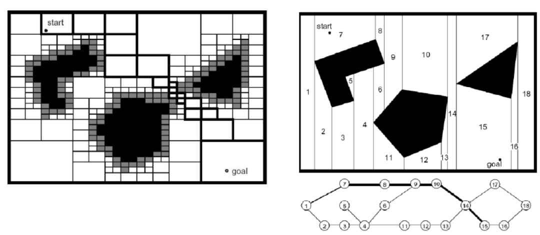

FIGURE 5. Exact cell decomposition and approximate cell decomposition. Source: Aggarwal and Kumar [30].

2) ROADMAPS

This approach aims to simplify the representation of the environment by transforming it into a graph that depicts feasible paths. Once the roadmap is established, it serves as a set of standardized paths. Consequently, trajectory planning is streamlined to connecting the robot's initial and final positions to the roadmap and finding a path between these two points. If a path exists, it is composed of three subpaths: one connecting the initial position to a point on the roadmap, another subpath within the roadmap, and finally, a subpath leading from the last chosen point on the roadmap to the final position. Notably, this technique assumes a static environment [30].

From this method, several variations have been proposed, including the VG and VD.

3) VISIBILITY GRAPH

A VG is created by connecting line segments between vertices of obstacles. Line segments that entirely reside within the free space region are incorporated into the graph. In trajectory planning, the starting and ending positions are depicted as vertices, forming a connectivity graph. A search algorithm is then employed to identify a free path within this graph. Figure 6 illustrates the concept of a VG.

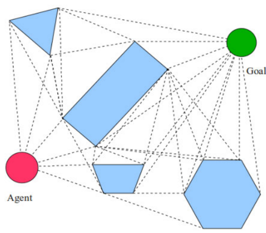

FIGURE 6. Visibility graph. Source: Costa and Tonidandel [31].

4) VORONOI DIAGRAM

VD are used for roadmaps [30]. Given a set X of n points in the plane, determine for each point p of X what is the region $V(p)$ of the points in the plane that are closer to p than to any other point in X. The regions determined by each point form a restricted plane called the Voronoi Diagram. Figure 7 shows the VD applied to 18 points. Paths derived from the VD are considered safe and reliable because obstacles are significantly distant from all path edges [30].

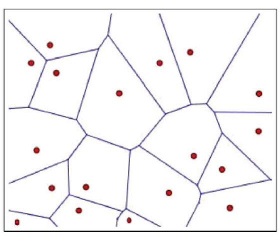

FIGURE 7. Voronoi diagram. Source: Aggarwal and Kumar [30].

5) RAPID-EXPLORING RANDOM TREE

A RRT is a data structure and algorithm that is designed for efficiently searching nonconvex high-dimensional spaces. RRT is constructed incrementally in a way that quickly reduces the expected distance of a randomly-chosen point to the tree. RRT is particularly suited for Path Planning problems that involve obstacles and differential constraints (nonholonomic or kinodynamic) [64].

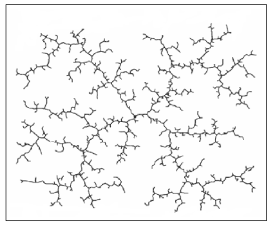

FIGURE 8. Rapid-exploring random tree. Source: Aggarwal and Kumar [30].

Different authors have proposed improvements and hybrid methods based on the RRT [46], [65], [66], [67], [68], [69], [70], [71].

6) PROBABILISTIC ROADMAPS

PRM, an algorithm for UAV Path Planning, is credited to Kavraki et al. [72], [73]. The fundamental concept of this method involves generating random samples from the robot's configuration space, testing their obstacle-free status, and connecting them based on proximity. Figure 9 illustrates the PRM technique.

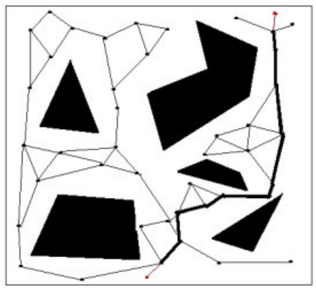

FIGURE 9. Probabilistic roadmaps. Source: Masehian and Sedighizadeh [74].

There are various variants of PRM, ranging from simple to sophisticated, that modify the sampling and connection strategy to achieve improved performance.

7) POTENTIAL FIELD

The Potential Field method involves determining the trajectory direction based on the resultant forces applied to the robotic system at each navigation moment. An important feature of this method is its applicability in dynamic environments, as there is no need to create any data structure beforehand.

In Path Planning, the robot is subjected to the action of a certain potential, which is determined by the configuration of the target and obstacles. The target is represented by a charge of opposite sign to the proof charge and the obstacles, by charges with signs equal to those of the proof charge. The resultant potential is designed to generate repulsive forces between the robot and obstacles, as well as an attractive force between the robot and the target.

TABLE 4. Aspects of classical methods UAV path planning.

Reference	FO	UAVs	Environment	Mode	Obstacles	Method
Gao et al (2022) [68]	Path Planning speed	Single	3D	Offline	Multiple	RRT, ACO, A*
Kiani et al (2021) [69]	Distance	Multiple	3D	Offline	Multiple	RRT_{GWO}, Adapted-RRT_{I-GWO}, and Adapted-RRT_{Ex-GWO}
Fulan et al(2022) [70]	Distance	Single	3D	Offline	Multiple	Heuristic RRT
Xu, Quian and Zhang (2021) [71]	Distance and the turning angle	Single	2D	Online	Multiple	Improved RRT algorithm
Dai et al(2022) [76]	Distance and time	Single	2D	Offline	Multiple	DA-APF
Huang and Teo (2019) [79]	Distance	Single	3D	Offline	Multiple	VG algorithms.
Huang, Xu and Zhen (2021) [80]	Distance	Single	2D	Offline	Multiple	IGV + Dijkstra algorithm+AG
Blasi et al(2022) [81]	Distance	Single	3D	Offline	Multiple	EVG
Li et al (2022) [82]	Not applicable	Single	3D	Offline	Multiple	VG
Zhjang et al (2018) [83]	Threat cost and the fuel cost	Multiple	2D	Offline	Multiple	Voronoi Graph algorithm
Tan et al (2021) [84]	Distance	Multiple	2D	Offline	Multiple	Voronoi Diagram +Tabu Genetic Algorithm
Huang et al (2021) [85]	Distance	Multiple	2D	Offline	Multiple	GVD- NSPP
Li and Liu (2022) [86]	Total energy consumption	Single	2D	Offline	Multiple	Voronoi diagram - Dubins geometric path and Floyd algorithm
Pinon et al (2022) [87]	Mission time	Multiple	2D	Offline	Multiple	Voronoi diagram + SA
Chen et al (2021) [88]	Path cost	Single	2D	Offline	Multiple	improved PRM method
Xu and Deng (2021) [89]	Exploration time, path length, and computational time	Single	3D	Online	Multiple	DEP + PRM method
Arias et al (2021) [90]	Distance	Multiple	2D and 3D	Online	Multiple	ACPRM algorithm
Chowdhury and Schwartz (2022) [91]	Distance	Single	2D	Offline	Multiple	r-PRM.
Ramasamy et al (2021) [92]	Energy and path time	Multiple	3D	Online	Multiple	PRM+Dijkstra algorithm
Alarabi et al (2022) [93]	Distance and numbers of turns	Single	2D	Offline	Multiple	PRM method
Wang et al (2021) [94]	Path time	Single	3D	Online	Multiple	hierarchical PRM method
Li et al (2022) [95]	Distance	Single	2D	Offline	Multiple	modified PRM algorithm
Chai et al (2022) [96]	Path time	Single	2D	Offline	Multiple	PSO+PRM algorithm
Muhammad et al (2022) [97]	Distance and path time	Single	2D	Offline	Multiple	PRM, RRT, A^* and GLS
Jang et al (2022) [98]	Planning time	Single	2D	Offline	Single	IK+PRM
Prasad and Ramkumar (2022) [99]	Optimal height and optimal transmit power	Multiple	3D	Offline	No	Dijkstra's algorithm
Orozco-Rosas, Picos and Montiel (2019) [100]	Distance	Single	2D	Offline	Multiple	APF + pseudo-bacterial genetic algorithm
Orozco-Rosas, Montiel and Sepúlveda (2019) [101]	Distance	Single	2D	Offline and online	Multiple	memEAPF
Orozco-Rosas et al (2022) [102]	Distance	Single	2D	Offline and online	Multiple	QAPF learning algorithm
Souza et al (2022) [103]	Distance	Multiple	3D	Offline	Multiple	Modified potential field method
Xie et al (2021) [104]	Not applicable	Single	3D	Online	Multiple	Improved artificial potential field algorithm
Feng et al (2021) [105]	Distance	Single	3D	Offline	Multiple	Hybrid algorithm based on obstacles'position prediction and the modified APF

