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SURVEY ARTICLE

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A systematic literature review of flying ad hoc networks: State-of-the-art, challenges, and perspectives

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Abstract

Unmanned aerial vehicles (UAVs), also known as drones, communicate, collaborate, and form flying ad hoc networks (FANETs) to perform many different missions, ranging from delivery tasks to agriculture applications. Recently, FANETs have been integrated with different technologies, such as artificial intelligence (AI), virtual reality, and Internet of Things. Such new avenues for the use of UAVs directly impact the research on FANETs and cause some major challenges, such as security and physical layer issues, resource management, and UAV positioning issues that need to be addressed. Several researchers have been working for the last few years to propose AI and machine learning (ML)-based solutions for different use cases in UAV-based networks. They present the limitations of the existing research work and highlight some possible future works on FANETs. However, exhibiting the trends in the UAV research papers in a quantitative manner is still required to motivate researchers to rethink the research on FANETs. Therefore, this study covers more than 170 scientific publications extracted from five trusted academic databases published from 2013 to 2021 to provide a thorough overview of the main research and development statistics in the area of FANETs, the open challenges existing in this area and the ML-based solutions to solve these challenges. In addition, the investigation of emerging technologies integrated with FANETs, as well as the simulation tools employed for evaluating FANETs' performance are discussed. Moreover, the future research directions in the area of FANETs are considered within a prospective vision discussion.

KEYWORDS

cellular networks, flying ad hoc network, machine learning, reinforcement learning, unmanned aerial vehicles/drones

1 | INTRODUCTION

In recent years, designing the collaborative systems of unmanned aerial vehicles (UAVs) commonly known as drones have become a major research topic in different areas, especially in robotics and artificial intelligence (AI) (C. Chen et al., 2018; Sultan et al., 2021). On the basis of available statistics,[1] the worldwide commercial UAV market size is growing. Around 1.1 billion dollars were invested in the aerial guided system industry in 2020. The global commercial UAV

[1]https://www.statista.com/statistics/1117058/global-commercial-drone-investments/

market is expected to reach *58.4* billion dollars in 2026. The significant investments in the aerial guided system industry show that UAVs are becoming more common in all-day applications.

Recently, different civilian and military applications are implemented using multi-UAV systems in which there is a swarm or formation of small UAVs. This approach brings together the concept of flying ad hoc network (FANET) of UAVs which allows a group of UAVs to communicate and cooperate towards completing their mission without human intervention. To accomplish their missions, the swarm of UAVs moves freely in the environment using different types of mobility models, which is an aspect that takes into account both the dynamics of the UAV network and the physical characteristics of the UAV platforms. It is important to notice that this paper refers to the word "FANET" as a network of UAVs (UAV–FANETs) and uses FANETs, UAV networks, UAV-networked systems, UAV-based networks, and networked UAV-systems interchangeably referring to the same concept.

Not only the continuous advance of the hardware has drastically impacted the FANETs of UAVs, but also the development of software, in particular in the area of AI, has been crucial (Garaffa et al., 2021). This advance benefits FANETs used in different application domains. As the FANETs become more intelligent, they manage to interact and make part of other systems, such as cloud-based ones and Internet of Things (IoT) Systems. In addition to the existing challenges in traditional FANETs, new issues arise, such as bottlenecks, latency due to centralized processing, lack of offline processing, and security issues. In this context, machine learning (ML) approaches offer promising models in AI domain to address these challenges with deep learning (DL) and reinforcement learning (RL)-based solutions.

As FANETs have been adopted by many industries, a deep insight into challenges and perspectives in FANETs are important subjects that need to be studied. A way to guide this study is by means of a Systematic Literature Review (SLR). SLR deals with the systematic collection, critical interpretation, and assessment of the quality level of relevant published papers on a given research topic by answering clearly formulated questions.

There is a small number of existing SLRs of FANETs that cover these topics, their joint applications, and their open challenges (Haula & Agbozo, 2020; Mualla et al., 2019; Rejeb et al., 2021; Stampa et al., 2021). However each of them only considers specific aspects and applications of UAVs. The SLR in Rejeb et al. (2021) provides a survey regarding UAVs in supply chain management and logistics. Mualla et al. (2019) and Haula and Agbozo (2020) only focus on UAVs in civilian applications, while in Stampa et al. (2021) they address public safety applications of UAVs. Such lack of extensive SLRs about FANETs in the literature motivates the employment of a comprehensive SLR methodology in this paper.

The main contributions of this paper can be summarized as follows:

- In addition to an extensive study of the existing academic research, this paper provides a thorough overview of the overall research and development statistics in the area of FANETs, the open challenges that exist in this area, the ML-based solutions to solve them, and the simulation tools that are employed for evaluating FANETs' solutions performance.
- Particularly, this SLR also introduces a discussion on possible ML-based solutions for FANETs, especially when it comes to the integration of UAVs with other emerging technologies, such as IoT, 5G/6G, Blockchain, and quantum communication, with a prospective vision on FANETs technology.

The research methodology employed for this SLR is described in Section 2. Section 3 answers the quantitative questions, including statistical questions (number of publications by year, countries, funding sponsors, and published patents). Section 4, answers the specific questions containing FANETs challenges and possible ML-based solutions, challenges of applying ML towards to address problems of FANETs, and the simulation tools, frameworks, and testbeds for FANETs' performance analysis. The future research directions of UAV–FANETs, including UAV-assisted 5G and 6G wireless networks, Blockchain-envisioned UAV communication in the 6G network, AI-enabled object detection in the UAV-networked system, Software Defined Network (SDN), Network Function Virtualization (NFV), Internet of Multiple-Input Multiple-Output things (IoMIMO)-based UAVs, quantum communication, three-dimensional (3D) beamforming, and reconfigurable intelligent surface (RIS)-enabled UAVs are discussed in Section 5. Section 6 concludes the paper.

2 | RESEARCH METHODOLOGY

SLR deals with the systematic collection, critical interpretation, and assessment of the quality level of relevant published papers on a given research topic (Kitchenham, 2004). In contrast to the traditional literature reviews, the SLR provides a more accurate and comprehensive level of understanding. Inspired by the SLR approach in Kitchenham et al. (2010), four well-defined steps are considered, including the definition of research questions in Section 2.1, the scientific databases in Section 2.2, the inclusion and the exclusion criteria in Section 2.3, and the review phase, research and development statistics in Section 2.4.

2.1 | Research questions raised in this SLR

The definition of the Research Question is the essential part of the systematic investigation which clearly defines a path for the research process. In this paper, the research is guided based on the central question:

> How do ML techniques improve the performance of Flying Ad Hoc Network?

Since ML techniques have been broadly employed in wireless networks, especially in FANETs of autonomous UAVs to train

TABLE 1 Research questions of the study based on the two types of questions: statistical and specific questions

Question type	Ref	Research questions
Statistical questions	RQ1	What are the research and development statistics on the area of FANETs? which includes six subquestions: (the number of publications by year (A), by countries (B), funding bodies (C), and the number of published patents (D).
Specific questions	RQ2	What are the main problems being researched regarding FANETs (open challenges)?
	RQ3	How ML approaches are being used to improve the performance of the FANETs?
	RQ4	What are the challenges of applying machine learning towards the main problems of the FANETs?
	RQ5	What are the common simulators, emulators, and test beds to implement the FANETs' scenarios?

Abbreviations: FANETs, flying ad hoc networks; ML, machine learning.

network nodes to control, monitor, and predict different communication parameters, such as traffic patterns, node positioning, the behavior of wireless channels, and so forth (Guerber et al., 2021; Oliveira et al., 2021), an opportunity was identified to propose this SLR covering this subject domain. However, as this subject is complex, other side topics needed to be included to make the SLR more useful and comprehensive. Table 1 shows the statistical and specific research questions on the area of FANETs. To illustrate the research and development statistics on UAV-based networks, the statistical question *RQ1* was raised which refers to the number of publications by year, by countries, and funding bodies, and the number of published patents. In addition to statistical questions, Table 1 shows specific questions (*RQ2–RQ5*) that help break up the study into easy steps to answer the central research question of the paper ("How do ML techniques improve the performance of Flying Ad Hoc Network?"). Since countering the current challenges in UAV-assisted networks may lead to an improved system performance in the future, question *RQ2* discusses the main open challenges of FANETs. After identifying the main problems and breaking the problem down into some subproblems, question *RQ3* provides the potential ML-based solutions to address the existing issues in UAV-assisted networks. It is important to know the challenges of applying ML techniques on FANETs' issues discussed in question *RQ4*, since it provides motivation for research and helps scholars to find the innovative solutions to address these challenges. Since evaluating the performance of UAV-based communication networks in the real world is a tough task that requires remarkable time and resources, question RQ5 addresses the common simulators, emulators to implement the FANETs' use cases.

2.2 | Scientific databases used to find the relevant published studies

This section shows the scientific sources used in the search for relevant papers from 2013 to 2022. This time frame was selected because the most relevant works were found from 2013 to 2021, and there is also an upward trend in this period in the number of published studies on this topic. In this paper, the relevant published studies are obtained from the ACM Digital Library,[2] Scopus,[3] IEEE Xplore,[4] Elsevier Science Direct,[5] Springer Link,[6] Google Scholar[7] academic databases, and Google Patents[8] based on the search terms provided in Table 2. Table 2 shows the five main search terms, including "flying ad-hoc network," "FANETs" "drone," cellular networks," "machine learning," "artificial intelligence," "reinforcement learning," and "federate learning" by considering the main keywords of the research questions, and the results obtained by applying these terms on different academic databases. Quotes were used around the phrases to find results that are exact match results, rather than the broad results. According to Table 2, *s*1 shows the related words and acronyms of UAV-assisted networks that are combined using the Boolean operator OR to show all the research investigated in the area of drones. Since *s*1 includes general terms combined by operator OR, it brings a huge number of results. Therefore, the first terms were refined with the inclusion of other search terms to acquire more specific results, and a total of 6579 papers were found by applying the second to fifth search terms. *s*2 and *s*3 try to find the research investigated on AI and ML techniques for UAV-assisted wireless networks by adding the terms ("cloud computing" OR "cellular networks") AND ("machine learning" OR "artificial intelligence") into the first term *S*1. To change the outcome of the search and obtain narrower terms, *s*4 connects the first search term by operator AND with the terms ("Reinforcement learning" OR "Federate Learning"). *s*4 shows the studies that take advantage of RL or federated learning (FL) techniques to address the challenges of UAV-based communication networks. To be more specific, and find out the publications that use ML, RL, and FL in 5G and 6G networks we combined ("Machine learning" OR "reinforcement learning" OR "Federate Learning") AND ("5G" OR "6G") into to the first search and make *s*5. The search started with terms found in relevant SLRs (Haula & Agbozo, 2020; Mualla et al., 2019; Rejeb et al., 2021; Stampa et al., 2021), then continued with the combination of these terms, and the creation of

[2] http://portal.acm.org
[3] https://www.scopus.com/
[4] https://ieeexplore.ieee.org/Xplore/home.jsp
[5] https://www.sciencedirect.com/
[6] https://link.springer.com/advanced-search
[7] https://scholar.google.com/
[8] https://patents.google.com/

TABLE 2 Definition of six search strings and obtained results from ACM, Scopus, Springer, ScienceDirect, and IEEE academic databases

Ref	Search string	Result ACM	Scopus	Springer	ScienceDirect	IEEE
*s*1	"flying ad-hoc networks" OR "UAVs" OR "Drones" OR "FANETs"	3451	65,624	33,189	22,027	13,261
*s*2	("flying ad hoc networks" OR "FANETs" OR "UAVs" OR "Drones") AND ("cellular networks") AND ("machine learning" OR "artificial intelligence")	36	46	179	295	47
*s*3	("flying ad hoc networks" OR "UAVs" OR "Drones" OR "FANETs") AND ("cloud computing" OR "cellular networks") AND ("machine learning" OR "artificial intelligence")	170	128	376	1165	135
*s*4	("flying ad hoc networks" OR "FANETs" OR "UAVs" OR "Drones") AND ("Reinforcement learning" OR "Federate Learning")	182	1157	213	923	526
*s*5	("flying ad hoc networks" OR "FANETs" OR "UAVs" OR "Drones") AND ("Machine learning" OR "reinforcement learning" OR "Federate Learning") AND ("5G" OR "6G")	103	139	97	591	73

Abbreviations: FANETs, flying ad hoc networks; UAVs, unmanned aerial vehicles.

new ones by considering the main keywords of the research questions as well. On the basis of the acquired results, the selected terms were refined until coming to those in Table 2.

