Survey paper

A review of AI-enabled routing protocols for UAV networks: Trends, challenges, and future outlook

Arnau Rovira-Sugranes [a,*], Abolfazl Razi [b], Fatemeh Afghah [c], Jacob Chakareski [d]

[a] School of Informatics, Computing and Cyber Systems, Northern Arizona University, Flagstaff, USA
[b] School of Computing, Clemson University, Clemson, USA
[c] Department of Electrical Engineering, Clemson University, Clemson, USA
[d] College of Computing, New Jersey Institute of Technology, Newark, USA

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ABSTRACT

Unmanned Aerial Vehicles (UAVs), as a recently emerging technology, enabled a new breed of unprecedented applications in different domains. This technology's ongoing trend is departing from large remotely-controlled drones to networks of small autonomous drones to collectively complete intricate tasks time and cost-effectively. An important challenge is developing efficient sensing, communication, and control algorithms that can accommodate the requirements of highly dynamic UAV networks with heterogeneous mobility levels. Recently, the use of Artificial Intelligence (AI) in learning-based networking has gained momentum to harness the learning power of cognizant nodes to make more intelligent networking decisions by integrating computational intelligence into UAV networks. An important example of this trend is developing learning-powered routing protocols, where machine learning methods are used to model and predict topology evolution, channel status, traffic mobility, and environmental factors for enhanced routing.

This paper reviews AI-enabled routing protocols designed primarily for aerial networks, including topology-predictive and self-adaptive learning-based routing algorithms, with an emphasis on accommodating highly-dynamic network topology. To this end, we justify the importance and adaptation of AI into UAV network communications. We also address, with an AI emphasis, the closely related topics of mobility and networking models for UAV networks, simulation tools and public datasets, and relations to UAV swarming, which serve to choose the right algorithm for each scenario. We conclude by presenting future trends, and the remaining challenges in AI-based UAV networking, for different aspects of routing, connectivity, topology control, security and privacy, energy efficiency, and spectrum sharing.[1]

1. Introduction

Unmanned Aerial Networks (UAVs) are an emerging technology that has opened its way into many fields and is expected to continue impacting the future of human life in the coming years. UAVs have already been utilized in many applications to provide fast, low-cost, on-demand, and precise monitoring and actuation services while minimizing human intervention and life-threatening risks. This covers many applications including transportation [1], traffic control [2], surveillance [3], border patrolling [4], search and rescue [5], disaster management [6], wireless network connectivity [7,8], smart agriculture and forestry [9], and remote immersion via mobile virtual reality [10–12]. Drones are also widely used in the military domain. For instance, Low-Cost UAV Swarming Technology (LOCUST) is a project by the US navy to utilize a swarm of autonomous drones to perform coordinated military attacks [13]. In addition to these commercialized use cases, many new applications are under design and implementation in academia and industry. For instance, surveying and mapping [14], volcano monitoring [15], UAV control by the brain [16], early warning of severe weather [17], plant protection [18], airborne wind energy harvesting systems [19], robotic herding of a flock of birds [20], Amazon Prime Air [21], and UPS drone delivery service [22] are only a few examples of many projects in their infancy steps.

Compared to piloted aircraft, satellite-based imaging, and ground-based sensing and actuation platforms, UAVs offer several advantages, including a small size, low operational and maintenance cost, less human intervention requirements, less operational hazard, autonomous control, more controlled imaging with adjustable zoom and angle of view, and higher maneuverability levels [23]. Therefore, the UAV

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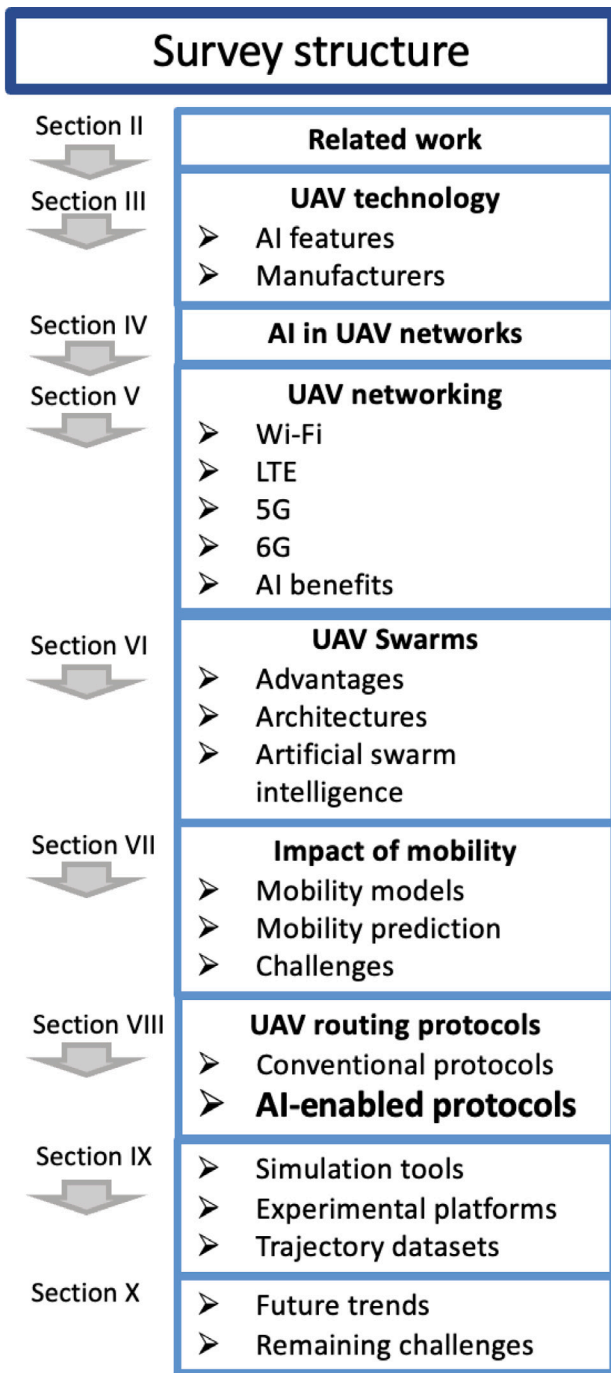- Future trends
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Fig. 1. The organization of this survey paper.

market has experienced continued growth in the past decades, from an estimated $19.3 billion in 2019 to a projected $45.8 billion market by 2025, which represents a Compound Annual Growth Rate (CAGR) of 15.5% from 2019 to 2025 [24].

Despite the following advantages in using drone technology, there still exist numerous challenges, and technical issues for implementing networking and control protocols for UAV-based infrastructures [23]. For instance, the limited payload of UAVs translates into constraints in power consumption, communication range, and computational limits that in turn may cause difficulties for networking, robust control, information acquisition and processing, autonomy, and task coordination. Another issue is the extreme dynamicity of UAV networks due to

their high speed, heterogeneous maneuverability levels, and obstacle-sparse flight zones, compared to ground vehicle networks with more predictable motion trajectories dictated by road patterns. Therefore, communication, control, path-planning, and information acquisition protocols that are primarily designed for ground platforms deem inefficient for UAV networks. For instance, connectivity of vehicular networks along roads necessitates optimal positioning of nodes or regulating their speed in a one-dimensional subspace that is not directly applicable to UAV networks. Likewise, autonomous driving and collision avoidance for drones have different constraints and requirements, compared to similar tasks in self-driving cars.

The goal of this survey paper is two-fold. First, we review UAV networks' features, including UAV technology, networking protocols, and swarms, with a focus on characterizing the impact of mobility on network topology, connectivity, and networking performance metrics. In this respect, we highlight the importance of having an accurate mobility prediction system for more efficient networking. Second, we review routing protocols designed for UAV networks, emphasizing AI-enabled routing protocols, which present better outcomes for high mobility networks [25–27]. Furthermore, we addressed the closely related topics of mobility models for UAV networks, simulation tools and public datasets, and relations to UAV swarming, which serve to choose the right algorithm for each scenario, as an additional contribution of this paper.

1.1. Motivation

Routing protocols developed for Vehicular Ad-Hoc Networks (VANETs) and other ground networks are not well-positioned to accommodate the requirements of UAV networks. As stated earlier, drones enjoy a higher mobility degree of freedom, compared to ground vehicles. This leads to a more vivid and fast-changing topology in comparison to VANETs [28]. Also, the lower node density of Flying Ad-hoc Networks (FANETs), compared to VANETs, raise connectivity issues due to the drones' limited communication ranges [29]. In terms of channel modeling, fading, and diversity phenomena, FANETs benefit from more accessible Line-of-Sight (LoS) links between UAVs and the use of smart directional antennas for collective beamforming, and similar techniques can offer higher gains [30,31]. From a different point of view, it also highlights the necessity of developing more accurate localization and tracking technology for aerial networks.

Furthermore, conventional routing protocols developed for VANETs merely rely on the node's prior information or current perception of the network topology, and do not perform well in maintaining connectivity. They either impose a large overhead for constantly updating the global network information or require a time-consuming route setup phase. Also, UAV networks are structure-free and not consistent with centralized routing protocols. Appropriate routing protocols for UAV networks should have properties like low complexity, low overhead, and preferably without the need for global knowledge and lengthy route setup stages, as discussed in [32]. The new generation of self-adaptive learning-based and topology predictive routing protocols learn the state of the network by experiencing and predicting dominant trends and constantly adapting to both minor or abrupt changes. This approach leads to a higher packet delivery ratio and energy efficiency. In this paradigm, decisions are made based on the anticipated network topology, and not solely based on the current state. These key requirements promote AI-enabled routing protocols to achieve superior performance [25–27]. Therefore, using AI methods to predict motion patterns of freely flying UAVs in a 3-dimensional space is an integral part of AI-based UAV protocols, while routing protocols for a 2-dimensional network of cars along the highway (as in VANETs) may not necessarily need this computationally-expensive component. This survey paper is devoted to highlighting recent developments in the AI-based routing protocols and analyzing their benefits and drawbacks when used in realistic situations.

Table 1
Most recent survey papers for routing protocols in Wireless Sensor Networks.

Year	Survey	Content included	Drawback	Application domain
2020	[33]	SDN-based routing, monitoring, cellular, satellite, security, placement, evaluation tools and future challenges.	Does not include routing protocols beyond SDN-based methods.	SDN-based UAV networks
	[34]	UAV classification, application, mobility models, routing protocols classification, challenges and open issues.	The review of predictive methods is not complete. It also excludes self-adaptive learning-based routing protocols.	UAV networks
	[29]	UAV communication networks issues, characteristics, design, applications, routing protocols, quality of service, and future open research areas.	Does not consider learning-based routing protocols.	UAV networks
	[35]	Network architecture and design, routing protocols including performance analysis and QoS metrics, and opening issues.	Routing classification only includes a few methods.	UAV networks
	[36]	UAV-UGV coordination, data gathering, monitoring, cellular communications, disaster management, computing and UAV-assisted routing.	Only considers routing methods for UAV-assisted networks, excluding routing protocols for UAV-to-UAV communications.	UAV-assisted networks
	[37]	Routing protocols for UAV-aided vehicular ad hoc networks with open research issues and challenges.	Only considers routing protocols for UAV-aided vehicular networks, excluding routing for UAV-to-UAV communications.	UAV-aided vehicle networks
2019	[38]	UAV design, architecture, routing protocols, open issues and research challenges.	AI-enabled routing protocols and their impact in dynamic networks are missing.	UAV networks
	[39]	Architecture, mobility models, routing techniques and protocols with a comparative study. Future challenges are also included.	Self-adaptive learning-based methods are not considered.	UAV networks
	[40]	UAV routing schemes, including objectives, challenges, routing metrics, characteristics, and performance measures, along with open issues.	It only briefly mentions adaptive routing protocols, missing most of the AI-enabled routing protocols.	UAV networks
2018	[41]	Routing protocols comparison and open research issues.	Does not include AI-enabled routing protocols, among others.	UAV networks
2017	[42]	Single-layer and cross-layer routing, challenges and open research directions.	Most of the routing protocols are suitable for vehicular networks, but not defined for UAV Networks.	Vehicular ad-hoc networks
	[43]	UAV architectures, projects, characteristics, applications and routing protocols, with emphasis in UAV security challenges.	Does not consider AI-enabled routing protocols and future trends.	UAV networks
	[44]	Position-based routing protocols with a detailed description and comparative study. Also, mobility models and UAV applications are described.	Includes position-based routing protocols only, which is just one type of UAV routing.	UAV networks
Our survey		UAV technology, UAV networking, UAV swarm formation, mobility models, UAV routing protocols, tools and public datasets to simulate real UAV network environments, future trends and remaining issues for UAV networking.	NA	UAV networks

The rest of this paper is organized as presented in Fig. 1. In Section 2, we investigate recently published survey papers to highlight the new content and additional aspects covered by our paper. Next, we review the UAV technologies used in military, industrial and commercial applications in Section 3. In Section 4, we emphasize the role of AI methods in improving the performance of UAV networking. Section 5 presents commonly used networking protocols, and UAV swarm formation methods are presented in Section 6. In Section 7, commonly-used UAV mobility models, and their impact on key networking characteristics, including connectivity, channel models, network topology, and routing efficiency, is investigated. Fundamentals of conventional and AI-enabled routing protocols, along with their stability under dynamic conditions, are provided in Section 8. Tools, public datasets, and remote experimentation infrastructures for testing routing protocols are reviewed in Section 9. Future trends and remaining issues are discussed in Section 10, followed by concluding remarks in Section 11.

2. Related work

There are a few recent review papers that survey routing protocols for ground and aerial networks. Other related papers that review UAV networks survey a broader set of aspects. Table 1 summarizes key topics covered in these surveys, along with key topics missing in each paper. To our knowledge, no paper provides a comprehensive and up-to-date review of AI-based routing protocols for aerial networks, which is our central focus.