Khatib [75] was the first to apply the artificial potential field (APF) approach to Path Planning for mobile robots. This approach is well-suited for real-time control of robots due to its clear physical meaning and simple mathematical description. Consequently, it has found widespread use in Path Planning [76]. Figure 10 illustrates mobile robot navigation using the APF approach.

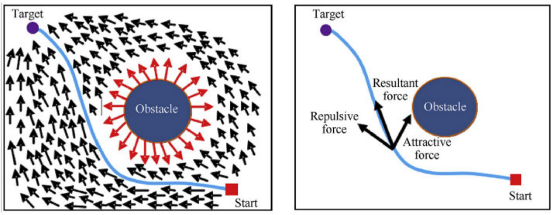

FIGURE 10. APF approach. Source: Choset et al. [77].

8) DIJKSTRA'S ALGORITHM

Dijkstra's algorithm was proposed by Dijkstra in 1959 [78], to obtain the shortest path in a directed graph with positive edge weights. Despite being old, this algorithm is still widely used in Path Planning problems and their variants, due to its simplicity and possibility of being integrated with other methods.

The Table 5 presents some advantages and disadvantages of classical methods for the UAV Path Planning.

TABLE 5. Advantages and shortcomings in the classical methods for UAV path planning.

Method	Advantages	Shortcomings
VG	Suitable for simple cases and static environment.	Inefficient in 3D environments, unsuitable for obstacles with complex shapes and large numbers.
VD	Suitable for real-time Path Planning and the generated paths are safe.	There is no guarantee of optimality in the generated paths.
RRT	Suitable for simple and static environment, easy implementation.	Quality of the generated path is not considered, there is no guarantee of optimality in the generated paths.
PRM	Suitable for static and complex environment, shortest path generation.	Long time processing due check collision.
APF	Fast convergence, low time complexity.	Trap situations due to local minimals, low performance in the presence of multiple obstacles.
Dijkstra	Shortest path generation, easy implementation, suitable for complex environment.	Not suitable for dynamic environments, high time complexity due blind search.

In this section, we analyze some works that address the problem of PP using classical methods. Most of the listed works utilize more than one classical method and take into account multiple obstacles. The distance factor is considered the primary consideration in the majority of these works. By employing variants and combinations of classical methods, the authors propose solutions for various applications within the realm of the Path Planning problem.

B. HEURISTIC AND META-HEURISTIC METHODS

Heuristic methods are exploratory algorithms designed to solve problems. While there are no guarantees that the solution found through them is optimal, they often provide a good approximation to real-world problems and demonstrate greater agility than exact methods when dealing with problems of larger dimensions. In the context of solving the UAV Path Planning problem, the literature features numerous algorithms based on heuristics.

Meta-heuristic algorithms are extensively employed for solving the UAV Path Planning problem. These algorithms can be broadly categorized into two main groups: single-based and population-based approaches [126]. The population-based approaches are further subdivided into Evolutionary-based techniques and Swarm Intelligence-based techniques.

1) A* ALGORITHM

In UAV Path Planning problem, the A* algorithm is a popular heuristic that was initially introduced by Hart et al. [106]. Numerous approaches utilizing the A* algorithm for UAV Path pPlanning have been proposed, demonstrating promising results.

Zhang et al. [107] address UAV Path Planning in a 3D environment, taking into account kinematics principles, the dynamic radar cross-section of stealth UAVs, and the network radar system. The authors propose a modified A* algorithm with the goal of achieving waypoint accuracy and improving the algorithm's search efficiency. In their simulations and analysis, they employ various algorithms, including the conventional A* algorithm, bidirectional multilayer A* algorithm, and modified A* algorithm, to address the penetration path problem faced by UAVs under different threat scenarios.

Li et al. [108] introduced a 3D space UAV Path planning model. They put forward an improved A* algorithm based on the R5DOS model, and they investigate the effectiveness and progressiveness of this proposed method through simulation experiments.

Mardani et al. [109] introduced two approaches based on the A* algorithm to optimize Quality of Service (QoS) in UAV Path planning. They aimed to optimize the path jointly in terms of distance and the throughput experienced by the drone.

Other works that use the A* algorithm or variants are described in the Table 6.

2) GREEDY ALGORITHM

A greedy algorithm is an approach for solving a problem by selecting the best option available at the moment. It does not concern itself with whether the current best result will lead to the overall optimal solution.

Han et al. [110] investigated a UAV-assisted IoT data collection system with the goal of minimizing energy consumption by jointly optimizing the deployment and flight trajectory of the UAV. They proposed a bilevel optimization approach. In the upper-level approach, the authors introduced an improved dandelion algorithm (IDA) to optimize the number and locations of footholds for the UAV. In the lower-level approach, they proposed an Iterated Greedy Algorithm to plan the UAV's flight trajectory using the results provided by the upper-level optimization.

3) SINGLE-BASED APPROACHES

Du et al. [127] introduced a modified Tabu search algorithm by integrating the Nawaz-Enscore-Ham (NEH) method into Tabu Search for addressing the multiple UAVs Path Planning problem. Simulation results demonstrated the superiority of the proposed algorithm in terms of time efficiency compared to other algorithms.

4) POPULATION BASED APPROACHES

Population-based approaches in the context of UAV Path Planning involve maintaining and enhancing multiple candidate solutions. These methods often leverage population characteristics to guide the search process. Examples of population-based approaches include evolutionary computation, genetic algorithms, and particle swarm optimization.

Another category of metaheuristics is swarm intelligence based which is a collective behavior of decentralized, self-organized agents in a population or swarm and inclues ACO, PSO and variants.

Regarding UAV Path Planning, Evolutionary based techniques includes: DE algorithm, NSGA-II algorithm [128], [129], HR-MAGA, SPEA [130], Multiagent Evolutionary Algorithm [131].

Chawra and Gupta [132] proposed a Salp-Swam optimization method for the selection of an optimal set of load-balanced Cluster Heads (CHs) and used Differential Evolution (DE) for multi-UAV Path Planning for data collection in a cluster-based Wireless Sensor Network. Experimental results showed that the DE algorithm outperformed GA and NSGA-II algorithms in terms of optimizing traveling time and path length.

Dai et al. [133] proposed a novel approach based on the integration of MILP into the GA for improving UAV Path Planning in a complex environment. Simulation results demonstrated the superiority of the proposed method compared to ACO and GA in terms of cost efficiency and energy optimization.

