Comprehensive Review of Drones Collision Avoidance Schemes: Challenges and Open Issues

Mohammad Reza Rezaee, Nor Asilah Wati Abdul Hamid, *Senior Member, IEEE*, Masnida Hussin, *Senior Member, IEEE*, and Zuriati Ahmad Zukarnain, *Member, IEEE*

***Abstract*— In the contemporary landscape, the escalating deployment of drones across diverse industries has ushered in a consequential concern, including ensuring the security of drone operations. This concern extends to a spectrum of challenges, encompassing collisions with stationary and mobile obstacles and encounters with other drones. Moreover, the inherent limitations of drones, namely constraints on energy consumption, data storage capacity, and processing power, present formidable obstacles in developing collision avoidance algorithms. This review paper explores the challenges of ensuring safe drone operations, focusing on collision avoidance. We explore collision avoidance methods for UAVs from various perspectives, categorizing them into four main groups: obstacle detection and avoidance, collision avoidance algorithms, drone swarm, and path optimization. Additionally, our analysis delves into machine learning techniques, discusses metrics and simulation tools to validate collision avoidance systems, and delineates local and global algorithmic perspectives. Our evaluation reveals significant challenges in current drone collision prevention algorithms. Despite advancements, critical UAV network and communication challenges are often overlooked, prompting a reliance on simulation-based research due to cost and safety concerns. Challenges encompass precise detection of small and moving obstacles, minimizing path deviations at minimal cost, high machine learning and automation expenses, prohibitive costs of real testbeds, limited environmental comprehension, and security apprehensions. By addressing these key areas, future research can advance the field of drone collision avoidance and pave the way for safer and more efficient UAV operations.**

***Index Terms*— Unmanned aerial vehicles (UAV), drone collision, collision avoidance, UAV navigation, drone swarm.**

Manuscript received 10 January 2023; revised 19 July 2023, 17 October 2023, and 1 March 2024; accepted 7 March 2024. Date of publication 25 March 2024; date of current version 2 July 2024. This material is based upon work supported by the Air Force Office of Scientific Research under award number FA2386-22-1-4018. The Associate Editor for this article was I. Ud Din. *(Corresponding author: Nor Asilah Wati Abdul Hamid.)*

Mohammad Reza Rezaee is with the Department of Communication Technology and Network, Faculty of Computer Science and Information Technology, University Putra Malaysia, Serdang 43400, Malaysia, and also with the Department of Information Technology, Faculty of Computer Science, Kabul Education University, Kabul 1001, Afghanistan (e-mail: mo.rezarezaee@gmail.com).

Nor Asilah Wati Abdul Hamid is with the Department of Communication Technology and Network, Faculty of Computer Science and Information Technology, and the Institute for Mathematical Research, University Putra Malaysia, Serdang 43400, Malaysia (e-mail: asila@upm.edu.my).

Masnida Hussin and Zuriati Ahmad Zukarnain are with the Department of Communication Technology and Network, Faculty of Computer Science and Information Technology, University Putra Malaysia, Serdang 43400, Malaysia (e-mail: masnida@upm.edu.my; zuriati@upm.edu.my).

Digital Object Identifier 10.1109/TITS.2024.3375893

I. Introduction

THE worldwide market for commercial and civil Unmanned Aircraft Systems (UAS) is anticipated to expand significantly. According to Single European Sky Air Traffic Management Research (SESAR), the European drone market will surpass 10 billion yearly by 2035 and 15 billion by 2050 [1], [2]. Moreover, based on the characteristics of the missions and application fields, small UAS and very low-level airspace operations would provide the most incredible market value. The expanding tendency will accompany a rise in traffic congestion and additional safety, reliability, and efficiency-related problems. Therefore, developing and deploying conflict management systems are prerequisites for UAS integration in civil airspace. Specifically, the National Aeronautics and Space Administration (NASA) in the United States (US) intends to develop a UAS Traffic Management (UTM) system that will let multiple UAS fly at low altitudes alongside other airspace users [2], [3].

According to the Federal Aviation Administration (FAA), there will be 2.4 million small hobbyist drones in the US by 2022, and the incidence of drone accidents is sharply rising along with the popularity and deployment of Unmanned Aerial Vehicles (UAVs) for consumer applications [4]. The FAA obtains over 100 monthly complaints of illegal and possibly dangerous UAV activity from pilots, residents, and law enforcement [4]. These kinds of accidents highlight the necessity for drone pilot education and training programs, as well as tighter regulations for offenders. FAA also highlights the significance of a collision-free route creation and navigation system for UAVs. It is just as essential to guarantee safe and risk-free UAV flying while using it inside. As a result, keeping UAVs stable in flight is becoming a significant priority means that the UAVs can identify and avoid stationary and relocating objects. Examples of static impediments include buildings and trees, whereas dynamic obstacles include birds [5].

One of the challenges is how to safely integrate drones into the airspace structure with other aircraft in an urban area. Technical, operational, and regulatory issues are involved. A few years ago, the European Union started an endeavor to adopt more airspace regulations [6]. The European Commission modified the UTM concept for Europe, added a framework of services and capabilities, and termed the outcome U-space [7]. Since then, the SESAR Joint Undertaking (SESAR JU) of the

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European Commission has funded various European research projects [7]. Some research projects concentrate on techniques and regulations that let drones fly in crowded areas without threatening other airspace users. For example, this includes U-space Separation in Europe (USEPE) projects, which investigate management and safe separation technology. The project uses geo-vectoring, high-speed corridors, and density-based management [8]. NASA's project called UAS Integration in the National Airspace System (NAS) intends to create collision avoidance technology [9]. Note that flight safety concerns aviation authorities like European Union Aviation Safety Agency (EASA) in Europe [10].

UAVs must have onboard collision avoidance systems due to their autonomy and ability to fly without base stations or humans. Adding cognitive decision-making tools to the autopilot system, like obstacle recognition and planning of paths, can increase autonomy and boost safety. There is an increasing need for dependable collision avoidance systems for public safety as UAV use increases, particularly in public spaces. Moreover, UAVs can travel to dangerous and inaccessible locations without jeopardizing people's lives. This emphasizes the significance of developing completely autonomous UAVs via basic research [11]. A group of UAVs can do powerful tasks that a single UAV cannot. Note that a fleet or swarm of UAVs may be used for larger and more complex applications and operations. Without preventing UAVs from colliding with one another, stationary and moving obstructions in the flight zone, a safe operation cannot be guaranteed under such circumstances. By creating an online motion route planning, coordination, and navigation system with collision prediction and avoidance, UAV swarm motion safety may be ensured [5].

The principle behind UAV path planning is that further distant cues are used to make broad judgments about the course to travel. Meanwhile, nearby ones are used to make fast choices about collision avoidance. The agent obtains high-level information about everything on the map via the global planner, a condensed representation of the entire environment map focused on the agent's position. Since the local planner is neither compressed nor scaled out, the local map provides detailed information about the region surrounding the UAV agent [12]. According to a recent study, location data is primarily used by UAVs to detect flight conflicts. There are several ways to locate a UAV, including satellite-based positioning, Automated Dependent Surveillance-Broadcast (ADS-B), Traffic Collision Avoidance System (TCAS), inertial navigation, and radar detection [13]. Nonetheless, unsolved concerns still prevent UAVs from being utilized on a big scale in urban areas. First, UAVs pose safety concerns to bystanders in populated areas, including the potential for injury to persons and damage to vital facilities [14], [15], [16]. The potential for a confrontation during flight is another significant obstacle. Since there are seasonal fluctuations in the need for air travel (for food delivery [17] and passenger transport), all UAV users must operate simultaneously in the same airspace [16], [18], [19]. These raise the risks for other UAVs collisions and unsafety.

Drones have revolutionized various sectors with their versatile applications, creating a pressing need for effective collision avoidance systems. These systems have given rise to numerous algorithms and strategies, yet current research predominantly focuses on stationary or limit obstacles. Unfortunately, many of these algorithms may not be suitable for drones with limited computational resources, and they often need to account for environmental factors such as wind, rain, and changing light conditions. The main UAV collision avoidance algorithms challenges are summarized in Table I.

TABLE I
UAV COLLISION AVOIDANCE CHALLENGES

Challenge:	Detail:
Level of algorithm view	Local view or global view.
Autonomy	AI computation costs
Diversity of obstacles	Static, dynamic, airplane or UAV, animals/ birds/ Human
Unknown environments :	Crowded city (High dense) or sparsely populated village (Low dense). High altitude or low altitude (inside jungle among trees/ inside city among budlings).
UAV limitations	Battery, data storage, computational power
Environment and weather changes	Fly indoors (inside buildings) or outdoors (city, mountains, desert), wind intensity and direction, foggy, rainy, and snowy weather, daylight or dark night.
Metrics for algorithm justification	Energy consumption, flight time, collision rate, Jerk, Velocity, Latency, communication and computational cost, distance to obstacle, wind speed and direction.
Simulation tool or Testbed for algorithm justification	Suitable simulator or testbed to cover all concerns and significant metrics
Mission completion in suitable time	Destination reaching and collision avoidance actions expenses: Amount of deviation from original route, flight time, energy consumption

Recent studies highlight the persistent hurdles in this field, underscoring the need for a comprehensive review to analyze existing research, methodologies, and achievements. For our literature study of UAV collision avoidance algorithms, we conducted a thorough search of databases such as IEEE Xplore, Scopus, and Google Scholar using precise keywords. We included recent, peer-reviewed articles and important works that matched very specific criteria. This guaranteed a thorough and up-to-date survey of UAV collision avoidance technologies and trends. This paper thoroughly examines collision avoidance techniques designed for Unmanned Aerial Vehicles (UAVs) to address obstacles hindering safe drone operations. We carefully examine the technologies and techniques used in each area, highlighting their distinct contributions and results. We explore incorporating machine learning methods, metrics, and simulation tools for verifying collision avoidance systems. Our study aims to highlight the key limitations of existing research and advances in drone collision avoidance technology by identifying critical areas for improvement and outlining future research directions to enhance the safety and effectiveness of UAV operations. The main contributions of this article are as follows:

1. We analyze various algorithm types, the utilization of Machine Learning (ML) mechanisms, the UAV communication network, and the challenges and limitations encountered in collision avoidance approaches.
2. We explore the metrics and simulation tools used and examine whether the proposed algorithms function as local or global planners.
3. We delve into algorithm capabilities, encompassing obstacle identification (both stationary and moving), the quantity and characteristics of obstacles, and features such as predictive abilities and reaching predefined destinations.
4. Lastly, we illuminate open challenges and future research directions in the field of drone collision avoidance.

The subsequent sections of the paper are structured as follows: The second part delves into the current state of the art concerning drone obstacle detection, collision avoidance, UAV swarm, and path optimization. The third part entails the evaluation and classification of the reviewed algorithms. In the fourth part, challenges and significant issues in collision avoidance approaches are discussed, while the fifth part presents lessons learned. Additionally, the sixth part addresses the future direction and open challenges of the research. Finally, the conclusion summarizes and concludes the paper.

II. Related Works

One remarkable technology that has spread from the military to civilian commercial industries is the drone or UAV. Many technologies, such as Artificial Intelligence (AI), computer vision, obstacle avoidance, and others, allow it to function as a pilotless aircraft [20]. UAVs' usage in civil applications is still growing, although airspace regulations have already been established. However, each country has its regulations, including weather conditions, maximum and minimum flying height, restricted flight zones, as well as mandatory usage of onboard sense and avoid systems [21]. Depending on various aerospace applications, UAVs are either remotely piloted vehicles, fixed-wing drones, hybrid fixed/rotary wing drones, robot planes, or pilotless aircraft. This ranges in size from tiny toys to enormous military aircraft. Furthermore, their payloads directly affect UAVs' size, battery life, and flight length. It can be anywhere from a few grams to several hundred kilos and contain communication equipment, cameras, radars, and sensors [22].

Drones that are tiny may take off and land practically anyplace that has UTM services [18]. The drone collects high-resolution footage of public traffic occurrences or testing scenarios from a bird's eye view and creates data. Other than that, the positions and motions of all visible road users may be retrieved with high precision from video recordings using semantic segmentation and tracking techniques. Due to the drone's perspective, the entire traffic scene may be photographed without cars being obscured by other vehicles. Moreover, measurements taken with a drone are incredibly efficient due to the simultaneous capture of all road users within the range of vision [23].

The regulatory structure for autonomous cars places a strong emphasis on four vital safety factors [24]: 1) deciding if a safety driver has to be in the car or whether the remote control is acceptable, 2) creating safety management plans or comparable standards, 3) requiring data collecting and reporting, and 4) outlining regulations regarding responsibility in the case of accidents or collisions.

A collision or conflict in the context of Air Traffic Management (ATM) refers to a situation where two or more(manned) aircraft suffer a loss of minimum separation.

Aviation organizations like the International Civil Aviation Organization (ICAO) determine the minimum distance between two planes [21], [26]. No minimum separation requirement is set for multi-UAV systems, despite the possibility of special legislation defining one and the assumption of work-specific values in certain studies [21], [27]. Drone separation criteria are defined by distance, time, or a mix of both. The distance-based technique establishes a drone safety area. However, it does not account for the intruder's speed, making it inappropriate for integrated operations. The time-based technique calculates relative speed by calculating the time to reach the Closest Point of Approach (CPA). Nevertheless, it is hard to visualize. Mix time and distance based are now employed to determine drone safety separation [27]. Conflict detection determines when to take action, while conflict resolution specifies how or what action should be taken [28], [29].

UAS improves production and reduces risk in several sectors. Hence, meeting flight regulations and expanding authorized flying zones is necessary to enable commercial services and incorporate UAS into airspace. Collision avoidance systems and clever trajectory planning further ensure UAS safety. Note that UAS collisions in dense traffic airspace is another concern. UAS must adjust their see-and-avoid capacity to identify and avoid other aircraft. Other than that, UTM requires intelligent collision-free trajectory planning [10]. A collision avoidance system involves three important parts [9]:

1. Sensing: Collects information about obstacles.
2. Detection: Foresees collision probabilities based on existing data.
3. Avoidance: Chooses and performs the right evasive maneuvers.

A network with flying nodes necessitates synergistic interplay across the four design-principal dimensions: control system, network and communication, information exchange, and situational awareness [45] has been detailed in Fig. 1. Two critical aspects of the multi-UAV system should be considered: coupling and networking. Networking characterizes the communication state of UAVs and the methods by which data are sent across the system. Meanwhile, coupling considers the interaction between UAVs [25], [46]. Centralized UTMs can see the entire system. However, delays in making judgements could make collisions more likely. Each UAS makes a local decision on how to prevent a collision, but UAS works together with other UAS in the same area. Therefore, distributed decision systems installed on UASs can resolve the issue locally, albeit local processing may cause an additional delay [10]. This section reviews recent surveys and ongoing research for addressing the issue of drone collisions and swarms.

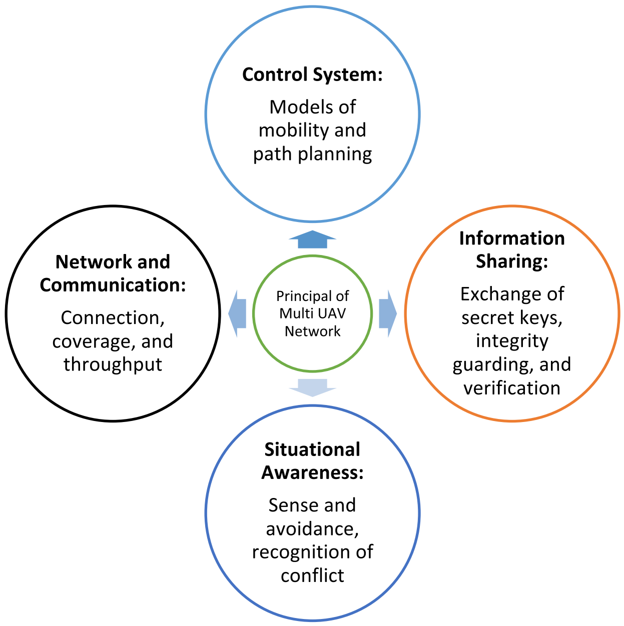

Fig. 1. The foundation of a network of multiple UAVs [25].