2.3 | Inclusion and exclusion criteria

After defining the search terms and gathering papers from the selected scientific databases, a selection process was performed. In this process, according to the inclusion and exclusion criteria presented in Table 3, all the publications that are not relevant to the goals of this survey were removed.

2.4 | Review phase or paper selection

The paper selection phase can be considered in three main steps, including *search*, *screening*, *and eligibility analysis*.

Search: First, the papers were retrieved from different digital databases based on search strings, and downloaded separately. According to Table 2, the first search term brings a huge number of results. The results obtained by applying the first term were refined with the inclusion of other search terms to acquire more specific results. As shown in Table 2 a total of *6579* papers were found by applying the second to fifth search terms. Papers in which search terms appeared in titles, keywords, and abstracts were selected for screening.

Screening: In this step, *1282* duplicate papers are removed and *3760* studies were excluded based on criteria provided in Table 3. To remove the duplicates, some tools are available, such as Menedely and Publish and Perish.[9]

Eligibility: Some papers that are not on the focus of this study, are deleted after reading the titles, keywords and in some cases the abstracts of the article. In some cases, in which the title and the abstract are not very clear about the proposed solution, a full-text analysis is required. Therefore, to apply eligibility criteria, the titles and abstracts of *561* were considered. Finally, the set of *177* most relevant papers (SLRs, research articles, surveys, and review papers) was included by reading the entire paper to answer the research question. The results are discussed in Section 3.

[9]https://onlinelibrary.wiley.com/doi/10.1111/j.1475-4983.2006.00617.x

TABLE 3 Inclusion and exclusion criteria used in paper selection procedure

Counts	Inclusion criteria
1	English peer-reviewed studies that provide answers to the research questions.
2	The studies consisting of literature reviews or systematic mapping studies.
3	Studies are published between 2013 and 2022.
4	References of closed related papers that are explicitly and specifically dedicated to ML techniques in cloud-based UAV systems.
5	Papers that cited the closed related papers and are explicitly dedicated to ML techniques in FANETs.
	Exclusion criteria
6	The studies that are not available for access.
7	Studies whose full text is not available.
8	Duplicated studies.
9	Studies are not in English.
10	Studies that are Loosely related (LR) to the search strings.
11	Studies that are not related to the research questions.

Abbreviations: FANETs, flying ad hoc networks; ML, machine learning; UAVs, unmanned aerial vehicles.

3 | QUANTITATIVELY ANSWERING THE RESEARCH QUESTIONS

In this section, a quantitative research approach is applied using statistical and mathematical tools to derive results and to provide possible answers to the first statistical question *RQ1* raised in Table 1. This question includes five subquestions. This section first discusses the result of the search process, the selection process, and the quantitative analysis of the selected papers. Then, it provides statistics about the four subquestions, including the number of publications by year (A), by countries (B), funding bodies (C), and the number of published patents (D).

Table 2 provides the search results extracted from the selected databases for five main search terms. As can be observed in Table 2, the first search string *s*1: (*"flying ad-hoc networks" OR "UAVs" OR "Drones" OR "FANETs"*) used returned papers with a broad range of subjects.

To give a more accurate answer to *RQ1*, the following analysis provides the considering *65,624* results obtained from *Scopus* database. Scopus was chosen since it covers a broader journal range and provides more advanced analytics, and higher quality, compared with other scientific databases.

3.1 | Publications by year

Figure 1 represents the number of studies on this topic according to their year of publication. According to Figure 1, a significant number of studies have been published from 2013 to 2020 which means that drone-assisted networks are becoming a major research topic. Such a growth can be justified by rapid technological changes, increasing labor cost, increase in delivery demand along with other reasons. In 2013, reputed companies such as Amazon started to take advantage of UAVs as a product delivery approach. Therefore, *2768* studies were published in 2013 as depicted in Figure 1. After the issuance of the permission of employing UAVs in commercial applications by the FAA, *4070* papers were published in 2015. The number of publications continued to grow in the following years and reached the peak of *12,033* in 2020 which is directly correlated with the growth of worldwide commercial UAV market size shown in Figure 2. As shown in Figure 1, the number of published articles in 2020 and in 2021 is very close to 2019. However, the number of published papers decreased by around 1000 in 2021 and reached *11,937*. This is because, the values of 2020 and 2021 are still being updated, since there are delays in indexing and making the published articles available.

3.2 | Publications by countries

Figure 3 shows which countries actively contribute in the UAV research area. Among represented countries, the largest number of studies were from the China and the United States (US), with *19,313* and *18,606* publications, respectively. This shows these two countries spend a huge amount of investment on UAV-based projects. Other than the China and US, the United Kingdom (UK), Germany, South Korea, Italy, India, Australia, France, and Canada have contributed to many UAV-based projects with *4137*, *3518*, *3365*, *3341*, *2786*, *2759*, *2709*, and *2670* publications, respectively. Currently international collaboration is very common in scientific publications. Measuring collaboration between different countries is done by assigning each paper to the relevant countries on the basis of the authors' institutional affiliations. For international collaborations, articles written by authors from more than one institution in the same country only count as one collaboration for that country.[10]

3.3 | Publications funding

As funding can motivate researchers to investigate the issues which require sensitive equipment in-depth, it is important to identify the agencies that support research on FANETs financially. According to Figure 4 National Natural Science Foundation of China, National Science Foundation spends billions of dollars on the research and production of UAVs by analyzing search results obtained from

[10]https://oecd.ai/en/elsevier

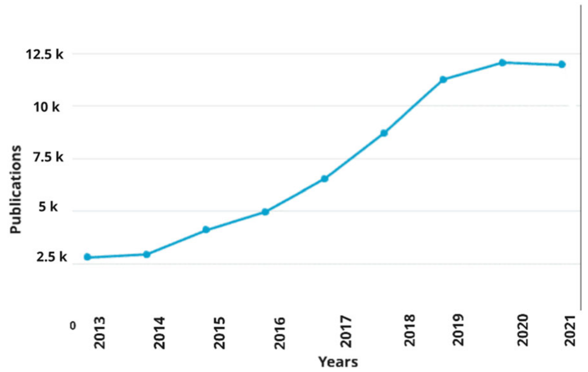

FIGURE 1 The number of UAV-based publications per year from 2013 by the end of 2021. UAV, unmanned aerial vehicle. [Color figure can be viewed at wileyonlinelibrary.com]

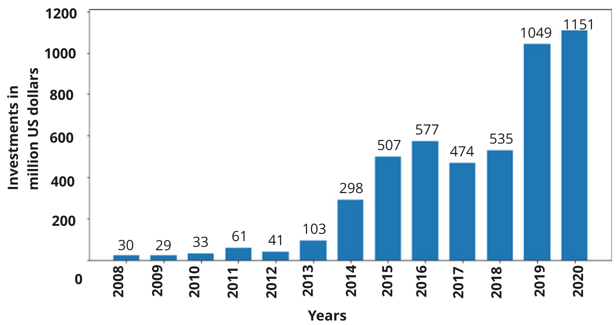

FIGURE 2 Worldwide investments in the aerial guided system industry, from 2008 to 2020. UAV, unmanned aerial vehicle. [Color figure can be viewed at wileyonlinelibrary.com]

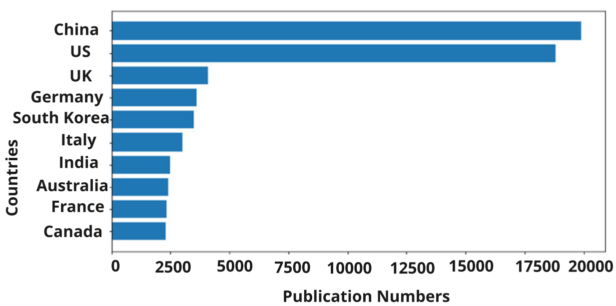

FIGURE 3 The list of 10 first countries, including, China, the United States, the UK, Germany, South Korea, Italy, India, Australia, France, and Canada, were actively engaged in UAV-based research areas. UAV, unmanned aerial vehicle. [Color figure can be viewed at wileyonlinelibrary.com]

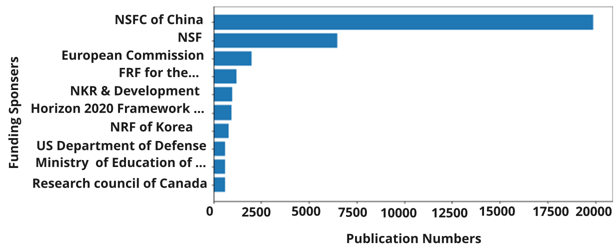

FIGURE 4 The list of 10 first funding sponsors in the UAV-based research area, including, National Natural Science Foundation (NSFC) of China, National Science Foundation (NSF), European Commission, National Research Foundation of Korea, US Department of Defense, Natural Sciences and Engineering, Research Council of Canada, and others. UAV, unmanned aerial vehicle. [Color figure can be viewed at wileyonlinelibrary.com]

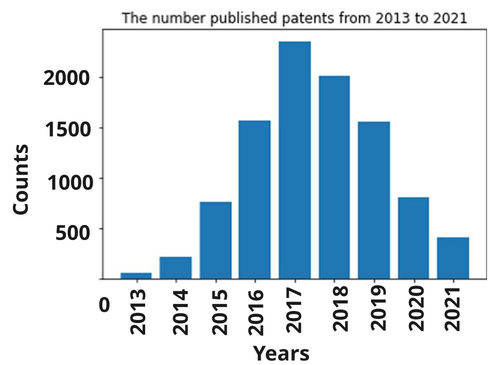

FIGURE 5 The number of worldwide published patents in the area of UAV-based networks. UAV, unmanned aerial vehicle. [Color figure can be viewed at wileyonlinelibrary.com]

Scopus. The other funding agencies shown in the figure are the European Commission, National Research Foundation of Korea, US Department of Defense, Natural Sciences and Engineering, and Research Council of Canada.