Xiao et al. [134] proposed a Neighborhood Based Genetic Algorithm (NBGA) for multi-UAVs dynamic Path Planning and UAV/UGV coordination. Simulations results showed that NBGA provides an optimal path length compared to the Center-Based Genetic Algorithm.

Huang and Fei [135] developed a Global Best Particle Swarm Optimization (GBPSO) algorithm for solving the fixed-wing UAV Path Planning problem. In comparison with PSO, modified versions of PSO, and DE, GBPSO proved to be more effective in terms of convergence speed, cost-efficiency, execution time, and path length optimization in simulations performed in a 3D complex environment with 7 obstacles and 18 obstacles.

Dewangan et al. [136] addressed the 3D multi-UAV Path Planning problem using the GWO method. Simulations in three different maps and comparisons with different algorithms, such as Dijkstra, A*, D* (Deterministic), IBA, BBO [137], PSO, GSO, WOA, and SCA [138], were conducted. The GWO method was found to be more effective than the other algorithms for the studied problem.

Jain et al. [139] proposed a modified MVO algorithm for 3D UAV Path Planning while maintaining coordination for target selection. Simulation results showed that the MVO algorithm performed better in most cases for finding an optimized path when compared to meta-heuristics GSO and BBO.

Zhou et al. [140] proposed a bio-inspired Path Planning algorithm for the 3D environment. The algorithm imitates the basic mechanisms of plant growth, including phototropism, negative geotropism and branching. When compared with A*, RRT, and ACO, the proposed algorithm demonstrated good Path Planning ability and reasonable parameter configuration.

Binol et al. [141] applied a MHS algorithm for the multi-UAV Path Planning problem. Experimental results revealed that the MHS algorithm is more effective than GA in terms of path cost, execution time, and convergence rate.

5) OTHER HEURISTIC ALGORITHMS

Freitas et al. [111] proposed Lin-Kernighan heuristic (LKH) algorithm for improving the UAV Path Planning in biological pest control applications. Experimental results demonstrated that the LKH algorithm outperforms ACO and GLS algorithms in terms of path length optimization, cost-efficiency, and execution time.

Yuan et al. [112] explored UAV Path Planning in a three-dimensional map. They introduced an improved Lazy Theta* algorithm, which includes neighbor node search, line-of-sight algorithm, and heuristics weight adjustment. Simulation results indicated that the enhanced Lazy Theta* algorithm is suitable for UAV Path Planning in complex environments with multiple constraints.

Rey et al. [113] introduced a modified Lazy Theta* algorithm for 3D UAV Path Planning, aiming to derive a safe and smooth path. The study includes comparisons with the A* algorithm, considering the new cost component, and the original Lazy Theta*, demonstrating the effectiveness of the proposed algorithm.

Regarding heuristic/meta-heuristic methods, from a comparative analysis of the works listed in the Table 6 we

TABLE 6. Aspects of heuristic methods in the UAV path planning.

Reference	FO	UAVs	Environment	Mode	Obstacles	Method
Chen et al (2020) [22]	Maximum flight time cost	Single	2D	Offline	Multiple	Improved A* algorithm
Danancier et al (2019) [55]	Travel time in threats	Single	2D	Offline	Multiple	Dijkstra's algorithm and Heuristic Waypoint Generation
Macias et al (2020) [56]	Energy consumption	Multiple	3D	Offline	No	Effective Large Neighbourhood Search approach
Xiang et al (2021) [114]	Distance	Single	2D	Offline	Multiple	ACO algorithm
Dhulkefl & Durdu (2019) [115]	Distance	Single	3D	Offline	Multiple	A* algorithm
Shi and Ng (2018) [116]	Waiting time	Single	2D	Offline	Multiple	A* algorithm
Shivan and Dhong (2020) [117]	Energy consumption	Single	2D	Offline	No	GA and Greedy algorithm
Fu et al (2018) [118]	path safety cost, length cost and smoothness cost	Single	2D	Offline	Multiple	Heuristic evolutionary algorithm
Ding et al (2018) [119]	Energy consumption	Multiple	2D	Offline	No	EVNS algorithm
Yang et al [120]	Flight time, energy consumption and operation risk	Single	3D	Online and offline	Multiple	GA and ACO algorithms
Dashkevich et al (2020) [121]	Distance	Single	2D	Offline	No	AG algorithm
Liu et al (2018) [122]	Information age	Single	2D	Offline	No	GA-based algorithm and DP-based method
Peng and Qiu (2022) [123]	Distance and collision-free	Multiple	3D	Offline	Multiple	M2M-DW algorithm
Kochare et al (2021) [124]	Maximize the utility of UAV	Multiple	3D	Offline	No	JSC Algorithm and VRC Algorithm
Xu et al (2021) [125]	Distance, threat terrain cost, azimuth angle variation	Multiple	3D	Offline	Multiple	Heuristic search method based on Greedy algorithm
Kiani et al (2022) [142]	Distance	Multiple	3D	Offline	Multiple	I-GWO and Ex-GWO
Yang et al (2020) [143]	Path length, average altitude, and hazard areas	Single	3D	Offline	Multiple	HR-MAGA
Li and Han (2018) [144]	Distance	Single	3D	Offline	Multiple	ACO algorithm
Benkhlifa et al (2021) [145]	Distance	Multiple	3D	Offline	Multiple	Improved SSO algorithm
Huan et al (2021) [146]	Distance	Single	3D	Offline	No	Improved ACO algorithm
Kang et al (2019) [147]	Distance	Single	2D	Offline	No	ACO algorithm and DBSCAN
Xu, Jiang and Zhang (2021) [148]	Cost of the flight path and distance	Single	3D	Offline	Multiple	MSGSA
Li et al (2020) [149]	Distance	Multiple	2D	Offline		Improved ACO algorithm and K-means Clustering Algorithm
Zhen et al(2020) [150]	Path length, height, and flight angle	Single	3D	Offline	Multiple	Improved multi-objective PSO algorithm
Sun et al (2020) [151]	Task completion time	Multiple	2D	Offline	No	CFSDP algorithm and ACO algorithm.
Sun et al (2020) [152]	Total task time	Multiple	2D	Offline	No	Improved ACO algorithm
Li et al (2021) [153]	Maximizes the total benefits of information collection from regions	Multiple	2D	Offline	No	GENERAL algorithm (based on GRASP metaheuristic)
Weihu and Bo (2019) [154]	Flight time	Single	2D	Offline	Multiple	ACO-based algorithm
Wang et al (2021) [155]	terrain model, mountain model and enemy radar threat model	Single	2D	Ofline	Multiple	ADAS
Ma et al (2020) [156]	Distance	Single	3D	Offline	No	K-means clustering algorithm and Memetic algorithm
Huang et al (2022) [157]	Distance	Single	2D	Offline	No	SA-PSO algorithm
Pan et al (2022) [158]	Cost of: inspection process, flight height, turning angle, path length	Single	3D	Offline	Multiple	GEO-DLS
Aslan(2022) [159]	Cost of threats and the cost of fuel	Single	2D	Offline	Multiple	centIPA
Golabi et al (2020) [160]	Distance, energy consumption, maximum cumulative path risk	Single	3D	Offline	Multiple	NSGA-II, NSGA-III and SPEA-II
Ren et al (2018) [161]	Time	Multiple	2D	Offline	No	PSO method
Wang et al (2022) [162]	Distance and error correction to ensure energy saving	Single	3D	Offline	No	NSGA-II

conclude that in this case the authors propose variants of existing methods by analyzing their performance based on some aspects of the Path Planning problem: complex and 3D environments and length of the obtained path. Furthermore, they provide a comparison with the classical method related to the developed variant.

The Table 7 presents some advantages and disadvantages of heuristic/ meta-heuristic methods for the UAV Path Planning.