A. Related Surveys

The primary focus of some related research is solely on vision-based obstacle avoidance during route design, apart from other collision issues that are discussed in this work. An overview of the planning issue in the context of UAV graphics applications is present in [38]. Different visual localization and mapping systems used for UAV navigation are discussed in [40]. In [39], the author highlighted current progress in utilizing UAVs for geoscience and remote sensing objectives. It detailed the development and optimal use of onboard sensors, flight planning, navigation issues, data processing, and analysis. Other than that, it also discussed vision-based and other sensors for collision avoidance. In [30] taxonomy of drone navigation algorithms is based on the level and features of autonomy provided. In reviewing the approaches for UAV route planning, [36] divides them into three categories: representational, cooperative, and non-cooperative.

Analysis and description of collision-avoidance processes and functions such as state sensing, conflict identification, and conflict resolution provided by [28]. Authors of [11] investigate various methods of collision avoidance and provide a comparison of their relative efficacy in a variety of situations. Additionally, multiple sensor types and their applications for UAV collision avoidance are discussed. Reference [42] reviews the sensors and detection methods used in anti- collision systems. Classification, control applications, and future industry and research interest areas for UAVs are present in [32]. Research [41] provides a review for advancing UAV collision avoidance approaches based on consolidating current legislation and standards concerning UAV collision avoidance. To avoid non-cooperative obstacles, article [43] thoroughly analyzes perception sensors, methods, and hardware designs for autonomous low-altitude UAVs. Nevertheless, these studies don't address the subjects of metrics, simulation tools and artificial intelligence in collision avoidance algorithms.

A thorough analysis of the principles of Deep Learning (DL) used in UAV-based photography and mapping is provided by [37]. An in-depth analysis of how ML may be used in networks with UAVs is provided in [22]. Research [34] concentrates on ML techniques to manage UAV flocks. It tackles UAV flock creation, management and coordination, UAV-based wireless communication networks, and ML applications to UAV-related difficulties. In [31], difficulties like control, navigation, and route planning are discussed. It reviews Reinforcement Learning (RL) techniques used in UAVs and how learning performs. There is a lack of thorough and precise examination and comparison of artificial intelligence algorithms used for drone collision prevention among existing studies.

In [33], an overview of drone applications in Software-Defined Networks (SDN)-enabled drone base stations, surveillance monitoring, and emergency networks are provided. A survey about topology controlling algorithms for drone swarms was prepared by [35]. The communication network among drones has yet to be thoroughly discussed to improve coordination and prevent collisions.

Most of the mentioned research does not discuss drone collisions and their algorithms in a deep and concentrated manner, or they have investigated the algorithms from a single dimension, such as a vision base. However, the themes of machine learning, metrics, simulation environment, UAV communication network, and the general strategy of local or global algorithms have not been accurately compared or evaluated. Given the rapid growth and development of drones as well as the extensive development of various collision avoidance plans in today's research, and the fact that the majority of the reviewed articles do not cover the most recent algorithms and significant factors mentioned, we discuss the most recent algorithms in this field. Table II summarizes the theme and significant aspects of previous review papers it this area.

B. UAVs Collision Avoidance Algorithms

There is a plethora of literature on drone collision avoidance, and these articles approach the topic from various perspectives. We classify recent algorithms and methods based on the overall approach to handling collision and examine merits and limitations. The following are the critical parts that have dealt with avoiding collisions in drone navigation and guidance (Fig. 2.):

1. Obstacle detection and avoidance: Detecting stationary and moving obstacles and avoiding colliding.
2. Collision avoidance algorithms: Algorithms focusing on forecasting and detecting collisions with obstacles and other drones.
3. Drone swarm: Algorithms involved in drone swarm formation and management while considering preventing collisions.
4. Path optimization: Considering barriers while optimizing the UAV flight route.

1) Obstacle Detection and Avoidance: The obstacle-detecting and avoidance skills of UAVs play an essential

TABLE II
SUMMARY OF RECENT SURVEYS ON UAV NAVIGATION

Author	Year	Theme	Remarks	Metrics Comparison	Simulation tools	UAV network	AI algorithms	Object detection	Path planning	Collision Avoidance	Drone Swarm
[30]	2021	Taxonomy of drone navigation autonomy	-Focus on UAV autonomation features and navigation parts. -Just mentioned research that refers to collision avoidance.				✓		✓	✓	
[22]	2019	UAV-based communications	-Study the application of ML approaches in UAV-based communications. -Review related issues to swarm communication.			✓	✓				✓
[31]	2021	Using AI and RL in drones	-Issues of control, navigation, and flight planning for UAVs were discussed. -Look over employing RL for UAV navigation, including using RL in collision avoidance and swarm.				✓		✓	✓	✓
[32]	2021	Drone type classification, control applications	-Drone control issues discussed. -Have a short definition of collision avoidance and swarm.							✓	✓
[33]	2020	Drone structure and networking	-Focus on drones' network, communication, and security.			✓					
[34]	2021	UAV flocks	-ML usages and techniques in drone flocking and management. -Did not discuss metrics and just named them.	✓			✓			✓	✓
[35]	2022	UAV swarm topology	-Topology control algorithms used in UAV swarms were discussed. -Did not discuss metrics and just mentioned them.	✓						✓	✓
[36]	2020	Path planning methods for UAVs	- UAV path planning approaches are classified and explored. -Discussed path planning algorithm by considering collision issues.						✓	✓	
[37]	2021	Deep Learning application in remote sensing by UAVs	-Deep learning algorithms and methods used in UAV imagery and mapping. -Discussed ML algorithms that are used for remote sensing.				✓				
[38]	2020	Path and view planning for UAVs	-Planning issue in the context of UAV graphics applications. - Limit to obstacle avoidance during path planning.					✓	✓	✓	
[39]	2022	UAVs in photogrammetry and remote sensing	-Comparison of drone sensor and camera types and data collection methods. -Focused on UAVs' different sensors and cameras type.					✓		✓	
[40]	2018	UAV vision-based navigation	-Discussed vision-based object detection/avoidance and path planning for UAV navigation. -Limited to vision-based techniques and methods.					✓	✓	✓	
[11]	2020	Collision avoidance strategies and modules	-Collision avoidance hardware and modules were defined. -Collision avoidance algorithms were categorized based on the type of algorithm and discussed.	✓				✓	✓	✓	
[28]	2022	UAVs collision avoidance	-Collision avoidance functions described. -Summary of sensing technologies, conflict identification, and resolution advances was given.			✓			✓	✓	✓
[41]	2023	Rule based approach for avoiding collisions	- Summary of current rules and regulations pertaining to avoiding UAV collisions							✓	
[42]	2023	Anti-collision sensors	-Reviews obstacle detecting techniques.					✓		✓	
[43]	2024	Perception sensors	-Review perception sensors, algorithms and hardware of UAVs					✓		✓	
[44]	2023	UAV Obstacle avoidance	-Concentrate on modules of sensors frequently employed for detection in indoors UAV environment.				✓	✓	✓	✓	
This Survey	-	UAVs collision avoidance	-Deep overview of collision avoidance issues and problems. -Discussion on AI solutions and metrics and drone swarm.	✓	✓	✓	✓	✓	✓	✓	✓

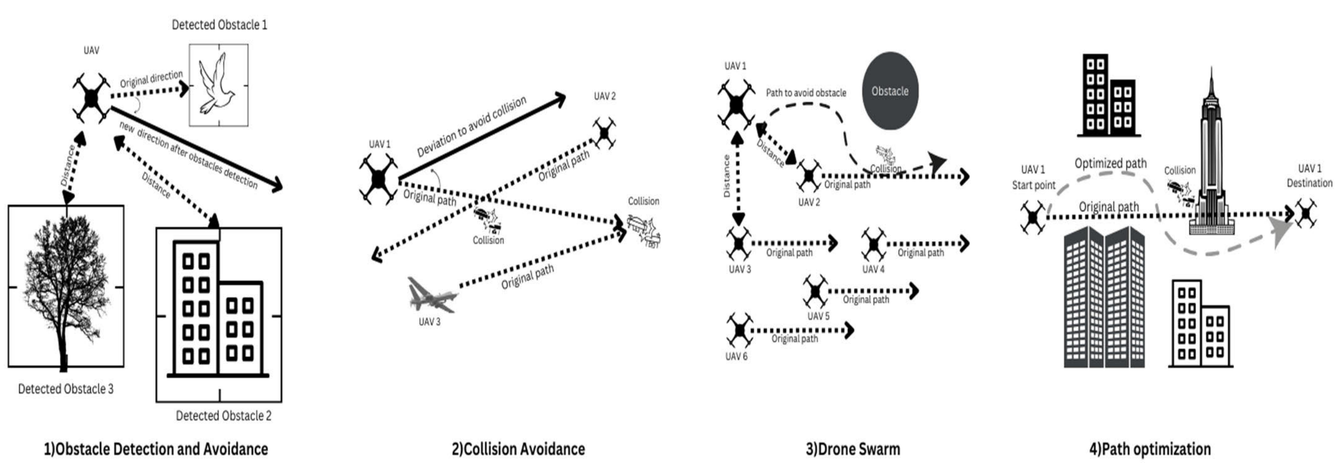

Fig. 2. UAV collision avoidance related algorithms.

role. Since UAVs operate in unfamiliar dynamic environments with several fixed or moving impediments, recognizing, and avoiding obstacles is critical [47]. There may be three distinct parts to the 3D navigation problem: recognizing obstacles, avoiding them, and finally arriving at the desired destination. In order to scan and find things around UAVs, many sensors have been used. For locating moving and stationary impediments in the vicinity of UAVs, several systems employ cameras. However, video camera data must undergo extensive processing in order to be converted into information that may be used to operate UAVs [48], [49]. Obstacle Detection and Avoidance algorithms may be classified according to many parameters, including the sensor type, obstacle type, avoidance technique, and environment type:

a) Sensor types: Obstacle Detection and Avoidance algorithms may use various sensors, including cameras, lidars, radars, sonars, or a combination of them, to identify obstacles based on the sensor type. Various algorithms have been developed to detect objects using cameras or other sensors and avoid collisions. In the meanwhile, several of these studies have concentrated on fixed objects. In [50] by RGB-D camera provides an environment-aware trajectory prediction approach based on the Markov chain and the states of monitored dynamic obstacles. This method suffers from high failure rates. To improve the UAV's collision detection system, a model with distributed spatial-temporal synaptic interactions is developed [51]. The model is motivated by locusts' ability to avoid collisions using a motion-based visual neuron called lobula giant movement detector. Nevertheless, the proposed method needs more sensitivity to small objects like wires and leaves. This is because it relies primarily on discriminating looming objects based on their image angular velocity and size.

This study [52] uses obstacle contour detection to estimate barriers' location coordinates and shape by analyzing the image attributes of unknown obstacles. Based on the combined colliding cone and alert criteria, a collision detection and alerting theory is presented out in [53]. A 3D vision cone model in [47] proposes for the obstacle detection issue. A Sliding-Mode Controller (SMC) is used to avoid obstacles and reach the objective. More boundaries enhance optimal motion direction but increase the algorithm's computing load. However, UAVs' eyesight is limited to one side, and covering different sides or directions requires more computational resources. The restrictions on the obstacle-detecting sensors include their area of view, precision, resolution, noise level, and sensitivity to interference from outside elements. For instance, lidars may be expensive and need much power, cameras may not see well in dim or foggy circumstances, and radars may need better resolution and angular precision [54].

b) Avoidance techniques: One straightforward collision-avoidance technique is the deterministic Model Predictive Control (MPC) with a no-entry region. Based on the observed data, the control target's distance from obstacles may be determined. MPC leverages the dynamics of UAVs to forecast and optimize upcoming control inputs, assuring viable trajectories with collision avoidance requirements and reducing the possibility of deadlocks brought on by many obstacles. Even when the UAV travels along a collision-free route, several obstacles might result in a condition known as a deadlock, in which the control target cannot reach the target point [55]. Authors of [56] used Nonlinear Model Predictive Control (NMPC) for motion planning and control integration to safely operate UAVs in a workspace loaded with fixed or moving obstructions. The use of NMPC in high-speed UAVs may be hampered by its well-known high computing cost. However, because of the mutual interference of regions in a noisy environment, deterministic MPC is prone to oscillations and collisions. Chance Constraints Model Predictive Control(CCMPC) with position chance constraints offers smoother motion planning than MPC [57] but position chance constraints alone are inadequate to maintain a safe distance from dynamic barriers. The fact that CCMPC requires more processing than deterministic MPC shows that it is computationally expensive. Nevertheless, chance constraints based on obstacle velocity can perform early collision avoidance and provide the most effective control input [55].

Recently, several studies have attempted to use machine learning techniques for obstacle detection and avoidance. Deep Neural Networks (DNNs) in computer vision and their application to vehicular autonomy have directly created navigation systems. This enables considerable automation of drone operation, a clear ambition [30]. A real-time obstacle avoidance system based on a regression CNN proposes to calculate distance-to-collision from a UAV camera [58]. The research employs a two-stream CNN to predict UAV collision distance in several directions. A trained CNN combines a unique local motion planning technique to turn distance estimations into velocity commands. If UAVs move among the mass of fixed impediments, as in the study of [59] in forests, suffer from obstruction due to limited local visibility.

c) Obstacle types: Obstacle Detection and Avoidance algorithms may handle several obstacles, including static or dynamic, regular or irregular, known or unknown, based on the type of obstacle. Research [55] focuses on developing and integrating obstacle velocity-based chance constraints with positional chance constraints to effectively handle both position and velocity uncertainties, particularly in noisy environments with high-velocity obstacles. This study's primary flaw is its assumption that the computation for the optimization will be finished within the control period and just tested in a 2D setting with two moving obstacles (velocity = 0.5 and 0.3 m/s) or three obstacles (Velocity =3.0 m/s) moving in the same direction. Additionally, it is presumed that the UAV can determine the precise position and speed of all obstacles and UAVs.

To avoid collisions involving a moving object, such as a tossed ball, [60] proposes an approach that employs Neural Network Pipeline (NNP) to forecast crashes and an Object Trajectory Estimation (OTE) technique that leverages optical flow. The biggest issue in related research is the drone's poor speed. In [61], Pixel Model Predictive Control controls the drone for high-speed racing while maintaining its distance from visibility gates. It employs Deep Optical Flow (DOF) learning, a self- supervised learning approach that does not need operator labelling. Autonomous racing and visual object tracking are the main objectives of the work. It predicts pixel model dynamics and future state trajectory to select the optimal control sequence.

In [62], the authors provide a technique for identifying drones using a DL strategy, particularly CNN. It relies on radio frequency signals sent by the UAV and its controller during real-time data transfer to function. The method might detect moving boundaries in space, such as drones, robots, and other electronic objects that can control. Nonetheless, the computing cost of implementing these approaches within a drone are substantial.

d) Environment types: Obstacle Detection and Avoidance algorithms may function in many situations, such as indoor or outdoor, urban or rural, congested or sparse, depending on the kind of environment.

Obstacle avoidance algorithm for the drone in building environment based on simplified geometry presented in [63]. It used 3D sensor data to locate and identify impediments like people or UAVs. The proposed technique combines a preregistered 3D room model with sensor data. Note that the proposed design includes Light Detection and Ranging (LiDAR) or stereoscopic cameras in a UAV for interior navigation. Other essential metrics like energy consumption and jerk were not considered for performance measuring of the proposed algorithm.