Here, we closely discuss the most notable papers from the last three years only, since newer papers usually tend to improve previous reviews and cover the most recent developments. In addition to recent studies, we also consider two fairly older papers for their remarkably unique content. One paper is [45], which provides a thorough review of routing protocols in inter-vehicle communication systems. This paper covers broadcast-based routing, multicast, and geocast-based routing, as well as unicast-based routing protocols, which is perhaps the most complete review for routing protocols developed for vehicular networks. Another review is a seminal paper by Gupta et al. [23] published in 2015, which offers a broad outlook and comprehensive review of important issues in UAV networks. Also, it reviews the concept of routing in networks subject to severe delays and disruptions, which is unique among the published papers.

A survey paper by Awang et al. in 2017 [42] provides a review of routing protocols for vehicular ad hoc networks describing existing single-layer and cross-layer routing algorithms. It offers a fluent review of routing protocol for VANETs along with a clear description of the advantages and disadvantages of each method. However, most of the methods mentioned in this paper are designed for VANETs, and not suitable for FANETs with substantially different constraints and requirements.

A review of routing protocols and security challenges in UAV networks is provided in [43]. This paper reviews different routing protocols developed for dynamic networks. Nevertheless, it does not include an important and emerging trend of AI-enabled routing protocols.

Another paper [44] provides a comprehensive review of position-based routing protocols for UAV networks. It nicely classifies routing protocols with a detailed description of each category. Also, the routing algorithms are compared based on various criteria and performance metrics. However, only position-based routing protocols are mentioned, excluding many other types of routing protocols developed for UAV networks.

In 2018, a paper titled "Routing protocols for Unmanned Aerial Vehicles" [41] compared the routing protocols from different stand-points. This paper sheds light on which methods are suitable for UAV Networks under different network conditions and application-oriented requirements. However, the provided review is not comprehensive, and many efficient routing protocols such as hierarchical, probabilistic and AI-enabled methods are not discussed.

In 2019, a survey paper offered a complete review of UAV network design, architectures, routing protocols, open issues, and research challenges [38]. Deterministic, stochastic, and social-network-based routing protocols are discussed, along with a qualitative comparison of their major features, characteristics, and performance. However, AI-enabled routing protocols and their role in accommodating dynamic networks are missing.

In [39], a comparative review of major existing routing protocols developed for FANETs, along with a careful analysis of their performance under different design constraints and planning strategies, is provided. However, the important class of self-adaptive learning-based methods is not discussed. Similarly, [40] offers a comprehensive review of routing schemes in FANETs, including objectives, challenges, routing metrics, characteristics, performance measures, and open issues. However, most of the AI-enabled routing protocols are not discussed.

The following are a few survey papers published in 2020. A recently published paper [33] reviews Software-Defined Network (SDN) and Network Function Virtualization (NFV) for UAV-assisted monitoring, cellular, and satellite communications systems. More specifically, this paper reviewed SDN-based routing. However, it only considers Air-to-Ground scenarios.

A review of mobility models and routing algorithms for FANETs is provided in [29,34], with the inclusion of UAV communication networks issues. Nonetheless, they exclude an important class of learning-based routing algorithms. A comparative analysis of emerging routing protocols for UAV networks under different conditions is provided in [35]. However, it includes only the position-based methods and ignores different implementations of proactive, reactive, and AI-enabled routing protocols.

Two recent works [36,37] offer an exhaustive review of communication protocols, applications, and security issues of UAV-assisted ground and vehicular networks. However, their center of attention is UAV-assisted routing, which excludes many routing protocols developed for the more general class of UAV-to-UAV communication in FANETs. In summary, almost all of the previously published surveys do not pay enough attention to the emerging class of AI-enabled routing protocols, which can be considered the most appropriate class of routing protocols for extremely dynamic UAV Networks.

3. UAV technology: military, industrial and commercial drones

Like many other technologies, the use of drones initiated in military domain, and soon afterward, made its way into industrial and commercial application. One of the key motivating factors was using drones in risky environments, and inaccessible areas with harsh conditions to minimize human risk.

Military-grade drones typically utilized advanced features (e.g., stealth), custom-built sensors, equipment, and weaponry, appropriate for military and reconnaissance missions in hostile environments [46]. For instance, hyperspectral and Light Detection and Ranging (LiDAR) sensors, AI-based object recognition, quantum cryptography, and multi-spectral targeting systems with infrared sensors are usually utilized in
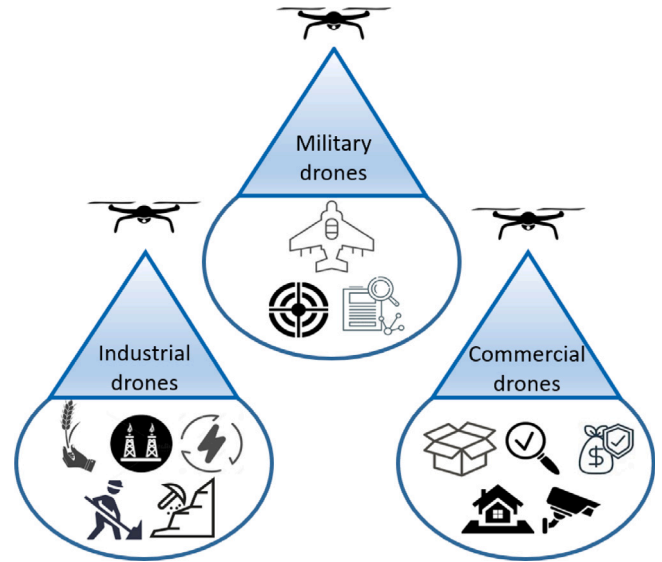

Fig. 2. Military, industrial and commercial drones.

more advanced technology, compared to commercial products [47,48]. For their proven performance and success in reducing casualties, the military sector invests heavily in the research and development of military drones [49]. UAVs in the military can be categorized based on their weight, range, speed, and specific capabilities. Based on their weight, we can differentiate class I, class II and class III drones. Class I refers to micro, mini, or small drones that weigh less than 150 kgs. Class II includes tactical drones between 150 and 600 kgs. Lastly, class III are strategic drones weighing more than 600 kgs [46].

Drones in industrial settings are used in a broad range of applications such as smart agriculture, forestry, mining, construction, weather and climate control, power plants, structural monitoring (buildings, dams, and bridges) and the energy sector (oil and gas refineries). In addition to high definition cameras, industrial drones are typically equipped with different types of sensors, including but not limited to LiDAR, Global Positioning System (GPS), range finders for collision avoidance, Positive-Intrinsic-Negative (PIN) diodes for motion detection, and pressure gauges [50]. Environmental and climate sensors such as temperature, humidity, air pollution, and chemical sensors are also embodied in industrial drones when necessary.

More basic drones are also used by ordinary people for regular tasks, ranging from hobby and entertainment to more complicated monitoring tasks. The applications of commercial drones are countless and include shipping and delivery, inspection, real state, security, insurance, life habitat monitoring, border patrolling, structural monitoring, entertainment, sports monitoring, fire monitoring, flood prediction, smart agriculture, forest monitoring, volcano monitoring, fishery, weather report, etc. Some deliverables from drones include 3D maps, orthomosaic, and actionable reports [51]. Commercial drones must meet the regulations set by the Federal Aviation Administration (FAA) for safe operation. For instance, commercial drones should have a maximum weight of 55 pounds and should operate at or below 400 ft above the ground when in uncontrolled (Class G) airspace. Otherwise, specific authorizations should be obtained for flying in controlled airspace (Class B, C, D, and E) [52].

Different types of UAV technology, including military, industrial, and commercial drones, are displayed in Fig. 2.

3.1. AI features

UAV technology has evolved in recent years. Modern UAVs are equipped with onboard computation boards powered by embedded

circuitry, Graphical/Tensor Processing Units (GPU/TPU), and Field-Programmable Gate Array (FPGA) boards that allow running light-weight deep learning (DL) algorithms for AI applications [53]. These AI chips, along with different sensors, allow UAVs to realize some levels of intelligence to improve performance in various applications, including those presented in Fig. 3. An alternative way is using UAVs with high payload capacity (e.g., xFold rigs Dragon X12 U11 drone with a payload size of 100 lbs) that can carry onboard huge computation servers. The motivation for embedding AI features into UAV technology comes from the importance of realizing low latency and fast processing of data for real-time applications. Therefore, using deep learning with AI-enabled chips by the UAVs can offer superior performance than streaming the raw data and running the applications on the ground-based processing centers [54]. This approach also substantially reduces the communication cost and satisfies the low-power requirements of UAVs compared to aggregating the information by the UAVs and running the applications on the cloud. Online processing also is desirable for real-time applications. However, this is not a general recipe for all applications. There exist some scenarios (e.g., low-cost single-hop communication for a single drone with relatively huge computation load), where raw video streaming and offloading the computation load to the cloud servers is advantageous [55]. Regardless of the computation load distribution between the drone and the ground servers, the benefits of AI algorithms are achievable.

AI hardware in modern UAVs consists of computing, storage, and networking parts [56]. Computing has been developing rapidly in recent years. However, storage and networking aspects still need more research to satisfy UAVs' diverse requirements. Particularly, there is a need for long-term storage and networking protocols for linking equipment to servers. Regarding the AI chip design, various technologies are available and under development, including GPU, TPU, reconfigurable Neural Processing Unit (NPU), neuromorphic chip architectures, and analog memory-based technologies. Based on the application-specific requirements and constraints, we can incorporate one or some of these designs. Lastly, we must acknowledge that producing AI hardware is a complex process [57]. Consequently, many of the tech leaders, such as Apple, Google, Microsoft, Intel, IBM, Nvidia, etc., are competing to design and build the most innovative AI technology, and we expect to witness more breakthrough developments in the coming years [58].

3.2. Drone manufacturers

Drone market is expected to grow to $63.6 billion by 2025, with 2.4 million global shipments by 2023, increasing at a 66.8% Compound Annual Growth Rate (CAGR) [59]. A large portion of the commercial drone market share in the US (about 77%) belongs to the DJI company. Intel, Vuneec, Parrot, GoPro, 3DR, HolyStone, Autel, SenseFly, and Kespry are among the top 10 drone market shares in the US [60]. Also, many companies use drones to provide 3rd party aerial solutions for different applications. For instance, PrecisionHawk is a North Carolina-based company that offers smart agriculture solutions [61]). Fortem Technologies offers AI-enabled interceptor drones that can hunt intruding drones [62]. The number of these companies grows larger than 100, and a list of such companies can be found in [63]. Commercial drones can offer service in many domains including emergency response, disaster relief, disease control, fighting crime, etc. [64].

4. Artificial intelligence in UAV networks

AI-based solutions help to solve complex problems related to UAV networking and operation by integrating computational intelligence into different aspects of UAV networks. The key idea is to incorporate AI algorithms into networking and control protocols to assist UAVs in perceiving the networks' and environments' overall conditions based on their limited observations. AI can also empower UAVs to process
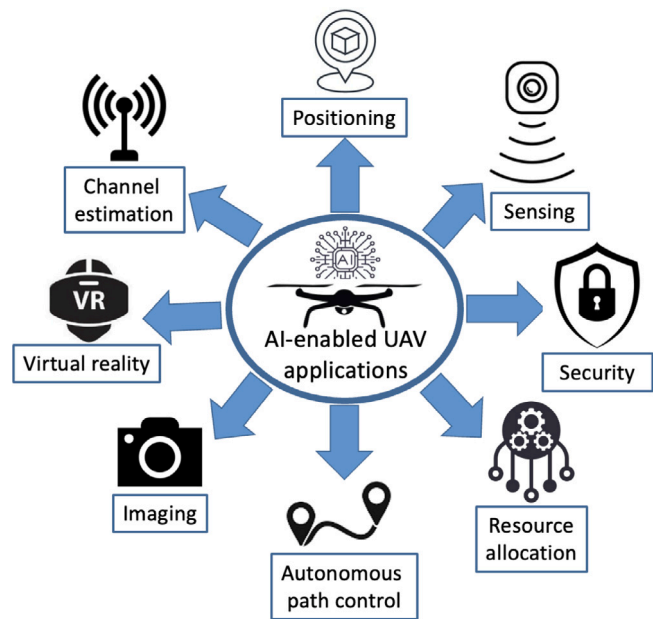
Fig. 3. AI-enabled UAV applications.

and interpret common patterns and anticipate future states and events when making decisions.

The benefits of using AI in UAVs are countless. For example, AI-based decision-making with real-time data allows continuous feedback in inaccessible areas to keep functions alive [65]. Also, training nodes by experience, in most cases, would result in more accurate results than taking actions blindly. Gathering information can facilitate resource management for energy optimization and trajectory design to avoid obstacles. However, these benefits come at a higher computational cost. In contrast to sophisticated scenarios, the value added by the AI methods in more straightforward scenarios, especially with no or limited training dataset, is negligible. Therefore, each scenario should be carefully investigated to analyze the benefits and drawbacks of using AI methods.

In [66], applications of AI methods to UAV-enabled wireless networking are listed. This paper summarizes different learning approaches including supervised and unsupervised learning, reinforcement learning and federated learning. Some areas where researchers introduced AI-based solutions include positioning and detection [67–69], channel estimation [70,71], virtual reality applications [11,72,73], imaging [74], autonomous path control [75,76], scheduling and resource allocation [77], security [78] and sensing [79], as shown in Fig. 3. Our paper focuses on the applications of AI in routing protocols while mentioning how AI is embedded into UAV technology, networking protocols and swarms, in general.

