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Federated Learning in UAV-Assisted MEC Systems: A Comprehensive Survey

YOUSSRA CHERIGUENE [1], WAEL JAAFAR [2] (Senior Member, IEEE), AND HALIM YANIKOMEROGLU [3] (Fellow, IEEE)

(Invited Papers)

[1]Laboratoire d'Informatique et de Mathématiques, Université Amar Telidji de Laghouat, Laghouat 03000, Algeria
[2]Department of Software and Information Technology Engineering, École de Technologie Supérieure, Montreal, QC H3C 1K3, Canada
[3]Non-Terrestrial Network Lab, Department of Systems and Computer Engineering, Carleton University, Ottawa, ON K1S 5B6, Canada

CORRESPONDING AUTHOR: Y. CHERIGUENE (e-mail: y.cheriguene@lagh-univ.dz)

ABSTRACT In recent years, the integration of Uncrewed Aerial Vehicles (UAVs) into Multi-Access Edge Computing (MEC) systems has emerged as a transformative paradigm revolutionizing the landscape of data processing and analysis. By leveraging UAVs as MEC platforms, computing and storage capabilities are extended closer to data sources, thus facilitating real-time data processing and enabling smooth decision-making. This synergy between UAVs and MEC not only enhances the efficiency of data-intensive applications but also unlocks new possibilities for innovative services across various domains such as environmental monitoring, urban planning, and emergency response. The escalating demand to harness big data for several applications, empowered by Artificial Intelligence (AI), heralds a new era of ubiquitous data-driven intelligent services. Traditionally, Machine Learning (ML) approaches involve aggregating datasets and training models centrally, which poses several security risks. Alternatively, Federated Learning (FL), as a decentralized ML method, enables users to collaboratively train their ML models without compromising the privacy of their data. This paper comprehensively overviews UAV-assisted MEC systems, which rely on ML for several services, by shedding light on the vast opportunities it presents and discussing how to tackle its related key challenges. Subsequently, we provide an in-depth survey of the fundamentals and enabling technologies of FL, a pioneering technique poised to democratize ML at the edge of wireless networks such as those supported by UAVs. Also, we conduct an extensive analysis to identify the various applications of FL in UAV-assisted MEC systems, along with a nuanced examination of their associated challenges and limitations. Finally, we discuss some of the most important future research directions.

INDEX TERMS Uncrewed aerial vehicle, UAV, federated learning, FL, Multi-Access edge computing, MEC.

I. INTRODUCTION

MULTI-ACCESS Edge Computing (MEC) has emerged as a way to directly deliver cloud computing services at the network edge. This promising technology can meet the computationally demanding and latency-sensitive task requirements and get over the restrictions of End Users (EUs) [1], [2]. However, MEC systems supported by conventional terrestrial infrastructure-based networks are not suitable for distant or hard-to-reach regions due to the high cost, unfeasibility, or destruction of the terrestrial network facilities in such areas [3], [4]. As a result, MEC enabled by Uncrewed Aerial Vehicles (UAVs)[1] is seen as a promising alternative for managing computation-intensive and latency-sensitive tasks in remote and disaster-prone areas [3], [5], [6]. Particularly, by leveraging the UAVs' significant advantages such as flexible 3D movement, strong Line-of-Sight (LoS) connectivity, and easy deployment, as well as increased mission time and heavier on-board payload,

[1]In this paper, the term "Uncrewed Aerial Vehicle (UAV)" is used in place of "Unmanned Aerial Vehicle" as a gender-neutral term and in alignment with evolving standards in scientific and technical writing. The acronym UAV is retained for continuity with established literature.

UAV-enabled MEC can effectively deliver computation services to mobile ground EUs in several contexts including military and civil, such as search and rescue and disaster relief missions [7], [8], [9], [10].