Figure 2 shows the worldwide commercial UAV market size is growing. As Figure 2 represents, in 2008 around *30* million dollars were invested in the aerial guided system industry, it increased and reached *1151* billion dollars in 2020. The global commercial UAV market is expected to reach *58.4* billion dollars in 2026.[11]

3.4 | Patents published worldwide in the area of UAV-based networks

To have an overall perspective about published patents in the area of UAV-based networks, the following string was used as a search criterion on Google Patents: "flying ad-hoc networks" OR "FANETs" OR "UAVs" OR "Drones" OR "aerial guided system" OR "autonomous aerial platform" OR "unmanned platform" OR "autonomous aerial device" OR "aerial robot" OR "autonomous aerial delivery" OR "aerial delivery." Since, some patents do not explicitly mention the terms "UAVs" or "drones" or "FANETs," other possible correlated terms were also part of the search. On the basis of the search term, the search resulted in *116,030* patents published in the selected time frame. Figure 5 compares the counts of published patents in different years from 2013 to 2021.

[11]https://www.statista.com/statistics/878018/global-commercial-drone-market-size/

This figure shows an upward trend as it is expected based on the investments spent on the aerial guided system industry (shown in Figure 2). In 2013, *1435* patents were published, this number increased by the following years and reached the peak number of publications *33,377* in 2021. The patents revolve around wireless power transformation, vehicle inspection, road condition detection, agricultural systems, wireless resource allocation, and wireless charging methods topics.

4 | ANALYSIS OF THE SPECIFIC QUESTIONS

This section answers the specific questions raised in Table 1. This section is divided into four subsections (research questions). The open issues in FANETs are discussed in Section 4.1 (*RQ2*), possible ML-based solutions to address the existing challenges in FANETs are addressed in Section 4.2 (*RQ3*), the issues arising after applying ML techniques in FANETs, are discussed in Section 4.3 (*RQ4*). The simulation tools, frameworks, and testbeds for FANET's performance analysis are explained in Section 4.4 (*RQ5*).

4.1 | Existing challenges and open issues of FANETs (*RQ2*)

This question addresses the fundamental challenges in FANETs (*RQ2*). In addition to UAV constraints shown in Figure 6—box *A*, the existing challenges in FANETs are presented as follows:

- *Physical Layer issues in Figure 6—box B*: According to Figure 6—box *B* the physical layer issues are discussed in the following:

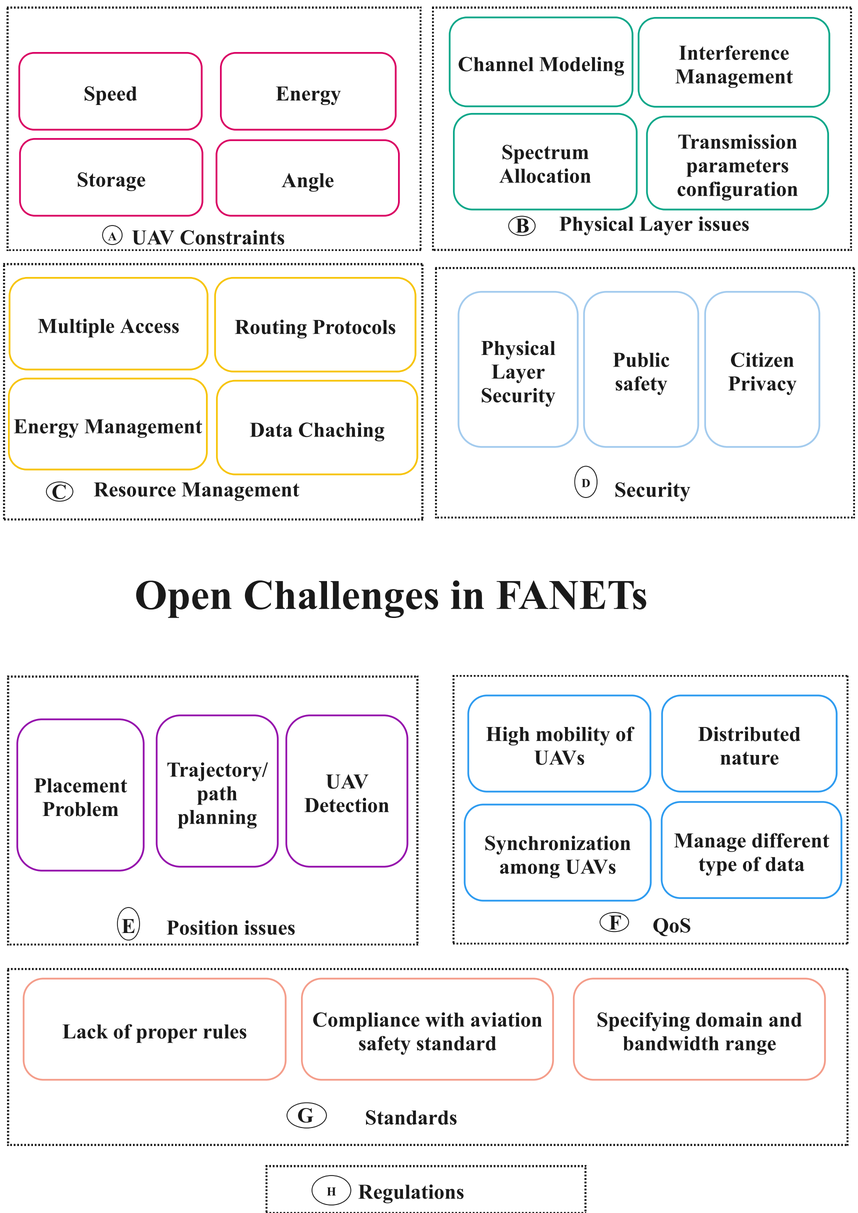

FIGURE 6 FANETs Challenges, including security and physical layer issues, standards, regulations, QoS, position issues, and UAV constraints. FANETs, flying ad hoc networks; QoS, Quality-of-service; UAVs, unmanned aerial vehicles. [Color figure can be viewed at wileyonlinelibrary.com]

- *Channel modeling*: In UAV-assisted networks, positioning and path optimization of the UAVs play a crucial role to provide efficient utilization of scarce communication resources, such as the electromagnetic spectrum. By taking into account locations and trajectories of UAVs, algorithms for accurate channel prediction and estimation in highly mobile environments, such as FANETs, have been proposed. There are two most common channel modeling for UAV networks, namely, air-to-air (A2A) channel modeling and air-to-ground (A2G) (Won et al., 2022). Unlike A2A channels, which are prone to free-space-path-loss-based models, A2G channels are very difficult to be modeled due to the blockages of high-rise buildings, but represent a very important factor that has to be considered (J. Chen & Gesbert, 2020; Kim et al., 2022; S. Zhang & Zhang, 2019). Predicting channel behavior is a challenging task because of several reasons. First, UAVs fly at various height levels which impacts on how channel impairments affect transmission. Second, the highly changeable mobility of UAVs and ground equipment are opposing reliable transmission, since propagation channels are vulnerable to suffering from spatiotemporal nonstationarity. In addition, fuselage shadowing which is associated with the size, altitude, and antenna placement of the UAVs, may lead to signal interruption. Therefore in the large-scale fading model, these influences are important. The diversity of the frequency band used in the UAV network which is ranging from sub-6 GHz to mmWave also affects channel characteristics. Finally, weather conditions, rainfall in particular lead to considerable attenuation due to scattering and absorption for frequencies above 10 GHz (Khuwaja et al., 2018; Q. Zhang et al., 2021).
- *Interference management*: Interference is an arising issue in both wireless networks and UAV communication systems. UAVs communicate with each other in the different parts of the radio spectrum shared with multiple other users. The available frequency bands for UAV transmissions in the radio spectrum are shown in Table 4. The radio propagation in the air is like free space propagation. Consequently, UAVs generate more interference to the networks in the uplink, also they face further interference in the downlink. Therefore interference management (avoidance or mitigation) techniques are required (Mozaffari et al., 2019; Rezwan & Choi, 2021).
- *Spectrum allocation*: The deployment of large-scale clusters of UAVs can perform a mission more efficient than a single UAV. However, providing reliable and stable communication between UAVs is essential. In this regard, spectrum resource allocation is an important factor that affects the quality of UAV communications and their cooperation. However, the quality of communication in UAV networks is sensitive to mutual interference due to the high demand for wireless resources and extreme congestion of spectrum resources. Therefore, more research needs to carry out in spectrum allocation which is a relatively new research area (J. Chen et al., 2019, 2021).
- *Transmission parameters configuration*: In FANETs, at the beginning of each transmission frame, the transmission parameters, such as noise power, the service rate each UAV requests, and fading coefficient of each A2A channel and A2G channel between every two UAVs, and between every base station (BS) and each UAV, respectively (Xu et al., 2021) need to be configured optimally to utilize wireless resources efficiently and to achieve reliable communication (Bithas et al., 2019).

TABLE 4 Available frequency bands for UAV transmissions in the radio spectrum

Frequency Bands	Applications
420–450 MHz	Emergency communications
902–928 MHz	Industrial, Scientific, and Medical (ISM) equipment, computer networking, repeaters, cordless phones, and amateur TV
1.24–1.3 GHz	Data, voice, GPS, and amateur TV
2.39–2.485 GHz	Wi-Fi, Bluetooth, wireless headphones, video and telemetry, microwave ovens, cordless phones
5.15–5.825 GHz	5G routers, Unlicensed National Information Infrastructure (UNII) devices

Abbreviations: GPS, global positioning system; TV, television; UAV, unmanned aerial vehicle; Wi-Fi, wireless fidelity.

- *Resource management in Figure 6—box C*: Resource management which tries to manage dynamically different resources, such as energy, bandwidth, transmit power, the number of UAVs, and UAV's flight time, is another challenging issue in FANETs (Mozaffari et al., 2019) according to Figure 6—box *C*. Multiple access and routing protocols, and energy management are described as follows.
  - *Multiple access and routing protocols*: The high-speed mobility degree of UAVs and terrestrial nodes lead to frequent topology changes. Therefore, routing protocols are needed to adapt the communication to the dynamic topology, high mobility, power constraints, intermittent links, and changing link quality (Gupta et al., 2016). The classical multiple access and routing protocols cannot fully support the dynamic nature of FANETs and topology modifications (Kim & Lee, 2018, 2020; Pasandideh et al., 2021). Therefore adaptive routing protocols are required to multiflow transmission, handling no neighbor problem, scalability issues, and directional antenna problem (Gupta et al., 2016; Mukherjee et al., 2019; Rezwan & Choi, 2021; W. Wang et al., 2017; M. Zhang et al., 2019; Z. Zheng et al., 2018).
  - *Energy management*: UAVs are equipped with limited battery and small payload capacity which support the functionalities, such as communication, flying, and computation. This kind of power source is insufficient to handle a mission. Therefore, optimizing the energy and power consumption is an essential factor which in turn, improves the overall network's performance (Gupta et al., 2016; Koulali et al., 2016; C. H. Liu et al., 2018; Sikeridis et al., 2018).