Fig. 4 presents a scenario on the importance of including AI techniques for optimal routing. Node 1 intends to send a packet to node 5 through the optimal path. The edge metrics represent an arbitrary performance metric such as distance, energy consumption, delay, bitrate, or a combination of these metrics. Consider a network of freely moving UAVs that transmit their info through queued and delay-tolerant communication. The network topology can change substantially during the transmission session while the data packets are waiting in the intermediate nodes' transmission buffer. Therefore, the optimal path, if found by the source node based on the initial network topology using a typical shortest path algorithm, may not remain optimal throughout the transmission. In Fig. 4, the blue and red circles, respectively, present the original and the updated positions of the nodes (after motions shown by dashed green arrows). A conventional algorithm would determine (1-2-3-5) as the optimal path from source node 1 to destination 5
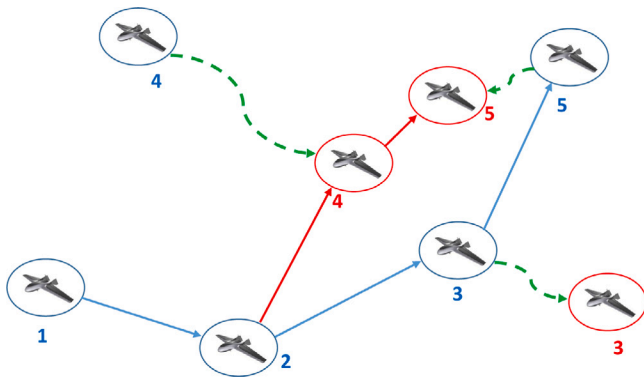
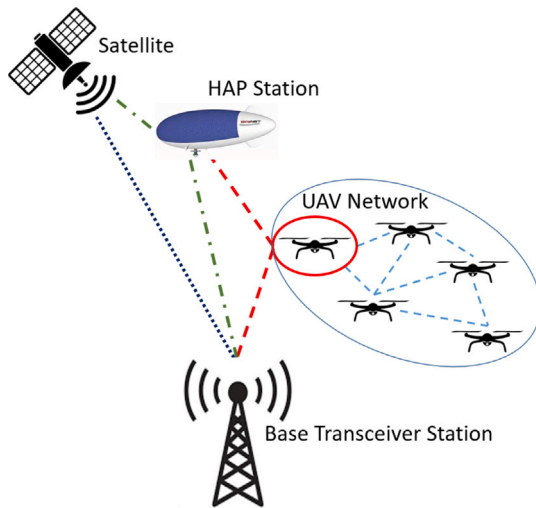**Fig. 4.** Scenario showing the importance of predictive routing [80].

Fig. 5. UAV Networking from different standpoints.

(represented by blue arrows) based on the original positions (blue circles). In contrast, a *predictive routing* selects the path shown by red color (1-2-4-5), taking into account the predicted network topology change (i.e., the position of the nodes when met by the data packets), while the packet is waiting in the transmission buffer of node 2.

5. UAV networking protocols

Different communication protocols can be used to transfer data among drones, to/from satellite and aerial control units through Air to Air (A2 A) communications, and from Air to Ground (A2G) (Fig. 5). Ground-based stations include standalone control units, larger servers, Internet gateways, and edge computers. As shown in Fig. 6, networking can be studied from different perspectives, especially from the communication, computation, and scheduling requirements and constraints. Most of the aerial monitoring platforms utilize ground-based or web-based servers for bulk processing, where drones collect and offload raw information into processing units. However, alternative methods such as on-the-fly processing using embedded light-weight GPUs/TPUs, Mobile Edge Computing (MEC), and fog computing for accelerated and near real-time processing are gaining more momentum recent years [81,82].

In most cases, the operation area is vast, far beyond the Line of Sight (LoS) communication range of a single UAV, hence using networked UAV platforms is unavoidable to ensure connectivity. One of the key design questions is choosing the best wireless technology (e.g., WiFi, LTE bands) with enough capacity and an acceptable Quality of Service

(QoS) both from the technical and feasibility, and economic points of view. Some efforts have been made to create a nationwide and high-speed broadband wireless network for public safety communications. For example, FirstNet offers a solution to deploy, operate, maintain, and improve the first high-speed, nationwide wireless broadband network dedicated to public safety that could apply to UAV networks in the near future [83]. The potential broadband wireless technologies include WiFi, 4G Long Term Evolution (LTE), 5G (with the 3rd Generation Partnership Project (3GPP) standard on 5G communication for drones), satellite communications, and dedicated public safety systems such as TETRA and APCO25. Also, Long Range Wide Area Network (Lo-RaWAN), which enables long-range communications at low powers, when high throughput is not necessary [84–86].

The following is a review of the most commonly used protocols in UAV networks, emphasizing their capability in handling the dynamicity of the network topology.

5.1. Wi-Fi

Most commercial UAVs use Wi-Fi (IEEE 802.11 series) for their communications, especially to a ground station (e.g., command and control commands in the uplink and video streaming in the down-link), as a low-cost, scalable, and affordable solution. Wi-Fi-based UAV networks can also be used for wireless backhauling [87]. Also, inter-drone communications can be powered by Wi-Fi provided that one node is defined as the Access Point (AP) to implement a local WLAN. This node may or may not provide access to the Internet. Apparently, one drawback of Wi-Fi is handling mobility and hand-off between the base stations, limiting the operation range of drones within direct access to the AP to a few miles. Although the throughput of Wi-Fi (theoretically between 54 Mbps for 802.11a to as high as 2.4 Gbps for 802.11ax [88]) is relatively lower than LTE and 5G, it is sufficient for most applications, including real-time high-resolution video streaming. In scenarios that long-range connectivity is required, Wi-Fi loses the game to licensed wireless systems when such networks are available. Some drones develop their proprietary communication protocol on top of Wi-Fi. For instance, the XFold spy x8 KDE U3 drone by Xfold Rigs [89] comes with a Futaba Commercial 14-channel.

5.2. LTE

LTE systems offer airborne connectivity beyond the LoS communications for drones. They improve the throughput and network connectivity due to the hard and soft hand-over mechanism [90]. Recent years have witnessed a surge of activities in using terrestrial LTE networks to provide connectivity to UAVs. A collaborative project has been initiated by FAA and the National Aeronautics and Space Administration (NASA) in the U.S. since January 2017 to build a system using LTE technology. To better understand the potential of LTE for small UAVs, the 3GPP has formed a study group to investigate enhanced LTE support for aerial vehicles since March 2017 [91]. The most notable drawback of using LTE and other cellular systems is the need to register drone transmitters with a service provider, which increases the operation cost and restricts the operation of drones to areas covered by the service provider. This is why using cellular systems is not as popular as Wi-Fi for drones.

Another key issue is that the LTE propagation plannings typically aim to serve the ground users; hence, the propagation maps are not optimized for aerial nodes. Therefore, LTE radio planning requires substantial revisions to serve UAV networks, especially when they scale up to large networks at higher altitudes and with a high-varying topology.
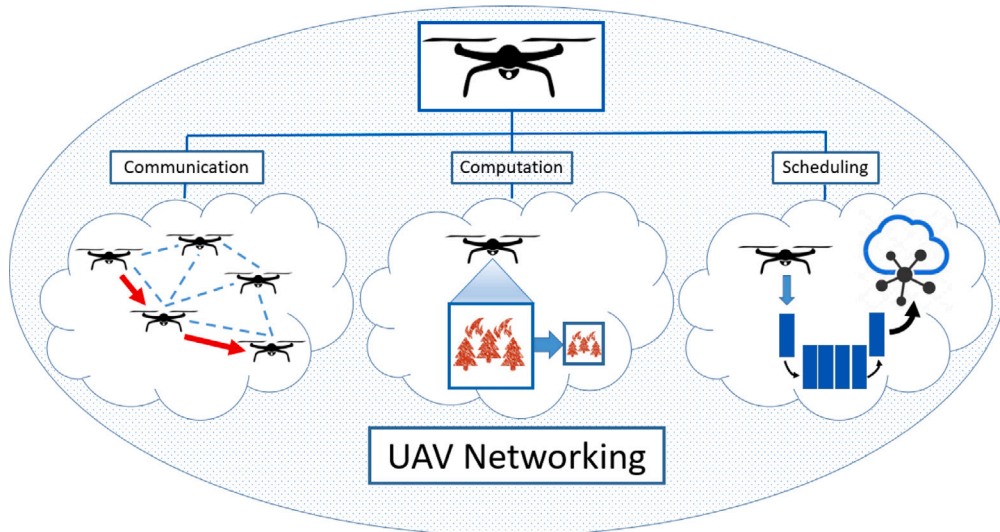
Fig. 6. UAV networking: different aspects.

5.3. 5G

Similar to LTE, 5G is also considered for drone communications when higher bitrates beyond 2.4 Gbps are required. It also enables the concept of *Internet of Things* (IoT) for drones, where a drone serves as a *thing* [92]. UAV-assisted communications have several promising advantages such as facilitating on-demand deployment, high flexibility in network reconfiguration, and enabling long-range LoS communication links. In some scenarios, drones serve as 5G radio stations (also called AP) to extend the coverage of 5G networks for ground users, especially for sensitive applications, such as public safety and post-disaster management [93–95].

5.4. 6G

The demand for higher throughput and bigger numbers of devices never stops, and 6G is on the way to serve these requirements. 6G, the next generation for wireless communication, is expected to provide intelligent, secure, reliable, and limitless connectivity at rates 100 times faster than 5G [96]. Similar to 5G, we expect that the UAV networks' diverse requirements such as low latency, reliability, and energy efficiency will be better served by 6G networks, and aerial nodes will be an integral part of 6G networks. Also, network intelligence is envisioned to be a key feature of 6G, which can assist in many connectivity-related applications [97], for example, in a blockchain-based solution for UAV communications [98]. Some of the challenges brought by the futuristic concept of *connected sky* include high mobility, interference, and connection to down-tilted antennas. It is expected that aerial nodes, when integrated into terrestrial nodes, will be instrumental in covering such issues and enhancing the 6G user experience.

5.5. AI benefits in UAV networking

Artificial intelligence for UAV networking can help with the reliability, connectivity, and security of wireless communication by offering data-driven solutions for key challenges of interference management, mobility management, and handover, cyber–physical attacks, and authentication [99]. For instance, [100] uses AI to predict transmission success and failures, to anticipate and avoid networking issues.

Among the aforementioned communication protocols, the most appropriate one should be selected based on the application-specific constraints and requirements. Several research efforts have been devoted to implementing new networking algorithms on top of these protocols, most of which have not yet been commercialized. For instance, the idea of spectrum sharing and spectrum leasing for drones is proposed to extend the connectivity of drones for high-speed and temporary service when wireless coverage is accessible, which integrates WiFi and Cellular access [101,102]. Also, beamforming can extend the communication range further and reduce the interference [103]. Indeed, UAVs provide a realistic scenario for distributed and cooperative beamforming, since transmit antennas can be spatially separated among UAVs [104]. The authors of this paper have proposed AI-enabled routing [105], compression [106], and task coordination [107] protocols to minimize the unnecessary information exchange among the UAVs and prolong their mission time.

6. UAV swarms

The concept of using UAV swarms is gaining more momentum in recent years. The idea is to use a sheer number of drones, in most cases miniaturized and limited-capability drones, to collectively perform a complicated mission with no or minimal operator intervention. This approach mitigates the drawbacks of using a single drone, such as limited allowable payload and limited sensing and actuation capabilities. A general architecture for task order in swarm environments is presented in [108].

6.1. Swarming advantages

The main advantages of using UAV swarms include shortening the task completion time, extending the coverage area, and reducing the operation cost. In the military domain, UAV swarms also increase the tactical mission's success rate by eliminating the reliance of the mission on a single drone's functionality, which can be subject to cyber-attacks and hijacking by an adversary. Using UAV swarms can also increase the unpredictability of the mission and overwhelm the enemy's defense system with a large number of potential targets in an interactive battleground. Further, UAV swarms are used to collectively find and fight enemy targets [109]. These ideas were behind the US navy's LO-CUST project to design UAV swarm attacks [13]. Also, swarm systems can be equipped with anti-jamming systems to more efficiently block cyber attacks [110]. UAV swarms which incorporate an authentication protocol using Physical Unclonable Functions (PUFs) can authenticate multiple devices at once with high scalability while being resistant to mobility, and multiple cyberattacks such as physical capture, cloning attacks, eavesdropping, and man-in-middle attacks [111,112].
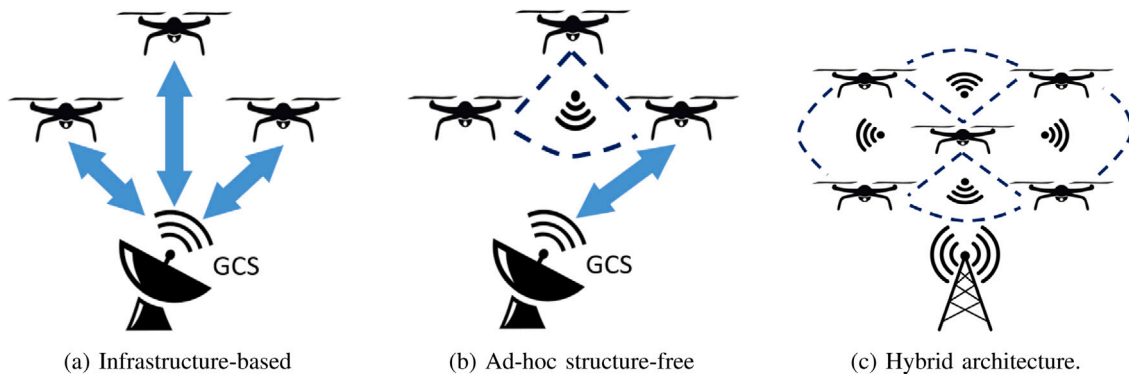
(a) Infrastructure-based   (b) Ad-hoc structure-free   (c) Hybrid architecture.

Fig. 7. Different architectures for UAV swarms.

The use of UAV swarms is not limited to military applications. They enable search and rescue missions over big areas [113]. Some agriculture duties such as watering or identifying sick plants are time-consuming, and using UAV swarms with minimal operator intervention would increase the efficiency of precision agriculture [114]. More applications for UAV swarms can be found in [115].

6.2. Swarm architectures

UAV swarm refers to scenarios when a sheer number of drones, most of which with similar sensing, networking, and actuation capabilities, collectively perform a designated monitoring or operation tasks [116]. For example, a swarm of drones can carry out a coordinated military attack [13]. UAV swarms function in the following different ways from the control and coordination point of view.