A rapid UAV navigation strategy for identifying and avoiding trees in the forest using visual perception has been proposed [59]. Neural Networks (NN) were used with DL approaches like nonlinear regression to explore drone system dynamics. Other than that, a deep Convolutional Neural Network (CNN) algorithm was employed for visual perception in the forest by detecting trees as boundaries. Due to high processing costs, all training and computations are offline and in flight, the trained model is employed.

When it comes to safety, smaller drones outperform bigger ones in intricate interior situations. Indoors, standard-sized quadrotors are considered dangerous, while nano-UAVs, with their small onboard computer, have dependability advantages, including decreased latency and less bandwidth needed. However, accomplishing autonomous navigation with nano-UAVs requires overcoming obstacles in trajectory planning and obstacle avoidance while maintaining energy efficiency; computing power must be a small portion of the total energy envelope to metric sustain flight length. Processing should only occupy a small portion, i.e., 10% of the total energy envelope, in order to allow onboard choices depending on the nano-UAV surroundings. For example, the highest computing power required for nano-UAV platforms such as the Crazyflie 2.1, where the entire power consumption, including the motors, is around 10 W, must be in the range of hundreds of megawatts in order to not significantly impact the flying duration [64], [65].

The challenges of obstacle detection and avoidance vary across different environments [66], encompassing congested or sparse areas, indoors or outdoors, cities or forests. For example, while walls, ceilings, doors, and furniture pose barriers in indoor settings, outdoor environments present unpredictable dynamics such as wind, birds, and other UAVs.

Nevertheless, existing algorithms often developed from the 2D situation of planar vehicles, which necessitates setting the UAV's height while avoiding obstacles. Other than that, 2D algorithms significantly decrease the UAV's trip efficiency. It will not look for a route around the closely spaced obstructions, leading to UAV crashes or tracking in a particular 3D environment [47].

Limitations in sensors and environmental factors like illumination and weather may cause a perception system failure. Another aspect is occlusion, which makes an object partially or entirely invisible. Comparing a truck to a dog suggest that objects may differ substantially in size and distance from the subject. The sensors' results vary greatly depending on the object's scale [67]. In a crowded space, the local vision and approach of the algorithms simply by avoiding obstructions regardless of the primary path and target may bring the drone to a dead end or trap.

Multiple constraints make using analytical tools and DL algorithms in indoor spaces difficult. The utility of NNs is also severely limited by a lack of training data and avoidance methods. Moving obstacles, such as people, provides another issue. The avoidance algorithm must forecast the movements of obstacles to select the safest and most efficient route [63]. While predictive approaches may be more resilient and dependable but need more computation and knowledge, reactive methods may be quicker and more straightforward. However, they may not provide global optimality or safety [68]. Because of the local approach and limited visibility, the bulk of the algorithms in this group face the difficulty of real-time reactions without considering the primary route and eventual goal. These deviations may take the drone to a closed or dead-end site without a path to the final goal. On the other hand, aimless deviations lengthen the flight path, increase flight duration, energy consumption, and decrease efficiency. At the same time, deviations without adjusting the acceleration and speed and taking the jerk metric into account may result in catastrophic harm to the drone or the cargo it transports. Table III presents a summary of related works on obstacle detection and avoidance.

2) Collision Avoidance: The term "collision avoidance" refers to the capability of UAVs to detect collisions and evade them without suffering any physical harm [36]. Scheduling, speed adjustment, and spatial dimension changing or rerouting are standard methods for collision resolution strategies. Note that pre-flight disputes may be avoided with proper scheduling. Preventing or resolving conflicts or congestion is possible by rearranging the departure time. Modify the flight's speed, which modifies the estimated arrival time for the flight's future waypoints. In addition, changing the estimated arrival time value may alter the time gap between two aircraft passing a waypoint. By adjusting the 3D geometric trajectory, spatial conflicts may be handled [16].

Collision avoidance for multiple UAS can address pre-plan, collaborative, and autonomous. The pre-plan technique entails centralizing information and preparing flights to avoid collisions. However, it limits scalability and flexibility. The collaborative approach entails UAS discussing their status and plans to resolve problems via transponders and systems such as ADS-B or Flight Alarm (FLARM) in Europe. Each UAS makes decisions based on its sensors, such as cameras, LiDAR, sonar, or radar, under the autonomous strategy. Numerous studies have applied various technologies to non-collaborative systems [10], [21]. ADS-B is a surveillance technology that combines Automatic Dependent Surveillance (ADS) and TCAS. ADS-B transmits critical aircraft data like

TABLE III
SUMMARY OF RELATED WORKS ON OBSTACLE DETECTION AND AVOIDANCE

Author	Solution	Remarks	Metrics	ML type	Algorithm hired
[59]	Obstacle detection in forest and take off dynamics	High computational costs	Height, velocity, thrust	Supervised learning	Deep CNN and Nonlinear regression
[62]	Drone detection using radio frequency	Relatively high computational cost	Accuracy, precision, recall and F1 score.	Supervised learning	CNN
[63]	Collision avoidance with fixed and moving obstacles inside building	Low UAV speed and used LiDAR sensors for obstacle detection	Time of computation on UAV	-	Simplified geometry
[61]	Predict movement of relevant pixels in robot planned rout	In dark or rainy weather, the performance of vision will decrease	Variation of roll, pitch, yaw angles, success rate, lap time	Self-supervised learning	Pixel Model Predictive Control and deep optical flow learning
[47]	Vision-based obstacle detection and avoidance	Vision limit to one side and covering more directions need high computational resources	Minimum distance to an obstacle, time step	-	Kinematic model
[56]	Model predictive control in 3D among a variety of moving objects to trajectory tracking	NMPC is well recognized for being computationally costly	Distance to obstacles, inverse time to collision	-	Nonlinear model predictive control
[58]	Obstacle avoidance system	High computational expense	Root mean squared error, time, distance to collision	Supervised learning	CNN
[60]	Vision-based collision avoidance with dynamic objects to trajectory prediction	High computational cost and processing hardware cost	Loss, accuracy, processing time, performance	Supervised learning	Neural Network Pipeline
[51]	Vision-based collision detection in agile flights	High computational cost and cannot detects small objects	Output MP (Magnitude of Preference), attenuation	-	Presynaptic Neural Network
[50]	Vision-based collision avoidance with dynamic and static objects	High failure rate in complex environments-	Obstacle detection errors in position and velocity	-	Markov chain-based prediction
[55]	Dynamic obstacle avoidance considering velocity and position of obstacle	Limit to 2D environment .Presumes UAV is able to assess the location and speed of all obstacle and UAVs.	Computational load, noise gain, prediction time	-	Chance Constraints Model Predictive Control (CCMPC)
[64]	Obstacle avoidance of nano drone	In a common and untested indoor setting, 100% reliability at 0.5 m/s	Flight speed, distance travelled, time spent in air, perceptual artifacts, delay		Model-free decision tree

position, altitude, speed, and transponder code, aiding in the forecast of UAV flight conflicts [13], [69]. The flight route of the UAV predicts based on the UAV position information in the ADS-B data field and collision resolution using speed adjustment, heading adjustment, and compound of them.

a) Pre-plan approaches: A collision avoidance algorithm that considers several no-fly zones is proposed in the [70] study. The plan is to utilize differential geometry to determine how to steer around polygonal obstacles with the minimum potential change in heading direction. A fixed-wing UAV's ability to change speed is restricted, using more energy than changing angle. In [71], a feasible solution to the above-mentioned issue is presented for real-time collision avoidance between numerous UAVs with uncertain acceleration. This technique combines the miss distance and mixed 3-D geometric approaches.

The computing burden of numerical optimization techniques is more significant than the rule-based or artificial Potential Field (PF) approaches compared with those in the article. According to the results, the method's flight time and computing time are longer than the comparative algorithm.

A paradigm for adaptive decision-making to optimize conflict resolution options for various conflict types utilizing explicable reasons suggest in [16]. However, meta-heuristic approaches are often built for static optimization issues and may fail to react swiftly to changing conditions and evolving threats in a dynamic UAV airspace environment, potentially resulting in collision risk.

A framework with centralized and distributed techniques using vertical motion to avoid drone collisions is given in [72]. The research results based on the A* Search algorithm indicate that, compared to a decentralized method, the centralized one mostly achieves the most optimal results. Due to the proposed algorithm's search and queuing nature, the method has high computational and running time for many UAVs.

An intelligent healthcare system based on UAVs was provided in [73] for monitoring, disinfecting, isolating gathering data, evaluating data, and providing statistics to manage the COVID-19 pandemic. However, the collision avoidance technique for UAVs relies on preset scope, layer, and route and demands greater movement adaptability. A drone flock topology develops in [74] for traffic surveillance. The study aims to employ the internet of vehicles and the SDN to decrease drone communication, load processing, and energy consumption costs. However, the proposed approaches need more mobility to deploy drones flexibly in multiple zones, and migrating drones from one region to another consumes substantial time and energy.

b) Collaborative approaches: In [75], it demonstrates how UAVs might collaborate to prevent collisions. The selective velocity obstacle approach allows UAVs to avoid collisions while conforming to airspace laws. The methodology broadens the usage of the velocity obstacle method and allows UAVs to choose one of three avoidance modes: avoid, maintain, or restore. The research focuses on small and slow UAVs that travel from 8 to 13 (m/s). Note that uncertainties of sensors in the sphere of avoidance with radii with a time 1.5 seconds before collision and solutions to cope with them were not considered.

In [21], the authors offers the Bounding Box algorithm based on a streamlined velocity obstacle-based method for preventing collisions between multi-UAVs. These algorithms change routes in real-time as required. Furthermore, the algorithm should depend on local observations to avoid information sharing amongst UAVs in the vicinity. It avoids conflicts by causing the UAVs to veer from their ideal path.

The study [10] describes distributed and automated collision avoidance systems for UAS. It employs a knowledge-based method to make intelligent decisions and avoid collisions by collecting data from local sensors, collaborative elements and coordinating with other UASs. It customizes aerial vehicles' maneuvers based on their flight plans, vehicle types, and collision scenarios. The PF technique establishes collision avoidance pathways, while the computationally efficient Constant Bearing Decreasing Range (CBDR) method predicts collisions. It is a cost-effective alternative to particle and Kalman filters, requiring regular sampling and essential data.

The technique described in reference [81] is a distributed collision avoidance strategy that relies on the elastic collision principle. It makes use of UAV-to-UAV information exchange in order to avoid collisions between UAVs. Nevertheless, it is limited in regulating speed to avoid conflicts and suffer from prolonged arrival times.

Research [76] examines air-to-ground ultra-reliable and low-latency communication for a moving ground user while operating many UAVs. Conflicting aircraft can communicate and establish cooperative approaches. Reference [2] proposes the idea of compound conflicts to define a multi-UAV conflict based on Multi-Agent Reinforcement Learning (MARL), considering conflicts with tight geographical and temporal bounds.

c) Autonomous approaches: The EuroDRONE UTM architecture comprises a geometry-based collision avoidance algorithm in drone-mounted transponders and a cloud-based software named DroNav [77]. EuroDRONE is a highly automated ATM system intended primarily for micro-UAVs operating at low altitudes. It also has several redundancies and fail-safe algorithms for conflict prevention/resolution [85] and asset management. Note that special hardware modules must be placed on drones to implement the plan. Consequently, given the plan's complexity, the multiplicity of layers, and the high cost, implementing the plan in smaller drone networks is not viable. In contrast, the Particle Swarm Optimization (PSO) technique has shorter flight periods while remaining near obstacles.

In [83], An RL collision avoidance system for fixed-wing UAVs uses geometric logic to represent conflicts and trains agents to prevent mid-air collisions with non-cooperative invaders. In [79], a DRL method based on CNN and LSTM network integration addresses avoiding multi-UAV collisions in complex scenarios. However, it does not consider the hardware and environmental interference aspects of UAVs. Furthermore, adopting LSTM networks could require more computer power and lengthy training periods. This method's fundamental components are offline training and online execution.

Conventional collision avoidance algorithms operate in discrete state and action spaces, limiting UAVs adaptability. Addressing this, [80] presents a two-layer resolution framework employing DRL for UAVs, enabling continuous action space and enhancing decision-making capabilities to provide adaptive avoidance strategies. In [86] RL contributions enable a drone to incorporate the time-related limitations of the 4D trajectory predetermined in the strategic phase. According to the DRL approach by [84], features that describe collisions between agents are explicitly represented as edges in a dynamic agents' social graph, and agents are encouraged to share observations in their neighborhood in an intrinsically partially observable environment.

Case study [87] investigates how traffic density affects the performance of an RL approach in dispute resolution tasks. The findings show that although conventional analytical approaches work better at first at lower traffic densities, RL becomes more effective as densities increase. Notably, training at a density greater than testing improves performance. This shows that training with more complicated situations yields denser reward signals and varied state transitions, improving efficacy. However, the key drawbacks are single-agent interactions, unanticipated performance declines in high-density training, and the need for more extensive domain investigation to draw generalizations about environment complexity for RL approaches.

The collaborative strategy, which makes use of technology like ADS-B, performs well for collision avoidance, but it is restricted by the reliance on external systems and the need for standardized communication protocols. Furthermore, the autonomous strategy, which depends on sensors for decision-making, provides flexibility but may face challenges in maintaining coordinated actions across several UAV in complicated airspace situations. Furthermore, both systems may be hampered by potential sensor accuracy and data latency restrictions, which can reduce the efficiency of collision avoidance measures.

To communicate and collaborate drones with other drones to prevent a collision in [74] SDN, [73] and [78] Internet of Drones (IoD), [10] Micro air vehicle link (MAVLink) and [77] LTE/4G networks are employed. In contrast, other researchers have ignored the difficulty of communicating with drones to share information to prevent collisions. Table IV summarizes references focusing on UAV collision avoidance, including the type of algorithms hired, metrics, drone communication network, and limitations.