TABLE 7. Advantages and shortcomings in the heuristic methods for UAV path planning.

Method	Advantages	Shortcomings
A*	Short path generation, near-optimal solutions, fast convergence.	Unsuitable for multi-objective UAV Path Planning optimization and dynamic environments.
GA	Efficient in dynamic environment, high time efficiency.	Optimal path not guaranteed.
Greedy	Easy implementation.	Optimal solution not guaranteed.
LKH	Intelligent optimization approach, near-optimal solutions.	High computational time.
Theta*	Short path generation, low time complexity in static environments.	Not appropriate for dynamic environment and sudden obstacles.
Evolutionary based	Optimal path, fast convergence, high computational efficiency.	High time complexity, unsuitable for real time Path Planning.
Swarm Intelligence	Speed convergence, fast solution generation, high path efficiency.	Optimal path not guaranteed, easy trap to local optima.
Single based	Efficient in dynamic environment.	Optimal path not guaranteed.

C. MACHINE LEARNING METHODS

Machine learning, a subset of Artificial Intelligence, empowers computers to respond without explicit programming. Machine learning-based algorithms fall into three categories: supervised learning, unsupervised learning, and reinforcement learning. These categories further encompass various algorithms, including clustering, classification, and linear regression, all of which find applications in UAV Path Planning [30].

Various machine learning-based methods were applied for solving the UAV Path Planning problem as summarized in Table 8.

1) ARTIFICIAL NEURAL NETWORK (ANN)

An ANN is a machine learning method that instructs computers on processing data in a manner inspired by the human brain. This network typically consists of three layers:

1) Input Layer: Processes the input elements.
2) Hidden Layer: Performs operations on the input data.
3) Output Layer: Provides response results and outputs.

This structure is illustrated in Figure 11.

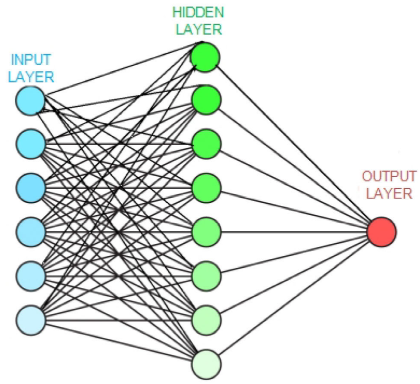

FIGURE 11. Artificial neural networks. Source: Aggarwal and Kumar [30].

Yan et al. [163] introduced an enhanced approach called the Dueling Double Deep Q-networks (D3QN) algorithm, which is based on the deep Q-networks algorithm for UAV Path Planning in dynamic environments. Simulations demonstrated the superior performance of the D3QN algorithm compared to DDQN and DQN in terms of stability, generating safe paths, and avoiding threats.

Shiri et al. [164] introduced a neural network-based Opportunistic Hamilton-Jacobi-Bellman (oHJB) approach to address the UAV online Path Planning problem. Experimental results demonstrated that oHJB outperforms other neural network-based algorithms in terms of path length, travel time, and energy consumption.

2) SUPERVISED LEARNING

"Supervised learning is a machine learning paradigm that employs a training set to teach models to produce the desired output. This training dataset consists of inputs paired with correct outputs, enabling the model to learn iteratively. The algorithm evaluates its accuracy using a loss function, making adjustments until the error has been adequately minimized [166]."

Radmanesh et al. [167] proposed a method based on Partial Differential Equation (PDE) to generate collision-free 3D trajectories for multiple UAVs operating in a shared airspace. Test results proved that the high-dimensional regression technique performed well compared to MILP in terms of path length and execution time.

Xie et al. [168] developed a RL algorithm based on the heuristic function, called MARER Q-learning, for the 3D UAV Path Planning problem. Simulation results shows that MARER Q-learning algorithm outperforms the ordinary Q-learning algorithm in terms of path generation, computational cost, and convergence speed.

3) UNSUPERVISED LEARNING

Unsupervised learning, unlike supervised learning, utilizes unlabeled data to discover patterns and solve clustering or association problems. This approach is particularly valuable

TABLE 8. Aspects of machine learning methods in the UAV path planning.

Reference	FO	UAVs	Environment	Mode	Obstacles	Method
Chai et al (2022) [17]	Threat cost, length cost, altitude cost	Single	3D	Offline	Multiple	MSFDE algorithm
Han et al (2022) [18]	Threat cost, fuel cost and collision cost	Single	3D	offline	Multiple	MSEL-ABC algorithm
Luo et al (2018) [174]	Distance	Multiple	3D	Offline	Multiple	Improved RL algorithm
Li et al (2018) [175]	Distance	Single	2D	Offline	Multiple	G-learning algorithm
Yuan et al (2022) [176]	Time	Multiple	3D	Offline	No	CNNs
Zhang (2021) [177]	Distance	Single	3D	Offline	Multiple	YOLO algorithm
Wai and Prasetia (2019) [178]	Energy consumption	Single	3D	Offline	Multiple	ANNS-PSO algorithm
Zhang et al (2018) [179]	Not applicable	Single	3D	Offline	Multiple	Q-learning algorithm

when subject matter experts are uncertain about common properties within a dataset. Unsupervised learning includes various clustering algorithms, such as Quality Threshold (QT) clustering and k-means clustering, which are employed in UAV Path Planning [169].

Tartaglione and Mariola [170] proposed an obstacle avoidance strategy based on QT clustering for detect and searching landmarks. They have also used the leader-follower technique to solve the optimization and coordination problems of UAVs.

4) REINFORCEMENT LEARNING (RL)

In recents years, RL has been widely used to solve the UAV Path Planning problem.

Cui and Wang [171] proposed a multi-layer Path Planning algorithm based on RL technique. The proposed RL approach consists of two layers of Q-learning, one is the lower layer Q-learning and the other is the higher layer Q-learning. The lower layer Q-learning aims at avoiding static obstacles and leads the UAV approaching to the terminal position. The higher layer Q-learning deals with the dynamic obstacles. Simulation results in different scenarios proved the effectiveness of multi-layer Q-learning algorithm.

Yang and Xiang [172] proposed an improved Q-learning algorithm based on Greedy and Boltzmann approaches into the Q-learning algorithm for solving the UAV Path Planning problem. Simulation results shows that the improved Q-learning algorithm provides the shortest path and generates minimum steps to reach the target compared to the original Q-learning method.

Kulathunga [173] investigated the potentials of both RL-based Path Planning and deterministic based Path Planning and how can incorporate the best of both to develop a fast and robust Path Planning approach in 3D environment. They proposed a hybrid approach that combines Monticalo tree search and RL-based approach to solve the same problem.

The works reviewed in the context of Machine Learning methods predominantly address dynamic and 3D environments, introducing variations to established classical methods. The assessments of the solutions obtained from these methods, including ANN, Supervised and Unsupervised Learning, and Reinforcement Learning, primarily focus on comparing path length, traveling time, and energy consumption.

The Table 9 summarize the advantages and disadvantages of the Machine Learning Methods.

D. MATHEMATICAL MODELS

In addition to the methods already reported, there are studies in the literature that address UAV Path Planning from the perspective of mathematical models. The approaches includes Linear Programing, Non-Linear Programming, and MILP. These methods often involve the utilization of solvers to tackle the proposed models.

The work presented in [180] introduces a trajectory planning method for cooperative Micro Aerial Vehicles

TABLE 9. Advantages and shortcomings in the machine learning methods for UAV path planning.