6.2.1. Infrastructure-based swarm architecture

In this architecture, a central node, mostly a Ground Control Station (GCS), collects and processes real-time information from all swarm members; and sends back control commands (e.g., navigation, sensor actuation, sampling rate, camera control, etc.) to the UAVs, as shown in Fig. 7(a). For instance, pre-planned paths can be revised during the mission to avoid collisions when facing unexpected obstacles based on the live video streaming by member UAVs [117]. The key advantages of this architecture include (i) feasibility of mission for low-capability UAVs by offloading the computation load to a more capable GCS, (ii) global optimality of the resulting decisions, and (iii) no need for complex networking algorithms for inter-UAV communications [118]. Also, realizing asymmetric security protocols such as Public Private Infrastructure (PKI), which requires Central Authority (CA) to allocate digital signatures is feasible [119]. However, it suffers from the well-known drawbacks of central systems such as (i) sensitivity to the GSC malfunction, hijack, or cyber threats, and (ii) the restriction of the mission area to the accessible range of the GCS.

6.2.2. Ad-hoc structure-free architecture

This architecture allows direct communication between UAVs with no need for APs or routers, and can utilize distributed decision making (Fig. 7(b)). This method eliminates the sensitivity of the mission to the GCS function and relaxes the constraints on the mission area. The cost paid is the need for more capable UAVs for local decision making and a routing protocol to accommodate dynamic network topology [120, 121].

6.2.3. Hybrid swarm architecture

This architecture makes use of a cellular network to connect UAVs while using distributed decision-making without the need for a central controller (Fig. 7(c)). This architecture leverages the strengths of network-based and structure-free architectures by enabling long-range missions with reliable networking among drones while not relying on

a central controller's function [114]. This architecture takes advantage of the high mobility and networking efficiency of M2M communication in LTE, and 5G wireless systems [122–125].

6.3. Artificial swarm intelligence

Artificial swarm intelligence, also known as swarm AI, is a technology that combines real-time inputs and uses algorithms to optimize the overall performance of the swarm [126]. The initial idea comes from the swarm intelligence found in natural systems, including ant colonies, bird flocking, animal herding, etc.

For UAV networks, it represents an aerial system that uses AI and data-driven methods to control the drones to achieve the designated goal [127]. In military drones, AI can be used to enhance UAV swarm operation by increasing the range, accuracy, mass, coordination, intelligence, and speed, with a potential impact on security and strategic stability [128]. Other examples include AI-based flight control for autonomous drones for real-time positioning without a centralized controller [129], as well as flight control for detection, localization, and tracking tasks while relying only on local spatial, temporal, and electromagnetic information [130]. In the upcoming years, we expect to see how UAV swarm AI can revolutionize many existing systems and create a new breed of applications. A key concern is the negative impacts that may be brought by the excessive power of autonomous UAVs that can jeopardize people's privacy and security. This issue is more critical when drones' control units are hijacked by cyber attacks. Therefore, a hot research area is developing security and privacy-preserving protocols for next-generation UAV networks.

7. Impact of mobility on communications

In this section, we investigate the impact of node mobility on data transmissions. We first review popular UAV mobility models as well as the techniques used to predict UAV mobility and network topology. We also review the challenges that mobility brings to connectivity control and optimal routing.

7.1. UAV mobility models

Mobility models are used to describe, model, and emulate UAV motion trajectories. Generative modes typically incorporate location, speed, and direction changes as model parameters. The following is the list of commonly-used mobility models that facilitate the analysis of UAV networks.

7.1.1. Random WayPoint (RWP) [131,132]

This segment-wise model includes linear and independent motions with constant speed and direction between a set of points called waypoints. Also, UAVs decide on their next action based on some fixed probabilities, and their motion does not depend on neighbor nodes. According to [133], RWP has two important variants, Random Walk Model (RWM) and Random Direction Model (RDM) [134]. This model can be used for both rotary and fixed-wing drones, and is the most appropriate for missions with pre-path planning.

7.1.2. Levy walk/flight [135]

This mobility model is similar to the random walk mobility model, with a distinction that the steps-lengths are not constant, rather random values that follow a power-law distribution. The truncated Levy walk model incorporates tendency of the node to stay in confined area with some randomness and hence has been shown to be a reasonable model for human walk and cellular users based on statistical analysis, compared to pure random models (like random walk and Brownian motion) and also random way points, as stated in [136,137]. We conjecture that the rotary drones in some missions may have mobility patterns to human and follow similar models. It is recognized by former works and some believe that Levy flight model is able to mimic movement patterns of aerial nodes over a larger time span where mixed effects may be experienced [138].

7.1.3. Gauss Markov Mobility Model (GMMM) [139]

This model is used to simulate the movement of UAVs in swarms, which incorporates controlled randomness to the speed and direction equations. It prevents sudden stops and sharp turns within the simulation region, to realize smooth and more realistic trajectories, especially for fixed-wing UAVs, and targeted missions.

7.1.4. Semi random circular movement [133,140]

Used to simulate the curved movements of UAVs when they hover at a constant altitude (e.g., for collecting imagery). It has a uniform node spatial distribution and outperforms random waypoints (in terms of connectivity and scanning coverage over 2D disk). The nodes move around co-centered circles to cover destinations located on the circle perimeters. Uniform distributions are used for directional and angular velocities and the node pause at each destination. Once a circle scan is finished, the node switches to the next circle.

7.1.5. Mission Plan-Based mobility model (MPB) [141]

In this mobility model, UAVs are aware of trajectory information and move according to a predetermined path to the mission area, where potential information is available. Start and end points are randomly assigned, but the velocity and the flight time are given.

7.1.6. PaPaRaZzi Mobility model (PPRZM) [142]

It is a stochastic mobility model that combines various models with a Markov state diagram. Each UAV chooses a movement type from a set of predefined motion patterns with different parameters. Each motion state's parameters are initialized randomly according to a given distribution and remain unchanged until the transition to another state with different motion parameters. A set of common motion patterns includes "Stay-at" "Way-Point", "Eight", "Scan", and "Oval", which are used in the original implementation of PPRZM. Results show that this model outperforms the RWP model in terms of geometric and network performance, since it brings the flexibility of switching between different modes.

Most of the aforementioned models consider independent motion trajectories for each drone. However, in some scenarios (e.g., UAV swarms), the motion of network members can be highly correlated. Several models are proposed to address this concept and realize correlated trajectories.

7.1.7. Distributed pheromone repel model [143]

This model uses a pheromone map to guide UAVs in reconnaissance scenarios. Each UAV maintains its own pheromone map, and scans the area of the corresponding map. The UAVs share information every few seconds to create a global pheromone map. UAVs turn right, left, or go straight with probabilities based on the pheromone smell. UAVs prefer areas with a low pheromone smell, so new areas are scanned. This model results in good scanning properties, but does not consider the network connectivity between UAVs that serve different areas.

7.1.8. Hybrid Mobility model with Pheromones (H3MP) [144]

This model is suitable for search and rescue applications. This hybrid mobility model combines Markov chains and pheromones to adapt to dynamic environments. Markov chains guide UAVs to promising areas, and pheromones guide information sharing that allows mobility management through UAVs. Results show the superiority of this method in detecting and tracking targets, compared to other pheromone-based methods.

7.1.9. UAV fleet mobility model [7]

This mobility model incorporates the remaining energy level, the area coverage, and network connectivity into the mobility decision criterion. After receiving information from its neighbors, each UAV determines its next movement based on these criteria. The direction and the speed of the UAVs are calculated using weighted vectors considering neighbor UAVs. Results show that this method outperforms random motion methods in terms of coverage and connectivity.

These models clearly are more appropriate to design motion paths for specific missions, and less appropriate for modeling general UAVs networks. Overall, a proper mobility model should be adopted for each application based on the drone types, the mission requirements, and the utilized path planning method.

7.2. Mobility prediction

Network nodes use radar-based and visual target tracking to perceive the network topology, at least in their close neighborhood. The purpose of mobility prediction is to go one step beyond and anticipate the future locations of the objects that form the network. These methods can be categorized into the following two mainstream trends, data-driven, and model-based methods.

7.2.1. Data-driven

This approach includes data mining and fuzzy methods, where frequent motion patterns are exploited by analyzing relatively large datasets. These methods indirectly capture the influence of the natural and human-made textures, user behavioral habits on the spatial and temporal variations of node mobility. For instance, *TAPASCologne* is a project to collect and publish datasets of vehicle motion patterns in the city of Cologne, in Germany with application to cellular network design [145,146]. Similar data-driven methods are proposed to model the motion patterns of pedestrians [147–149], vehicles [150,151], animals [152] and other mobile users. In a similar line of research, node mobilities are not exploited directly, rather traffic distribution trends are extracted [153,154]. Although these methods are useful in the network planning phase, their primary goal is to characterize general properties of the motion of a population of objects in different settings. Therefore, they are not well suited for predicting the position of single objects, which is influenced by the real-time node decisions. For such scenarios, model-based prediction methods are more appropriate.

7.2.2. Model-based

In this approach, the smoothness of the motion paths is used to predict the future locations of mobile objects, typically in an online fashion. These methods include piecewise segment methods [155], Hidden Markov Models (HMM) [149], Levy flight process [136–138], Bayesian methods [156,157], Manifold learning [158], Kalman filtering [159,160], fuzzy zone-based method [156] and mixture Gaussian models [156]. Each method relies on a model that is appropriate for a different class of mobile objects, including pedestrians, indoor mobile users, vehicles, etc. Indeed, these methods rely on an underlying model, which is customized for a specific object with a different mobility model such as random walk [161], Random Waypoint (RWP) [162], HMM [149], Gaussian Morkov Mobility Model (GMMM) [163], Brownian motion [164], Linear model via Durbin's curve [165], and mixture models [166]. Consequently, they are not applicable to a network of heterogeneous nodes and fail in balancing between the randomness and predictability of node's mobility.

7.3. Mobility-related networking challenges

High mobility nodes, especially when not properly predicted, pose critical challenges to the communication performance in terms of connectivity and routing optimality. Mobility of nodes translates to the network dynamicity that can disrupt the information exchange by losing connectivity and undermining the routing efficiency. In extreme cases, the network can breakdown into isolated islands. Different approaches can be taken to overcome the loss of connectivity in UAV networks. One main approach is *topology control* to avoid connectivity issues, which can be seen as jointly optimizing the networking and control aspects. For instance, the idea of the dynamic placement of new nodes in locations to cover connectivity holes is introduced in [167]. ML methods can assist with achieving this goal by modeling and predicting network topology, traffic mobility, spectrum availability, and channel states. An online learning procedure is used in [168] to adjust the UAVs to their radio transmission parameters, based on the perceived topology while revising their flight paths. The authors of [169] propose a Chaotic Ant Colony Optimization approach (CA-COC) to maximize the coverage area while preserving the connectivity. Another method to improve network connectivity is ECORA [170]. This method uses geographic protocols considering positioning prediction and link expiration time by excluding links with approaching expiration time from the path selection algorithm. These methods usually aim to enhance network connectivity by controlling the network topology. Recently, the idea of using predictive and self-adaptive learning-based routing protocols gained a lot of attention to use ML methods to enhance networking efficiency. One approach is predicting network topology changes and incorporating the predicted network topology into the networking decisions [105,171]. These methods are more appropriate for separating the networking layer from mission-based path-planning algorithms. Also, prediction-based positioning is more appropriate for scenarios that the nodes have limited connectivity or on-demand link establishments which are costly to share location information, nodes which are prohibited from sharing their locations for privacy and security concerns, nodes which belong to different and even adversary and competing networks, and nodes whose motion trajectories are subject to constant changes due to using autonomous on-the-fly control systems.

8. Routing protocols for UAV networks

This section reviews routing protocols, emphasizing the role of ML methods to accommodate the requirements of UAV networks.

Routing protocols can be categorized in many different senses, as shown in Fig. 8. Regardless of their reaction to topology changes, routing algorithms can be divided into centralized and distributed algorithms (Fig. 8, layer 1). In centralized algorithms, the global network topology is known for a central node, which can share with network members. Therefore, the source node can execute a local algorithm to find the optimal end-to-end path. In distributed algorithms, the nodes are not aware of the entire network topology, and they have partial knowledge about their local subnetwork topology. In these methods, either sequential methods are used to break down finding the optimal end-to-end path into piece-wise sub-problems; or methods like "hello messages" are used to discover the network topology.

Routing algorithms can also be classified into deterministic and probabilistic algorithms based on the optimization approach or equivalently the resulting route's randomness (Fig. 8, layer 2). Deterministic routing refers to a non-stochastic decision-making policy, where the resulting routes are fully and explicitly determined under given assumptions, network conditions, and decision rules. On the other hand, in probabilistic algorithms, the resulting routes are probabilistic; hence the actual paths are selected in run-time by the nodes based on a set of rules and probabilities.

From a different standpoint, we can classify routing protocols into static and dynamic routing protocols (Fig. 8, layer 3). In static routing protocols, the route is established based on the initial network topology without considering the changes which occur during the transmission. These algorithms are appropriate for static networks and low-volume transmissions. On the other hand, in dynamic routing protocols, the resulting end-to-end path can change over time to accommodate node mobility. Therefore, they are more suitable for UAV networks and will be discussed in more detail in this paper. Dynamic routing algorithms have different variants based on how paths are determined in response to network topology changes. Main categories include proactive, reactive, hybrid, position-based, topology predictive, and self-adaptive learning-based routing methods.

To investigate the performance of different routing protocols in UAV networks, we first present the key characteristics of these routing methods in Table 2. Next, we review different implementations of each category and investigate their use for highly dynamic UAV networks.

8.1. Conventional routing protocols

In this section, we briefly review routing protocols that were mainly introduced for low-speed ad hoc networks. These routing protocols do not adapt to high mobility and abrupt changes we find in UAV networks. Therefore, most of them are not applicable for high-speed UAV applications.