- Security in Figure 6—*box D*: Due to the highly dynamic nature of FANETs, uncontrollable environment, wireless links, heavy computations, important latency, and collaborative characteristics, traditional security techniques are not appropriate for UAV-networked systems. It is difficult and challenging to determine whether a UAV-networked system is secure or not according to the main security criteria, including integrity, availability, authenticity, confidentiality, and reliability. As Figure 6 box *D* shows, the security issues in FANETs are physical layer security (PLS), public and citizen safety which are discussed as follows:
  - *PLS*: The operation of the wireless network needs to be protected against various attacks, ranging from active and passive eavesdropping to jamming or spoofing due to the LOS environment. In that regard, the PLS solutions need to be investigated to enhance the privacy level of wireless transmissions (Bassily et al., 2013; B. Li et al., 2019; Mukherjee et al., 2014).
  - *Public safety*: The deployment of UAVs provides enabling public safety in different situations and applications, such as police force missions (to provide better accessibility than police force in difficult situations, search and rescue, and to inspect an armed person from a safe distance), correctional facilities (to fight contraband in prison system), and natural disasters. During natural disasters in which some ground BSs are out of service and there is no alternate path available for communications, flying nodes act as BSs to provide temporary communication or as monitoring nodes for evaluating the condition of vital infrastructures and environmental attributes (Bithas et al., 2019; Sikeridis et al., 2018).
  - *Citizen privacy*: People privacy is another challenging issue that needs to be addressed before permitting UAVs to fly in the national airspace. In other words, citizen privacy should be protected before commercializing UAVs for civilian operations and missions (Chriki et al., 2019).
- *Position issues in Figure 6—box E*: The position issues are of at most importance in multi-UAV network systems, as the optimal locations of UAVs significantly affect mission and network performances (Kim & Lee, 2018, 2020). Position optimization and trajectory design have been always challenging issues in UAV systems that are shown in Figure 6 box *E*.
  - *Placement problem*: The UAVs can be either utilitized to fly and move continuously, for which the path planning design is a significant research direction, or operate in a quasistatic way, for which UAVs optimal positioning is a major research line. UAV placement problem which tries to maximize the coverage region is a nonconvex problem and proved to be NP-hard (X. Liu et al., 2019; Lyu et al., 2017) in general. In UAV placement problem, UAVs horizontal and/or vertical positioning, inter-UAV safety distance maintenance, cost, UAV numbers, coverage rate, and users–UAV connectivity are important factors needed to be considered in the deployment problem (Gao et al., 2021; Ghazal, 2021; Kim & Lee, 2018, 2020; Lahmeri et al., 2021; Q. Liu et al., 2018; Masroor et al., 2021a; Rahimi et al., 2021; J. Yang, Liang, et al., 2021; C. Zhang et al., 2021).
  - *Trajectory/path planning*: One of the essential factors to optimize the UAV network's performance is UAV trajectory design or path planning (Mozaffari et al., 2019). When several UAVs are launched from different known initial locations, the issue is to create 2D trajectories, with a smooth velocity distribution along each trajectory, aiming at reaching a predetermined target location, while ensuring collision avoidance and satisfying specific routes and coordination constraints and objectives (Kim & Lee, 2018, 2020; Nikolos et al., 2007).
  - *UAV detection*: UAVs can be detected by ground BSs which perform an indirect discovery or by direct self-reporting. In FANETs, there are some challenges due to the density of mobile UAVs, numerous obstacles, NLoS propagation conditions, and the variation of light. Therefore, traditional detection approaches such as LiDaR sensors, radar, electro-optical sensors, and computer vision cannot be applied to address these challenges. As a result UAVs detection is an open issue (Rezwan & Choi, 2021).
- *QoS in Figure 6—box F*: Quality-of-service (QoS) metrics affect the performance of FANETs directly in which various types of data such as delay-sensitive data, video, and real-time audio can be transported. QoS constraints such as ensuring high coverage probability, throughput, and reliability as well as low latency, packet loss, and proper bandwidth, need to be considered. Path planning determination to provide service, protection against jamming attacks, and synchronization among UAVs are QoS-related issues that must be addressed. However, providing a comprehensive approach to support QoS in FANETs is a challenging task due to the highly mobile UAVs and the distributed nature of this network (Chriki et al., 2019; M. A. Khan et al., 2017; Rezwan & Choi, 2021). The difficulties of providing QoS in FANETs are shown in Figure 6—box *F*.
- *Standards in Figure 6—box G*: The existing networking standards are not able to fully address the challenges of UAV-networked systems and suitable standards are required for FANETs (Srivastava & Prakash, 2021). Several organizations carry out FANET's standardization, such as ISO/TC 20/SC 16,[12] ASTM International,[13] American National Standards Institute (ANSI),[14] Joint Aviation Authority (JAA),[15] and European Organization for the Safety of air navigation (EUROCONTROL).[16] According to Figure 6 box *G* the open challenges regarding the standardization are discussed in the following:
  - *Lack of proper rules*: One of the reasons that UAVs cannot be commercialized for civilian applications is the lack of appropriate rules and standards. Nearly all of the FANETs applications are provided for the military missions, the public use of UAVs may cause more complicated rules (Chriki et al., 2019).

[12] https://www.iso.org/committee/5336224.html
[13] https://www.astm.org/
[14] https://www.ansi.org/
[15] https://jaato.com/virtual-home/
[16] https://www.eurocontrol.int/

- *Compliance with aviation safety standard*: To ensure that there is no interference with the aviation industry, UAV standards must comply with the aviation safety standards.
- *Specifying domain and bandwidth range*: UAV network takes advantage of different wireless communication bands, such as UHF (Ultra High Frequency between 300 and 3000 MHz and 3 GHz), and L-band (1–2 GHz), VHF (Very high frequency 30–300 MHz), C-band (4–8 GHz), and Ku-Band (12–18 GHz). which at the same time used in various application areas, such as satellite communications and GSM networks. Since in FANETs there is communication with both UAVs and ground, the standard bands are needed to reduce the congestion problem. However, UAV standardization is still a challenging issue (Ahmadi et al., 2017; Srivastava & Prakash, 2021).

- *Regulations in Figure 6—box H*: Although FANETs bring many advantages, UAVs face bans in some countries due to privacy and ethics. Privacy, security, collision avoidance, public safety, and protecting data are the main concerns that need to be addressed by developing airspace regulations and registration of UAVs to control UAVs' operations while considering different factors, such as the spectrum, altitude, type, and speed of UAVs (Ahmadi et al., 2017; Chriki et al., 2019; Mozaffari et al., 2019; Shakhatreh et al., 2019; Srivastava & Prakash, 2021). The main criteria considered to make UAV regulations are as follows (Stöcker et al., 2017):
  - *Applicability*: UAV regulations are applied to determine the scope by considering the weight, type, and role of UAVs.
  - *Operational limitation*: It is related to restrictions on UAVs locations.
  - *Administrative procedures*: In some cases, particular legal procedures such as visiting authorities and acquiring required services and documents are needed for using UAVs.
  - *Technical requirements*: UAV regulations are required for control, communication, and the mechanical capabilities of UAVs.
  - *Implementation of ethical constraints*: UAV regulations can be varied in various geographical regions (rural and urban areas) and countries due to privacy protection.

4.2 | ML-based solution for FANETs problems (*RQ3*)

AI has been involved in various areas, ranging from speech recognition to wireless communication. Moreover, ML is one of the branches of AI that provides algorithms to train machines and help them to make decisions based on data and their experience. AI, ML, and DL have been widely employed in wireless networks operations in which train network nodes and elements to control, monitor, and predict different communication parameters, such as traffic patterns, node locations, the behavior of wireless channels, and so forth.

UAVs are becoming a very important part of wireless communication networks. However, the challenges discussed in Section 4.1 in this area need to be addressed. In this regard, among available solutions, some ML techniques are expected to provide some effective solutions for the various issues and problems identified in UAV-based communication systems. On the basis of the challenges discussed in Section 4.1, the ML-based solutions can be classified as shown in Figure 7. Table 5 provides brief descriptions and the main contributions of several recent surveys focusing on AI, supervised and unsupervised learning algorithms, DL and RL algorithms, and FL methods for UAV communication-based networks. According to Table 5, Lahmeri et al. (2021), Brik et al. (2020), and Nguyen et al. (2021) focus on the latest ML and FL methods employed in UAV-based communication, discussing the current limitations and challenges. Brik et al. (2020) discuss the federated DL concept to improve the communication overhead and data privacy of UAV-based wireless networks, and Nguyen et al. (2021) highlight the FL–IoT services and applications in UAV networks. While Sharma et al. (2020), Bangui and Buhnova (2021), Hassija et al. (2021), Luong et al. (2019), Feriani and Hossain (2021), Ullah et al. (2020), and Mekrache et al. (2021) provide an overview on AI and ML techniques in UAV-based network in which Sharma et al. (2020), Pradhan et al. (2023), and Rovira-Sugranes et al. (2022) focus on AI-empowered techniques, Bangui and Buhnova (2021) and Hassija et al. (2021) focus on ML methods used to provide safety of the UAV-based network, and Ullah et al. (2020), Luong et al. (2019), and Mekrache et al. (2021) discuss DL and deep reinforcement learning (DRL) algorithms used in

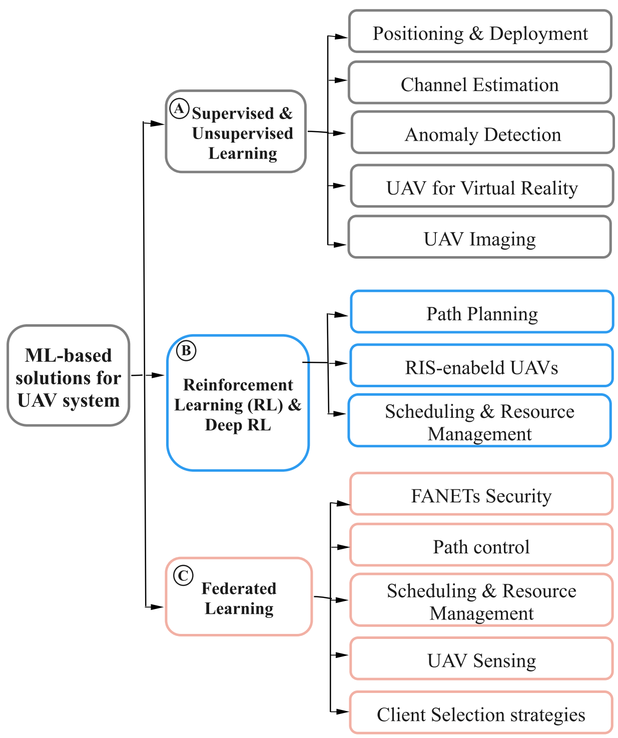

FIGURE 7 ML-based solutions, including supervised and unsupervised learning, reinforcement learning, and federated learning algorithms provided for FANETs' issues. FANETs, flying ad hoc networks; ML, machine learning; RIS, reconfigurable intelligent surface; UAV, unmanned aerial vehicle. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 5 Relevant surveys in the context of AI, ML, DL, and UAV communications