Method	Advantages	Shortcomings
Neural Networks	Suitable for dynamic environment and solving multi-objective Path Planning.	Long time consuming, unsuitable for real-time UAV Path Planning, optimal solutions not guaranteed.
Reinforcement Learning	Efficient for multi-UAV Path Planning and to deal with UAV's manoeuvrability.	More resources requirements in terms of UAV's memory and energy, solutions often not optimal.
Supervised Learning	Near-optimal solutions, suitable for complex environments.	Long processing time, less efficient in large datasets training.
Unsupervised Learning	Efficient in uncertain environments, convergence to near optimal solutions.	Unsuitable in real-time UAV Path Planning, long processing time.

(MAV) and UAV systems using convex optimization theory. The authors establish a motion model for the system and analyze the control process. The trajectory planning problem for the UAV is considered, with the objective of minimizing energy consumption and arrival time. The study simplifies the system by focusing on one MAV and one UAV. The authors employ the MOSEK solver for computer simulations and compare its performance with other solvers such as SEDUMI, GUROBI, and SDTP3. The results indicate that MOSEK is more suitable for the addressed problem.

In [181] they address the problem of trajectory optimization of UAVs multi-rotor in a multiphase optimal control framework with field area coverage and energy as two separate performance indices to be maximized and minimized, respectively. The endurance of the LiPo battery imposes severe constraints on the operational time of an electric UAV during an agricultural mission, therefore, drone Path Planning is critical to maximize the field area coverage and minimize the operational field and minimize the operational cost for image acquisition per flight. The authors present the mathematical formulation for the optimal control problem with several constraints through a Nonlinear Programming model. Computer simulations considering one UAV were performed through Matlab using GPOPS-II, that is a software applied for solving multiphase optimal control problems using the Legendre-Gauss-Radau method. In addition, DJI Phantom 4.0 with sensor is considered in simulating the trajectories.

In [182] the multi-UAVs Path Planning problem is approached from the perspective of optimization in terms of flight angle constraint and sampling interval distribution for radiation source location. The mathematical formulation considers that the range of flight angle is inversely proportional to the distance between the UAV and the radiation source. The changes of UAV altitude and flight speed are not considered in this work, the model is not affected by the range of flight altitude and maximum climb angle, but the path is limited by the minimum radius curve in addition to the cost function. That is, if the flight radius exceeds the performance limit of the UAV at this point, the path needs to be corrected. Computational experiments were performed considering three UAVs. These experiments were divided in two parts, one focusing on the flight of flight and the other focusing on interval sampling.

Certainly, the works highlighted in this section demonstrate the effectiveness of mathematical models in addressing UAV Path Planning challenges. The use of optimization techniques and solvers allows for rigorous problem formulation and efficient solution finding. If you have specific questions about any of the mentioned works or if you'd like more details on a particular aspect of mathematical modeling in UAV Path Planning, feel free to ask.

E. HYBRID METHODS

From the previously reported methods, there is a class of methods that arises from the combination of two or more methods and is called "hybrid methods."

In the UAV Path Planning problem, several ways of hybridization are possible, the most used are: combining two classical methods, combining a classical approach with heuristic, combining a classical method with meta-heuristic, and combining two meta-heuristics.

Zhang et al. [183] proposed an improved algorithm combining APF method and RRT-Connect algorithm for solving UAV Path Planning problem in complex static environment, in order to reduce the cost of the UAV flight. Simulation results showed that proposed algorithm outperforms the traditional RRT, RRT-Connect, and APF algorithms in terms of optimal path length and execution time.

Shen and Li [184] proposed an improved APF algorithm based on the combination of APF and RRT algorithms for solving the UAV Path Planning problem. The robustness of proposed hybrid method was evaluated in a 2D environment with 6 circular obstacles and it proved to be more effective than the APF in terms of path length.

Naazare et al. [185] developed a hybrid approach based on the VG algorithm and A* algorithm. Simulations were performed in real area and in test environments with a real UAV and results showed that the proposed algorithm provides an optimal path.

Ge et al. [186] proposed an improved pigeon-inspired optimization algorithm (PIOFOA) for solving the 3D UAV Path Planning in a dynamic environment of oilfields. A simplified oilfield environment model is built, which contains many dynamic obstacles and is used to simulate actual oilfield environments. The cost function is defined to find optimal paths, which includes: total length, average height, total time and total electricity consumption of the route. Compared with some other methods, simulation results show that the proposed PIOFOA method is more effective.

Qu et al. [187] presented a novel hybrid algoritm combining GWO and RL algorithm, named RLGWO, for the UAV Path Planning problem. Simulations results were performed in 3D environment considering 8 static obstacles. Comparisions with various meta-heuristic algorithms showed that RLGWO it is robust and effective in terms of convergence time, path cost computation, and collision avoidance.

Ghambari et al. [188] proposed a hybrid algorithm that combines TLBO with GA algorithm for solving the UAV Path Planning problem. The performance of proposed hybrid algorithm was validated in both 2D and 3D areas with the presence of obstacles randomly distributed. Comparisions with original TLBO algorithm in terms of best path generation, time efficiency, and collision avoidance were performed and showed the robustness and superiority of proposed algorithm.

Qu et al. [189] proposed a novel hybrid approach combining GA, Dijkstra and APF methods for solving the global optimal Path Planning problem to fixed-wing UAVs in multi-threat environments. The performance of the hybrid method was validated in both 2D and 3D environments using 20 obstacles. Simulation results showed the robustness of the proposed hybrid algorithm by obtaining a short and safe route.

Indeed, the application of hybrid methods, combining classical methods with heuristics or other techniques, reflects the versatility of these approaches in addressing the diverse challenges posed by UAV Path Planning. These hybrid methods often leverage the strengths of different approaches to achieve improved performance in terms of efficiency, optimality, and adaptability to specific scenarios.

F. ANALYSIS OF METHODS FOR UAV PATH PLANNING PROBLEM

In order to analyze the state of the art of methods for UAV Path Planning, we have described in the previous sections the classical methods, heuristic methods, meta-heuristic methods, machine learning methods, mathematical models and hybrid methods.

G. REGARDING OBJECTIVE FUNCTION AND QUANTITY OF UAVs CONSIDERED

As for the FO, analyzing the Tables 4, 6, 8 and10 the factors that were considered in the works analyzed were (the distance factor was the most considered): distance, energy/fuel consumption, path cost, threat cost, task completion time, maximum flight time cost, travel time, path safety cost, utility of UAV, speed and angles, total time. Still in relation to the FO, we have mono and multi objective models in the literature analyzed, as well as works that consider more than one factor in the objective function, but assign weights to such factors so that the FO has only one objective.

TABLE 10. Aspects of hybrid methods in the UAV path planning.

Reference	FO	UAVs	Environment	Mode	Obstacles	Method
Sun et al (2022) [15]	Energy consumption and distance	Multiple	3D	Offline	Multiple	SOCP algorithm and hp-adaptive pseudospectral method
Pang et al (2022) [16]	Fatality risk, property damage risk, and noise impact	Single	3D	Offline	Multiple	EDA-CostA^* algorithm
Hohmann et al (2021) [45]	Minimizing risk, path length travel time, energy consumption	Single	2D	Offline	No	hybrid evolutionary approach combining Evolution Strategy (ES) with the Dijkstra's algorithm
Deng et al (2018) [190]	Distance	Single	3D	Offline	Multiple	Dijkstra's algorithm and SA algorithm
Shao et al (2021) [191]	Total performance parameter cost, path length cost, terminal constraint, mountain cost and radar detection cost	Multiple	3D	Offline	Multiple	PSO-GPM method
Wang et al (2021) [192]	Distance	Single	3D	Online	Multiple	Hybrid algorithm combining SA and PSO
Li et al (2022) [193]	Energy consumption and cost of threat	Multiple	3D	Offline	Multiple	Hybrid algorithm combining A* and Q-learning
Xing et al (2022) [194]	Total time	Single	3D	Offline	No	Hybrid RL algorithm
Li et al (2020) [195]	Speed and angles	Single	3D	Online	No	EKF-SLAM and HP adaptive pseudo-spectral algorithm
Banerjee et al (2022) [196]	Energy consumption and time	Multiple	3D	Offline	Multiple	EDTP and ARMA prediction model
Huynh et al (2022) [197]	Time and energy consumption	Multiple	2D	Online	No	k-means clustering method and convex optimization algorithms
Debnath et al (2020) [198]	Distance	Single	2D	Offline	Multiple	ECoVG

The number of UAVs considered is directly related to the application developed in each paper, and in the literature analyzed this number varies from 1 to 10 drones.