8.1.1. Static routing protocols

Static protocols are mainly designed for networks with static or slow-varying topology, meaning that the optimal end-to-end path for any source–destination pair does not change over time. Static routing algorithms consider the initial network topology when finding the best path. Generally, in this approach, the global network topology is known to a central node (which can also be shared with network members). Therefore, the optimal paths for all source–destination nodes are calculated and programmed in terms of routing tables. In other words, each intermediate node receives a packet, passes the packet to the next node determined by the routing tables based on the destination address. These algorithms are suitable for structured networks, but some modified versions are proposed for UAV networks. Examples of such algorithms include shortest path algorithm (Dijkstra's and Bellman–Ford's algorithms) [172], shortest-path-aided back-pressure [173], Multi-Level Hierarchical Routing (MLHR) [174], Load Carry and Deliver Routing (LCDR) [174], and Data-Centric Routing [174].
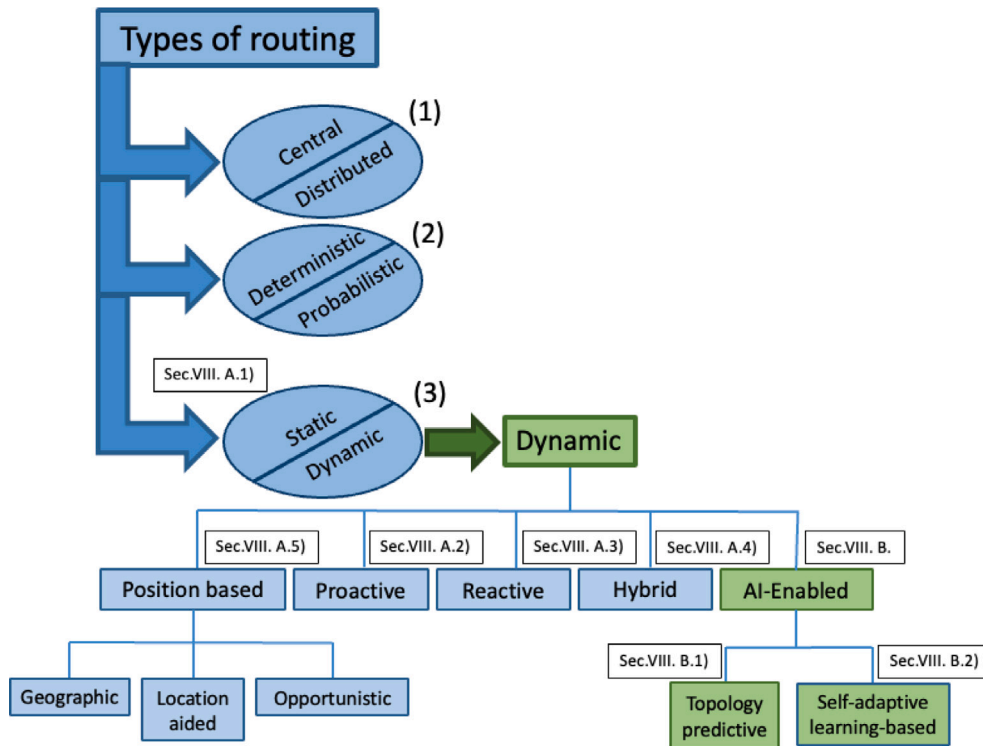
Fig. 8. Routing classification based on different criteria and dynamic types of routing protocols.

Table 2
Types of routing.

Routing protocol	Central/distributed	Deterministic/Probabilistic	Scalable	Mobility	Global info	Discovery message	AI aspect
Static	Central	Deterministic	Yes	Static	Yes	No	No
Position-based	Distributed	Deterministic	Yes	Low speed	No	No	No
Proactive	Distributed	Deterministic	Bigger overhead	Low speed	Yes	Hello message	No
Reactive	Distributed	Deterministic	Longer RREQ	Low speed	No	RREQ & RREP	No
Hybrid	Distributed	Deterministic	Complexity	Low speed	No	Hello message	No
Hierarchical	Distributed	Deterministic	Yes, into clusters	Low speed	Yes	Hello message	No
Probabilistic	Distributed	Probabilistic	Adds complexity	Low speed	Yes	No	No
Topology predictive	Distributed	Deterministic	Yes	Dynamic	No	Depends	Yes
Self-adaptive learning-based	Distributed	Deterministic	Yes	Dynamic	No	Depends	Yes

8.1.2. Proactive routing protocols

Proactive routing protocols can be implemented as table-driven methods, where optimal paths are found for all source–destination pairs based on the global network topology. The routing tables are filled accordingly at all nodes to guide the packets link-by-link to their final destinations. In applications like UAV networks, routing tables should be updated if optimal paths are changed due to varying network topology or link budgets. The main advantage of this approach is that the route can easily be calculated and established. In case of a link break-down, new links can be re-established quickly. However, it may impose a large overhead for time-consuming topology exploration and path discovery, such as using hello packets to learn the network topology. Some important implementations of proactive routing algorithms designed for UAV networks include Optimized Link State Routing (OLSR) [175], Directional Optimized Link State Routing (DOLSR) [176], Multidimensional Perception and Energy Awareness OLSR (MPEAOLSR) [177], Dynamic Dual Reinforcement Learning Routing (DDRLR) [178], Destination Sequenced Distance Vector (DSDV) [179], BABEL [180], Cluster head Gateway Switch Routing (CGSR) [181], Wireless Routing Protocol (WRP) [182], Topology Broadcast based on Reverse Path Forwarding (TBRPF) [183] and Better Approach To Mobile Ad hoc Network (BATMAN) [184].

8.1.3. Reactive routing protocols

Reactive routing protocols create on-demand routing information. It means that the route discovery process is executed only when a transmission session has to be established. The main benefit of this approach is its reduced overhead, especially in the low-traffic regime. On the other hand, in case of a route failure, the re-establishment of a new route can take a long time. The following are some important implementations of reactive routing protocols: Dynamic Source Routing (DSR) [185], Ad hoc On Demand Distance Vector (AODV) [186], Dynamic Topology-Multipath AODV (DT-MAODV) [187], Associativity-Based Routing (ABR) [188], Signal Stability-based Adaptive routing (SSA) [189], Message Priority and Fast Routing (MPFR) [190], Dynamic Backup Routes Routing Protocol (DBR2P) [191], Dynamic MANET On-demand (DYMO) [192] and Time Slotted On-demand Routing (TSOR) [193].

8.1.4. Hybrid routing protocols

Hybrid routing protocols combine proactive and reactive routing features. The route is initially determined with a proactive protocol. However, a reactive routing protocol is activated when a substantial network topology is recognized or a previously established route breaks. Some important implementations of hybrid routing algorithms designed for UAV networks are Zone Routing Protocol (ZRP) [194] and Temporarily Ordered Routing Algorithm (TORA) [195].

8.1.5. Position-based routing protocols

Position-based routing protocols find the optimal route based on the location information. For example, the next node can be selected based on its distance to the current node or to the destination. The key disadvantage of these methods are their dependence on accurate positioning and tracking systems. Some important implementations of position-based routing algorithms proposed for UAV networks include: Greedy Perimeter Stateless Routing (GPSR) [196], Greedy–Hull–Greedy (GHG) [197], Greedy–Random–Greedy (GRG) [198], greedy forwarding [199], Energy-Balanced Greedy forwarding Routing (EBGR) [200], Greedy Distributed Spanning Tree Routing (GDSTR) [201], Cross-layer Link quality and Geographical-aware beaconless Opportunistic routing (Xlingo) [202], Adaptive Forwarding Protocol (AFP) [203], Reactive-Greedy-Reactive (RGR) [204], scoped flooding and delayed route request RGR [205], beaconless opportunistic routing [206], Location-Oriented Directional MAC (LODMAC) [207], Extremely Opportunistic Routing (ExOR) [208] and Location-Aided Routing (LAR) [209].

8.1.6. Hierarchical routing protocols

Hierarchical routing protocols consider nodes arranged hierarchically, where the lower layers can form clusters. Each node typically holds information only about its neighbors stored in a table that is updated through hello packets. Each cluster head communicates with the rest of the cluster heads to select the best path. Cluster-Based Routing Protocol (CBRP) [210], Enhanced Cluster head Gateway Switch Routing (ECGSR) [211] and Fisheye State Routing (FSR) [212,213] are examples of recently-developed algorithms for UAV networks.

8.1.7. Probabilistic routing protocols

Probabilistic routing protocols find multiple routes from source to destination, which can be selected based on probabilistic mechanisms to cope with network congestion and security. Some examples of these algorithms used in UAV networks are random walk routing [214] and MIMO-based random walk routing [215].

8.2. AI-enabled routing protocols

In this section, we study the AI-enabled routing protocols, which use the learning power of ML algorithms for optimal route path selection based on a more accurate perception of the network topology, channel status, user behavior, traffic mobility, etc. These algorithms bridge the two networking and AI research areas to implement modern networking, especially for dynamic UAV networks. These algorithms can be viewed as state of the art and are not included in most previous survey papers. The following is a fairly comprehensive list of AI-based algorithms.

8.2.1. Topology predictive routing protocols

The main feature of topology-predictive routing protocols is using ML algorithms to predict the node's motion trajectories (as an approximate of the network topology, if the communication range of nodes is known) and incorporate them into the path selection mechanism.

Here, we review some of the proposed routing protocols that use mobility or trajectory prediction approaches to enhance the performance of routing algorithms for UAV networks.

- **Learning-based Adaptive Position MAC protocol** [216]: This routing protocol proposes an adaptive hybrid communication protocol by integrating a novel Position-Prediction-based directional MAC protocol (PPMAC) and a Self-learning Routing Protocol based on Reinforcement Learning (RLSRP). The performance results show that the proposed PPMAC overcomes the directional deafness problem, which happens when the transmitter fails to communicate with the receiver due to having the receiver's antenna oriented in a different direction. Also, RLSRP provides an automatically evolving and more effective routing scheme, appropriate for autonomous FANETs.

- **Predictive Dijkstra's** [80,105]: This routing protocol assumes that the intermediate nodes' locations when the packet is supposed to meet them are predicted using ML methods. Then, it incorporates this predictive information into the path selection criterion based on Dijkstra's shortest path algorithm. Results show superior performance compared to the standard Dijkstra's algorithm, especially when higher velocities are applied. The achieved performance gain is dependent upon the prediction accuracy. Two important shortcomings of this method is its reliance to accurate trajectory prediction methods, and the need for global location information exchange.

- **Predictive greedy routing** [32]: Distance-based greedy routing algorithm solves the issues of [105] and relies solely on the UAVs' local observations of their surrounding subnetwork. Each node estimates the location of its neighbors (e.g., using model-based object motion trajectory prediction) and selects the next node that makes maximum progress toward the destination node. This method adapts to highly dynamic network topology. Moreover, it has low complexity and low overhead with no need for an initial route setup. Simulation results show considerable improvement, compared to centralized shortest path routing algorithms.

- **Predictive Optimized Link State Routing (P-OLSR)** [217,218]: This routing protocol is an advanced version of OLSR routing protocol. This algorithm exploits GPS information and calculates an Expected Transmission (ETX) count metric to estimate the quality of the link when finding the optimal path. Numerical results show that the P-OLSR outperforms other algorithms such as OLSR and BABEL under dynamic network topology.

- **Geographic Position Mobility Oriented Routing (GPMOR)** [219]: This routing protocol proposes an efficient and effective geographic-based routing protocol that uses the Gauss–Markov mobility model to predict the movement of UAVs to eliminate the impact of highly dynamic movements. This approach selects the next hop according to the mobility relationship in addition to the Euclidean distance to make more accurate decisions. Experiment results show that this approach provides effective and accurate data forwarding solutions. Moreover, it decreases the impact of intermittent connectivity and achieves a better latency and packet delay rate than other position-based routing protocols.

- **Mobility Prediction Clustering Algorithm (MPCA)** [220]: This routing algorithm is appropriate for clustered UAV networks. It finds the highest node reliability to select the cluster head. Then, it predicts the network topology using the Trie data structure dictionary prediction and link expiration time mobility model. Also, this approach ensures the stability of cluster formation.

- **Robust and Reliable Predictive (RARP)** [221]: This routing protocol combines omnidirectional and directional transmission schemes with dynamic angle adjustment. This method features a hybrid use of unicasting and geocasting routing protocols using the location and trajectory information. The intermediate node locations are predicted using 3-D estimation; then, directional transmission is used toward the predicted location, enabling a longer transmission range and tracking topology changes. The authors show that their method reduces path re-establishment and service disruption time and achieves higher successful packet delivery rates.

- **Scoped Flooding and Mobility Prediction-based RGR (SFM-PRGR)** [222]: This algorithm is a modified version of RGR. This method associates with data packets mobility prediction information, including velocity, direction, and timestamp, to compute the distance between the current node and its neighbors. Then, if the next hop is out of range, the approach directly switches to GGF to save dropped data packets, making it a better approach for dynamic networks.

- **Q-learning-based Geographic adhoc routing protocol (QGeo)** [223]: This is an ML-based geographic routing scheme to reduce network overhead in high-mobility scenarios. The basic idea is that nodes make geographic routing decisions distributively, utilizing a reinforcement learning method without knowing the entire network topology. It consists of location estimation, a neighbor table, and a Q-learning module. The location estimation module updates the current location information reported by the GPS or other localization methods. Their results show that QGeo provides a higher packet delivery rate and a lower network overhead than previously reported routing protocols.

- **Predictive Ad-hoc Routing fueled by Reinforcement learning and Trajectory Knowledge (PARRoT)** [224]: This is another ML-powered routing protocol, which exploits mobility control information for integrating knowledge about the future motion of the mobile agents into the routing process. Each agent estimates its own future position based on the current position and propagates the result to other nodes. This algorithm achieves higher robustness and a significantly lower end-to-end latency compared to similar algorithms previously reported. This algorithm is appropriate for separating networking from path planning layer or when the paths are planned on the fly, since the nodes are assumed to be unaware of their future locations.

- **Fuzzy Logic Reinforcement Learning-Based Routing Algorithm (FLRLR)** [225]: This algorithm uses fuzzy logic to determine the neighbor nodes in real-time. Then, by using the future reward method of reinforcement learning, this method reduces the average number of hops through continuous training. Simulation results show lower average numbers of hops and high link connectivity, compared to the Ant Colony Optimization (ACO) algorithm.

8.2.2. Self-adaptive learning-based routing protocols

Most learning-based routing protocols use Reinforcement Learning (RL) to make routing decisions by continued and online learning of the environment and their decision consequences on desired performance metrics such as delay, throughput, energy efficiency, and fairness. A key advantage of RL-based algorithms is their abstract formulation which brings independence from topology prediction and channel estimation. This comes from the concept of learning from experience.