Reference	Description	Key contributions
Lahmeri et al. (2021)	AI for UAV-based communications	It discusses using unsupervised and supervised ML, RL, and FL techniques in UAV system problems, the current limitations, challenges, and a set of interesting open problems
Sharma et al. (2020)	Communication and networking technologies problems associated with UAVs	It discusses the challenges of using AI techniques for the future UAV communication systems
Bangui and Buhnova (2021)	Advances in ML-Driven Intrusion Detection in VANETs and UAV system	It discusses different ML techniques to protect VANET and UAV communications
Brik et al. (2020)	The application of FL in UAV networks	It discusses the federated deep learning concept to improve the communication overhead and data privacy of UAV-based wireless networks ranging from 5G networks and beyond, Edge computing and caching, IoT to FANETs
Nguyen et al. (2021)	The use of FL in various key IoT applications	It discusses the use of FL in UAV networks smart cities, and industry, highlighting the FL–IoT services and applications and current challenges and possible directions for future research in this area
Hassija et al. (2021)	Security-critical drone applications and security-related challenges in UAV-based communication	It discusses different ML algorithms that are used to detect malicious drones in the network and to detect safe paths
Luong et al. (2019)	The use of deep reinforcement learning (DRL) in modern networks, for example, IoT and UAV networks	It provides a tutorial on DRL from fundamental concepts to advanced models in order, to address the issues of UAV-based
Feriani and Hossain (2021)	Multiagent Reinforcement Learning (MARL) for AI-enabled wireless networks, such as Mobile edge computing	One section of this survey discusses MARL for UAV-assisted (MEC) and UAV networks wireless communications
Ullah et al. (2020)	The UAVs challenges, potential applications, and regulations	One section of this survey discusses optimal trajectory design using DLR algorithms
Mekrache et al. (2021)	The application of RL and DRL to vehicle networks	It discusses the DL and DRL algorithms that are used to address the issues of vehicle networks, such as UAV-based communication
Pradhan et al. (2023)	The role of AI Models for UAV Communications	It concludes the use of UAVs in real-time scenarios using AI-empowered techniques
Ben Aissa and Ben Letaifa (2022)	Open issues and applications of Machine Learning for UAV Communications	It discusses the ML solutions for air-to-air (A2A), air-to-ground (A2G) and ground-to-air (G2A) communications
Baig and Shahzad (2022)	Improve UAV Communication and Networking using AI and ML techniques	It discusses and compares Unsupervised and Supervised ML for UAVs-based issues

(Continues)

TABLE 5 (Continued)

Reference	Description	Key contributions
Rovira-Sugranes et al. (2022)	It discusses AI-enabled routing protocols for UAV networks	It provides a review on 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

Abbreviations: AI, artificial intelligence; DL, deep learning; FANETs, flying ad hoc networks; IoT, Internet of Things; ML, machine learning; RL, reinforcement learning; UAV, unmanned aerial vehicle; VANET, vehicular ad hoc network.

UAV-based networks. The contributions of the surveys provided in Table 5 are important, since they provide a comprehensive introduction of possible AI/ML/DL/FL-based solutions for different use cases in UAV-Based networks, present the limitations of the existing research work and highlighting some possible future works that motivate researchers to rethink the research on FANETs. To sum up, FL-based methods are more adequate for many UAV-enabled wireless applications and will have the most impact in the future of UAV-assisted applications.

(a) Supervised and unsupervised learning in Figure 7—box A:

The FANETs issues that can be addressed by supervised and unsupervised learning methods are discussed as follows according to Figure 7 box *A*:

- *UAVs' positioning and deployment problem*: UAVs are employed in disaster management and emergency conditions where infrastructure is devastated and the lack of services and communications are essential issues to address. In this regard, low cost and high mobility, multiple UAV-mounted BSs are sent to target regions to provide temporary wireless communication services. UAVs horizontal and/or vertical placement, distance, cost, UAV numbers, coverage rate, and users–UAV connectivity are important factors needed to be considered in the deployment problem (Gao et al., 2021; Ghazal, 2021; Lahmeri et al., 2021; Q. Liu et al., 2018; Masroor et al., 2021a; Rahimi et al., 2021; J. Yang, Liang, et al., 2021; C. Zhang et al., 2021). ML algorithms are used to predict the optimal position of the UAVs by identifying the overloaded traffic areas by predicting users' demands and positions (Nouri, Abouei, et al., 2021; Nouri, Fazel, et al., 2021; Oliveira et al., 2021). According to Oliveira et al. (2021), among ML approaches tested for predicting users' positions, Gradient Boosting and Random Forest provide the best result, while Lasso, Ridge, and ElasticNet are tied at the last place.
- *Channel estimation*: Channel state information (CSI) highly impacts the performance of the UAV communication systems. ML techniques can be used to predict and 3D model the complex UAV-to-UAV and ground-to-UAV channels (J. Wang et al., 2021). According to the literature *K*-Nearest Neighbors, Artificial Neural Networks, SVR, and Random Forest algorithms can be used to estimate the channel path loss, considering several important parameters, such as transmitter and receiver altitudes, the propagation distance, the elevation angle (Lahmeri et al., 2021), the direction of arrival information, the channel gain information, and the relative position information (Fan et al., 2019; Song & Ko, 2020; P. Yang, Xi, et al., 2021; Q. Zhang et al., 2021).
- *Anomaly detection*: In UAV communication-based network the animosities and any malfunctioning that is happen during UAVs' missions need to be detected to provide a safe flight (Dutta et al., 2021; Lahmeri et al., 2021). Hyper anomaly detection, which identifies abnormal observations and data samples, is a hot topic in hyperspectral image processing (S. Wang et al., 2021). Using an anomaly detection system, UAVs are prevented to do missions when there are motor malfunctioning, insufficient battery capacity, and loss of communication (Lu et al., 2018). In UAV imaging platforms (Guo et al., 2020), monitoring and surveillance systems, the UAV camera plays a vital role in abnormal behavior detection representing any security risk in video footage (Chriki et al., 2021). However, anomaly detection, which aims to apply specific feature extraction techniques to the videos recorded by UAVs, is a complex task due to the lack of data sets from UAVs in real conditions as available data sets have been designed for surveillance with fixed cameras and variable and dynamic varying ambient brightness and large-scale backgrounds. The choice of features affects the ability to detect specific anomalies. ML techniques and DL methods can extract relevant features that are used as the input to the anomaly detection system by automatic learning representations from raw data (Bozcan & Kayacan, 2020).

(b) RL and DRL in Figure 7—box B:

RLs continuously identify new data patterns through a process of reward and punishment. While supervised methods employ one training step to create a classification model, reinforcement methods collect feedback throughout the model's usage and continuously update it (Dulac-Arnold et al., 2019; Szepesvári, 2010).

The RL model used in the context of FANETs, contains five main elements, including agent which is UAV in FANETs, environment, value function, reward signal, and policy. The model-based RL and the model-free RL are two main categories of RL problems (Anokye et al., 2021). RL can provide good solutions for various decision-making problems. However, for complex problems in which a large state space and action are required, RL shows limited performance. Therefore, DRL which estimates the states using NN, can be a proper choice. DRL allows the computational agents make decisions from unstructured input data in unseen situations, opposing the traditional RL techniques, such as Q-learning (Lahmeri et al., 2021; Rezwan & Choi, 2021). Deep Deterministic Policy Gradient (DDPG; Rodriguez-Ramos et al., 2019), and Deep Q Network (DQN) are two popular DRL algorithms used in UAV networks (Anokye et al., 2021). However, DRL requires higher computational complexity and more memory than traditional ML approaches (Hu et al., 2020). In particular, when online RL is applied to a UAV-based communication system where UAVs have high-speed mobility, many safety devices are needed to compensate for problems caused by the high complexity.

According to Figure 7—box *B* the RL and DL algorithms can address the following issues in FANETs:

- *Autonomous path planning*: Recently the guidance, navigation, and control (GNC) system of UAVs which provides an autonomous navigation by following a desired path defined by observed information, has become popular research area (Cui & Wang, 2021). In the GNC system, UAVs can make intelligent decisions, therefore a high autonomy for UAVs is implemented (Lahmeri et al., 2021). However, reaching such a high-level control strategy of UAVs (autonomous level) is a challenging issue because of the frequent topology changes in FANETs and UAVs' constraints, such as limited UAVs' power. ML approaches, especially RL with their powerful learning ability have been widely employed in unmanned systems in which the action policy is optimized based on the interaction between environment and agent (UAV). RL-based path planning methods are more flexible than traditional ones, such as A* and RTT algorithms (Chang et al., 2021). Q-learning-based strategies, S-MGD, Sarsa, Multiagent RL (MAXQ), DQN, DDQN, mutual and Decaying DQN are RL algorithms that have been investigated for UAV path planning (Bayerlein et al., 2021; He et al., 2021; Qie et al., 2019; Yan et al., 2020).
- *Schedule, and resource management*: Beyond path planning for UAV-based communication systems, UAV-assisted resource management, scheduling smart UAVs, content caching, and network planning are very demanding in 5G and 6G networks where higher throughput, increased data rate, lower overhead, lower interference, and better coverage and support of a massive number of devices are required (Jung et al., 2021). The reasons why UAVs are widely employed to assist resource management that can be performed in a distributed or centralized, include: UAVs can quickly manage resources requested by overloaded users in the network. In addition, further growth of capacity and coverage of the system is easy to accommodate using UAVs. UAVs that can fly and operate missions in various altitudes can provide services for users and devices rapidly (Munaye et al., 2021). The multiple UAVs do time-limited missions due to their lack of battery capacity. Therefore, the scheduling approaches that enable UAVs to cover temporally and spatially distributed events in the geographical areas of interest over a long period, are required (Ghazzai et al., 2019). RL techniques such as Q-learning, DQN network coupled with a Long Short Term Memory network and MultiAgent Reinforcement Learning have facilitated resource management and scheduling in UAV-based communication systems (H. Yang, Zhao, Xiong, et al., 2021; Y. Yuan et al., 2021).