The evolution of wireless communication infrastructures, coupled with the pivotal role of UAVs in data acquisition for tasks such as monitoring and remote sensing missions, has led to an unprecedented surge in data volumes and the need to treat the latter efficiently. To leverage the potential of this data, Artificial Intelligence (AI), particularly Machine Learning (ML), has emerged as a cutting-edge technology capable of delivering smart services and applications [11], [12]. ML models are adept at tackling diverse tasks by uncovering hidden data patterns, thereby enabling valuable predictions [13]. Conventionally, ML model training occurs on centralized servers, where datasets are collected, stored, and processed in a single location before being used to train ML models on one or multiple servers [14]. However, this centralized approach poses limitations for several emerging wireless network applications and may introduce challenges such as increased communication overhead, data security risks, and high propagation delays [15]. Given these challenges, Federated Learning (FL) has emerged as a promising solution to address the limitations of centralized ML [16], [17]. FL is a distributed ML paradigm that enables participants (e.g., UAVs) to collaborate and construct a global ML model without releasing their local data to a central aggregator, such as an Edge Computing (EC) server [18]. Through FL, the volume of data transmitted to the server is substantially minimized, as only model updates are sent, thus easing the strain on network resources [19]. Moreover, FL safeguards the privacy and security of endpoints by enabling model training at the data generation source [20].

A. PREVIOUS SURVEYS

MEC has been recognized as a key technology for 5G and beyond wireless communication systems, offering a potential complement to traditional cloud computing. Moreover, the integration of UAVs with MEC is poised to play a crucial role, introducing an additional layer of computational mobility to deliver services that are fast, efficient, and secure. The growing interest in UAV-enabled MEC has led to a significant surge in research articles in this field. For instance, the survey in [21] presented a systematic literature review on UAV-enabled MEC. The study meticulously selected and analyzed several research papers through a multi-stage process that adhered to predefined eligibility criteria. The primary contribution of this survey is the comprehensive classification of research in the UAV-enabled MEC field into distinct categories, including energy efficiency, resource allocation, security, architecture, and latency. Also, authors of [22] offered an extensive overview of UAV-aided MEC-enabled Internet-of-Things (IoT) networks, emphasizing the significance of security in various use cases and scenarios. It proceeded by presenting an analysis of research works focusing on security solutions tailored for the UAV-aided MEC-enabled IoT environment. The discussion spanned the adoption of information-theoretic techniques, alongside the exploration of security methodologies that would leverage emerging technologies such as blockchain and ML. Additionally, the paper investigated the issues of node identification and authentication using software-based and hardware-based approaches. In [23], the authors conducted a thorough examination of the literature about UAV-enabled MEC systems, with a particular emphasis on system modeling and optimization techniques across five key domains: Energy efficiency, resource allocation, trajectory control, latency, and security. Within each domain, recent advancements, and crucial discoveries, as well as the advantages and drawbacks are meticulously highlighted. Furthermore, proposed techniques pertinent to each domain are scrutinized and discussed, with a focus on performance metrics and constraints.

On the other hand, other surveys focused on the application of AI/ML in wireless networks. For instance, the study of [24] categorized state-of-the-art works into three distinct classification systems: 1) Based on the application scenarios, 2) centered around the AI algorithms, and 3) based on the AI training paradigms. Also, the study provided a curated collection of frameworks, tools, and libraries used within AI-infused UAV systems. The findings underscored the broad spectrum of applications for AI in UAV systems, such as UAV path planning and resource allocation. The study [25] pioneered the investigation of FL in UAV systems. This work explored FL-based applications within UAV-enabled wireless networks, ranging from 5G networks and beyond, IoT, edge computing/caching, to Flying Ad-hoc Networks (FANETs). In [26], a comprehensive background study about FL architecture, categories, mechanisms, operations, and optimization has been provided. Then, FL-facilitating technologies in wireless networks are discussed. Finally, the related challenges and research directions are identified. In contrast, the survey [27] consisted of a taxonomy of blockchain based FL in UAV systems. This paper introduced a reference architecture and conducted a comparative analysis of conventional blockchain-based UAV networks. Also, it presented a logistics case study illustrating the application of blockchain-based FL in UAVs within the context of 6G networks. In [28], the authors conducted a systematic review of existing literature about the integration of FL in MEC environments. The paper outlined the protocols, architecture, framework, and hardware prerequisites for implementing FL within MEC environments. In [29], edge computing key issues have been examined, followed by a comprehensive overview of conventional solutions and an appraisal of their constraints. Moreover, the article discussed leveraging AI for EC, and its intersection with other fields such as smart city and security. The survey [30] examined UAV-assisted MEC architectures. It delved into the UAV-enabled MEC setups for IoT and exposed the contributions of Deep Learning (DL) and ML to address task offloading, latency, energy consumption, and security issues. In [31],

TABLE 1. Comparison of existing surveys.