The concept of RL for optimized routing is shown in Fig. 9. Initially, the scenario is represented by state s_1, where node or agent A_1 has two candidate neighbors A_2 and A_3 to send its packet. Consequently, we must select between action a_1 or a_2 based on the reward expected for each action a at state s, defined as $Q(s, a)$. Once we select the appropriate action, the agent A_1 obtains an immediate reward from the environment, r_1 or r_2, respectively. Next, we start the same process in a new state s_2, where decisions are made based on the new environmental conditions and the learned policy in terms of actions-rewards relations. The end goal is to find an optimal policy in which the cumulative reward over time is maximized by assigning optimal actions to each state [226].

RL-based routing was first introduced in [228], where Q-Routing considered packet forwarding as an application of Q-learning. This method demonstrated superior performance compared to a non-adaptive algorithm based on the pre-computed shortest paths [229]. The essence of Q-Routing is gauging the impact of routing strategies on a desired performance metric by investigating different paths in the *exploration* phase, and using the discovered best paths in the *exploitation* phase. Exploration imposes an overhead to the system, but is critical for finding newly emerged optimal paths, especially when the network topology undergoes substantial changes. An inherent challenge is to adaptively solve the trade-off between the exploration and exploitation times to accommodate the dynamicity of the network topology.

The following is a summary of learning-based routing protocols mainly based on Q-Routing to show they evolved over time to better serve dynamic UAV networks.
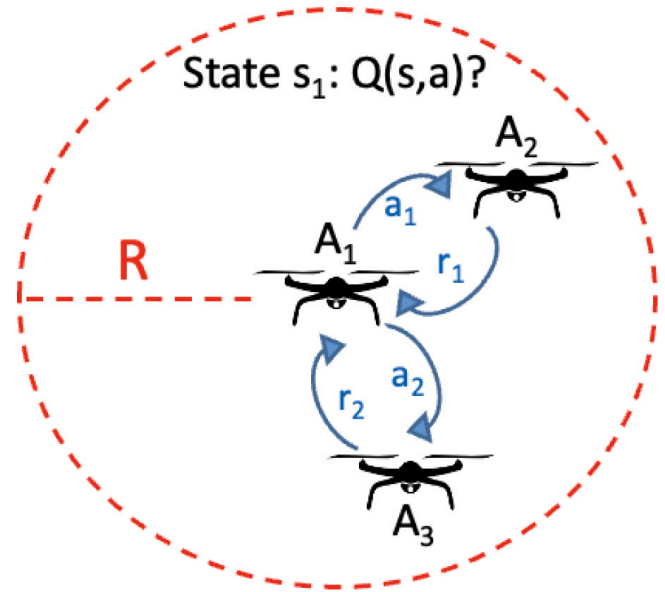

Fig. 9. Illustration of the RL-based routing [227].

- **Q-Routing** [228]: The first proposed Q-Routing protocol operates based on learning from experience. Each node stores the expected time to the destination through any of its neighbors as Q-values in a Q-table. Each node selects the next node that minimizes the expected travel time to the destination. Once a packet is received by a node, it sends back the real travel time to the previous node to updates its Q-values for the next round.

- **Predictive Q-Routing (PQ-Routing)** [230]: This method is an extension of the conventional Q-Routing that addresses the exploration–exploitation trade-off and fine-tunes the routing policies for the low network loads. Their approach was based on learning and storing new optimal policies under decreasing load conditions and reusing the learned best experiences by predicting the traffic trend. Their idea was to re-investigate the paths that remain unused for a while due to the congestion-related delays. The probing frequency is an adjustable parameter to be tuned based on the path recovery rate estimate. Their proposed results showed that PQ-Routing outperformed the Q-Routing in terms of both learning speed and adaptability. However, PQ-Routing requires large memory for the recovery rate estimation. Also, it is not accurate in estimating the recovery rate under varying topology change rates (e.g., when nodes start to moving faster). Furthermore, this method only works for delays arising from the queuing congestion and not delays coming from the network topology change.

- **Dual Reinforcement Q-Routing (DRQ-Routing)** [231]: The key idea of this algorithm is to use forward and backward explorations by the sender and receiver of each communication hop, by appending information to the packets they receive from their neighbors. Simulation results prove that this method learns the optimal policy more than twice faster than the standard Q-Routing. A comparative analysis of learning-based routing algorithms is provided in [232], where the performance of the self-adaptive Q-Routing and dual reinforcement Q-Routing algorithms are compared against the conventional shortest path algorithms. Their results showed that the Q-learning approach performs better than the traditional non-adaptive approach under scenarios with increasing traffic that causes node and link failures. However, Q-Routing does not always guarantee finding the shortest path and does not explore multiple forwarding options in parallel.

- **Credence-based Q-Routing (CrQ-Routing) and Probabilistic Credence-based Q-Routing (PCrQ-Routing)** [233]: These two methods dynamically capture the traffic congestion to improve the learning process to select less congested paths. Both methods adapt to the current network conditions much faster than the conventional Q-Routing.

- **Full-echo Q-Routing** [228]: Another technique proposed to accelerate the learning speed of conventional Q-Routing is the *full-echo* approach. In conventional Q-Routing, each node only updates the Q-values for its selection (the best neighbor). In contrast, in the *full-echo* routing, a node gets each neighbor's estimate of the total time to the destination, which helps update the Q-values accordingly for each of the neighbors.

- **Full-echo Q-Routing with Adaptive Learning Rate** [234]: A more recent work added adaptive learning rates to the *full-echo* Q-Routing to improve the exploration performance. Results show that this technique reduces the oscillations of the *full-echo* Q-Routing for high load scenarios.

- **Adaptive Q-Routing with Random Echo and Route Memory (AQRERM)** [235]: An extension of the previous work is AQRERM, which improves the performance of the baseline method in terms of the overshoot and settling time of the learning process, as well as the learning stability.

- **Poisson's probability-based Q-Routing (PBQ-Routing)** [236]: This approach uses forwarding probability and Poisson's probability for decision making and controlling transmission energy for intermittently connected networks. Results show that the delivery probability is almost twice bigger than for Q-Routing, and the overhead ratio is reduced to half.

- **Delayed Q-Routing (DQ-Routing)** [237]: This routing protocol uses two sets of value functions to carry out random delayed updates to reduce the overestimation of the value function and improve the rate of convergence. Experiments show that this method also improves the learning rate.

- **QoS-aware Q-Routing (Q^2-Routing)** [238]: This method includes a variable learning rate based on how big are variations in Q-values and ensures the traffic Quality of Service (QoS). Results show that this method outperforms the well-known ad-hoc routing algorithms in dynamic environments under QoS constraints.

- **Q-Network Enhanced Geographic Ad-Hoc Routing Protocol Based on GPSR (QNGPSR)** [239]: This routing protocol uses Q-network as an approximator to estimate the quality of different routing paths. Then, it makes forwarding decisions based on the estimated Q-values. Also, the neighbor topology information is introduced to estimate the environment and node states. QNGPSR is trained off-line when the signal propagation model is determined. Therefore, online-learning is not necessary, which reduces the computational load. Results show a higher packet delivery ratio and a lower end-to-end delay compared to the original GPSR.

- **Adaptive and Reliable routing protocol with deep reinforcement learning (ARdeep)** [240]: This is a deep RL-based adaptive and reliable routing protocol that formulates routing decisions with a Markov Decision Process model to characterize the network variations automatically. It considers link status, the packet error ratio, the expected connection time of the link, the remaining energy of nodes, the distance between the node and the destination when making routing decisions to precisely infer the network environment and make more appropriate forwarding decisions. Simulation results show that ARdeep outperforms the existing QGeo and conventional GPSR routing protocols.

- **Traffic-aware Q-Network enhanced routing protocol based on GPSR (TQNGPSR)** [241]: Traffic-aware Q-network enhanced geographic routing protocol based on Greedy Perimeter Stateless Routing (GPSR). This algorithm uses the congestion information of neighbors and evaluates the quality of a wireless link by the

Q-network algorithm as a traffic balancing strategy. Then, the protocol makes routing decisions based on the evaluation of each wireless link. Results show an improving performance in terms of packet delivery ratio and end-to-end delay.

- **Q-learning based Multi-objective optimization Routing protocol (QMR)** [242]: This novel Q-learning-based multi-objective optimization routing protocol adaptively adjusts the learning parameters based on the dynamicity of the network. The authors proposed a new mechanism to explore some undiscovered potential optimal paths while exploiting the acquired knowledge by re-estimating neighboring relationships to select the more reliable next hop. Results show a higher packet arrival ratio, lower delay, and energy consumption than the preceding Q-learning-based routing methods.

- **Q-Learning-based Fuzzy Logic for Multi-Objective Routing algorithm in Flying Ad Hoc Networks (QLFLMOR)** [243]: This multi-objective Q-learning-based fuzzy logic algorithm facilitates the selection of the routing paths in terms of the per-link and overall path performances. The optimal routing path to the destination is determined by each UAV using a fuzzy system with link-level and path-level parameters. The link-level parameters include the transmission rate, energy state, and flight status between neighbor UAVs, while the path-level parameters include the hop count and successful packet delivery time. Simulation results show that the proposed method can maintain low hop count and energy consumption and prolong the network lifetime.

- **Adaptive UAV-assisted Geographic Routing with Q-Learning (QAGR)** [244]: This algorithm uses fuzzy-logic and Depth-First-Search (DFS) algorithms to calculate the global path routing. As it is designed for UAV-Assisted networks, the vehicle on the ground maintains a fix-sized Q-table that converges with a well-designed reward function and forwards the routing request to the optimal node by looking up the Q-table filtered according to the global routing path. Results show a good performance in packet delivering and end-to-end delay.

- **Fully-Echoed Q-Routing with Simulated Annealing Inference for Flying Adhoc Networks (FESAIQ-Routing)** [227]: This routing protocol is a full-echo Q-Routing with an adaptive learning rate controlled by Simulated Annealing (SA) optimization, where the *temperature* parameter captures the influence of the nodes' mobility on the Q-value update rates. The soft variation of the exploration rate not only optimizes the exploration rate, but also accommodates abrupt changes in the network dynamicity. Simulation results show better performance than previous state-of-art Q-Routing algorithms.

A summary of some of these routing protocols is presented in Tables 3 and 4 with some characteristics for each routing protocol, as well as some comparative results to provide an idea of how these routing protocols perform under certain circumstances.

9. Tools and public datasets

In this section, we review tools and public datasets available for simulating real UAV networking environments. We investigate their features and capabilities, emphasizing their use for testing networking solutions (e.g., routing protocols) for UAV networks under different conditions.

9.1. Simulation tools

UAV simulation tools emulate virtual environments to model UAV flights in close-to-reality situations. It gives the convenience of evaluating the performance of UAV networks in virtual environments at much lower costs and trouble before testing in real scenarios. The choice of the appropriate simulator depends on both the testing objective and

Table 3
Performance comparison table for topology predictive routing protocols.

Algorithm	Objective performance				Results
	Energy	Delay	Throughput	Connectivity	
PPMAC+RLSRP [216]		✓	✓	✓	Compared to DMAC, LODMAC, OLSR, GPMOR, RARP, IMAC+OLSR: • Lowest network delay and longest path lifetime • Highest route setup success and data delivery ratio. • Better successful throughout without retransmissions.
Predictive Dijkstra's [80,105]		✓			Compared to conventional Dijkstra's algorithm: • Up to 25% decrease in end-to-end delay for 100 nodes.
Predictive greedy routing [32]	✓		✓		Compared to conventional Dijkstra's and static greedy: • Higher probability of success (up to 100%). • Energy consumption reduction (up to 30%).
P-OLSR [217,218]			✓	✓	Compared to OLSR and BABEL: • Cuts down the outage time by at least 85%. • Achieves a more stable goodput.
GPMOR [219]		✓	✓		Compared to GPSR and GLSR: • Better packet delivery ratio (up to 250%). • Lower average delay of the network (up to 50%).
MPCA [220]			✓	✓	Compared with LID, HD and WCA: • Up to 500% increase in clusterhead duration. • Up to 70% lower reaffiliation frequency.
RARP [221]			✓	✓	Compared to conventional AODV: • Up to 30% increase in route setup success rate. • Higher average path lifetime.
SFMPRGR [222]		✓	✓		Compared to AODV, RGR, and MPRGR: • 10% increase in packet delivery ratio. • 20% reduction end-to-end delay.
QGeo [223]		✓	✓		Compared to GPSR and QGrid: • Up to 50% increase in packet delivery ratio • 20% reduction in end-to-end delay.
PARRoT [224]		✓	✓		Compared to AODV, OLSR, GPSR and B.A.T.M.A.N: • Higher packet delivery ratio (at least by 45%). • Lower end-to-end latency
FLRLR [225]		✓		✓	Compared to Fuzzy Logic and ACO: • Up to 20% lower average number of hops. • Around 30% higher connectivity.

the list of features offered by each simulator. Some simulators incorporate the Motion of Capture (MOCAP), which allows simulating UAVs' natural movements [257]. Another tool is MAVLink, a lightweight messaging protocol for communicating with drones to test communication protocols and algorithms. Software In The Loop (SITL) is a hardware-free simulation environment that facilitates simulating real-time UAV operations. It includes a c++ code to directly implement autopilot operation on the user's computer for testing [258].

The list of tools for simulating UAV networking is large and still growing. A comparative analysis of some popular simulation tools, including X-Plane [247], FlightGear [248] (compatible with MATLAB Simulink), Gazebo [249], JMavSim [250], Microsoft AirSim [251], and UE4Sim [252], is presented in Table 5. The first four simulate the UAV motions solely based on physics laws and do not support MOCAP. On the other hand, Microsoft AirSim and UE4Sim support MOCAP by using Unreal Engine 4 (UE4), an open-source tool that simulates UAV movement using physics along with a high-quality trajectory creation engine. AirSim is considered a platform for both AI research and training [259]. AirSim is empowered with deep learning, computer vision, and reinforcement learning features to generate and utilize training datasets [260]. Also, UE4Sim simulator benefits from a built-in and robust DL-based approach for real-time autonomous driving that does not require manually collected training data. For this reason, Microsoft AirSim and UE4Sim are considered two of the

best simulators currently available. By combining AI components, these simulators allow researchers to simulate their algorithms in near-real environments, with the opportunity to develop better algorithms for AI-based networking and control tasks.