(c) FL in Figure 7—box C:

FL, one of the most robust and secure cloud infrastructures, has been implemented in 2016 by Google to execute ML algorithms in a decentralized manner in constrained networks composed of a central node and several users such as UAV networks in which there is no need to download the training set to a central server (Nguyen et al., 2021). While standard ML techniques need to centralize the training data in a data center or on one machine (Lahmeri et al., 2021). According to Figure 7 box *C*, FL can provide promising solutions to address the following issues in FANETs:

- *FANETs security*: In FANETs, the sensitive information carried by UAVs is at risk of different malicious, communication attacks, wireless fidelity (Wi-Fi) attacks, and cyberattacks (Dahiya & Garg, 2020; Mowla et al., 2020). FL-assisted approaches are promising solutions. There are available unbalanced data at the different nodes and the huge number of interacting nodes in FANETs, and FL performs well in such a scenario. FL can address the unbalanced data and provide efficient communication (Bekmezci et al., 2016; Yazdinejad et al., 2021)
- *Path control*: The autonomous control of a massive number of UAVs that move from a source to a destination to accomplish a mission is a difficult control task. This is because some randomness sources such as wind might lead to inter-UAV collisions. Path control is a promising solution in this regard. DL-based path control has been investigated in several studies (Aggarwal & Kumar, 2020; Challita et al., 2018; Q. Liu et al., 2020; Yan et al., 2020; Zhao et al., 2018). Recently, the real-time UAV path control frameworks have been proposed using mean-field game theory and FL in which the model parameters will be shared between UAVs. By doing so, UAVs can consider the impact of locally nonobservable samples on the learning process (Donevski et al., 2021; Lahmeri et al., 2021; Shiri et al., 2020).
- *Scheduling and resource management*: Resource management in UAV-based communication networks aims to improve QoS, provide better coverage of users, reduce the cost for end-users and address the challenges with the lack of resources, such as frequency, charging, energy, channel, cost, spectrum allocation, trajectory, data offloading, backhaul, and other resources in UAV-assisted networks (Masroor et al., 2021b). Recently, FL algorithms have been used to facilitate resource management and scheduling in UAV-assisted networks and to address the existing challenges. When it comes to FL, the network needs to be composed of one UAV as a leader (FL UAV server) and a group of following UAVs

which run an FL algorithm on their local data set and send the local updates to the FL UAV server. After aggregating all the local updates, the UAV leader performs a global update to the global model (Masroor et al., 2021b; H. Yang, Zhao, Xiong, et al., 2021; T. Zeng et al., 2020). However, this huge amount of exchanging updates between nodes negatively affects the transmission delay, fading, antenna gain, and interface which destructively impacts the performance of the FL algorithm.

- *UAV sensing*: UAVs provide a reliable, versatile, powerful, and flexible platform for acquiring data and detecting a target, and identifying its real location in real-time as they can be equipped with any kind of active and passive sensors. The low-cost visual sensors are widely mounted on UAVs to detect the target in surveillance applications as they support different types of analysis methods. Although using UAVs provide many advantages in remote sensing technology in comparison with manned systems, there are some issues (Asadzadeh et al., 2022; Lahmeri et al., 2021) that can be addressed by FL techniques. For example, for predicting the air quality index throughout integrating sensor-based and vision-based air quality sensing, FL can be applied to provide an accurate visual model-based, enabling UAVs to learn from haze images with a higher accuracy than conventional approaches (Y. Liu et al., 2021).
- *Client selection strategies*: Selecting a proper UAV to participate in the learning process of FL, which impacts the overall accuracy, is a difficult task for FL. In this context, the FL technique can be improved by some client selection strategies that provide a prioritization approach to select better clients (UAVs) for calculating the global update to the model (Lahmeri et al., 2021; Lim et al., 2021; Y. Wang et al., 2021).
- *Content caching*: Content caching is one of the most promising technologies to reduce the backhaul congestion links and latency in 5G and 6G networks. In addition to backhaul congestion and latency, the energy efficiency of 5G and 6G networks is also important and need to be addressed. According to the energy efficiency formula provided in Khuwaja et al. (2021), which is defined as the ratio of the area spectral efficiency for the successful content delivery to the average power consumption of the network, the energy efficiency of the cache-enabled networks is more effective than the traditional networks. Contents are stored in caches at the small-cell BSs such as heterogeneous flying BS (UAV-BS) so that users can request and access the required content locally during peak hours to decrease the burden on backhaul (Wei et al., 2021). UAVs provide flexible access, meaning that they can take the caching content closer to the users, and they can be used as flying BS or cache to speed up the transmissions (Al-Hilo et al., 2021). However, there are some challenges such as UAV deployment in this context. Therefore, intelligence FL-based content caching solutions for 5G and 6G networks composed of UAV-BSs and ground BSs, have been proposed. Using FL techniques, users do not need to share explicitly their content preference and reporting because using FL, the cached content in various BSs will be accurately predicted based on mobile users preferences (Khuwaja et al., 2021; Lahmeri et al., 2021).

4.3 | Main challenges of applying ML towards the main problems of FANETs (*RQ4*)

There are some challenges when it comes to implementing ML techniques for FANETs of UAVs. The first issue is, how to select a suitable ML technique to address the problem among the huge number of available ML techniques (Sharma et al., 2020). In addition, to ML be properly utilized, considerable training data is required. However, in fact, the data that UAVs can learn to communicate in three dimensions (3D) is currently insufficient. Other existing challenges of using AI/ML techniques in the UAV network are discussed in the following.

When it comes to implement supervised and unsupervised learning algorithms to overcome the existing challenges of UAV-based communication systems, new issues have emerged. First, most of the existing UAVs have limited computing capacity. In other words, they are not equipped with powerful graphics processing unit (GPU), central processing unit (CPU), and power that are required to execute heavy ML techniques. Therefore, the cloud computing is one of the interesting solutions to train models and do computational tasks. However, in this solution UAVs have to communicate back and forth with the cloud which in its turn increases the communication costs and again leads to the power constraint problem QoS-related challenges. Therefore executing ML algorithms on-board is a solution that is known as on-device learning dedicated to constrained devices. In addition, FL is one of the promising solutions to address the execution of ML on-board which was already discussed (Lahmeri et al., 2021).

In terms of RL, although it provides many advantages in comparison with supervised and unsupervised learning, the applicability of RL in real-world issues such as self-driving and autonomous flying tasks is still doubtable. It is almost impossible to perfectly understand the high-varying environment, explore the action space to discover surroundings and exploit the knowledge in such an environment. Regarding FAA regulations, in some countries, UAVs are not allowed to fly over all regions and have altitude constraints so that they can only fly in the operator's field of sight (Bithas et al., 2019). As a result, such regulations prevent the development of RL for various UAV-based applications. To sum up, the majority of existing studies focus on providing autonomous path planning for UAVs using RL techniques, the Q-learning approach in particular. However, a classical Q-learning algorithm requires full knowledge of the environment, which is impossible due to the high-varying nature of the UAV network. Therefore this algorithm might be slow. DRL techniques such as Q-learning NN and DDPG are promising approaches in path planning problems. The other applications such as event scheduling and resource management have not been investigated well which has led to an unbalanced research content towards path planning applications (Anokye et al., 2021; Lahmeri et al., 2021; Rezwan & Choi, 2021; Rodriguez-Ramos et al., 2019).

As already mentioned, UAVs can perform distributed ML algorithms for terrestrial wireless devices without the presence of any centralized BS, and the ground wireless nodes do not require to send any raw data to the UAVs during the learning process. In other words, the wireless nodes take advantage of their local data sets to train ML models, then send the local model parameters to an FL UAV server to aggregate the model. Next, the FL UAV server broadcasts the parameters to related nodes for a new round of local model training. This will continue until a target learning accuracy is achieved. Since raw data is kept at devices, privacy is preserved, and the network traffic congestion reduces.

However, due to the exchanging ML models parameters across the heterogeneous UAV networks which contain different types of UAVs with various GPUs and CPUs, and the high mobility of UAVs and devices, the UAVs' task consensus and FL convergence are negatively influenced by transmission latency. Therefore the convergence of the FL algorithm is not always guaranteed (H. Yang, Zhao, Xiong, et al., 2021).

In addition, the scalability problems might happen while using FL techniques, due to the high exchange of updates between FL UAV servers and devices which leads to the massive communication loads in the training step (Lahmeri et al., 2021).

4.4 | Simulation tools, frameworks, and testbeds for FANET's performance analysis (*RQ5*)

Evaluating the performance of UAV-based communication networks in the real world is a tough task that requires remarkable time and resources. Frequent topology changes and the high degree of mobility of the UAVs in FANETs make the practical evaluation of UAV performance a challenging, costly, and time-consuming task. In addition, due to some regulations of using UAVs in most countries, some cyber-attack resistance evaluation tests for UAV networks are not allowed (Chriki et al., 2019). Therefore, many flexible simulation tools, frameworks, emulators, and testbeds have been developed to make it possible to create, implement, test, and evaluate schemes virtually without requiring real-world implementation. They provide the possibilities for UAVs flights, mobility models, and UAVs management. However, choosing an adequate tool has always been an issue for researchers. In most cases, it is not possible to switch between simulation tools as they all differ in functionality and use. If the evaluation tool is selected wrong, it will take a considerable time and effort from the researcher to learn, implement the simulation scenario.

Therefore, this study provides the information about FANETs analysis tools, such as

- *AVENs*: It is a flight control simulator that implements co-simulation between the XPlane Flight Simulator and an OMNeT++/INET simulation for modeling UAV communication.
- *CUSCUS*: It is a simulation architecture for networked control systems which are based on two well-known solutions in both the fields of networking simulation (the NS-3 tool) and UAV control simulation (the FL-AIR tool).
- *Simbeeotic*: It is used to evaluate microaerial vehicle swarms.
- *UAVSim*: It is an OMNeT++-based UAV simulator and it is useful for cyber security analysis in UAV-based networks.
- *UTSim*: It is useful for air traffic simulation and capable of simulating UAV physical specification, control, navigation, sensing, communication, and avoidance in environments with stationary and mobile objects.
- *FANETSim*: It is a Java software able to consider a set of flying UAVs in the sky that provides connectivity to the users inside the considered map.
- *Netsim*: It provides three various versions NetSim Pro, Standard, and Academic. It has a very intuitive graphical user interface (GUI).
- *OMNeT++*: It is a modular, extensible, component-based network simulator used for research and commercial purposes.
- *NS2*: It is a discrete event simulator used for networking research which simulates transmission control protocol (TCP), routing, and multicast protocols over wired and wireless (local and satellite) networks.
- *NS3*: It allows the simulation of both IP and non-IP-based networks. It is suitable for performance evaluation of mobile ad hoc and TCP networks.
- *OPNET*: It provides a powerful GUI and animation but involves significant costs.
- *ROS-NetSim*: It is a ROS package that acts as an interface between robotic and network simulators.
- *MATLAB*: It provides different example applications involving both fixed-wing and multirotor UAVs. It has a UAV Toolbox and the ability to do AI/ML as it also has a Statistics and ML Toolbox.
- *TOSSIM*: It is a BSD-licensed OS designed and for low-power wireless devices. It is widely used in both academia and industry.
- *QualNet*: It is a powerful simulation tool for UAV research focusing on network security.
- *GloMoSim*: It is widely used for research purposes and is very scalable. It does not offer good documentation, which makes it less user-friendly.
- *YANS*: It is a lightning-fast Docker-based network simulator.
- *ONE*: It generates node movement using different movement models and visualizes both mobility and message passing in real-time in its graphical user interface. ONE can import mobility data from real-world traces or other mobility generators.
- *SSFNet*: It is a scalable simulation framework network model and designed for the expansion of the higher network, including topology, protocols, traffic, and so forth.
- *RoboNetSim*: It integrates multirobot simulators with network simulators for communication-realisticsimulation of networked multirobot systems. It has been applied to interface the NS-2, NS-3, and ARGoS, Player/STAGE simulators.
- *Mininet-Wifi*: It is an extension of the Mininet SDN network emulator by adding or modifying classes and scripts.
- *SIMU*: It cannot be used directly in FANETs as it is tailored for 2D vehicles, but it can integrate with OMNeT++ and NS3.
- *FlynetSim*: It is an open-source synchronized UAV network simulator which works based on NS3 and Ardupilot.