H. REGARDING ENVIRONMENT, MODE AND OBSTACLES

As for the environment, the two-dimensional (2D) was considered by most of the works analyzed in this review.

Regarding the mode, most of the works analyzed consider the offline mode, due to the nature of application considered.

In UAV Path Planning problem, considering obstacles it is necessary and the works analyzed consider, for the most part, multiple obstacles. In addition, the works also consider static and dynamic obstacles with different shapes in order to simulate a real environment.

I. REGARDING PATH PLANNING TECHNIQUES

Regarding the classical methods, several approaches are developed to solve the UAV Path Planning problem: RRT, VD, APF, VG, PRM and Dijkstra. The Table 5 provided the advantages and disadvantages of each approach and we can conclude that the main advantage is the ease of implementation of the analyzed methods regarding UAV Path Planning, providing good solutions in terms of optimization, speed to generate paths and effectiveness static environments with simple obstacles.

The APF and RRT methods are widely used in UAV Path Planning and different variants of both methods have been proposed in the literature, to name a few works [100], [101], [102], [201], [202], [203], [204], [205], [206]. The RRT, on the other hand, manages to deal with the issue of obstacles, but the path length is not considered, which is one of the weak points of this method. To work around this RRT problem, the Dijkstra method is used, as it finds the shortest path between two nodes. VG and VD are classical algorithms that can be used to solve real-time UAV Path Planning problems, although VD does not guarantee the optimality of the obtained paths and VG it is ineffective in environments with complex obstacles' shapes.

Regarding the heuristic methods, the Table 7 presents the advantages and disadvantages of each approach and then we make some considerations. Several heuristics have been proposed to try to overcome the disadvantages of the classic methods and obtain more effective solutions for UAV Path Planning, with the A* heuristic being one of the most used in this context. This heuristic obtains optimal paths quickly in terms of convergence and robustness, but it is not very efficient when the problem is multiobjective and the environment is dynamic. Greedy and LKH are two effective heuristics to solve UAV Path Planning due to their simplicity and ease of implementation, but their computational time is high. Finally, the Theta* heuristic overcomes the drawbacks of the previous ones and obtains the shortest path in acceptable computational time, however it is not suitable for dynamic and complex environments.

With regard to machine learning methods, there are also several approaches used in the context of UAV Path Planning. The Table 9 presents some advantages and weaknesses of each approach. Neural networks is the oldest technique in this category and therefore one of the first to be used to solve UAV Path Planning, and can be used for multiobjective problems, dynamic environments, obstacles of complex shapes, obtaining robust solutions quickly. However, it presents high computational complexity and is characterized as a black box, since it is not always possible to clearly understand the step by step to obtain the solution. To overcome these difficulties, supervised and unsupervised learning techniques can be used and present good solutions with less computational complexity. Furthermore, the reinforcement learning-based technique has been widely used, as described in Section VI-C, and is efficient for uncertain and dynamic environments as well as for optimizing energy consumption However, like the other techniques in this category, the main weakness is the long processing time for real-time problems.

The mathematical models are solved using some of the techniques described above or even through solvers such as CPLEX form IBM [165]. There are several different ways to approach UAV Path Planning using mathematical optimization. Different restrictions can be considered, as well as different factors in the objective function that can have only one objective or more than one (in this case the problem is called multiobjective). Factors such as distance, energy consumption, travel time are the most common to be considered for UAV Path Planning. The MILP model is one of the most used to model UAV Path Planning, as it allows to consider integer or mixed variables and constraints.

Regarding hybrid methods to solving the UAV Path Planning, several approaches are developed and present relevant improvements as they take advantage of the strengths of the methods used in each combination and overcome the limitations of each individual method precisely because they combine more than one method. In order to take advantage of each method, the hybridization of classic methods, for example, uses the RRT that can handle obstacles better than APF and VG, providing safer and collision-free paths. Dijkstra's algorithm is used in combination with other classical for finding the shortest path. Although, the classic methods need all the information from the environment to plan the paths, which results in a long processing time. This drawback is overcome by combining classical methods with heuristics and different approaches have been proposed for UAV Path Planning.

Given the above regarding the different techniques used in the UAV Path Planning problem, analyzing their advantages and disadvantages, we can conclude that they are all important and that the choice depends on the application to be carried out.

1) TYPES OF DRONES, TYPES OF PATH PLANNING TECHNIQUES AND UAVs APPLICATIONS

In the previous sections, we listed different UAV Path Planning techniques in the general context, analyzing attributes related to the modeling of the problem: objective function, environment, time of domain, mode, types of obstacles, number of UAVs considered and nature of the solution adopted, since Path Planning strategies are usually related to some specific application.

In this section, we present an overview of the types of applications for which Path Planning techniques can be used. In addition, we analyze the types of drones that can be used in different applications based on Path Planning techniques.

Elmeseiry et al. [207] presents an review about types of drones and different classifications of UAVs were proposed. The first classification refers to the size: ultra-small UAVs, including MAVs and NAVs, small UAVs, mid, and large UAVs. Classifications according to the range, endurance, maximum altitude, weight and configuration-based were also represented and discussed.

Still, according to the authors, in addition to those classified in the review article, the U.S. Department of Defense [208] categorized UAVs into five groups based on the Maximum Take-Off Weight (MTOW), altitude, and speed. The Group 1, are hand-launched and portable UAVs, used in applications involving reconnaissance, surveillance and target acquisition; Group 2 are medium-sized UAVs, which are also suitable for reconnaissance, surveillance, target acquisition navigation, photography and filming. Group 3 are larger UAVs than those in Group 1 and Group 2; Group 4 operates at the same altitude as Group 3 and they are larger than the previous groups. In this case, they can be used in the long-awaited delivery of goods. Finally, in the Group 5, are the largest UAVs that can be used in applications wide-area surveillance and penetrating attacks [207].

Shakhatreh et al. [209] presents an extensive bibliographical review on UAV civil applications and their challenges. The authors presented valuable considerations on the following applications: real-time monitoring, providing wireless coverage, remote sensing, search and rescue, delivery of goods, security and surveillance, precision agriculture, and civil infrastructure inspection; relating the most suitable types of drones as well as the challenges and trends of future research for each application.

Ghamari et al. [210] presents a review of the current applications of UAVs for civil and commercial purposes focusing challenges and communication requirements associated with UAV-based communication systems. A detailed analysis of the main characteristics of UAVs is provided by the authors: payload size, flight mechanism, flight altitude, coverage range, flight time and maximum speed.

As for the applications with the use of UAVs and the Path Planning techniques listed and analyzed in this work, we can say in general that the hybrid methods and the most recent and adaptable techniques: machine learning, artificial intelligence, convolutional neural networks can be used and adapted for the most common applications made with the use of drones: precision agriculture, search and rescue operations, surveillance, remote sensing, navigation, photography and filming and delivery of goods.