9.2. Experimental platforms

Experimental platforms enable testing networking protocols in emulated network setups. Most experimentation platforms can be executed on a standalone computer or High-Performance Computing (HPC) servers. However, larger experimentation platforms typically consist of custom-built hardware with a set of simulation and operation software packages, programming environment, and web-based user interface to enable remote experimentation for the research community.

The most commonly-used experimental platforms are Network Simulator (NS-3) [261], and OPNET [262]. NS-3 is an open-source, free, and discrete-event network simulator for Internet and networking systems, enabling testing different layers of networking protocols, including routing protocols in MAC and Network layers. OPNET is an open network simulator used to simulate the function and performance of different networking systems. It is known for its power and versatility to create and simulate different network topologies. OPNET Technologies considers requests for free access for academic use.

Table 4

Performance comparison table for self-adaptive learning-based routing protocols.

Algorithm	Objective performance			Results
	Energy	Delay	Throughput	
Adaptive Q-Routing Full-echo [234]		✓		In comparison to Q-Routing and Dual Q-Routing: • Smaller average delivery time.
AQRERM [235]		✓		Compared to Q-Routing, DRQ-Routing and AQFE: • Better overshoot and settling time of the learning. • Lower average delivery time.
PBQ-Routing [236]	✓	✓	✓	Compared to Q-Routing, Epi-R, PRoPHET and HBPR: • Delivery probability almost gets doubled. • Lower energy use and overhead reduced to half.
Q^2-Routing [238]		✓	✓	Compared to AODV and EQ-Routing: • Lower packet delay. • Higher packet success ratio.
DQ-Routing [237]			✓	Compared to Q-Routing: • Much higher average reward of DQ-routing. • More likely to choose best action.
QNGPSR [239]		✓	✓	Compared to OLSR, AODV and GPSR: • Up to 65% lower end-to-end delay. • Up to 35% higher packet delivery ratio.
ARdeep [240]		✓	✓	Compared to QGeo and conventional GPSR: • Up to 30% higher packet delivery ratio. • Up to 30% lower average end-to-end delay.
TQNGPSR [241]		✓	✓	Compared with AODV, OLSR, GPSR, and QNGPSR: • Outperforms in terms of the packet delivery ratio, end-to-end delay, and throughput.
QMR [242]	✓	✓	✓	Compared to other Q-learning based routing methods: • Higher packet arrival ratio, lower delay and energy consumption.
QLFLMOR [243]	✓	✓	✓	Compared to conventional fuzzy logic and Q-value-based AODV: • Lower hop count and energy consumption and longer network lifetime.
QAGR [244]		✓	✓	Compared to ARPRL [245], U2RV [246], GPSR and AODV: • Up to 300% higher in packet delivering ratio. • Around 50% lower end-to-end delay and up to 90% reduction in average number of hops.
FESAIQ-Routing [227]	✓		✓	Compared to Q-R, REE-R, PE-R, AFEQ-R and SAHQ-R: • Reduction in energy consumption between 7% to 82%. • Increase of up to 264% in packet delivery ratio.

Table 5

UAVs simulation tools.

Simulator	Free access	ROS Interface	MOCAP	MAVLink	SITL	Obstacles	Usability
X-Plane [247]	No	No	No	Yes	Yes	Yes	Medium
FlightGear [248]	Yes	No	No	Yes	Yes	Yes	Medium
Gazebo [249]	Yes	Yes	No	Yes	Yes	Yes	Easy
JMavSim [250]	Yes	Yes	No	Yes	Yes	No	Easy
Microsoft AirSim [251]	Yes	No	Yes	Yes	Yes	Yes	Medium
UE4Sim [252]	Yes	No	Yes	No	No	Yes	Medium

Table 6

UAVs experimental platforms.

Experimental platform	Interface	Free access	MAVLink	Compatible pilot software
QGround-Control [253]	Graphical	Yes	Yes	PX4 Autopilot, ArduPilot
Mission Planner [254]	Graphical	Yes	Yes	PX4 Autopilot, Ardupilot
MAVProxy [255]	Command	Yes	Yes	Ardupilot
UGCS [256]	Graphical	Yes, but limited	Yes	DJI, Innoflight, Micropilot, Mikrokopter, Microdrones, Parrot

Some other simulators are developed specifically for UAV networks. For instance, ROS-NetSim [263] is a Robot Operating System (ROS) package, which acts as an interface between robots (UAVs in this case) and network simulators. ROS-NetSim accurately replicates Perception-Action-Communication (PAC) loops. Moreover, ROS-NetSim is tunable to account for a large range of communication fidelity and complexity.

Another UAV-specific simulator is UB-ANC University at Buffalo's Airborne Networking and Communications Testbed (UB-ANC) [264], which is an open platform that facilitates rapid testing and repeatable

Table 7
UAVs trajectory datasets.

Trajectory datasets	Size/Length of flight	Description
Blackbird [272]	10 h of flight data from 168 flights.	Large-scale, aggressive indoor flight dataset collected using a custom-built quadrotor platform. Over 17 flight trajectories and 5 environments at velocities up to 7.0 m/s.
KAUST [273]	11.172 Gb including all material.	Trajectories, proxy meshes and images generated for path planning on real and synthetic scenes. It includes a benchmarking tool allowing new trajectories to output camera images for reconstruction.
Mid-Air [274]	420k frames representing 79 min of drone flight records extracted out of more than 5 h of flight.	Multi-purpose synthetic dataset for low altitude drone flights. Data corresponding to flight records of a flying quadcopter recorded in different climate conditions, including a test set for benchmarking.
UZH-FPV [275]	Over 27 flight sequences, with more than 10 km of flight distance.	Visual-inertial odometry dataset from a drone racing quadrotor with fast laps around a racetrack trajectories, as well as free-form indoor and out trajectories around obstacles.

comparative evaluation of airborne networking and communications protocols at different layers of the protocol stack. It enables the flexible deployment of novel communications and networking protocols, with emphasis on modularity and extensibility.

A recently established experimentation center is Aerial Experimentation and Research Platform for Advanced Wireless (AERPAW) in the North Carolina State University (NCSU) [265,266]. This NSF-funded center integrates drones and 5G wireless technology to provide increased coverage and connectivity, high throughput aerial monitoring, and improved signals and location data. The idea is to allow U.S. researchers to test new ways of increasing wireless speed and capacity in an experimental infrastructure, where nodes are mobile with the ability to transmit and receiving radio/video waves from user devices while moving on demand. This can be convenient under disaster relief circumstances, in which existing cellular networks may be damaged. Moreover, it is expected to make an impact in time-sensitive deliveries, smart agriculture, autonomous driving, and accident control applications [267].

Another remote experimentation Platform is the Open Wireless Data-driven Experimental Research (POWDER) that operates as a highly flexible, remotely accessible, end-to-end software defined platform supporting a broad range of wireless and mobile related research [268]. This NSF-funded center has many features and capabilities including a massive MIMO base station and Software-Defined Radios (SDRs) that advances competitors in scale, realism, diversity, flexibility, and access. More advanced routing protocols which require function virtualization and SDR technology can be tested in this environment before implementing in UAV networks.

We can also find experimental platforms that act as a ground control station operating artificial UAVs. These platforms can be used to test communication protocols developed for UAV networks in simulated environments. Depending on the test scenario and objectives, we can select from a list of available software packages. These platforms include QGround-Control [253], Mission Planner [254], MAVProxy [255] and UGCS [256], as presented in Table 6.

Some experimental platforms use a graphical interface for user convenience, and some are command-line-based to provide more flexibility. We analyze the inclusion of MAVLink and the tools' compatibility with pilot software. We found that PX4 Autopilot, Ardupilot, ROS, DJI Pilot, Innoflight, Micropilot, Mikrokopter, Microdrones, and Parrot are open-source autopilot systems capable of controlling autonomous vehicles, with a variety of aircraft operation scenarios, such as aerial mapping, surveying, and more applications.

It is worth mentioning that some of the mentioned experimental platforms offer AI capabilities for networking research. For instance, NS-3 has NS3-GYM [269], and NS3-AI [270] extension modules that enable applying AI to network simulations in NS-3. The key idea is to provide a high-efficiency solution to allow data interaction between NS-3 and other AI frameworks and encourage the use of AI in networking research. Also, AERPAW and POWDER contain AI embedded into hardware for superior detection, tracking, and classification of UAVs [271], as well as for spectrum-maximizing resource allocations.

9.3. Trajectory datasets

Trajectory datasets consist of recorded data from real-time UAV flights that are useful for simulation purposes. The idea is to test new methodologies or protocols using trajectory data that mimic real-world situations. The bigger the size of the dataset, the more variability of flight trajectories is incorporated. In Table 7, we compare some UAV trajectory and imagery datasets available for all users that can be helpful in simulating unmanned aerial monitoring platforms. These datasets include Blackbird [272], KAUST [273], Mid-Air [274] and UZH-FPV [275]. We observe that each dataset offers UAV motions with different characteristics. The most appropriate dataset should be selected based on the specific test requirements and conditions. There exist many UAV datasets containing UAV imagery, as well as aircraft trajectory datasets. However, they do not exactly reflect UAV motion patterns, which is the main feature in path planning and routing scenarios. Therefore, there is a need to produce more relevant UAV trajectory datasets. Some methods use real data to train deep learning algorithms for trajectory design and recognition [276,277]. Having access to accurate trajectory datasets will allow researchers to develop better solutions for real-world scenarios.

10. Future trends and remaining challenges

Despite the recent advances in developing ML-powered networking protocols for UAV networks, there still are challenges and issues that would be the center of attention for coming years. From the communication perspective, most technical challenges arise from the limited payload, processing power, and structure-free and highly dynamic nature of unmanned aerial platforms [278–282]. This section summarizes part of these challenges and the future outlook of UAV networking technology from different perspectives, including AI integration, energy efficiency, security, regulations, etc.

10.1. AI integration

Using AI to accelerate networking is the dominant research trend, as discussed in this paper. AI is shown to offer superior performance for communication, control, and operation of autonomous UAVs under different networking scenarios [25–27]. Moreover, it can optimize network management and reduce their complexity [283]. We believe that the current networking designs have not yet fully utilized the power of AI-based solutions, and further research is on the way to integrate AI and networking paradigms by using more advanced ML algorithms [67], RL-based decision-making [284], and deep learning [285] for different aspects of networking, including sensing, scheduling, routing, spectrum sharing, path planning, and resource allocation.

However, it is worth mentioning that the use of AI-based methods can bring up new challenges, and needs to be studied carefully. For instance, AI methods can help to predict the future locations of the network nodes and potential link losses, and hence improve the power

consumption by avoiding the transmission of hopeless packets that will be lost during the transmission. However, the use of AI methods can add to the computation complexity and CPU power use in power-constrained UAVs. Therefore, the right choice of the routing protocol should be based on the application-specific requirements and design constraints. Then, as a future solution, we need to study if the effect of including AI techniques into our model is worth the complexity that will be added, which could be affecting other important aspects such as the network lifetime and power consumption.

10.2. Connectivity

Maintaining connectivity for UAV networks remains an important issue considering the limited communication range of commercial UAVs, which is typically limited to a few miles, while the coverage area in some applications like forest fire monitoring, disaster management, and wildlife monitoring can scale to hundreds of miles [286–288]. Connectivity loss can cause packet drop, frequent link re-establishment, shortened link lifetime, prolonged delays, and ultimately disrupt the mission and compromise the user QoE. Recent methods use ML methods to predict network topology change ahead of time and avoid connectivity loss by learning-based routing [105,220,222,224]. Another approach is including the link remaining time or path lifetime into the routing criteria [37]. Other methods try to identify and resolve the connectivity loss by methods such as placement of new UAVs and link re-establishment mechanisms [219].

One of the potential future trends would be integrating online path planning methods with networking algorithms to realize topology control with minimal connectivity issues. This approach is feasible in many real-world scenarios where the coverage area is defined, but there is a high degree of freedom in UAV's motion paths (e.g., search and rescue scenarios, regular forest monitoring, etc.). Also, connectivity is dependent on the interference caused by objects and environmental factors. Therefore, using more advanced AI methods to predict the influence of network nodes, environment, and surrounding objects on networking quality, can mitigate connectivity issues. In some applications with sparsely distributed nodes, intermittent connectivity is unavoidable. Also, connectivity can be caused by UAVs that ran out of battery. Developing AI methods to predict and accommodate such conditions is another potential research direction [34].

10.3. Routing

In Section 8, we studied AI-enabled routing protocols, which use ML algorithms to predict network topology directly (e.g., predictive routing methods [32,105]) or indirectly (e.g., RL-based methods [242,243]) and use it for the route selection process. However, there still exist challenges to be addressed.

Most routing protocols consider a fully connected network, whereas in reality, link breakages exist, causing routing protocols to fail [289]. Also, node mobility in routing protocols is mostly developed for and tested in 2D spaces, whereas UAVs move in 3D spaces. The third research challenge is developing vision-based target tracking methods to predict network topology, noting that future UAVs will be equipped with Graphics/Tensor Processing Units (GPU/TPUs), capable of running deep learning methods for video processing. Developing probabilistic and priority-based routing protocols to prioritize packets with critical and confidential content is another potential research direction. Finally, extending RL-based method to accommodate non-linear motions and implementing light-weight routing protocols for miniaturized UAVs are two important remaining challenges.

10.4. Energy efficiency

UAVs are highly constrained in payload and battery lifetime. The available energy should be optimally used for navigation, sensing, actuation, transmission, and data processing [290]. Therefore, developing energy-efficient networking to prolong mission time and extend coverage area is usually considered a top priority in UAV networks [291, 292].