3) Drones Swarm: Recent studies have suggested collaborative ways to improve drone activities toward reaching objectives beyond individual capabilities. This is because drones' skills still need improvement to manage complex events and appropriately handle growing volumes of data. Aside from employing a limited number of UAVs, a swarm of UAVs may also work together to perform complicated tasks

TABLE IV
SUMMARY OF ARTICLES ON UAVS COLLISION AVOIDANCE

Author	Solution	Remarks	Metrics	Algorithm hired	Drone Network
[76]	Controlling several UAVs while avoiding inter-UAV collisions to tracking moving ground users.	Focus on UAVs air to ground communication and ignore drone-to-drone communication and latency.	Latency, Error Rate	Multiagent DRL and graph attention exchange network	-
[2]	Collision avoidance between UAV with cooperative approaches.	Small action space (turn left or right) and did not consider the altitude, speed changes and energy consumption of drones.	Loss time steps, compound conflict episodes, separation losses, cumulative reward evolution	Graph Convolutional Reinforcement Learning	-
[16]	Adaptive decision-making framework to optimize conflict resolution strategies.	Replanned routes were not suitable for real-time or undefined accidents.	Operating cost, number of collisions, flight delays	Meta-heuristic stochastic fractal search	-
[74]	Monitor road traffic using drones, considering avoiding collisions.	Movement and trajectories are fixed and predefined, and high time and energy expenses for changing zone.	Energy consumption, delay, Jitter, computational Load, execution time	-	SDN
[73]	Using drones for COVID-19 monitoring.	UAVs have static and predefined routes for collision avoidance and have no flexibility.	Time, area, execution time, simulation time	-	IoD
[75]	UAV cooperative autonomous collision avoidance.	UAV speed is 8 to 13 m/s and didn't consider sensor uncertainties in 1.5-sec of avoid sphere.	Violation probability	Selective velocity obstacle	-
[77]	Drones' architecture for conflict resolution and asset management.	Need special module and redundancy of multilayer construction. PSO requires less fly time while maintaining proximity to obstacles.	Total flying time to waypoint, minimum intruder/obstacle distance	Differential geometry concept	LTE/4G
[70]	Collision avoidance algorithm that considers several no-fly zones.	The flight time and computing time of the method are slightly longer than the comparative algorithms.	Distance to an obstacle, flight time, the computational cost	Differential geometry concept	-
[78]	UAV's location privacy and collision avoidance.	Spiral movements lessen drone collisions but cannot prevent them. The strategy will not work in crowded areas.	Coverage rate, trajectory matching accuracy, intermediary airway competition rate	Mix zone location privacy protection	IoD
[72]	Centralized and decentralized collision avoidance approach.	High Algorithm computational and time costs for a large number of UAVs.	Path cost	A* Search Algorithm	-
[13]	UAV collision avoidance.	Ignores the discussion of a network as a foundation for data collecting.	Latitude error, longitude error, and comprehensive error	ADS-B	-
[10]	UAS collision avoidance in a dense traffic scenario.	Does not consider weather conditions or other external factors.	Conflict avoidance rate	CBDR and Potential Field	MAV-Link
[21]	Multi UAVs collision avoidance.	High flight distance and flight time.	Distance travelled, conflicts produced, flying time	Bounding Box	-
[79]	Multi UAVs collision avoidance with static/dynamic obstacles	Limit to short paths with low speed (1 m/s) UAVs and 2D movements.	Average minimum path, average path , average time, success rate	Deep reinforcement learning	-
[80]	Passing through a small gap	Limit to passing through narrow gap in wall and didn't consider static or moving obstacles	Success rate, reward	Reinforcement learning	-
[81]	Distributed Multi UAV collision avoidance algorithm	Limit to velocity adjustment to avoid collision	Arrival Time in second, Intrusion Distance in m	Elastic collisions between spheres	D2D
[82]	Avoiding Collisions with Multiple UAVs in Urban Settings	Assumed barriers like UAVs and buildings are all elliptical and cylindrical forms and max UAV speed is 6 m/s	Success rate, computational time, flight distance,	DRL (deep deterministic policy gradient (DDPG))	
[71]	Multi UAV collision avoidance	Supposing UAVs' location and speed are known	Distance among UAVs, velocity , turning rate, computational cost	Geometric and miss distance method	-
[83]	Collision avoidance for fixed-wing UAV	Limit to max 3 fixed wing UAVs with 1 conflict	Distance at closest point of approach ,heading changes, reward, steps	RL with Geometric-based logic	-
[84]	Handle tactical collisions for air traffic controllers.	Taught models may acquire novel knowledge from novel scenarios but cannot retain knowledge from past cases.	length of resolution activities, additional nautical miles, collisions solved , number of resolving actions, and reward	Graph convolutional reinforcement learning	-

in much larger regions [88]. Several solutions have addressed cooperative surveillance, rescue missions, and patrolling and tracking. Other strategies have concentrated on collaborative planning, a refinement process wherein collaborating organizations might alter current plans following intentions. Obstacle avoidance, route overlap avoidance, scheduling trajectories, and other challenges are studied in this context [89]. It is important to note that deploying several UAVs as opposed to one has a variety of benefits, which summarize below [25]:

1. Several concurrent intermediations
2. Lower detectability
3. Greater precision
4. High scalability
5. More effectiveness
6. Low price
7. Team member complementarities

Usage scenarios for UAV swarms that may use in both urban and rural settings depict in Fig. 3 [88].

When considering the problems of piloting a swarm of drones, two significant concerns are the creation and maintenance of the swarm and collision avoidance [90], [91], [92]. The primary focus of collision avoidance is on the capacity of individual drones to plan their paths such that they do not collide with other drones or with environmental barriers [91]. Despite formation, algorithms determine where one drone is concerning the others [92], [93]. A formation in swarm

Fig. 3. Usage scenarios for UAV swarms [88] (©2018 IEEE).

robotics is a preferred configuration of the robots in a swarm, a particular configuration or shape of places that the many robots attempt to maintain for one another [92]. In swarm formation flight, UAVs perform a variety of maneuvers like accelerating, decelerating, coordinated motions, and turning in different directions. Other than that, each formation member must maintain a minimum distance from other members to avoid collisions with other nodes in the swarm and external barriers [92], [94]. Three general approaches can be utilized to classify UAVs formation control algorithms [92], [95], [96]:

- Structure-based technique: navigates all the drones in the swarm formation as though drones were one large drone and follows the same course.
- Leader-follower approach: each drone functions independently and autonomously by following the leader and maintaining its position.
- Behavior-based method: drone chooses one of several behaviors per a predetermined plan [92].

To solve the leader-follower flocking problem of UAV swarm distributed angle test rule employed in [97]. It enables each UAV to establish its adjacent set using locally sensed information, lowering the communication overhead of the whole swarm. A leader-follower-based strategy for formation-collision co-awareness by utilizing the thin-plate splines algorithm to reduce collisions and maintain swarm formation suggest in [92]. However, it assumed that all obstacles were fixed, and no information was lost in the communication channel. The [98] project attempts to discover realistic routes without collision for UAV fleets based on weather-dependent energy consumption limitations to decrease UAV load. Note that UAVs fly following forecasted weather pathways by focusing on wind direction and speed. Nevertheless, the method will only work in predictable weather since drone flights are set based on weather expectations.

An online approach for finding safe pathways for swarms of UAVs to fly together without colliding provides in [5] utilizing geographical locations and Complex Event Processing (CEP). Each UAV is assigned a random, greedy choice to predict collisions and find the optimal routes to avoid them. The method requires a lot of data, energy, and time to follow other drones' positions and paths and cannot precisely update their movements. Apart from that, incomplete Global Positioning System (GPS) data might cause UAVs to crash into one other or fixed or moving obstacles. It may withdraw or reverse UAVs to analyze safer trajectories. In a busy flying zone, it may not be possible to compute a bypass route for all drones, therefore putting some drones in hovering mode.

A self-organized collision avoidance model for actual drones that combines a bio-inspired Reward-modulated Spiking Neural Network (RSNN) is proposed in [99]. The concept allows for decentralized decision-making and allows individual drones to learn effectively and autonomously from their local observations, resulting in the creation of swarm intelligence. While individual drones learning from local observations is helpful, it may hinder the system's ability to adapt to global changes or situations that demand coordinated actions. On the other hand, [93] suggests a graph-theory-based formation control technique for UAV swarms with implicit leaders. The method may struggle to adapt to situations where explicit leader selection or change is necessary. The federated learning method is used in [100] to develop the NN-based Mean Field Game (MFG) theory. It exchanges NN model parameters with drones. Other than that, powerful CPUs are required to acquire the control rules at different UAVs. Due to the constraint, the MFG framework cannot be utilized for real-time applications like massive UAV control. The MFG framework reduces the substantial communications required to control many UAVs.

The authors in [89] suggests a five-step approach based on software agent interactions to manage a swarm of drones collectively. The study uses a methodology inspired by fireflies' ability to attract prey to persuade drones to cooperate and handle current events. A swarm cooperative formation control algorithm based on consensus theory joined improved artificial PF to avoid collision among UAVs and other fixed or moving obstacles presented in [101]. Yang [26] invented the biomimetic firefly algorithm to solve nonlinear optimization problems. However, this method may take longer than others to defuse ongoing incidents. It is related to unpredictable event distribution, which may require agents to negotiate before acting.

The distributed TCA introduced by [102] used discrete PSO-based articulation points. To reduce signals and simplify scattered administration, it identifies articulation points to split the network. Each UAV learns its topology and adjusts transmission power to have lower communication overhead and minimize power usage. It employs the "swarm intelligence" of its many members. In the field of AI, swarm intelligence is a field that focuses on group dynamics in multi-agent systems. The swarm intelligence concept is founded on the idea that, rather than a complex controller governing the system's global behavior, it is more effective for the system's constituent agents to work together to demonstrate the intended behavior [103]. A kind of swarm intelligence, the PSO algorithm allows each UAV to decide its following iteration location based on individual and collective experiences.

In order to create a control framework for guiding a swarm of drones to achieve position-specified locations while avoiding collision with objects and other drones, [104] uses control barrier functions and quadratic programming. Research [105] examines the mission and flight planning problems of a diversified fleet of fixed-winged and fuel-driven UAVs. The study adds waypoint assignment and flying trajectory calculation to its benchmark [106]. A swarm of unmanned aerial aircraft to supplement vehicles in tracking traffic is proposed by [107]. However, these investigations focused on communication and computing among UAVs and neglected to precisely address the crucial issue of collision in drone swarm.

Using existing deep reinforcement learning, teaching multiple UAVs flocking and obstacle avoidance is challenging due to complex environments, limited perception, and lengthy training. The speed and efficiency of learning may be greatly increased by using curricular learning [80], [112], [114], [115]. Curriculum learning, breaking the task into progressively harder subtasks, offers promise, but adapting it to multiagent scenarios remains an open question. For a huge-scale fixed-wing drone flock, [113] developed an attention-based embedded module to address swarming and collision avoidance issues. Reference [112] introduces a task-specific curriculum to teach decentralized collision-avoidance flocking to multiple UAVs in obstacle-rich settings, with a multiagent actor-critic approach and knowledge transfer mechanisms for efficient learning. However, the leader flies alone on the predetermined path, disregarding environmental barriers and the method limits to 2D environment and fixed obstacles. Using many UAVs as mobile edge clouds for many users was proposed in [109]. Meanwhile, UAVs should maintain a particular distance from one another to avoid a collision.

Using the MDP, the computing offloading problem with dynamic UAV mobility and UAV failure over multi-UAV mobile edge computing investigate in [110]. In [108], the authors suggest a framework for coordinating video analytics across a fleet of drones. Reference [111] focuses on UAV-to-device communication and locations without considering how UAVs maneuver.

The drawbacks of the investigated solutions for UAV swarm collision avoidance include processing requirements that limit real-time applicability. Furthermore, decentralized learning from local observations may impede adaptability to global changes or coordinated activities, offering a problem. Furthermore, applying curriculum learning to multiagent settings for flocking and obstacle avoidance is problematic. Some deep reinforcement learning algorithms for multi-agents are limited to 2D environments with defined barriers, restricting their application. Finally, structure-based techniques may be rigid and inflexible, making them less responsive in changing situations. Single points of failure and communication delays make leader-follower approaches prone to collisions. In collision avoidance, behaviour-based techniques may lack global coordination, exhibit unpredictable emergent behaviours, and introduce response time delays. Combining these strategies may be required to overcome collision avoidance constraints in swarm systems. Table V summarizes reviewed research in drone swarms, considering factors such as application domain, algorithm type, network architecture, and metrics used in justification and evaluation.

The coupling between swarm formation control and collision avoidance is crucial since collision avoidance must be addressed to maintain the formation. Similarly, swarm formation must be considered to prevent collisions [92]. The UAVs should be able cooperatively to execute various tasks in a swarm. Hence, UAVs must return to their planned configuration after avoiding obstacles and safely reach their destination by consensus on their location and speed.

Since drones may be employed in flocks in many missions today, more studies must be conducted on controlling and directing drones in swarms during missions. Note that most studies have been done on a single or small number of drones or swarm formations without considering a real mission. Research [102], [107], [109], and [110] established that drone swarms have ignored the problem of drones colliding with one another. Other than that, some sources like [73] and [74] have offered algorithms that restrict drones' freedom of movement to a predetermined route or restricted region. The collision avoidance procedure while maintaining the swarm formation comprises two significant aspects. Reorganizing the swarm to avoid a collision as it approaches an obstruction and restarting the formation after it has passed the barrier. Most existing works still need to closely integrate dynamic formation maintenance and collision avoidance techniques since they focus on either maintaining the formation or preventing collisions [92].

4) Path Optimization: Path optimization is a method for determining a viable, optimal or near-optimal, shortest, smoothest, and least-expensive route between the initial location and a destination of choice point while considering certain operational restrictions [116], [117]. Significant challenges to UAV optimal path planning include collision avoidance, route length, time efficiency, cost efficiency, energy efficiency, and completeness [36]. The classical motion planning framework comprises front-end path searching and back-end path generation. Note that front-end path searching involves three categories: search-based, sampling-based, and learning-based methods. Search-based methods like Dijkstra and A$*$ search for safe paths in a graph representation. Meanwhile, sampling-based methods like Probabilistic Roadmaps (PRM) and Rapidly Exploring Random Tree (RRT) obtain possible paths through random sampling. DL and RL have also been applied in path planning. However, current methods face paths too close to obstacles and lack smoothness, necessitating trajectory generation to optimize the path and ensure smooth execution for UAVs and robots [118].

Third-party risk concerns arise when UAVs crash into persons and cars. In addition, UAVs may cause infrastructure damage and noise pollution. Path planning reduces hazards by avoiding high-risk regions before the flight, but most approaches concentrate on flying distance or energy cost metrics without considering risk cost. In [119], the author provides a flight route optimization approach based on a cost-based Dijkstra algorithm. This includes mortality risk, property damage risk, and noise effect, expanding third-party risk modeling and assessment indicators. However, compared to the distance-based Dijkstra algorithm, the average flight distance of the route rose by nearly 20%, resulting in a significant rise in energy consumption. Reference [116] employs the Dijkstra algorithm to locate short pathways with minimum deviation from obstacles. However, the system just addresses predetermined rectangular-shaped obstacles.

TABLE V
STATE OF THE ARTS ON DRONES SWARM

Author	Solution	Remarks	Metrics	ML	Algorithm	Drone Network
[100]	Collision among UAVs in the presence of wind dynamics	-Collecting information from neighbours' UAVs causes communication overhead. -Information limited to UAV neighbours.	Motion energy, communications payload, velocity alignment, number of collisions, velocity, distance travelled	Federated learning	Mean-field game & Federated learning	Wireless
[5]	Drone swarm collision avoidance	Tracking positions and movements of other drones have a high cost.	Average Route Length, length of the longest route, number of Collisions, computation time	-	Complex event processing	-
[89]	Collaborative planning for managing events	Need more processing time to neutralize current events in certain circumstances.	Processing time, total reward, energy usage, approaching event locations without warning	-	Firefly Algorithm & MAS-based solution	Ad hoc
[108]	Swarm task offloading and communications:	Just focus on drone communication and did not discuss collision issues	Accuracy, latency, and energy	Supervised learning and RL	MDP	Ad hoc
[109]	Using swarm as mobile edge clouds	Drones must maintain a minimum distance to prevent collisions without offering any strategy.	The average number of completed tasks, deviation, success rate, energy consumption	-	Greedy algorithm	-
[110]	UAVs swarm as mobile edge computing device	Did not refer to UAVs' communication and navigation issues.	Convergence rate, energy consumption, task failure rate, average processing time	Distributed DRL	MDP	-
[111]	Multi-UAV downlink communication	Focus on UAV-to-device communication and location without addressing how UAVs shift location.	Transmission rate	Unsupervised learning	Graph neural networks	-
[98]	Routing for UAV fleets that avoid collisions	Separate paths and destinations devise to avoid collisions in the same group leading to inefficiency in intense scenarios.	Energy consumption, wind speed and direction	-	Approximate calculation techniques	-
[102]	Topology Control algorithm for UAV swarm	Limited to network and communication issues in drone swarm	Link robustness, network connectivity, link length	-	Discrete particle swarm optimization	Wireless
[92]	Swarm formation and collision avoidance	Assumed that all obstacles are fixed and no information lost in the communication channel.	Velocity, relative separation among drones, temperature variation and energy	-	Thin-plate splines algorithm	-
[101]	Swarm cooperative formation control & collision avoidance	Altitude management is disregarded.	Relative height and distance among UAVs	-	Artificial Potential Field	-
[93]	Swarm formation Control	Every follower only detects followers within the sensing range, which is impacted by weather and other obstacles.	The velocity of vehicles, trajectories of vehicles	-	Graph theory	-
[105]	Trajectory planning of inhomogeneous swarm	Complex instances take longer due to computational complexity.	Computation time, fuel consumption, solution time, number of UAVs velocity, altitude, wind velocity	-	Mixed-integer nonlinear programming	UHF/VHF
[112]	Leader-follower Swarm obstacles avoidance	Limit to fix obstacles and fixed-wing UAVs	Average reward, average distance. ,collision rate.	Multi Agent DRL	MDP, Recurrent attention multi- agent actor–critic	Pixhawk2 via MavLink3
[113]	Flocking collision avoidance	Don't consider other static and dynamic obstacles	Average reward, distance and heading difference , collision rate	Multi Agent DRL	MDP, deep deterministic policy gradient	Wireless
[104]	Real-time collision-free placement of multi UAV	UAVs have extremely low speed.	Position error, the separation between agents, and the distance to barriers, position, speed, angular speed, and thrust	-	Quadratic programming mixed control barrier functions	-

Research [118] improved the trajectory generation approach based on B-spline curves and A∗ search. Note that the method entails defining an optimization function with control points to solve an optimization issue and achieve the optimal trajectory. The approach improves accuracy over previous methods [120] by calculating a security threshold based on the upper-bound principle of B-spline error. The authors of [121] suggest a hierarchical visual control strategy for quadcopters to follow visual pathways inside, incorporating collision avoidance, visibility, and visual tasks. The method employs a single monocular red, green, and blue (RGB) camera for 2D information, allowing for real-time reactive route following without needing 3D reconstruction or motion planning. To direct the quadrotor [122] introduces a perching trajectory-generating system that computes perception-aware, collision-free, and dynamically feasible moves. The method solely considers stationary impediments such as powerlines, other moving obstacles, and environmental restrictions not considered.