- *J-Sim*: It is a powerful tool, but it is relatively complicated to use and has a longer execution time than NS3.
- *BonnMotion*: It is a Java software that creates and analyzes mobility scenarios and is widely used as a tool for the investigation of mobile ad hoc network characteristics.
- *GAZEBO*: It is a robotics simulation platform to test algorithm and build AI/ML platforms for UAV applications. It can connect to a robot control framework (ROS).
- *AirSim*: It is an open-source platform for AI research to experiment with computer vision, DL, and RL algorithms for UAVs.

Table 6 helps researchers to identify and to choose the right FANETs performances analysis tools (Chowdhury et al., 2021; Gill et al., 2021; Hentati et al., 2018; Kang et al., 2016).

5 | FUTURE RESEARCH DIRECTIONS FOR FANETs

On the basis of the papers analyzed in this study, selected future research directions regarding UAV-based communication systems are discussed in this section. This section is divided into eight subsections, including UAV-assisted 5G and 6G wireless networks (Section 5.1), Blockchain-envisioned UAV communication in the 6G network (Section 5.2), AI-Enabled Object Detection in UAV-networked system (Section 5.3), IoMIMO Things-based UAVs (Section 5.4), SDN and NFV (Section 5.5), Quantum Communication (Section 5.6), 3D beamforming (Section 5.7), and RIS-enabled UAVs (Section 5.8).

5.1 | UAV-assisted 5G and 6G wireless networks in Figure 8—Cell *A*

The ever-increasing use of UAVs in various applications makes UAVs a major part of beyond 5G and 6G wireless networks in near future to offer secure, cost-effective, and reliable wireless communications and coverage improvement. In this regard, cellular networks serve multiple UAVs acting as flying BSs/user equipment to provide wireless connectivity (Masaracchia et al., 2021; H. Yang, Zhao, Nie, et al., 2021). However, enabling robust UAV operations faces several key barriers and challenges, including security and safety of UAVs and airspace control. In addition, providing efficient connectivity for flying UAVs face several challenges, such as interference routing and mobility issues (I. U. Khan et al., 2020), Sidelobe and Antenna tilt (Mozaffari et al., 2021). Figure 8—cell *A* shows an overall structure of the UAV-assisted 6G networks and the usefulness of blockchain for these networks. As illustrated in Figure 8—cell *A*, blockchain which is a decentralized and transparent database (Nguyen et al., 2022), creates the secure communication system in which UAVs are considered as blockchain clients and communicate with each other and ground BSs to exchange information and perform their missions. UAVs, network operators, and users store and trace their data on the ledger with a distributed control.

5.2 | Blockchain-envisioned UAV communication in the 6G network in Figure 8—Cell *A*

Blockchain technology is a promising solution to mitigate the issues related to the UAV network, shown in Figure 6. The integration of blockchain and 6G technologies in UAV-based communication, which is shown in Figure 8—Cell *A*), is an interesting field of research that needs more effort and investigation. In such integration, 6G supports the communication among UAV, satellites, and ground stations, and guarantees the reliability of vehicle-to-server connectivity and Vehicle to Everything (Amin et al., 2015). Blockchain provides a decentralized environment to the UAV and improves UAV communication. Blockchain-assisted UAV communication in 6G environment brings interesting research directions (Aggarwal et al., 2020; Alladi et al., 2020; Kumari et al., 2020), such as security and privacy, scalability, path planning, storage capacity, and optimizing UAV energy consumption which is discussed in Table 7.

5.3 | AI-enabled object detection in UAVs in Figure 8—Cell *B*

Object detection is a component of computer vision applications and can be supported by UAVs equipped with many sensors and high-resolution cameras as can be observed in Figure 8—Cell *B*. DL algorithms have widely been employed for object detection (Sandino et al., 2021). However, aerial object detection is much more complex than general object detection scenarios. First, UAVs capture a multitude of object sizes, such as bicycles, buses, trucks, and so forth, due to their large field-view. The deeper layer of NN can detect large objects easily but detecting objects that are very small in size and also crowded would be a challenging task. The crowded objects with low-resolution images also make it difficult to classify each of them separately with distinguished boundaries. Therefore, managing various objects together is a challenging task for DL-based models. In addition, due to limited computational resources and power constraints of UAVs, it is difficult to carry out DL inference in UAVs to do object detection tasks. Finally, addressing the occlusion problem in aerial images captured by UAVs is more difficult than general object detection scenarios (Jain et al., 2021; Rabah et al., 2020). In other words, aerial object detection is almost impossible due to the very small size of the objects, variation in surrounding illumination, occlusion and the shadowing of objects by trees and high buildings.

5.4 | IoMIMO things in Figure 8—Cell *C*

Massive multiple-input multiple-output (MIMO) is one of the key technologies in developing 5G network and it can enable other wireless networks, such as cellular-connected UAV communications. However, the performance that massive MIMO provides depends on accurate CSI of both UAVs and ground users at the GBSs (de Freitas et al., 2012; Marinho et al., 2013b). On the other hand, to have a

TABLE 6 Simulation tools and testbeds for UAV systems performance analysis (Pasandideh et al., 2022)

Name	Type	Mobility model	Operating system	Programming language
AVENS[a]	Simulator	Linear Mobility	Linux, Windows, MacOS	N/A
CUSCUS (Zema et al., 2017)	Simulator	Micromobility	>Ubuntu 14.04	N/A
Simbeeotic (Kate et al., 2012)	Simulator and Testbed	N/A	Linux	Java
UAVSim (Javaid et al., 2013)	Testbed	Well-defined mobility framework	Windows, Linux, and MacOs	C++
UTSim (Al-Mousa et al., 2019)	Simulator and a framework	N/A Linux	Windows	C#, JavaScript, Unity Script, or, BOO coding languages
FANETSim (Tropea et al., 2020)	Simulator	Grid	Linux	Java
Netsim (Veith et al., 1999)	Simulator	RW, RWP	Windows, MacOS or	C
OMNeT++ (Varga, 2010)	Simulator	FP, RWP, RW	Linux, MacOS	C++, high-level
NS2 (Issariyakul & Hossain, 2009)	Simulator	RW, RWP, GM, MG, RPGM	Linux, Windows, MacOs	C++, with an OTcl interpreter as
NS3 (Vasiliev et al., 2014)	Simulator	RW, RWP, RD, GM, MG, RPGM	Linux, Windows, and MacOS	C++, Python
OPNET (Durham et al., 2009)	Simulator	RW, Group mobility, RWP, RD	Windows, Red Hat, and CentOS	C, C++
ROS-NetSim (Calvo-Fullana et al., 2021)	Simulator	N/A	Linux	C++
MATLAB (Ribeiro & Oliveira, 2010)	Simulator	SRCM, PSMM	Windows, Linux, and MacOs	C, C++
TOSSIM (Levis & Lee, 2003)	Testbed	RWP	Linux,	C++
QualNet (Y. Zheng et al., 2014)	Simulator	RWP, Group mobility	MacOs, Linux	C++.
GloMoSim (Gu et al., 2000)	Simulator	RWP, Group mobility	Linux, Windows	C, Parsec
YANS (Lacage & Henderson, 2006)	Simulator	N/A	MacOS, Ubuntu	Python, C, C++
ONE (X. Li et al., 2012)	Simulator	RWP	Linux, Windows, and MacOS	Java
SSFNet[b]	Simulator	MG, RPGM, RW, RWP, GM	Linux, Solaris, and Windows NT using JDK1.2 and higher	Java, C++
RoboNetSim (Kudelski & Gambardella, 2013)	Framework C++,	It provides good mobility patterns	MacOs Linux, Windows,	Python
Mininet-Wifi[c]	Emulator	RW, RWP, TruncatedLevyWalk, GM, RandomDirection, Reference Point	Any Ubuntu Distribution from 14.04	C++,

(Continues)

TABLE 6 (Continued)

Name	Type	Mobility model	Operating system	Programming language
SUMO (Sugiura, 2018)	Simulator	N/A	Windows, Linux, or MacOs	C++, Python
FlynetSim (Baidya et al., 2018)	Simulator	GM, MG, RPGM, RW, RWP, RD	Ubuntu Distributions	Python
J-Sim[d]	Simulator	RWP	Linux, Windows, and MacOS	Tcl, Python, and Perl
BonnMotion (BonnMotion, 2011)	Mobility generator	RW, RWP, GM, MG, RPGM, and more	Linux, OSX	Java, Windows
GAZEBO (Bernardeschi et al., 2018)	Simulator	High-speed Mobility	Linux, Linux virtual machines	C++
AirSim (Madaan et al., 2020)	Simulator	N/A	Windows, Linux	C++, C#

Abbreviation: UAV, unmanned aerial vehicle.
[a]http://hdl.handle.net/10125/41924.
[b]http://www.ssfnet.org/.
[c]https://mininet-wifi.github.io/.
[d]https://sites.google.com/site/jsimofficial/downloads.

sustainable and reliable intelligent world, pervasive IoT adoption is required, in which wireless devices suffer from limited capacity batteries. Although wireless power transfer (WPT), energy harvesting (EH), and energy-efficient communication techniques have been employed to address this issue, IoT services are still looking for fully autonomous things without power constraints. The green IoT can be obtained using UAVs infrastructure and a new concept called the IoMIMO, which is still in its infancy stages, as IoT connectivity has constraints and requirements that are totally different from broadband connections (Cetinkaya et al., 2020; Huang et al., 2021; Marinho et al., 2013a; Taştan & İlhan, 2021; Yilmaz & Denizer, 2020).