A parallel research direction to solve energy issues of UAVs is developing new battery technologies, such as hydrogen fuel cells [293], and enhanced lithium-ion batteries [294]. Also, Radio Frequency (RF) transmission can be used for Wireless Power Transfer (WPT) [295], which provides controllable and sustainable energy supply for UAVs [296,297]. Further research is required to improve the use of WPT by reducing the distance between charging stations and UAVs, the random energy arrivals, and the scalable nature of UAVs [298,299]. Another research direction is considering mmWave communications for UAV networks, energy beamforming, and the optimized placement of wireless charging stations. Integration with 5G, and 6G wireless systems are also research topics related to energy optimization. A few routing protocols consider energy as a routing criterion. Developing multi-objective and constrained optimization methods for routing protocols to enhance routing efficiency, while maintaining maximal connectivity and minimizing energy consumption is an important future direction. Further research is required to develop energy-aware routing protocols. Some recent works offer storing data and postponing calculations to the future to reduce power consumption while flying [300].

Another potential solution can be using energy-efficient ML and DL algorithms for networking, such as energy-efficient convolutional neural networks [301]. However, new challenges come into place when we use the mentioned techniques. First, it is misbelieved that reducing the energy consumption of the algorithms does not necessarily lead to a reduction of the overall energy consumption. Second, in some scenarios, measuring the energy consumption becomes redundant since energy and time are correlated, and time is already measured. Third, it might be hard to measure the energy consumption, making it time consuming and impractical [302]. Despite a few scenarios where these statements are true, we can find that reducing the energy consumption of the algorithms used will impact positively the overall energy consumption and also, measuring energy consumption can offer a unique overview, compared to time consumed. Last, there are some solutions that can model the energy consumption of different algorithms [303], as for example Alphabet's DeepMind.

10.5. Spectrum management

Enabling high-rate, low-latency, and ultra-reliable wireless communications in UAV networks is a necessity for future applications. Currently, UAVs use different communication protocols, including WiFi, LTE, LoRA, and 5G for A2 A and A2G communications. In recent years, progress has been made in obtaining additional dedicated radio-frequency spectrum (5030–5091 MHz) for drone operations [279]. In addition to the usual ways of power management, interference control, spectrum-efficient networks, the use of different spectrum sensing, spectrum sharing, and spectrum leasing is considered to extend the service area of UAVs [101,102,304,305], especially in unexpected and harsh conditions such as disaster management.

In a different line of research, some models offer using fiber optic communications [306], laser [307] and LiFi [308] to provide a faster and more efficient way for transmitting large amounts of data over long distances to cover the increasing demand for bandwidth. These methods would alleviate the spectrum scarcity issue. However, more research is expected to solve optical communications' specific issues, including sensitivity to interference and adaptive antenna steering.

Table 8
Remaining issues and future directions.

Open issues	Problems	Future directions
• AI integration	• Current networking designs have not yet fully utilized the power of AI-based solutions. • The use of AI methods can add to the computation complexity and CPU power use in power-constrained UAVs.	• Use ML, RL and DL techniques for different aspects of networking, including sensing, scheduling, routing, spectrum sharing, path planning, and resource allocation. • Study if AI improves performance and does not impact negatively network lifetime and power consumption aspects.
• Connectivity	• Link failures bring limited network lifetime. • Communication links between UAVs are extremely vulnerable. • Connectivity is dependent on the interference caused by objects and environmental factors.	• Use ML methods to predict network topology change ahead of time and avoid connectivity loss by using learning-based routing. • Consider techniques that enhance link lifetime by adding link remaining time or path lifetime into routing criteria. • Resolve the connectivity loss by methods such as placement of new UAVs and link re-establishment mechanisms. • Integrate online path planning methods with networking algorithms to realize topology control with minimal connectivity issues.
• Routing	• Most routing protocols consider a fully connected network, whereas in reality, link breakages happen. • Node mobility in routing protocols is mostly developed for and tested in 2D spaces, whereas UAVs move in 3D spaces. • Non-linear motions are not considered in current routing protocols. • Miniaturized UAVs have limited battery lifetime.	• Design a routing protocol that considers intermittent connectivity into the routing selection process, as well as 3-dimensional space. • Design a topology-predictive routing to accommodate non-linear motions. • Develop vision-based target tracking methods for GPU-powered UAVs to predict network topology. • Develop a light-weight AI-powered routing appropriate for miniaturized UAVs.
• Energy efficiency	• UAVs are highly constrained in payload. • Battery designs are limited in energy optimization trends. • Only a small portion of routing protocols considers energy or power as a routing criteria.	• Develop energy-efficient networking to prolong mission time and extend coverage area as a top priority. • Develop new battery technologies, such as hydrogen fuel cells and enhanced lithium-ion batteries. • Use RF transmission for WPT. • Consider mmWave communications, energy beamforming and placement optimization of wireless charging stations. • Examine energy-aware routing future directions to incorporate energy level in the decision-making criteria to extend path lifetime. • Use energy-efficient ML and DL algorithms for networking, such as energy-efficient convolutional neural networks.
• Spectrum management	• Spectrum unavailability can cause the loss of command and control of the aircraft. • Spectrum remains vulnerable to unintentional or intentional interference.	• Spectrum sharing and spectrum leasing techniques using advanced AI-based solutions. • Optimal communications including sensitivity to interference and adaptive antenna steering can optimize data acquisition objectives.
• Security and user privacy	• UAVs are usually subject to different security attacks. • Aerial monitoring systems may exchange imagery with people's private information, which requires higher protection levels. • Conventional PKI-based asymmetric security solutions are not feasible due to the lack of central authority to issue digital signatures. • Jamming attacks can also disrupt UAV missions.	• Use hardware-driven security keys for UAV authentication and enable the non-repudiation feature. • ML methods can be used to detect and eliminate jamming, or provide an additional reference for positioning verification. • Develop secure routing schemes that alleviate security issues while finding optimal paths.
• Operational regulations	• Lack of or ambiguity of regulations and standards for UAV operations, characteristics, safety requirements, secrecy and privacy considerations, and allowed airspace.	• Develop certification standards and air traffic requirements for UAV operations that are universal. • Use AI software for regulation compliance to ensure safety of confidential information, risks mitigation and instant response to new regulatory requirements.

10.6. Security and user privacy

Developing secure and privacy-preserving networking methods is another key challenge for UAV networks. UAVs are usually subject to different security attacks, including physical hijacking, jamming attacks, cyber-attacks, man-in-the-middle attack, intruding malicious nodes, channel interception, and denial of service, especially when flying over adversary territory [43]. Also, aerial monitoring systems may exchange imagery with people's private information, which requires higher protection levels.

A key challenge in structure-less UAV networks is that using conventional PKI-based asymmetric security solutions is not feasible due to the lack of central authority to issue digital signatures. Therefore, methods based on distributed certificate [309], key pre-distribution algorithms [310,311], and blockchain security [312] are under investigation. Also, the idea of using hardware-driven security keys for UAV

authentication and enabling the non-repudiation feature is recently proposed as a potential future direction [313]. Jamming attacks can also disrupt UAV missions, especially when they rely in GPS positioning. Using alternative localization methods [314], as well as, designing a secure handover mechanism which is resistant to both passive and active attacks [315], can solve this issue. Also, machine learning methods can be used to detect and eliminate jamming, or provide an additional reference for positioning verification [316]. Another emerging research trend is developing secure routing schemes that alleviate security issues while finding optimal paths [317].

10.7. Operational regulations

Another hindrance to the widespread use of drone technology is the lack of or ambiguity of sufficient regulations and standards for UAV operations, characteristics, safety requirements, secrecy and privacy

considerations, and allowed airspace. In the US, the FAA is responsible for developing certification standards and air traffic requirements for drones. For instance, flying drones above class G airspace and in autonomous modes require special permits from the FAA that can take a long time. Also, international coordination would help develop global regulations, noting that different territories follow different standards and regulations. For instance, currently, there exist three different regions, including (i) region 1 that covers Europe, Africa, and parts of the Middle East, (ii) region 2 that covers America, and (iii) region 3 that covers Asia and the Pacific, which have different frequency bands for UAV operations. One more potential solution would be using AI software for regulation compliance, which ensures increased safety of confidential information, risks mitigation and instant response to new regulatory requirements. This way, we could find AI-enabled drones authorized for use in different regions, following the operational regulations at each specific area.

10.8. Summary of challenges

We identified the need for (i) advanced AI methods to precisely predict networking conditions and environmental factors, (ii) integrative networking and topology control for extended connectivity, (iii) vision-based tracking methods for GPU-powered UAVs, (iv) topology-predictive routing to accommodate non-linear motions, (v) developing light-weight AI-powered routing appropriate for miniaturized UAVs, (vi) distributed structure-free extension of asymmetric security protocols based on key pre-distribution, hardware-driven keys, blockchain, and distributed certificate methods, (vii) ML methods to recognize and combat jamming attacks, (viii) energy-efficient low-power and low-complexity networking, (ix) AI-based spectrum sharing and leasing policies, security-aware mission planning, and (xi) universal regulation and guidelines for UAV operation, as top key issues that are worthy of investigation by the research community. A more detailed summary of the remaining challenges and future trends is included in Table 8.

11. Conclusion

The dominant trend of UAV systems is departing from single-drone systems to networked autonomous drones to accomplish complicated tasks at lower cost and time. The idea of using AI-based networking and control protocols to accommodate dynamic situations has recently gained a lot of attention, thanks to the advances in AI and deep learning methods powered by fast and affordable computational platforms. Here, we focused on the most recent AI-based methods that aim to model and predict network topology to facilitate more efficient information flow for aerial networks. This important class of routing protocols is overlooked or not received the deserved emphasis in previous survey papers.

In this paper, we reviewed AI-based routing protocols designed for UAV networks, highlighting the benefits and costs of each type, along with available testing and implementation tools, relations to mobility models and networking protocols, and connection to UAV swarming. These methods include the direct use of ML methods for topology prediction, as well as learning-by-experience approaches. We also reported substantial improvements of the most recent methods in terms of connectivity control, successful packet delivery rate, transmission delay, and throughput for AI-based routing protocols, compared to conventional methods. We also provided our perspective on the future trends for AI-based networking, which mainly center around developing method for more accurate environment perception, vision-based tracking, light-weight DL algorithms appropriate for on-board processing, AI-based spectrum sharing, and security-aware networking.

Declaration of competing interest

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

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Arnau Rovira-Sugranes received his Ph.D. in Informatics and Computing from the School of Informatics, Computing and Cyber Systems (SICCS) in Northern Arizona University (NAU), Flagstaff, AZ, USA, in August 2021. Earlier, he graduated with a Master of Science in Informatics in 2019 from Northern Arizona University and a Bachelor's degree in Industrial Electronics and Automation Engineering in 2016, from Rovira i Virgili University. After graduating, he worked in an automotive seating and electrical systems company before starting his Ph.D. program.

His research interests include machine learning and data mining, communication and routing protocols and graph theory for flying ad-hoc wireless networks (FANETs), which produced peer-reviewed publications on predictive based solutions for Internet of Things. Also, he has served as an IEEE conference/journal paper reviewer and symposium moderator.
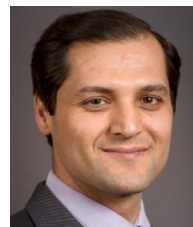
Abolfazl Razi is an assistant professor in the School of Informatics, Computing and Cyber Systems at Northern Arizona University (NAU). He received his B.S., M.S. and Ph.D. degrees, all in Electrical Engineering, respectively from Sharif University (1994–1998), Tehran Polytechnic (1999–2001), and University of Maine (2009–2013). Prior to joining NAU, he held two postdoctoral positions in the field of machine learning and predictive modeling at Duke University (2013–2014), and Case Western Reserve University (2014–2015). He is the recipient of several competitive awards including the Best Research of MCI in 2008, Best Graduate Research Assistant of the Year Award from the College of Engineering, University of Maine in 2011, and the Best Paper Award from the IEEE/CANEUS Fly By Wireless Workshop in 2011. His current research interests include smart connected communities, biomedical signal processing, wireless networking, Internet of things, and predictive modeling.

Fatemeh Afghah is an Associate Professor with the School of Informatics, Computing, and Cyber Systems, Northern Arizona University (NAU), Flagstaff, AZ, USA, where she is the Director of Wireless Networking and Information Processing (WiNIP) Laboratory. Prior to joining NAU, she was an Assistant Professor with the Electrical and Computer Engineering Department, North Carolina A&T State University, Greensboro, NC, USA, from 2013 to 2015. Her research interests include wireless communication networks, decision making in multi-agent systems, radio spectrum management, and artificial intelligence in healthcare. Her research has been continually supported by NSF , AFRL, AFOSR, and ABOR.

She is the recipient of several awards including the Air Force Office of Scientific Research Young Investigator Award in 2019, NSF CAREER Award in 2020, NAU's Most Promising New Scholar Award in 2020, and NSF CRII Award in 2017. She is the author/co-author of over 80 peer-reviewed publications and served as the organized and the TPC chair for several international IEEE workshops in the field of UAV communications, including IEEE INFOCOM Workshop on Wireless Sensor, Robot, and UAV Networks (WiSRAN'19) and IEEE WOWMOM Workshop on Wireless Networking, Planning, and Computing for UAV Swarms (SwarmNet'20).

Jacob Chakareski is an Associate Professor in the College of Computing at the New Jersey Institute for Technology (NJIT), where he holds the Panasonic Chair of Sustainability and directs the Laboratory for AI-Enabed Virtual and Augmented Reality Immersive Communications and Networked Systems. His research interests span next generation virtual and augmented reality systems, UAV IoT sensing and networking, fast reinforcement learning, 5G wireless edge computing and caching, ubiquitous immersive communication, and societal applications. He received the Adobe Data Science Faculty Research Award in 2017 and 2018, the Swiss NSF Career Award Ambizione (2009), the AFOSR Faculty Fellowship in 2016 and 2017, and Best Paper Awards at ICC 2017 and MMSys 2021. He completed his Ph.D. degree at Rice and Stanford in Electrical and Computer Engineering, held research appointments with Microsoft, HP Labs, and EPFL, and served on the advisory board of Frame, Inc. His research has been supported by the NSF, NIH, AFOSR, Adobe, Tencent Research, NVIDIA, and Microsoft. For further info, please visit www.jakov.org.