The Artificial Potential Field (APF) algorithm leads an agent using scalar potential field gradients, like electric charges in an electric field. Agent and obstacles are comparable charges, while agent and objective are opposite charges. APF helps the UAV avoid obstacles and reach its destination with an additional rotational force to prevent it from getting stuck. Simplicity and efficiency make the APF Approach a viable collision avoidance technology. However, it cannot guarantee an optimal path and often confines the agent in local minima, especially in complicated or crowded settings or head-on collisions.

Approaches like Particle Swarm Optimization [137] and ant colony swarm optimization [138] have been introduced to address these issues. Rotational vector fields around obstacles have also been employed to prevent local minima during head-on collisions [131], [132]. Reference [132] employed the rotating component of the repulsive force to resolve local minima. The study [134] introduces an enhanced APF algorithm that incorporates the Fibonacci Sphere technique for route planning of UAVs. This integration allows for accurate obstacle avoidance and effective evasion of local minima in three-dimensional settings. In [131], a repulsive potential field is proposed to avoid local minima during head-on collisions using a rotational component and an eccentric Region of Influence (ROI) around obstacles. This approach ensures smoother obstacle avoidance while minimizing acceleration. Nevertheless, it limits multirotor UAVs with speeds up to 10m/s, and the quality and precision of obstacle detection and localization sensors may affect its efficacy.

Making the neural perception module output compatible with quick and precise model-based trajectory planners and trackers will enable high-speed, agile flying [123]. Authors in [123] addresses the issue of a quadrotor's stable, agile flying in a dynamic environment. Here, perception and control are the two subsystems used in the strategy. From a single image captured by a forward-facing camera, the perception system employs a CNN to forecast a destination direction in local image coordinates, along with the required navigation speed.

The control system creates a minimum-jerk trajectory monitored by a low-level controller using the navigation target generated by the perception system. In [124], a time-optimal quadrotor trajectory is modeled using a multi-fidelity Bayesian optimization framework based on numerical simulation, real-world flying experiments, and analytical approximation. Using a black-box Gaussian process model, the study classifies possible trajectories as viable or impractical. The method can shorten the trajectory durations for assessed trajectories. However, the optimized trajectory has a nearly four-fold increase in snap and yaw acceleration.

Based on NNs, a trajectory prediction algorithm has been presented in [125]. It identifies the trajectory and avoids barriers amongst the trees in a dense forest, as well as in demanding urban situations and emergency events. Nevertheless, the success rate rapidly reduces to under 60% when the forward speed hits 10 (m/s), demonstrating that the algorithm performs poorly at high speeds. An integer programming formulation mix with a column-generating technique was developed for drone routing problems [127]. Note that the work focuses on reducing how much time drones spend flying and charging overall.

In [49], UAV at each time step, gathers information from several sensors to recognize the existence of the objects in its immediate area. It employed a partly visible state that focuses primarily on the UAV's immediate surroundings rather than the whole deployment region, which results in a slow UAV and substantial computing costs. UAV track planning approach based on Graph Attention Network and Deep Q Network to solve the problem of mission failure caused by erroneous data acquired from UAV during flight present by [128]. It uses the camera to capture photographs and then runs them through a ResNet that has previously been trained to recognize and classify different items within those pictures. Moreover, it employs a Graph Attention Network to connect sensor-measured flight state data to real flight state data to construct a flight-state optimization model.

Based on Q-Learning, [126] proposes an application paradigm in which a UAV collects user tasks at close range and offloads them to edge servers through predetermined pathways. This includes carefully selecting the flight routes with the shortest flying distance without considering collisions with objects and other UAVs. Reference [130] suggests a MARL technique. It considers variables like the number of UAVs, charging capacity, and collision avoidance to tackle the challenging route planning issue.

Coverage path planning aims to maximize target area coverage within the available flight time. On the other hand, path planning for wireless data harvesting aims to acquire information from stationary Internet of Things (IoT) devices scattered across a vast geographical area [12]. Local and global map data fusion is crucial for autonomous UAV path planning, especially when utilizing Deep Reinforcement Learning (DRL) techniques such as Double Deep Q-networks (DDQNs) introduced by [139]. This approach enables effective integration of both local and global map information, optimizing the path planning process for UAVs. However, it increases the computational complexity, especially as the network size grows. Reference [86] presents a technique for resolving tactical conflicts using deep reinforcement learning with non-cooperative UAVs according to a time reward set with an estimated arrival time. This approach introduces a reward criterion based on the estimated time to reach the next pre-defined waypoint. The goal is simultaneously avoiding collisions and arriving at the following 4D waypoint on time, minimizing the likelihood of subsequent conflicts.

The method described in [135] utilizes Euclidean Geometry to estimate intercepting points by using a specified safe perimeter in the form of a square area. Research [133] incorporated a sliding-mode-based reactive control algorithm and a dynamic programming-based global path planning system to operate UAVs in 3D environments. Nevertheless, it suffers from high computational complexity and is dependent on cloud computing resources for processing.

UAVs play crucial roles in time-sensitive missions requiring cooperation, such as simultaneous strikes, formation flying, and cooperative surveillance. All the UAVs in the group must arrive at their locations simultaneously or within a predetermined window. By including an accurate time dimension to the traditional three spatial ones, four-dimensional (4D) trajectories may reduce trajectory uncertainty and boost mission success rates [129]. In [129], the author blends the bio-inspired general tau theory of harmonic motion to develop a set of collision-free 4D trajectories that can direct multi-UAVs from any starting point to their endpoints at the moment of arrival. Nevertheless, the algorithm's complexity and computing intensity, combined with the necessity for precise sensor data, may limit its real-time usability and scalability in dynamic multi-UAV situations.

The path optimization methods for UAV collision avoidance have limits, such as issues with path smoothness, which frequently result in trajectories that are too close to obstacles. In addition, most of the approaches suffer from low UAV speed, ignoring moving obstacles, flight time, and energy consumption, and limited and localized perception and the risk of occlusion in vision-based algorithms. While search-based and sampling-based methods can be computationally intensive, deep learning (DL) and reinforcement learning (RL) methods for path planning can also be demanding in terms of computational resources. This limitation can affect the real-time performance of the algorithm, especially for UAVs operating in dynamic environments, and striking a balance between collision-free and smooth trajectories remains a challenge that necessitates careful optimization. Table VI depicts the kinds of algorithms, measurements, and limitations discovered in previous research on UAV path optimization.

III. Evaluation and Classification

In light of those mentioned earlier, we classify and evaluate the research concerning intelligent navigation and collision management issues in drones.

A. Local and Global Planning

Various algorithms are confined to preventing collisions without taking the primary route and mission of the drone into account. The algorithm will fail throughout the mission due to the drone's battery size restrictions and flying lifetime. Subsequently, algorithms may be classified into three types based on their application:

1. Local Planner Algorithms: Due to more precise and complete awareness of the environment [12], these algorithms may be applied in interior settings or complicated metropolitan situations outside buildings.
2. Global Planar Algorithms: These algorithms perceive the environment and depend on geographic position [12] and can only be employed in wide situations with a great distance between obstacles.
3. Combined Global and Local Planner Algorithms [130]: The algorithm accurately covers the environment. As a result, it may be utilized in indoor and congested urban situations when approaches are not committed to GPS.

Given the nature of local and global algorithms, it is realistic to claim that most suggested algorithms concentrate on one of these two categories, with just a few studies focusing on combining both.

Generally, navigation techniques may be categorized into two diverse groups. The first category consists of map-level global planners that can calculate the quickest or most viable route between two points on a map. Dijkstra and RRT are traditional algorithms in the field. The second approach is the local planner, which aims to provide a viable, collision-free path for steering the UAV away from obstacles [47]. In visual and laser Simultaneous Localization and Mapping (SLAM), UAVs may navigate without a Global Navigation Satellite System (GNSS). It uses sensors by utilizing monocular or stereo photos in real-time to map the surroundings and locate the camera [140], [141], [142]. Feature-based and direct visual SLAM algorithms cannot recognize tiny objects, requiring time of flight, infrared, or ultrasonic sensors to improve collision avoidance close to objects (typically 2 m) [39]. Table VII provides whether an algorithm is executed on a global or local planner level. Most algorithms for avoiding collisions, swarm, and optimizing routes are global. This means they may be unable to detect all stationary or moving objects.

Table VII provides a broad overview of current studies on drone navigation and safety in collisions with other objects and drones, as well as a general comparison of the suggested algorithms, their nature, and their testing environment.

According to Table VII, the proposed algorithms can be classified into the following types of obstacles:

a) Collision with fixed obstacles
b) Collision with moving obstacles
c) Collision with multiple obstacles (Crowd Space)
d) Collision with other drones

Table VII indicates that some frameworks have concentrated on just one of the scenarios. Some algorithms have investigated two or more of the above barriers. However, each of them faces the limitations of needing a prior map of the environment or complex and expensive infrastructure.

One of the areas that have gotten less attention in the studied algorithms is collision prediction. Most algorithms are accomplished with approaches like analyzing the route before moving or viewing the obstacle using sensors and cameras Most of the above collision avoidance strategies assume. barriers are circular or elliptical. No-fly zones are frequently vast and specified as 4D polygons. Thus, the assumption may need to be more feasible and efficient. Approximating a big zone as a cylinder might lead to excessive flight plan modification, increasing battery danger. In metropolitan areas, there may be no passage between the cylindrical structures. Considering irregularly shaped barriers and tactical deconfliction is crucial for UAV operations in challenging areas [77].

B. Algorithm's Type

Several notable contributions propose aviation dispute resolution strategies. Geometric [135], [143], force field [131], [132], optimum trajectory [119], and Markov Decision Process (MDP) [108], [110] approaches are the most used [144]. Numerous suggested algorithms using mathematical approaches [5], [72], [89], [105], [129] and ML [100], [128] need a strong processor and memory space, which cannot accommodate most UAVs operating in the real world.

TABLE VI
SUMMARY OF UAVS PATH OPTIMIZATION ALGORITHMS

Author	Solution	Remarks	Metrics	AI Technique	Algorithm hired
[123]	Trajectory generation in high speed	Did not consider energy usage in performance metrics.	Task completion percent, success rate, best lap time, jerk	Imitation learning	Perceptual awareness of a CNN Train
[124]	Trajectory optimization	Optimized trajectory has almost four times larger snap and yaw acceleration.	Trajectory time, smoothness	Supervised Learning	Gaussian process classification
[125]	Trajectory prediction and obstacle avoidances	The success rate reduces to under 60% when the forward speed hits 10 m/s.	Success rate, forward speed, processing latency, rotation latency	Supervised Learning	convolutional neural network
[122]	Generating perching trajectories	Moving impediments and environmental constraints were not considered.	Collision avoidance constraint, line reprojection error, line chirality and segment visibility	-	Nonlinear Programming optimization
[126]	Task offloading to UAVs and trajectory planning	Did not consider other environmental hazards like objects and UAVs.	Algorithm performance of user nodes.	RL	Q-Learning ,MDP
[127]	Drone routing algorithm	Limit to one drone and did not refer to the multi-drone routing problem.	Accuracy, impact to accuracy, number of classification outputs	Supervised Learning	Decision Tree and k-Nearest Neighbours
[128]	UAV track planning	Relatively high computational cost.	Velocity deviation rate	DRL	Graph Attention Network and Deep Q Network
[129]	Collision-free path planning for multiple UAVs	Low Performance due to the complexity of the algorithm.	Mean execution time, trajectory generation performance, distances of most dangerous UAV with others	-	Bio-inspired general tau theory of harmonic motion
[119]	UAV path optimization	Flight distance rose over 20% compared to the distance-based Dijkstra.	Cost, flight distance, computational time, Average percentage of the time	-	Extension of the Dijkstra with heuristic information
[12]	UAV path planning	Limited to fix obstacles, not considering energy and flight time in metrics.	Collection ratio, collection ratio, and landed	DRL	DDQN
[121]	Visual path following	Vision algorithms for point feature recognition and tracking are not efficient in low-textured & high-speed.	Errors of the visual task, velocities	-	Homography-based visual servo control
[130]	Multi-UAV trajectory optimizing	Utilizes a safety controller that relies only on a grid-based representation of the environment for collision avoidance.	Communication fulfilment, collection ratio, collection ratio, and communication	DRL	DDQN
[118]	UAV trajectory generation	Low UAV velocity (maximum 2 m/s).	Velocity, acceleration, planning time, trajectory running time, length, and smoothness	-	B-spline curves and A* search
[49]	Path optimization based on UAV sensors	The UAV employs a partly visible state that prioritises its local surroundings rather than the full deployment region .	Percentage of collision, probability of a distribution function of extra travelled distance and number of success before a failure	DRL	Probabilistic model, DQN
[116]	Path planning based on obstacles interest points	limit to fixed specified rectangular forms barriers with interest points defined at their corners to decrease path.	Total distance travelled, error in trajectory tracking, execution time	-	Dijkstra
[131]	Path planning while multiple obstacles avoidance	Limit to fix obstacles and multirotor UAVs with speeds up to 10m/s, depending on sensors quality	Acceleration, UAV and. barrier shortest distance	-	Cauchy Artificial Potential Field
[132]	Path optimization among multi obstacles	Limit to fix obstacles ,and UAV maximum velocity is 1 m/s in real experiment.	Repulsive force	-	Artificial Potential Field
[133]	UAV path planning in 3d environment	Suffer from high computational cost	Path distance, cost / time	-	Dynamic programming
[134]	Path planning among static obstacles	Limits to static obstacles	Distance between endpoint and destination, number of obstacles, dispersion of velocity field, energy	-	Artificial Potential Field
[86]	Conflicts in logistics transportation with non-cooperative UAVs	Higher accidents in dense airspace compare to manned aircrafts	Success rate, flight duration, collisions for every 10,000 hours of flying	DRL	A* Algorithm
[135]	Path planning around multiple obstacles	Limit to fixed obstacles and 2D environment	Flight time, number of obstacles, distance	-	Euclidean Geometry
[136]	Route optimization and collision avoidance in UAV control	Low success rate (66%)	Rate of success, speed of learning, and performance in avoiding collisions.	DRL	Soft actor–critic and hindsight experience replay

On the other hand, owing to the delay and time necessary for setting up and training these algorithms, their implementation in real-time is not anticipated, and the present latency may result in operation failure or drone collisions.