The use of drones is growing every day due to scientific and technological advances, making different applications possible. Each application may require a specific type of UAV to meet the stringent requirements imposed by federal aviation regulations, the nature of the environment and the required quality of service. Therefore, analyzing the most suitable types of drones for each application and, in turn, the related Path Planning techniques is increasingly necessary and important, and in this section we present an overview of this topic.

VII. UAV MISSION PLANNING

In this section, we delve into UAV mission planning, also referred to as target allocation. We've compiled and compared some works in this domain. Mission planning involves the assignment of tasks to UAVs, taking into account the capacity constraints of the UAVs and the environmental conditions of the mission. Factors considered often relate to the specific application, which can range from military applications to pattern recognition and target search.

Wang et al. [211] provide an extensive review of UAV mission planning, focusing on UAV Path Planning. The authors discuss various works related to UAV mission planning and also introduce a mathematical model and algorithm for UAV task assignment. The paper includes an analysis of algorithms specifically designed for UAV Path Planning.

Yu et al. [212] focus on a military application within UAV mission planning, specifically addressing the cooperative mission planning of multiple heterogeneous UAVs in cross-regional joint operations. The study takes into account resource allocation and mission priorities. A multi-objective optimization problem is formulated, aiming to minimize the makespan while maximizing the expected value. The authors propose an improved genetic algorithm to solve this optimization problem.

Gao et al. [213] address the challenge of cooperative mission assignment for heterogeneous UAVs, taking into account multiple task types such as classification, attack, and verification tasks. The authors propose a multi-objective optimization model for the problem, considering mission gains and UAV losses. Conditional probability theory is employed to model the objective functions. The study utilizes an improved multi-objective genetic algorithm to solve the formulated optimization problem.

He et al. [214] tackled the challenge of quickly recognizing target points in a complex environment using multiple drones. The authors introduce a mission planning model with the primary objective of maximizing reconnaissance benefit. To address this problem, a task planning algorithm based on ant colony optimization is proposed to enhance the performance of the artificial fish swarm algorithm.

Huttner and Friedrich [215] conducted a systematic review of mission management user interfaces for UAVs. Acknowledging the pivotal role of user interfaces in UAV mission planning and control, the authors analyze 25 articles published between 2017 and 2023.

Shi and Zhang [216] presented a multi-objective model for UAV swarm mission planning, taking into account factors such as range cost, damage cost, attack benefit, and various constraints. To address this problem, the authors proposed an adaptive genetic algorithm, introducing improvements to the crossover and genetic operators for enhanced performance.

Yu and Lee [217] addressed the challenge of surveillance and monitoring in a designated area. They proposed a Multi-UAV Cooperative Search Algorithm for path assignment, enabling collaborative UAV searches that involve both search and motion tasks. The proposed approach determines the UAV routes, facilitating the swift coverage of the mission area by multiple UAVs within a limited time.

Li et al. [218] addressed the multi-UAV Path Planning problem for target coverage tasks in dynamic environments. They proposed an ACO-VP algorithm by introducing a variable pheromone enhancement factor and a variable pheromone evaporation coefficient into the ACO algorithm. Furthermore, they adopted a greedy strategy to choose the optimal number of UAVs and determine the target point allocation scheme.

Song et al. [219] present a survey on the mission planning problem for Multi-UAVs. The authors compare the characteristics of mathematical programming methods, heuristic algorithms, negotiation algorithms, and neural networks.

Zeng et al. [220] proposed a Bayes risk-based mission planning method for UAV-based damage inspection by minimizing the UAV path length and the associated structural health monitoring costs through a multi-objective optimization model. In the computational tests of the proposed method, the authors consider a UAV equipped with LIDAR to complete the task of damage inspection.

Zu et al. [221] address the Path Planning problem and task assignment. They propose a method using the Hunter-Prey Optimizer Algorithm (HPO) and a task allocation mechanism, aiming to achieve collaborative Path Planning for multiple UAVs in complex tasks.

Sun et al. [222] studied the mission planning framework for the passive UAV synthetic aperture radar (SAR) system. The solution methodology includes defining the framework for the mission planning problem in the context of the SAR system, considering mission specification, illuminator selection, and Path Planning. The problem was modeled as a single-objective optimization problem involving multiple constraints.

The works listed in this section are basically divided into applications related to the mission planning problem ([212], [213], [214], [216], [217], [218], [220], [221], [222]) and literature reviews including both mission planning and Path Planning ([211], [215], [219]).

VIII. DEPLOYMENTS AND INTEGRATION IN IoD

The IoD is considered the future trend and has been a focal point in recent literature due to its flexibility and adaptability in diverse and complex scenarios, as well as its ability to leverage other networks. Given the complexity of IoD, various requirements are necessary for enabling applications in this context, including aspects such as security, privacy, scalability, communication protocols, and integration with other networks [13], [27], [57].

The integration and communication of UAVs within terrestrial and space environments are primary factors that shape the architecture of the IoD. In this context, considerable work is still needed to establish seamless connectivity among various spaces through effective communication protocols. Several factors, such as scalability, reliability, data rate, and coverage, are identified as key considerations for future research in works addressing IoD [13], [19], [27], [60].

IoD facilitates various applications, particularly in urban settings, and stands as a pivotal concept for developing smart cities. Figure 3 illustrates some applications in urban scenarios. Irrespective of the specific application, drones are required to navigate from one point to another, avoiding collisions. This could involve tasks such as collecting information, monitoring environments, pattern recognition, image capture, or even delivering goods. Consequently, UAV Path Planning emerges as a crucial research focus in the context of IoD.

The UAV Path Planning within the IoD framework is a highly intricate problem, influenced by various factors such as energy consumption, path length, softness, cost, power, and computational time. The challenges are exacerbated by the dynamic and uncertain nature of environments, featuring obstacles of diverse forms. Furthermore, IoD introduces distinctive characteristics, including the management of self-organized aerial traffic flow, ensuring fair access to shared wireless communication channels, and addressing security and privacy concerns at all levels [53]. These characteristics pose fundamental challenges for maintaining the Quality of Service (QoS) of drones, necessitating efficient Path Planning, lightweight communication protocols, and robust security and privacy measures.

Given the intricacies of UAV Path Planning and the specific demands of an IoD scenario, a pivotal research question at the heart of this work is the feasibility of implementing and integrating the UAV Path Planning methods previously described within the IoD framework. To the best of our knowledge, this review represents the first attempt in the literature to comprehensively address UAV Path Planning techniques specifically within the context of IoD.

Analyzing the existing methods for UAV Path Planning, which were described in detail through the analysis of several works in the literature published between 2018 and 2022, as well as the advantages and disadvantages of each method, we can point out that UAV Path Planning in IoD has the characteristics fundamental: 3D and dynamic environment, obstacles of different shapes, uncertain information, real-time planning, well-established communication between all layers that make up the IoD, prevention of collisions and attacks, security and privacy requirements. This is why UAV Path Planning in IoD is still a challenge and requires development of tools, tests in realistic scenarios, integration with other networks, definition of the air environment and implementation of rules about it.

In this work, the existing methods for UAV Path Planning were classified into: classic, heuristic, meta-heuristic, machine learning, mathematical models and hybrid methods. Based on the analyzes and considerations described throughout this work, the IoD requirements and characteristics of UAV Path Planning, we list some possibilities for implementing methods to solve it in an IoD scenario. Let's see.