Moreover, IoT-based UAV is a new research topic that takes advantage of location identification and tracking with the advancement of aerial technology. However, identifying the location of the wireless nodes is a challenging task. Therefore, I. U. Khan et al. (2021) provide a received signal strength identifier controlled long-range communication technique in IoT-based UAV. I. U. Khan et al. (2021) construct 2D and 3D models to gather more accurate information on the nodes by measuring the signal strength. An example of IoMIMO-enabled UAV network can be observed in Figure 8—Cell *C*, in which a UAV acts as flying BS using A2G mmWave beams to expand wireless coverage, and provides multi-Gigabit transmission towards ground users in 5G systems via thing-to-thing or people-to-thing communications.

5.5 | SDN and NFV in Figure 8—Cell *D*

UAV networks face some crucial performance issues and challenges such as complex, manual, and time-consuming network management which in turn leads to many interoperability problems. Recently, some studies have employed SDN and NFV technologies to mitigate the network management complexity and enhance the drone assistance for the next generation of mobile networks. However, the integration of SDN and NFV in UAV-assisted networks is still at the infancy stage of development and there are still some unresolved issues that require scrutiny by researchers, including hardware resource constraints, power limitation of UAVs, high density and mobility of UAVs, and failure of SDN controller and NFVs (Das et al., 2019; Gebremariam et al., 2019; Sami Oubbati et al., 2020). A typical SDN-based UAV network is shown in Figure 8—Cell *D*. According to Figure 8—Cell *D*, in the data plane, a swarm of UAVs that perform a specific task act as forwarding nodes and provide necessary communications to users within their transmission range. On the other hand, the SDN controller in the control panel manages and control the whole network.

5.6 | Quantum communication

Quantum computing is a rapidly-emerging technology that can speed up computation and provide real-time solutions for problems too complex in classical systems using the laws of quantum mechanics (Vista et al., 2021). Recently, Quantum communication is being used as a promising technology to ensure robust security of information exchange in UAV-assisted 5G and 6G mobile networks, while supporting many applications. In addition, Quantum Evolutionary Algorithms are used to allocate tasks among a network of heterogeneous resource-constrained UAVs in a remote and highly dynamic environment, where the energy and resources available at

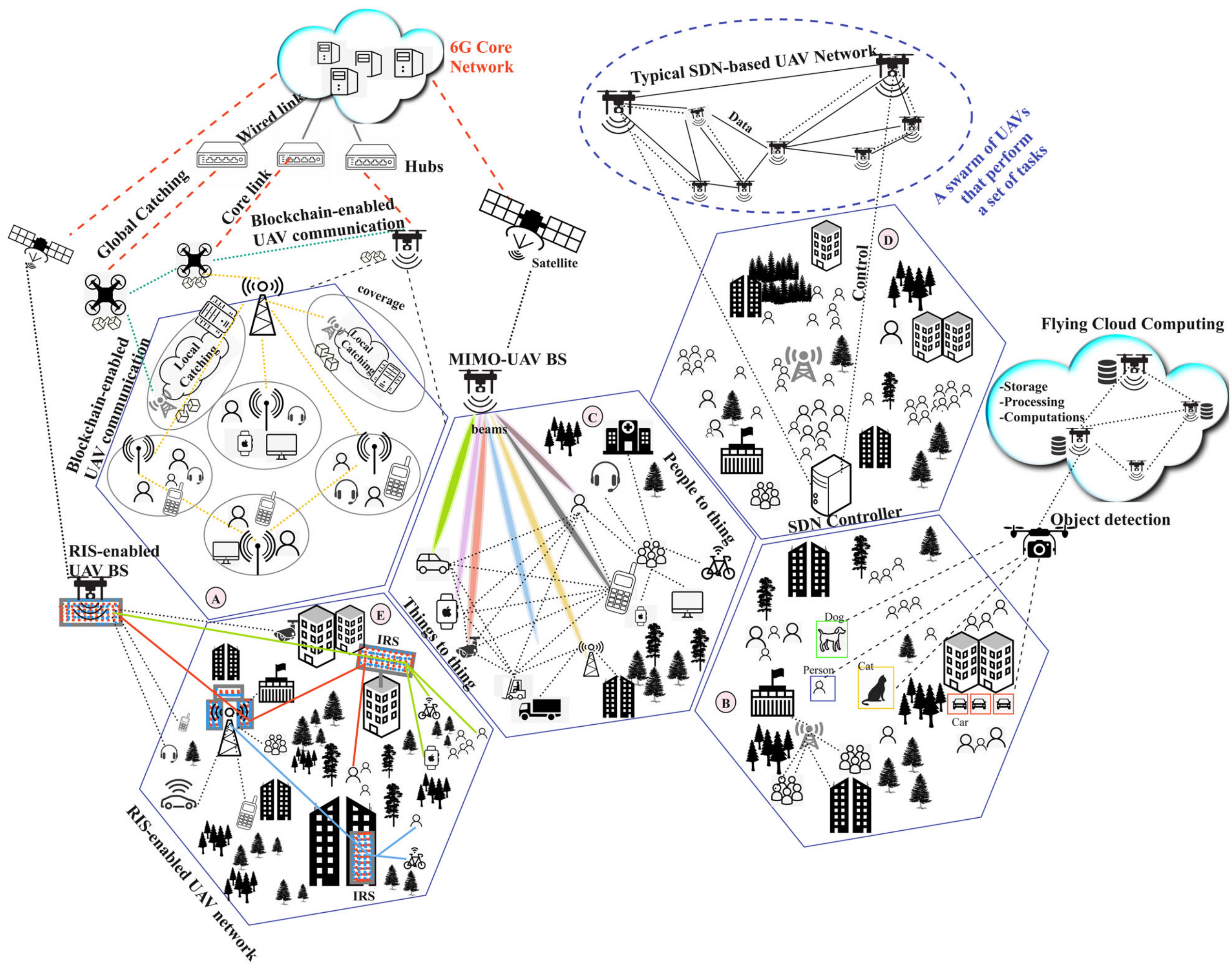

FIGURE 8 Future FANETs directions, including 5G and 6G networks, blockchain enabled UAV communication, SD, NFV, IRS-enabled UAV networks, 3D beamforming, and RIS-enabled UAV networks. 3D, three-dimensional; BS, base station; FANETs, flying ad hoc networks; IRS, intelligent reflective surface; MIMO, Multiple-Input Multiple-Output; NFV, Network Function Virtualization; RIS, reconfigurable intelligent surface; SDN, Software Defined Network; UAV, unmanned aerial vehicle. [Color figure can be viewed at wileyonlinelibrary.com]

the UAVs are limited (Mousavi et al., 2019). Quantum Annealing is also used to solve a binary optimization problem to derive an optimal scheduling plan in a UAV-enabled IoT network (Vista et al., 2021). However, when it comes to using quantum communications, an open issue arises, which is signal degradation due to weather conditions (Vista et al., 2021). The attenuation of a signal transmitted through the UAV-assisted 5G or 6G quantum-based mobile networks, significantly and directly degrades the performance of quantum communication.

5.7 | 3D beamforming in Figure 8—Cell *C*

Three-dimensional beamforming is a promising solution to improve the performance of cellular-connected UAV communications. According to Figure 8—Cell *D*, GBSs which are equipped with full-dimensional antenna arrays are capable of performing fine-tuned 3D receive or transmit beam-forming with improved intercell interference mitigation for communicating with UAVs. The 3D beamforming can also generate high system throughput based on the location of the UAV which is not practical in traditional cell sectorization based on 2D directional antennas. In addition, location-based 3D beam-forming schemes in UAV-enabled mobile relaying systems optimize the beamforming direction and trajectory of the UAVs to minimize the secrecy outage probability of the system (Colpaert et al., 2020; Huang et al., 2020; Q. Yuan et al., 2019; Y. Zeng et al., 2019).

5.8 | RIS-enabled UAVs in Figure 8—Cell *E*

The 6G wireless communication networks aim to provide widely dimensional wireless coverage, full connectivity, full-vertical application, and adequate bandwidth and achieve ultrahigh data rates (Long et al., 2021). In this regard, intelligent reflective surfaces (IRS) is a promising technology for 6G that can intelligently control a wireless

TABLE 7 Research directions in blockchain-assisted UAV communication in 6G environment

Research direction	Description
Privacy	Secure and tamper-proof information sharing between the blockchain network and the UAV needs to be well addressed.
Security	Blockchain-based UAV network can overcome many attacks that UAV applications face, including eavesdropping, hijacking, and so forth, due to connections and open links, using the blockchain properties, such as security, transparency, and immutability.
Scalability	A swarm of UAV is able to form the scalable multi-UAV networks help make fast and effective communication and ubiquitous connections for ground users using the 6G wireless communication network.
Storage capacity	As the UAVs suffer from lack of storage capacity, the details of collected data scanned by UAVs and the time stamp at which the block was added, can be directly transmitted to a cyber–physical system connected to a blockchain. Therefore information about data can be easily stored and monitored. However the blockchain-based storage capacity is still in its infancy.
Low latency	Some of the UAV real-time applications such as remote surgeries requires ultralow latency in blockchain-based communication network obtained by using a 6G wireless communication infrastructure.
Efficient path planning	However many studies have investigated UAV path planning problem, there are still many open issues, such as efficient trajectory and route planning. Therefore, providing an efficient path planning is still required for blockchain-based UAV in 6G wireless communication infrastructure.

Abbreviation: UAV, unmanned aerial vehicle.

environment, control the wavefront, including frequency, amplitude, phase, and even polarization by massive tunable elements. As presented in Figure 8—cell *E*, IRS can direct a signal to the target position using this set of passive, tunable and reflective elements. UAV-assisted IRSs have been investigated to improve spectrum efficiency in which IRS is employed to reflect the signal towards UAVs equipped with small BSs. There are two main scenarios in this context as shown in Figure 8—cell *E*. First UAV-BS that carry the IRS, act as the passive relay in both downlink and uplink communications between group users and ground BSs. In the second scenario, buildings equipped with IRS help UAV's communications (Basharat et al., 2021; Z. Chen et al., 2021; Z. Li & Chen, 2021; Long et al., 2021).

6 | CONCLUSIONS

This SLR presents a comprehensive review of Multiple Unmanned Aerial Vehicle Networks from traditional and ML-enabled wireless communications perspectives. The main goal of this paper is to discuss the challenges in FANETs, possible AI, supervised and unsupervised learning algorithms, DL and RL algorithms, and FL methods for the challenges of UAV communication-based networks, as well as to provide a prospective insight of future research in FANETs in a quantitative manner. Therefore, an extensive literature review was performed to find the most relevant publications on these topics in which more than 170 publications extracted from five trusted academic databases published from 2013 to 2021 were considered. The research investigated on FANETs and the worldwide commercial UAV market size show an upward trend from 2013 to 2021 which means drone-assisted network is becoming a major research topic. Such a growth can be mainly justified by rapid technological changes and advances, increasing labor cost, and increase in delivery demand. It is also worth mentioning that the largest number of studies were from China and the United States. To sum up, regarding the possible AI/ML/DL/FL-based solutions for different use cases in UAV-based networks, FL-based methods are more adequate for many UAV-enabled wireless applications and will have the most important impact in the future of UAV-assisted applications.

AUTHOR CONTRIBUTIONS

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

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