Rule-based [97], [100] and geometry-based [70], [77] methodologies, artificial PF [101] algorithms as well as numerical optimization [118], [120] methods are used to prevent UAV collisions. They are easy to implement, but each platform and use case needs distinct rules. Artificial PF approaches are also susceptible to the narrow channel problem. When there are several obstacles, minimal separation is not ensured. Hence, rule-based and artificial PF techniques need less computation than numerical optimization. Numerical optimization may minimize separation and optimize energy or time [77]. Most studies optimize swarm [5], [73] behavior globally to optimize collective decision-making. NN-based collision

TABLE VII

SUMMARY OF ALGORITHMS CAPABILITIES, COLLISION TYPE, ML METHOD, AND SIMULATION TOOLS

Article	Obstacle Type				Method		ML Type			Multi UAV	Destination Reaching	Path planning	Global planner or Local planner	Demonstration Method		
	Static objects	Moving objects	Other UAVs	Multiple obstacles	Prediction	Avoidance	Supervised	Un-supervised	RL					Real Testbed	Simulation	Demonstration Tool
[63]	✓	✓	✓	✓	✓	✓	✓				✓	✓	Local	✓		Testbed
[123]							✓				✓	✓	Global and Local	✓	✓	Gazebo and testbed
[61]	✓	✓		✓			✓				✓	✓	Local		✓	Flight Goggles
[76]			✓			✓	✓		✓	✓	✓	✓	Global		✓	Python 3.6 and Pytorch
[100]			✓			✓			✓	✓	✓	✓	Global		✓	Simulator not mentioned
[59]	✓						✓						Global		✓	ROS-gazebo
[124]							✓					✓	Global	✓	✓	Multicopter simulation and testbed
[125]	✓			✓			✓					✓	Global and Local	✓	✓	Tensorflow in Python and C++, and testbed
[47]	✓	✓		✓							✓		Local		✓	Matlab
[56]	✓	✓		✓							✓		Local		✓	ROS Kinetic framework and V-REP
[5]	✓	✓	✓	✓		✓				✓	✓	✓	Global		✓	Developed a software simulator
[74]			✓			✓				✓			Global		✓	AnyLogic
[89]	✓	✓	✓		✓	✓				✓			Global		✓	GAMA agent-based simulation framework
[62]			✓				✓						Global		✓	Python script and open-source Keras API
[108]	✓	✓					✓		✓	✓			Global	✓		Testbed
[126]									✓		✓	✓	Global		✓	Simulator not mentioned
[127]							✓				✓	✓	Global		✓	Java and Python
[73]						✓				✓			Global and Local	✓	✓	AnyLogic and JaamSim simulators and Testbed
[2]			✓		✓	✓			✓	✓	✓	✓	Global		✓	Air Traffic Simulator BlueSky
[58]	✓			✓	✓	✓	✓						Local	✓		Testbed
[16]					✓	✓				✓		✓	Global	✓		Real-world urban environment
[122]	✓					✓					✓	✓	Local	✓		Real quadrotor
[75]			✓		✓	✓				✓			Global		✓	Matlab
[77]	✓		✓		✓	✓				✓	✓	✓	Global	✓	✓	Numerical simulation and testbed
[98]						✓				✓	✓	✓	Global		✓	IBM ILOG programming environment
[70]	✓	✓	✓	✓	✓	✓						✓	Global		✓	Numerical simulation
[129]					✓	✓				✓	✓	✓	Global		✓	Matlab
[119]	✓			✓		✓					✓	✓	Global		✓	Simulator not mentioned
[12]	✓					✓			✓		✓	✓	Global and Local		✓	Python
[78]			✓			✓				✓		✓	Global		✓	IoDSim integrated with OMNeT++
[92]	✓		✓	✓	✓	✓				✓	✓		Local		✓	SwarmLab and Python
[72]			✓		✓	✓						✓	Global		✓	Developed a simulator
[101]	✓	✓	✓			✓				✓			Global		✓	Numerical simulation
[60]		✓			✓	✓	✓						Local	✓	✓	Simulator not mentioned, and testbed
[93]			✓			✓				✓		✓	Global		✓	Numerical simulation
[121]	✓			✓		✓					✓	✓	Local	✓		Testbed
[51]	✓												Local	✓		Testbed
[13]			✓		✓	✓					✓	✓	Global		✓	Matlab
[130]			✓			✓			✓	✓		✓	Global and Local		✓	Monte Carlo simulation
[105]			✓			✓				✓		✓	Global		✓	Numerical (GUROBI)
[118]	✓			✓		✓						✓	Local	✓	✓	Matlab and testbed
[10]			✓		✓	✓				✓		✓	Global		✓	SIMUdrone and HIL simulation
[21]			✓			✓				✓	✓	✓	Global		✓	Simulator not mentioned
[49]	✓	✓		✓		✓			✓		✓	✓	Local		✓	OpenAI Gym
[116]	✓			✓		✓					✓	✓	Local		✓	MATLAB's UAV Toolbox
[50]	✓	✓		✓	✓	✓						✓	Local	✓	✓	C++ with ROS/Gazebo
[55]		✓		✓	✓	✓				✓		✓	Local		✓	Matlab(Numerical simulation)
[131]	✓			✓		✓				✓		✓	Local	✓	✓	Ardupilot SITL (Software-in-the-loop)
[132]	✓			✓		✓						✓	Local	✓	✓	Gazebo
[79]	✓	✓	✓	✓		✓			✓	✓	✓	✓	Local		✓	ROS-STAGE platform
[112]	✓		✓	✓		✓			✓	✓	✓	✓	Global		✓	Numerical simulations and high-fidelity HITL simulation
[80]	✓					✓			✓			✓	Local	✓	✓	PX4 firmware in Gazebo
[113]			✓			✓			✓	✓		✓	Global		✓	Numerical simulation and semi-physical simulations

TABLE VII

(Continued.) SUMMARY OF ALGORITHMS CAPABILITIES, COLLISION TYPE, ML METHOD, AND SIMULATION TOOLS

[81]			✓		✓		✓	✓		Global		✓	Matlab
[133]	✓	✓			✓			✓	✓	Local and Global		✓	Matlab
[134]	✓			✓	✓			✓	✓	Local		✓	Matlab
[83]			✓		✓	✓	✓			Global		✓	OpenAI Gym
[71]			✓		✓		✓		✓	Global		✓	Numerical simulation(Matlab)
[82]	✓		✓		✓	✓	✓	✓		Local		✓	Simulator not mentioned
[86]			✓		✓	✓	✓	✓	✓	Global		✓	Numerical simulation
[135]	✓			✓	✓				✓	Global		✓	Matlab
[104]	✓		✓	✓	✓		✓			Local	✓	✓	Crazyflie
[84]			✓		✓	✓	✓			Global		✓	simulated real-world operational conditions
[136]	✓			✓	✓	✓		✓	✓	Local		✓	Simulator not mentioned
[64]	✓	✓		✓	✓					Local	✓		Crazyflie

avoidance [100], [111], [125] requires plenty of training data for actual drones. Mathematical optimization approaches discovered the optimum route for all agents in the environment but did not allow for independent learning.

Evolutionary algorithms concurrently evolved the swarm's collective behaviors to find all agents' ideal parameters. Apart from that, offline pre-training and global optimization usually require much time. and extensive calculations, making them difficult to implement in real-world, online decision-making settings [99].

C. Automation and Artificial Intelligence

The complexity, variety, and technological advancements of modern UAV missions drive their pursuit of greater autonomy and flying stability [136]. As a result, autonomous UAVs with pre-programmed routes, identification, and avoiding obstacles algorithms on computers have been developed [135], [145], [146]. In the bulk of the reviewed algorithms, supervised learning methods are used to identify and avoid obstacles. In supervised learning, algorithms employ input and output data sets. It can only be used with adequate labeled data like object detection and avoidance algorithms. Other than that, unsupervised learning techniques need training data without labeled output. In unsupervised learning, data is clustered, or patterns are discovered [22]. Given the agent's interaction with the environment, RL algorithms are suitable for collision avoidance and swarm algorithms. The taxonomy of UAV navigational problems according to the ML techniques used in the surveyed literature is presented in Fig. 4.

Despite recent attention, few publications use DL approaches for semantic scene interpretation of UAV photos [37], owing to the high spatial resolution and 3D data collection capacity. DL papers concentrate on image classification, semantic segmentation, and object recognition [39]. Although CNN is the most popular architecture for UAV remote sensing and picture applications, CNN, Long Short-Term Memory (LSTM), and Generative Adversarial Networks (GAN) are gaining traction as viable alternatives for future UAV remote sensing efforts.

RL is learning to optimize a numerical reward signal by mapping the environment to actions [147]. The core of RL is a clever, interactive agent with a definite goal. Hence, policy, reward, value, and environment models are critical components of RL. The policy specifies the agent's course of action. Rewards are delivered to an agent by the environment in response to an action. Meanwhile, the environment model reflects the ambient behavior that aids the algorithm's efficiency by enabling it to comprehend its environment. RL algorithms may use agents to explore their environment [31], [148]. When RL is paired with deep learning's superior comprehending capabilities, RL is more efficient at generating decisions than humans in practically unlimited state space [82]. Apart from that, it may train for many cycles without context knowledge and yet learn to make the most effective choices. Therefore, RL is more crucial than other ML algorithms in avoiding UAV collisions.

Reinforcement learning has already been suggested, along with other approaches, for automating the conflict detection and resolution function in ATM [149]. In summary, the proposals currently have limitations in handling complex traffic conditions. They only consider decisions for individual agent in situations where there are conflicting pairs of agents. Additionally, they rely on an all-knowing agent to resolve conflicts in specific areas, and this agent has a limited range of actions to resolve conflicts. The suggested methods have not undergone training, testing, and validation in real-life scenarios. Consequently, they do not provide insights into the advantages and constraints of reinforcement learning techniques in actual operational environments [84]. Collision resolution methods that rely on multi-agent reinforcement learning face challenges in achieving high success rates, particularly in scenarios with high agent density [2], [76], [79]. This is primarily due to the inherent non-stationarity in multi-agent reinforcement learning, which makes it difficult for an agent to accurately predict the actions of other agents, as well as the dynamic nature of the environment [150].

Reinforcement Learning (RL) has the benefit of rapid processing speed. Applying reinforcement learning (RL) techniques to solve Constraint Satisfaction Problems (CSR) involves two primary stages. The first phase entails training the neural network implemented on an agent inside a specifically designed reinforcement learning environment to obtain an effective policy (training process). Subsequently, the agents

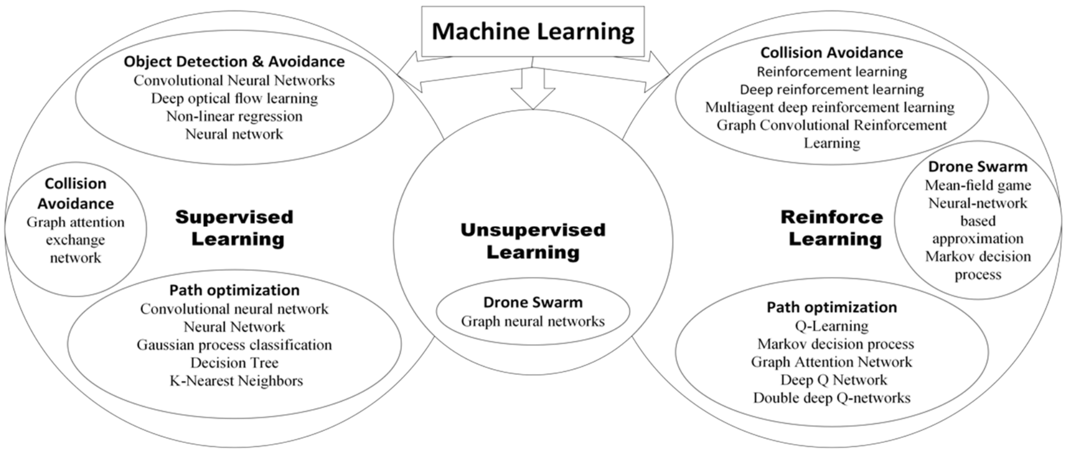

Fig. 4. Machine learning algorithm types used for drone collision avoidance and swarm.

equipped with the taught neural network are deployed to a cognitive radio instance to resolve the problem (solving process). While the training process is often characterized by its time-consuming nature, the solution procedure is typically executed swiftly. After training the neural network, the solution process becomes rapid and effective, especially in intricate and densely populated situations. Reinforcement learning (RL) approaches provide a substantial portion of computational resources to the training phase, enabling them to promptly adapt to environmental changes by making real-time updates to decision-making [150].

Safe Reinforcement Learning (SRL) is a specialized area under RL that focuses on training agents to develop policies that optimize anticipated returns in situations when it is crucial to maintain acceptable system performance and safety throughout the learning and deployment stages [151].

Smoothness actions in controllers based on reinforcement learning are crucial for practical use, and current approaches focus on manipulating rewards. However, there are difficulties in adjusting parameters and ensuring the correct behavior [152].

Many current studies in the reinforcement learning topic concentrate on a few agents, ignoring the importance of agent collaboration in decision-making or focusing entirely on individual agent choices. The simultaneous execution of actions by independent agents results in a non-stationary environment since each agent's activities cannot wholly explain environmental changes. This brings diversity into the learning process. Furthermore, some techniques only examine a subset of dispute resolution behaviors [84].

Deep reinforcement learning (DRL) emerges as a promising solution. In particular, Soft Actor-Critic, an off-policy DRL algorithm that optimizes stochastic policy within a maximum entropy framework, stands out as a promising solution. It has advantages over its predecessors, such as a deep deterministic policy gradient, in handling large states and action spaces with superior robustness and exploration. Nevertheless, because of the maximum entropy character of the framework, Soft Actor-Critic 's effectiveness may decrease throughout the steady-state period. In order to improve learning outcomes even without goal achievement, Hindsight Experience Replay enhances DRL algorithms such as DDPG by allowing learning from successes and failures comparable to human learning processes. Though Hindsight Experience Replay can handle huge state and action spaces, its reactivity to hyperparameters makes it unstable [136].

Imitation learning for vehicle collision avoidance [153] improves some challenges of RL training in the preliminary stages. It may also be efficient for UAV collision control algorithms. Various AI and ML training methods need servers with substantial processing power and data storage and cannot be trained and implemented on drones directly. Therefore, implementing drones and providing hardware is a significant challenge. A further challenge is possibly having a communication network with the appropriate bandwidth to collect the required training data from other parts of the drone networks.

D. Metrics

Tactical conflict resolution techniques disregard the time limits of the predefined strategic trajectories, which may cause drones to miss their next trajectory points during tactical conflict resolution. This might exacerbate secondary conflicts and even cause a "domino effect" [86], [154]. Existing empirical studies have supported the extensive use of AI in drone algorithms. However, algorithms have yet to be done without considering the primary constraints of drones, such as their high energy consumption or limited capacity for data processing. Most metrics utilized in collision prevention algorithms depend on the proposed algorithm's collision rate. Other than that, lack of metric consistency is the case regardless of the amount of energy consumption, computational capability, or data storage the suggested algorithms have. Providing intelligent algorithms or collision avoidance that is practical for the conditions and limitations of UAVs is one of the fundamentals that cannot be disregarded. It is especially important when considering the constraints that currently exist in UAVs. The lack of homogeneity in the domain's measurements is one problem to draw attention to it. Some studies use measurements particular to the environment to assess their methodology [9].