- Hybridizing meta-heuristics with more classical approaches as well as meta-heuristics with machine learning algorithms for optimizing the UAV Path Planning in IoD.
- Apply the latest machine learning and meta-heuristic techniques to solving multi UAV Path Planning in IoD.
- Incorporate uncertainties and quality of service to UAV Path Planning in IoD and formulate mathematical models adding restrictions related to communication protocols, security and privacy information as well as considering the multiobjective problem taking into account energy consumption, distance traveled, time, and information of the environment.
- For the integration and implementation of the Path Planning problem in IoD, we can say that the hybrid methods are the most suitable, precisely because they combine more than one technique and take advantage of their advantages, trying to overcome their weaknesses.

In the face of this intricate and still visionary scenario, numerous challenges and areas for development emerge. The multifaceted characteristics and diverse requirements make it exceedingly challenging for a single work to encapsulate the entirety of this landscape. Consequently, existing works in the literature delineate the intricacies of the scenario, delving into considerations about UAV Path Planning within the IoD environment - a pivotal trend shaping the future.

IX. DISCUSSION AND FUTURE WORK

Although they have many papers addressing the drone Path Planning problem especially in recent years, there are still several open research questions on the topic. In this section, we list some directions for future work regarding the UAV Path Planning problem.

- **Path Planning in three-dimensional environments and time domain**: different applications, such as delivery, monitoring, data collection require the use of drones, but the environment of such applications, in general, is complex and full of uncertain factors, so studies and optimization methods are needed for the Path Planning of UAVs in real time in three-dimensional space. And, despite the great potential of Path Planning in 3D environment, the difficulties are much greater and the problem is much more complex than Path Planning in 2D environment, and it is necessary to consider kinematic, geometric, physical and temporal constraints, flight risk levels, airspace restrictions, for example. Currently, Path Planning algorithms in 3D environment for UAVs are urgently needed, especially in complex environments such as urban areas caves, and forests.
- **Mathematical models for the Path Planning problem of UAVs**: the need to consider multi-objective optimization is one of the main factors that were not addressed in the models found in the analyzed works. Several works considered more than one factor in the FO, but attributed weights to these factors making the FO with a single objective. By considering the multiobjective FO, pareto optimal solutions can be obtained taking all factors into consideration, and this makes the mathematical modeling of the UAV Path Planning problem more realistic. It is also necessary to consider the constraints that have already been addressed in the previous item.
- **Experiments**: regarding the experiments, all the analyzed works perform some kind of computational simulation and some of them perform real simulations, usually before the computational simulation. However, these real simulations were UAV in the sense of data collection, prototype tests to be used later in the computational simulations and this is due to the complexity of real simulations as well as the rules for the use of drones, among other factors. But for the use of UAVs to be possible in the most different applications it is necessary to work with real experiments. Another characteristic with respect to the experiments is the number of UAVs considered. Obviously, the complexity of considering several UAVs is immense, but this is a necessary future work so that the use of UAVs especially in urban centers becomes a reality.
- **Optimization techniques**: in the analyzed literature as well as in older works, several optimization techniques are used, modified to create new techniques, there is also the combination of more than one technique or method to obtain feasible and good solutions to the UAV Path Planning problem. Regarding the analyzed works, we can list: Heuristic methods, GA, SA, Evolutionary algorithms, ACO, Neural networks, Hybrid algorithms, Deep Learning, Exact methods, Dijkstra's algorithm, A^* algorithm, I-GWO, Ex-GWO algorithm, Memetic algorithm, metaheuristics, ABC, Greedy algorithm, Machine Learning, YOLO, GRASP, HR-MAGA, SPEA, among others. Although we have practically listed methods that cover all the major groups of optimization techniques, future research combining different methods, such as artificial intelligence methods

with heuristic methods, fuzzy inference methods, and variants of more widely used methods, such as heuristics, is still possible. This need is due to the complexity of the problem of the UAV Path Planning in real environments, and the different constraints that can be considered.

- **Integration of different segments**: The integration and communication of UAVs with terrestrial and space environments is a primary factor and involves the architecture of the IoD. In this sense, there is still a lot of work to be done in order to make the different spaces connected to each other via communication protocols. For this different factors need to be considered: scalability, reliability, data rate, and coverage. These factors are listed as future research in works addressing IoD [13], [19], [27], [60].
- **Security and privacy**: security and privacy are crucial factors in the UAV Path Planning problem. Security is related to the possible attacks on the UAVs, threat areas that need to be diverted by the UAVs during the aerial path to be traveled, operability of the UAV (power consumption is an essential factor to be considered for the UAV to fly safely). In the context of IoD, security and privacy is considered at different layers: application layer, transport layer, and physical layer [19]. In addition, information privacy also needs to be addressed in future work, given the UAV's connectivity to ground and air space, large amounts of data need to be stored securely [53], [199], [200]. Therefore, these two factors are relevant and in need of future research involving them. Also with regard to security, it is important that the path to be followed by the UAV is safe, so the security factor addresses several aspects in the problem of UAV Path Planning problem.
- **IoD and smart cities:** smart cities are connected cities made up of smart things that can collaborate intelligently and automatically to improve quality of life, save lives, and sustain resources. Recently, the advent of UAV technology has played a vital role in improving many real-time applications of smart cities [54]. In this context, there is still much to be done, research involving UAVs and smart cities becomes more and more necessary, the integration of IoD with smart cities will make possible much desired applications such as delivery through UAVs. For this, it is necessary to have policies to encourage the use of drones by promoting the economy of the sector, together with the development of technologies such as DAA (Detect and Avoid) and UTM (UAS Traffic Management), which are necessary steps to increase the operational scope of UAVs and make IoD applicable in order to make smart cities possible.

X. CONCLUSION

The UAV Path Planning is a fundamental problem in the areas of robotics and automation, smart cities and IoD, and has been studied by several researchers around the world, especially in recent years.

In this work, we approach the UAV Path Planning problem, the methods to solve it, the aspects considered in more than 200 works of the literature published between 2018 and 2022 aiming to trace directions of the implantation and integration with the IoD. Furthermore, we present an overview of the IoD scenario based on existing works in the literature as well as on the mission planning problem.

Although widely studied, the Path Planning problem is fundamental and necessary in different applications involving drones and the technique to be used to obtain good results for this depends strongly on the nature of the application to be carried out.

We analyze classical, heuristic, meta-heuristic, machine learning, mathematical models and hybrid methods, providing a comparative analysis, presenting the advantages and disadvantages of each one, as well as summarizing in tables some aspects of UAV Path Planning: quantity of drones, objective function, environment and obstacles.

The analysis presented throughout this paper is useful in identifying the main research results on UAV Path Planning, and is leveraged in this paper to highlight trends and open questions. Below, we list some of them:

1) Three-dimensional Path Planning in the context of IoD considering the energy consumption and safety of drones.
2) Multi-objective mathematical modeling of UAV Path Planning.
3) Route planning in smart cities considering the IoD.
4) Development of tools that contribute to the advancement of real applications in IoD.

The main challenges in this context are:

1) Airspace regulation so that it is possible to develop real applications with drones, such as the delivery of goods.
2) The UAV Path Planning in IoD on real time considering energy-efficient and safety.
3) Integration between drones and other means of transport, such as trucks, buses, in order to generate practical and safe applications in the context of IoD, contributing to making cities smart.
4) Development of tools and methodologies from real experiments that consider several drones.

Finally, it is worth highlighting that this work took into account a considerable number of recent papers and the analyzes and conclusions were based on them with the aim of providing an overview, research questions and challenges of the Path Planning problem in the context of IoD in terms of optimization.

This work contributes to leverage the state of the art of UAV Path Planning in IoD, in addition to highlighting challenges and some possibilities for future work in this complex scenario involving IoD and UAV Path Planning.

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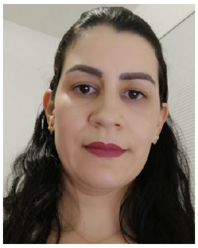

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