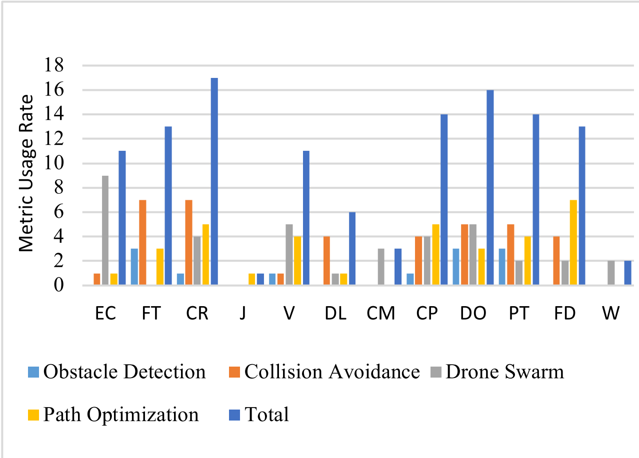

Fig. 5. Summary of metrics used for validation. Energy Consumption (EC), Flight Time (FT), Collision Rate (CR), Jerk (J), Velocity (V), Delay/Latency (DL), Communication Cost (CM), Computational Cost (CP), Distance to Obstacle (DO), Processing Time (PT), Flight Distance (FD), Wind Speed and Direction (W).

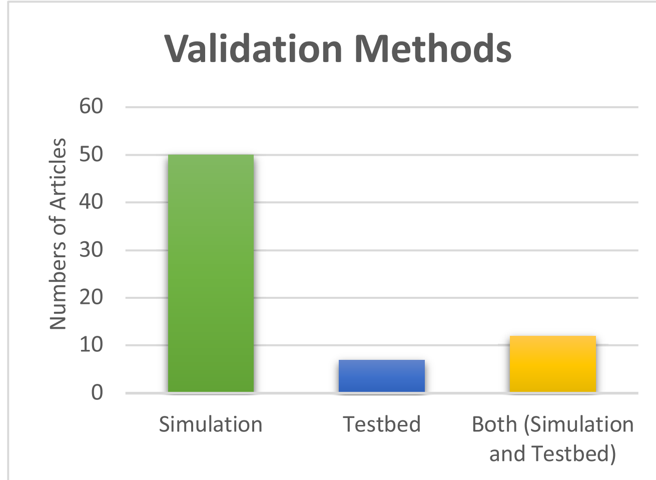

Fig. 6. Validation methods.

We examined the important metrics used in the reviewed collision avoidance articles. Fig. 5 depicts the ratio of using different metrics to evaluate the effectiveness of reviewed UAV collision avoidance algorithms. The Tables III, IV, V, VI and Fig. 5 demonstrate great diversity and heterogeneity using investigation metrics. Many studies need to pay more attention to crucial elements like energy consumption, velocity, and flight time. They represent a severe problem in completing missions due to drone energy limits. The failure to address speed and flight length is partly due to a need for more understanding of mission planning and scheduling. Most research has focused on the cost of calculations, which will be significant given the constraints of the processing capability of drones.

Perceptual latency is the time it takes to take in information from the environment, process it, and utilize it to make decisions [155], [156], [157]. It is a crucial measure to consider when developing algorithms to prevent accidents. Perception delay becomes increasingly important when the UAV and object travel at greater relative speeds [60]. Jerk [123], wind speed [98], and direction [105] are seldom used metrics, which may make using the offered solutions in real-world scenarios problematic. Furthermore, drones may experience extreme shaking and unexpected movements due to the lack of consideration of jerk measurement, which may negatively influence the drone's performance and increase the energy used. Moreover, inadequate consideration for wind intensity may cause drones to deviate from their planned direction, mishaps, and accidents with barriers and other nearby objects.

One of the main elements disregarded or bypassed in many algorithms is the energy consumption of collision avoidance algorithms. Algorithms move away from the barrier by modifying the angle of movement to avoid collision, change their direction, or raise or reduce the speed or altitude, all of which substantially impact the UAV's energy consumption. The more significant deviation from the main path causes more time and distance for the drone travel and more energy spent. Meanwhile, some collision prevention algorithms have attempted to cut energy consumption by shortening the distance between the drone and the barrier [92], [158], lowering deviation from the primary path [49], and minimizing motion energy [100]. In [100] goal is to minimize the remaining trip distance by maximizing the speed towards the destination, and minimizing the anticipated speed in the opposite direction of the destination. It also reduces kinetic energy and acceleration control energy by minimizing the proxy terms speed and acceleration. The restricted speed change and higher energy consumption of a fixed-wing UAV are evident compared to its angle-changing counterpart [71]. However, most research has no priority list for avoidance activities to conserve more energy.

E. Validation and Simulation Methods

Simulations of drone traffic demonstrate a variety of traffic densities, from 0.001 to 22.37 flights per square kilometer. Simultaneous drone flights per square kilometer can be a suitable metric for comparing simulations with different settings and traffic structures. Free flying requires densities greater than 1.0 simultaneous flights per square kilometer [8], [159]. Given the high expense and inherent danger of conducting actual collision tests with several drones in a swarm, most researchers have instead relied on simulation to demonstrate the efficacy of their approach, as illustrated in Fig. 6. The described methods have been tried and assessed on various simulators based on Table VII. Many algorithms need the necessary capabilities due to the absence of comprehensive simulators with high capabilities. However, most suggested algorithms have only been evaluated via simulation since building algorithms in the real world is expensive. As a result, these algorithms may encounter significant difficulties in the actual world owing to the restrictions in the simulation environment. Algorithms need adaptability for environmental and meteorological issues like wind and rain.

Simulating have shown their value as a beneficial tool for training and testing in autonomous drones. Nevertheless, they demonstrate constraints compared to actual experiments conducted in the real world. In case study [125], the efficacy of the acquired strategy diminishes considerably at high velocities, namely when reaching or above 10 m/s. Furthermore, there is a significant disparity between the simulated and actual drones regarding dynamics and perception. Many reasons, such as aerodynamic effects, motor delays, and the decline in battery voltage, may explain this discrepancy. Perception delay is a significant concern that is more noticeable while traveling fast. Notwithstanding these difficulties, simulations continue to be an essential intermediary in advancing high-speed autonomous systems.

The case study [160] emphasizes the limits of simulations in contrast to genuine testing, particularly when comparing experiments and simulations. Although the findings are generally consistent, variations become apparent, especially in situations when there is a loss of communication packets. This loss substantially influences collision avoidance approaches and the time it takes to respond. Packet loss, particularly noticeable at increased relative velocities, hinders the starting point of collision avoidance maneuvers, restricting both the distance and speed of response. Nevertheless, the collision avoidance algorithm somewhat reduces these impacts, guaranteeing collision avoidance even in the presence of a 10% loss of packets. Another notable difference is seen in speed patterns at large magnitudes when actual UAVs have difficulties attaining and sustaining their maximum speeds owing to battery constraints.

Consequently, the simulated tests exhibit reduced minimum relative distances compared to the actual trials. Furthermore, disparities emerge due to variations in acceleration between models, where unmanned aerial vehicles (UAVs) accelerate evenly, and actual tests, when external elements such as wind affect acceleration. Finally, discrepancies in GPS measurements during experiments result in asymmetrical outcomes compared to simulations. This impacts the goals' initial placements and accuracy, exacerbating the differences between the experimental and simulated results.

Fig. 7. in the case study [160] provides a compelling visual representation, emphasizing the disparities in paths, speeds, and closest proximity between the simulation and actual experimental results. The graphic depiction highlights the constraints of simulations in contrast to real-life testing.

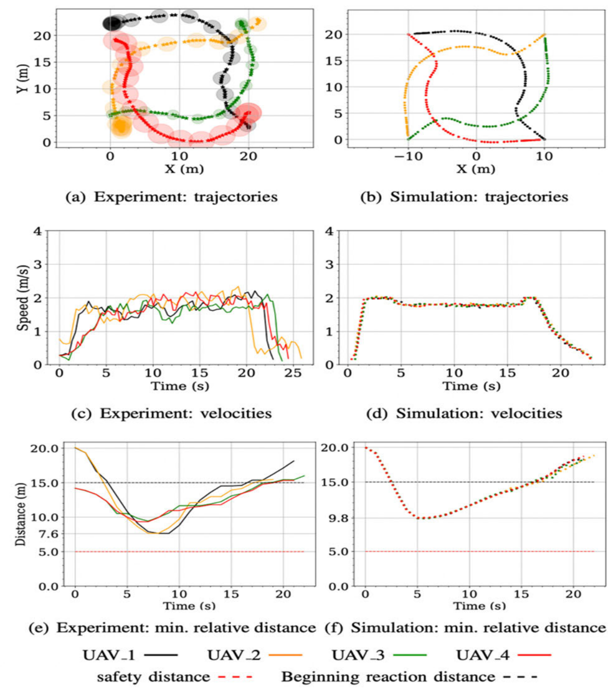

Fig. 7. Comparison of simulation and real experiment [160] (©2020 IEEE).

F. UAVs Communication Network

Researchers must focus on networked communication due to the multi-UAV systems' explosive expansion and growing relevance. Network communication differs from typical wireless networks regarding mobility, networking models, and communication requirements [25]. UAV communications are crucial in 5G and future networks, especially for control linkages. However, getting precise Channel State Information (CSI) is challenging due to the dynamic wireless environment brought on by high-speed UAV movement. Accurate prediction models for non-stationary channels are required to overcome the difficulty and provide trustworthy CSI for efficient UAV control [161]. UAV swarms need dependable control signal transmission. UAV swarms use a mobile ad hoc network (MANET) or a vehicular ad hoc network (VANET) for low-speed mobile terminals in a two-dimensional space. The existing communications protocol stack also ignores UAV-specific communications models and quality of service issues. As more UAVs join a network, wireless connection breaks, and end-to-end latency rises [88].

In most studies on collision avoidance [2], [16], [70], [75], [76] and drone swarm [5], [98], [107], [109], [110], [111], drone-to-drone networks and communication should be discussed in detail and addressed. In some cases where drone networks and communication linkages have been studied, the fundamental problems, such as inclement weather like snow and rain, wind and lightning, and uneven terrain like mountains, have either been overlooked or not considered in the frameworks. Some research, like [73], [74], and [77], proposed frameworks for collision avoidance using centralized networks. Other researchers [89], [100], and [108] in drone swarms offer peer-to-peer networks for a drone to drone communications. Scalability concerns plague VANETs' designs since deploying services in a large-scale, dense, dynamic topology is challenging. These designs are stiff, difficult to manage, and need more control, flexibility, and adaptability. Other than that, these limitations hamper system functionality and hinder creativity, often leading to the underutilization of network resources [162]. In some proposed systems, drones communicate with their neighbors to avoid collisions. Lack of awareness about other UAVs approaching drones from afar poses a substantial issue in preventing collisions.

To optimize inter-swarm communication, a study distributed UAV swarm networks in various forms without centralized control. ML approaches that cluster UAVs by location, sensor type, and data type are essential for multi-UAV cooperative data transfer [22]. SDN may provide flexibility, scalability, and programmability to UAVs ad hoc networks using existing network resources more efficiently and introducing new services [74], [162]. Nevertheless, the vast majority of SDN-based systems presented are infrastructure-based and centralized [162]. The dynamics of the drone network provide communication and reliability problems for centralized and ad hoc networks. Building a centralized network platform, including ground or air stations for centralized networks, will cost significantly. Nevertheless, it will be expensive for the drone in ad hoc networks since each drone must separately gather and process the data of other drones to prevent a collision. Moreover, drones' limited capacity to keep and analyze data and energy limitations have posed various concerns while utilizing an ad hoc network. On the one hand, the need for safer and more reliable communication and failure to consider environmental problems will make it difficult and dangerous to develop and use most of the suggested algorithms for drone collision avoidance in the real world.

IV. Discussion

Since ATM and UTM differ in size, platform, and non-segregated operating airspace, the algorithms created for ATM may not provide enough safety and efficiency for UTM. Collision avoidance algorithms, which direct each UAV to maintain a safe distance from vehicles and no-fly zones while in flight, are one of the essential services that need further development and validation for UTM [77].

Drone automation has been investigated, by several solutions for drone automation have been created. Note that changes in the weather and environment provide considerable obstacles. There is a broad spectrum of drone activity and application in many sectors and diverse types of drone action based on operational missions. Other than that, takeoff to attain the desired height, selecting and altering path, reducing, and increasing velocity and altitude, and avoiding collisions with fixed and moving objects and other drones are all included. UAVs need sophisticated solutions, algorithms, and frameworks. Due to drones' capabilities, restrictions, and expanding utilization in various industries, new challenges are emerging.

A. UAVs Security

One crucial concern that still needs to be addressed in the evaluated studies is the security of the UAV network and data. It may threaten both the security and data processing of the UAV and the overall efficiency of the proposed framework. Safe UAV-to-UAV communication links are critical to protecting UAV collision avoidance systems from attackers.

One significant difficulty is ensuring the security of sensitive data from drones or UAVs, such as position and location. Note that UAVs lack encryption and are vulnerable to hijacking. Hacking and cyber liability are serious concerns while utilizing UAVs. UAVs are prone to data leakage concerns during military operations. Hackers may seize entire control of a UAV to steal data, invade privacy, or engage in illicit activities such as smuggling [163]. In many presented studies, drones exchange their precise position and flight time with neighboring drones or other equipment in other areas to avoid a collision. Aside from privacy concerns, it may seriously endanger the drone. Safe drone-to-drone communications using blockchain, proposed in [164], would increase the computational burden [78]. The location privacy protection technique applies to the IoDs and integrates with other network environments and heterogeneous applications vulnerable to location assaults. For the IoD, [165] proposed a scheme for drones' anonymity and untraced ability. However, none of these security methods hired in mentioned collisions avoidances systems except in [166].

To guard against a location assault, a mechanism called MixDrones [78] was developed, where drones may modify their in-flight airways in a mix zone. UAVs confront security difficulties like hijacking, denial-of-service attacks, and GPS signal spoofing. These assaults may result in a loss of control, an interruption in communication, network congestion, and unreachability issues. Meanwhile, there are countermeasures for single UAV networks, with the multi-UAV systems needing algorithm development. Current simulation test beds and emulators are inadequate, necessitating the development of customized tools [167]. Security evaluations often ignore UAV software and hardware variances, necessitating uniform security solutions applicable to all kinds. Other than that, data leakage and compromised commands are two ground control systems vulnerabilities that may be prevented using authentication. Various attacks use weaknesses such as misdirection, eavesdropping, manipulation, and interception [163].

The safety of UAVs and UAV operations is highly stressed in the present in effect UAV-specific legislation. However, the discussion of safety is often technical (weight or height of flight), focuses on vehicle registration, and emphasizes user certification. Privacy often comes second regarding UAV-specific law. Nevertheless, the General Data Protection Law (GDPR) offers a foundation for data collection and processing privacy [24].

B. Ethical Implications of Drone Collision Avoidance

The development of drone collision avoidance systems is both a technological and an ethical problem [41]. Drone usage for humanitarian and commercial purposes presents several moral conundrums and issues, including privacy, security, accountability, transparency, and trust. Drone collision avoidance technology, for instance, needs to safeguard the dignity and privacy of individuals. Additionally, it needs to guarantee the security and dependability of the drones' info. Furthermore, it must make clear who is accountable and liable for any dangers or damages brought on by drone collision prevention technologies. It should also be responsible to the public and stakeholders and transparent. Lastly, drone users and beneficiaries need to promote acceptance and confidence. In line with humanitarian ideals and values, these ethical concerns must be considered throughout drone collision avoidance technology's design, development, and implementation [168].

The rapid advancement of drone technology has provided numerous advantages across diverse domains, including but not limited to package transportation, surveillance, and search and rescue operations and humanitarian. Nevertheless, similar to any novel technology, ethical considerations necessitate meticulous deliberation. A primary ethical issue associated with drone collision avoidance technology is the possibility of infringing upon individuals' privacy. Uncrewed aerial vehicles equipped with cameras and other sensors can gather vast data, encompassing visual images and recordings of individuals and their actions. This data can be utilized for monitoring objectives, potentially encroaching upon individuals' private rights.

Another ethical concern arises from the possibility of unintended harm to non-targeted individuals or entities, commonly called collateral damage. Drones have the potential to inflict unintentional damage to individuals and assets in the event of malfunction or wrong usage. This can give rise to legal and ethical quandaries, particularly in circumstances where the application of physical coercion is implicated. Unfortunately, most related research does not refer to or oversee ethical problems.

C. Destination Reaching

Many studies and suggested algorithms concentrate on avoiding obstacles by deviating from the path without assessing the cost of deviation from the mission path during the entire drone flight until it reaches its target. The cost of deviating from the path increases flight time, energy consumption, and the computational load of alternative route processing. It is vital to include reaching its destination as well as the time and energy required to complete the flight. This is to provide a more realistic comparison of the suggested algorithm and avoid risks during the flight in actual missions.

D. Real-Time Reaction

When UAVs struggle to capture moving scenes, they must monitor a moving target in real-time, estimate target and environment updates, design a plausible trajectory, fly along the trajectory, avoid obstacles, complete the firing mission, and manage crises [38], [169]. Adding more sensors would increase the amount of data to be analyzed, thereby requiring more processing resources [64] and processing time.

More commercial platforms (fixed-wing and rotor) have developed autonomous takeoff, landing, and advanced flight acquisition capabilities during the last five to ten years [39], [170], [171]. These systems rely on pre-planned flights and GNSS. Only some modern models can recognize and avoid obstacles. However, more recent commercial platforms include extra sensors (cameras and distance sensors) to identify significant barriers. They also prevent collisions by forbidding them from flying too close to objects or stopping them before the crash [39].

Most suggested algorithms, like [119], are pre-planned and lack the necessary responsiveness in emergency maneuvers and real-time situations to avoid collisions and hazards. As a result, more usage of AI to forecast real-time occurrences will be a fundamental need to avoid collisions and disasters. Drones will need vast information to analyze in real-time to provide a broad and real-time perspective of the surrounding area. Furthermore, while pre-planning plans to optimize the path and avoid collisions, it cannot identify and avoid moving impediments, particularly other drones, making the execution of these plans' real-time response a severe issue.

E. Scalability

Efficiency is critical for conflict resolution in crowded airspace, requiring real-time decision-making to guarantee safety. However, scalability necessitates that the algorithm manages different aircraft counts, mainly as UAS often includes many UAVs. The algorithm must also be robust to adjust to shifting conditions and uncooperative aircraft. Due to their training in settings with a constant number of invaders and subsequent retraining for situations with varying intruder counts, many current reinforcement learning systems need to improve on scaling issues, leading to increasing computing complexity. Reference [152] suggested deep reinforcement learning method for dispute resolution is image-based to address this difficulty. By describing aircraft as pictures rather than discrete states, this technique enhances scalability and can handle any number of aircraft. Furthermore, the suggested approach combines accurate observation data with hypothetical data based on past physics knowledge to improve conflict identification and resolution.

In large Multi-Agent Systems, agents often need more global environmental knowledge, restricting their capacity to make intelligent judgments. Furthermore, as the number of agents increases, maximizing activities collectively becomes difficult due to the vast range of alternative states and actions. As a result, traditional MARL experiences scaling problems, particularly with exponential agent increments. To address this constraint, current research has focused on addressing scaling issues in MARL by adding mean field theory [172].

The capacity to handle many controlled flights and transparency in operations are essential concerns for any AI technology used in collision detection and resolution operational situations. Scalability is essential for maintaining high-quality solutions in environments with higher levels of traffic without compromising the safety and efficiency of flights. Operational transparency has not been sufficiently addressed in a collision avoidance environment nor verified for any of the current AI-based methods [84].

F. Adaptability to Different Environments

Heuristic-based search approaches are dependable and efficient for accomplishing collision avoidance and resolving conflicts among small numbers of UAVs—the most typical situation in reality today. Nevertheless, collision avoidance pathways developed by this technique may suffer from secondary conflict difficulties, making it less appropriate for UAV conflicts, particularly in congested airspace. The goal of optimal control techniques is to minimize the time delay between UAVs; however, due to their relatively sophisticated theories, which might increase processing and impair anti-interference capabilities, these approaches cannot match real-time requirements [82].

Geometric algorithms, optimum control theories, and heuristic algorithms are some of the most often used techniques for dispute resolution. However, there is a need for more commonly acknowledged dispute-resolution methods. This is largely due to conflicts that often arise in dynamic contexts, resulting in uncertainty. Traditional approaches depend on deterministic models, necessitating unique models for each situation, which may be difficult if the environment changes during computing. While certain optimum control approaches show promise in dealing with uncertainty, they need extra operations, such as defining flight priority or predicting trajectory for multi-aircraft conflicts. Furthermore, these approaches often use complicated models that fail to match the computing requirements of real-time situations. As a result, there is a critical need for a real-time multi conflict resolution approach that can effectively adapt to changing situations [150].

The agent may be continuously controlled in its movements according to the excellent execution efficiency of DRL methods like the deep deterministic policy gradient (DDPG). Nonetheless, the DDPG takes too long to train agents, which makes it challenging to act fast when the urban environment changes significantly, and the agent has to be retrained [82]. Adapting to various unknown surroundings with diverse types of static and dynamic impediments remains a significant challenge for UAV collision systems, demanding further study.

G. Real-World Applicability

Many techniques have yet to be trained and tested on actual surveillance data, instead relying on flight plans and synthetic datasets. The suggested approaches do not include real-world training, testing, or validation. Therefore, they must provide insight into the benefits and drawbacks of reinforcement learning techniques in operational situations [84]. Most previously stated collision avoidance strategies assume constant speed for moving obstacles. However, in reality, varying speeds of objects in uncharted areas pose a significant challenge, highlighting the crucial need for real-time collision avoidance in dynamic airspace for safe UAV operation.

Due to sensor limitations, computational complexity, communication constraints, and ethical and legal considerations, existing collision avoidance algorithms for UAVs face challenges in practical implementation. To address these constraints, it is crucial to evaluate and compare the effectiveness of various collision avoidance techniques in practical, standardized benchmarks and testbeds. A significant obstacle in this regard is the lack of standard datasets and metrics covering different elements of collision avoidance. Moreover, current experimental configurations and simulation platforms may not accurately replicate the environmental factors influencing UAV flight dynamics and sensor accuracy. Therefore, there is a need to provide more authentic datasets, metrics, and sophisticated simulation platforms to support UAV collision avoidance research and ensure secure and dependable operation in real-world situations.

V. Lesson Learned

Several valuable learned lessons from the issues mentioned above can be summarized as follows:

When considering collision methods, a comprehensive approach is required. Note that combining different algorithms to cover different collisions can be costly and inefficient.

Relying solely on a global planner algorithm to ensure UAV safety is insufficient. Small obstacles that can endanger UAVs may go unnoticed without a local real-time plan. Conversely, the local planner algorithms rely on global strategies, particularly during high-speed maneuvers. Since most local planner algorithms are vision-based, their limited vision range may cause them to collide with moving obstacles or other UAVs approaching them.

Local obstacle detection frameworks, such as obstacle detection algorithms, lack an accurate grasp of the larger environment, including other objects and drones. Furthermore, global algorithms, like swarm and routing algorithms, need a better understanding of the specifics of barriers and minor impediments. Composite frameworks that detect remote and close obstacles, tiny or gigantic, may be a viable option. Other than that, the algorithms may consider drone limits and the actual geometry of barriers rather than simplifying them to cylinders and spheres. Hence, it will lessen the risks of a collision, the amount the drone diverges from its intended course, and the amount of energy it needs to operate.

Sudden and abrupt movements on a steep slope in delivery drones may cause cargo damage or render the drone inoperable. It may cause the target to lose control of activities such as target pursuit. As illustrated in Fig. 5, most proposed algorithms ignored the jerk measures. As a result, metrics like jerk should be considered in the algorithms to avoid damage to the drones or cargo by providing smooth trajectories and motions. Furthermore, collision avoidance maneuvers should be confined to reasonable deviation angles and speed variations to minimize such issues.

VI. Future Research Direction and Open Issues

After thoroughly examining existing research, we identified some unresolved challenges in drone collision avoidance that can help advance the field in the future:

- UAV collision algorithms have a substantial problem in adapting to unknown surroundings with fixed and moving impediments, especially in dense environments, requiring additional investigation.
- Further studies will need to focus on finding methods to detect and anticipate the location and velocity of unknown moving obstacles and high-speed UAVs in real time.
- Future studies should focus on enhancing the low success rate (66%) [136] and decreasing the lengthy training period of Deep Reinforcement Learning (DRL) models.
- Limited recent research has addressed the critical concerns of high-speed flying and nimble maneuvering in urban environments.
- Uncertainties in sensor and camera performance, particularly during weather changes and at night, may be addressed and resolved in future investigations.
- Network and communication challenges faced by cooperating agents, especially in multi-agent learning systems, are particularly significant in inclement weather conditions such as rain and snow.

- Enhancing the smoothness of actions [152] and prioritizing action space of agents in RL are important aspects for future exploration.
- Future research may focus on conducting thorough examinations of scalable ML and RL techniques to address conflicts involving a large number of UAVs with high density and wide area.
- Developing integrated global and local planner algorithms like [12] may improve the accuracy and efficiency of global algorithms for identifying tiny and moving objects.
- After detecting a collision, the reviewed frameworks resort to various movement strategies for preventing collision, such as horizontal deviation, velocity adjustments, vertical maneuvers and rerouting. In the future, researchers can combine more movements mentioned above depending on priority, condition, and kind of drone, the cost of energy spent, and the flying duration till returning to the main path.
- One of the significant issues in the drone network is the need for more appropriate information about other drones and the restrictions on their communication which may lead to collisions. As a result, one of the fundamental criteria for preventing collisions is the development of an ideal algorithm or communication structure between drones, which has received little attention in recent research and might be one of the subjects for future studies.
- A few researchers, like [98] and [100], have studied the influence of wind and changing weather conditions in their study work, which might be one of the aims of future research owing to the sensitivity of UAVs and the risk of more accidents in adverse weather.
- The effectiveness of ML algorithms for UAV automation may be investigated regarding computing efficiency and UAV hardware design.
- Important metrics such as energy usage, flight duration, speed, jerk, computation, and communication cost may be addressed while comparing and evaluating the algorithms.
- With a deeper understanding of the environment and the impacts of weather conditions, more comprehensive simulators and tools can be employed.

In the future, we will concentrate on drone communications and networks and the autonomous collision avoidance using ML.

VII. Conclusion

This study thoroughly reviewed drone collision avoidance algorithms, considering criteria such as algorithm type, obstacle characteristics, metrics, and applications. Despite continued progress, drone collisions remain a challenge. Several critical characteristics must be addressed to anticipate drone collisions accurately. These include:

Since most local algorithms suffer from issues like becoming trapped in congested locations, they require a comprehensive understanding of the overall route and destination. Integration with global algorithms can help overcome these challenges. However, global algorithms often need a thorough understanding of barriers, particularly small ones that could cause collisions or result in significant deviations from original routes. Integration with local algorithms presents a viable solution to this issue.

Given the potential and expanding applications of artificial intelligence, further research and testing in real-world settings are necessary to ensure that these technologies adhere to drones' structural constraints, including capacity, processing speed, and energy efficiency. However, utilizing multiple machine learning algorithms in real-world settings remains challenging due to their poor success rates, especially in reinforcement learning. Enhancing machine learning algorithms' capabilities and integrating them with other existing algorithms is essential to improve outcomes and instill trust.

While algorithms for identifying and locating obstacles have advanced significantly, particularly with the use of deep learning, challenges persist in agile maneuvers, such as detecting small, fast-moving objects and adapting to various environmental factors. These factors include variations in snow and

TABLE VIII
Abbreviations and Notations

Abbreviation	Definition
UAV	Unmanned Aerial Vehicles
UAS	Unmanned Aircraft/Aerial Systems
ML	Machine Learning
UTM	UAS Traffic Management
CNN	Convolutional Neural Network
RL	Reinforcement Learning
DRL	Deep Reinforcement Learning
ADS-B	Automated Dependent Surveillance-Broadcast
IoD	Internet of Drones
TCAS	Traffic Collision Avoidance System
GNSS	Global Navigation Satellite System
NN	Neural Network
PSO	Particle Swarm Optimization
FAA	Federal Aviation Administration
NASA	National Aeronautics and Space Administration
GPS	Global Positioning System
SESAR	Single European Sky Air Traffic Management Research
ATM	Air Traffic Management
US	United State
SDN	Software-Defined Network
LiDAR	Light Detection and Ranging
NMPC	Nonlinear Model Predictive Control
MARL	Multi-Agent Reinforcement Learning
m/s	Metre per Second
PF	Potential Field
MFG	Mean Field Game
RRT	Rapidly Exploring Random Tree
DDQN	Double Deep Q-networks
SLAM	Simultaneous Localization and Mapping
MDP	Markov Decision Process

rain, day and nighttime lighting conditions, densely populated cities, mountains, and wooded areas.

Comprehensive simulators are still needed to integrate all relevant metrics and simulate the unique circumstances necessary for testing drone algorithms. Therefore, creating more sophisticated simulators that accurately replicate natural-world scenarios and testing and assessing suggested algorithms in actual test beds are crucial steps to ensuring effectiveness and establishing credibility.

APPENDIX

The utilized Abbreviations and Notations are detailed in Table VIII.

ACKNOWLEDGMENT

Any options, finding, and conclusion or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the United States Air Force.

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Mohammad Reza Rezaee is currently pursuing the Ph.D. degree in computer networking with the Department of Communication Technology and Network, Faculty of Computer Science and Information Technology, University Putra Malaysia (UPM), Selangor, Malaysia. He is an Assistant Professor with the Department of Information Technology, Faculty of Computer Science, Kabul Education University (KEU), Kabul, Afghanistan. His research interests include autonomous vehicles, swarm intelligence, computer networks, cryptography, and cloud computing.

Nor Asilah Wati Abdul Hamid (Senior Member, IEEE) received the Ph.D. degree in computer science from The University of Adelaide, in 2008. From 2013 to 2015, she was a Visiting Scholar with the High-Performance Computing Laboratory, George Washington University, Washington, DC, USA. She is currently the Deputy Director of the Institute for Mathematical Research, University Putra Malaysia (UPM), Selangor, Malaysia. She is also an Associate Professor with the Department of Communication Technology and Network, Faculty of Computer Science and Information Technology, UPM. She has authored or coauthored more than 80 journals and conference proceedings in her research area. Her work was funded by the government and some by industry. Her research interests include parallel and distributed high-performance, cloud, and data-intensive computing. She received the CUDA Teaching Center Award from NVIDIA, in 2015, and established the CUDA Laboratory. She serves as a reviewer for various renowned journals and conference proceedings.

Masnida Hussin (Senior Member, IEEE) received the Ph.D. degree from The University of Sydney, Australia, in 2012. She is currently an Associate Professor with the Department of Communication Technology and Network, Faculty of Computer Science and Information Technology, Universiti Putra Malaysia, Malaysia. She was involved in several network projects, such as cloud computing, network cloudification, and green computing. She has published several numbers of articles related to parallel and distributed computing. Her research interests include resource management, such as scheduling, allocation, and edge analytics for large-scale parallel and distributed computing. She has become an editorial board member/reviewer in several national and international journals.

Zuriati Ahmad Zukarnain (Member, IEEE) received the bachelor's and master's degrees in physics and education from Universiti Putra Malaysia (UPM), Selangor, Malaysia, in 1997 and 2000, respectively, and the Ph.D. degree in quantum computing and communication from the University of Bradford, U.K., in 2005. She is currently a Professor with the Department of Communication Technology and Network, Faculty of Computer Science and Information Technology, UPM. Her research interests include computer networks, distributed systems, mobile and wireless networks, network security, quantum computing, and quantum cryptography.