Ref.	Year	UAV Appl.	EC	Edge AI	FL	FL Appl.	Limitations
[21]	2022	✓	✓✓✓	✓	✓	⊖	*The application of FL in UAV-assisted MEC has not been discussed.*
[24]	2023	✓✓✓	✓✓	✓✓	✓	⊖	*Lack of focus on FL and MEC.*
[25]	2020	✓✓	✓	✓✓	✓✓✓	✓	*Lack of overview depth due to the paper's brevity.*
[26]	2023	✓	✓✓✓	✓✓✓	✓✓✓	✓✓	*Lack of focus on UAV networks and a restricted exploration of frameworks' architectures.*
[27]	2022	✓	✓✓	✓✓	✓✓✓	✓	*Focused mainly on the security aspects of FL implementation.*
[28]	2022	✓	✓✓✓	✓✓✓	✓✓✓	✓	*Lack of focus on UAV networks, and weak discussion about frameworks' architectures.*
[22]	2022	✓✓	✓✓	✓✓	✓	⊖	*Lack of focus on FL applications, and predominance on its security.*
[29]	2023	⊖	✓✓✓	✓✓✓	✓	⊖	*Lack of focus on UAV systems and FL applications.*
[23]	2024	✓✓✓	✓✓✓	✓	✓	⊖	*Lack of focus on ML methods.*
[30]	2021	✓✓✓	✓✓✓	✓✓✓	✓	⊖	*Lack of focus on FL and predominance of RL in the discussion.*
[31]	2019	✓	✓✓✓	✓✓✓	✓✓	✓	*Main focus on ML rather than on networks.*
[33]	2021	✓	✓	✓	✓✓✓	✓✓✓	*Lack of discussion on FL applications in UAV and wireless systems.*
[34]	2021	⊖	✓	✓	✓✓✓	✓✓✓	*Lack of discussion on FL applications in UAV and wireless systems.*
[36]	2023	⊖	✓	✓	✓✓✓	✓✓✓	*Main focus on the security of FL, without attention to FL application in UAV systems.*
[32]	2025	⊖	✓✓✓	✓✓	✓	⊖	*Broad coverage of distributed ML on edge devices; lacks FL focus in UAV-assisted MEC.*
[35]	2024	✓✓	✓✓✓	✓✓✓	⊖	⊖	Covers ML in UAVs broadly, and does not include FL or MEC integration.
Our Survey	**2025**	✓✓✓	✓✓✓	✓✓✓	✓✓✓	✓✓✓	–

the authors emphasized integrating ML at the wireless network edge, thus facilitating dependable and low-latency communications. They presented the foundational elements of ML and focused on the shift from centralized cloud-based model training to decentralized approaches such as FL. Moreover, through case studies, they highlighted edge AI's importance to advance future networks.

The survey in [32] addresses distributed ML on edge devices in application domains such as smart homes, intelligent transportation, and industrial monitoring. It explores processing limitations, data heterogeneity, privacy concerns, and aggregation schemes in edge environments, providing a taxonomy of parallelism patterns, distributed architectures, and optimization metrics.

Other surveys focused on FL and its opportunities. For instance, the survey presented in [33] delineated the FL architecture, system models, designs, application domains, privacy and security considerations, and resource management aspects. Also, authors of [34] summarized recent advancements in FL by examining employed techniques to enhance FL efficiency, ensure data privacy, and secure the system against cyberattacks. The survey in [35] presents an in-depth review of cutting-edge ML techniques applied to UAV communications, covering supervised, unsupervised, and reinforcement learning methods. In [36], a comprehensive study of FL-related cyber threats and their mitigation strategies has been discussed. In addition, a taxonomy of adversarial attacks and defense methods has been presented. Through extensive experiments, the authors yielded insights regarding the dynamics between attacks and defense mechanisms.

B. CONTRIBUTIONS AND ORGANIZATION OF THE SURVEY

While several surveys exist on FL in general wireless or edge computing environments, they often focus narrowly on specific aspects such as security or communication efficiency without considering the unique characteristics of UAV-assisted MEC networks. In particular, in this survey, we target the intersection of FL within UAV-assisted MEC where aerial mobility and resource constraints fundamentally shape algorithmic and system design choices. Additionally, this work identifies critical limitations in existing studies and presents a detailed research roadmap by outlining key open challenges and unexplored areas. Table 1 summarizes

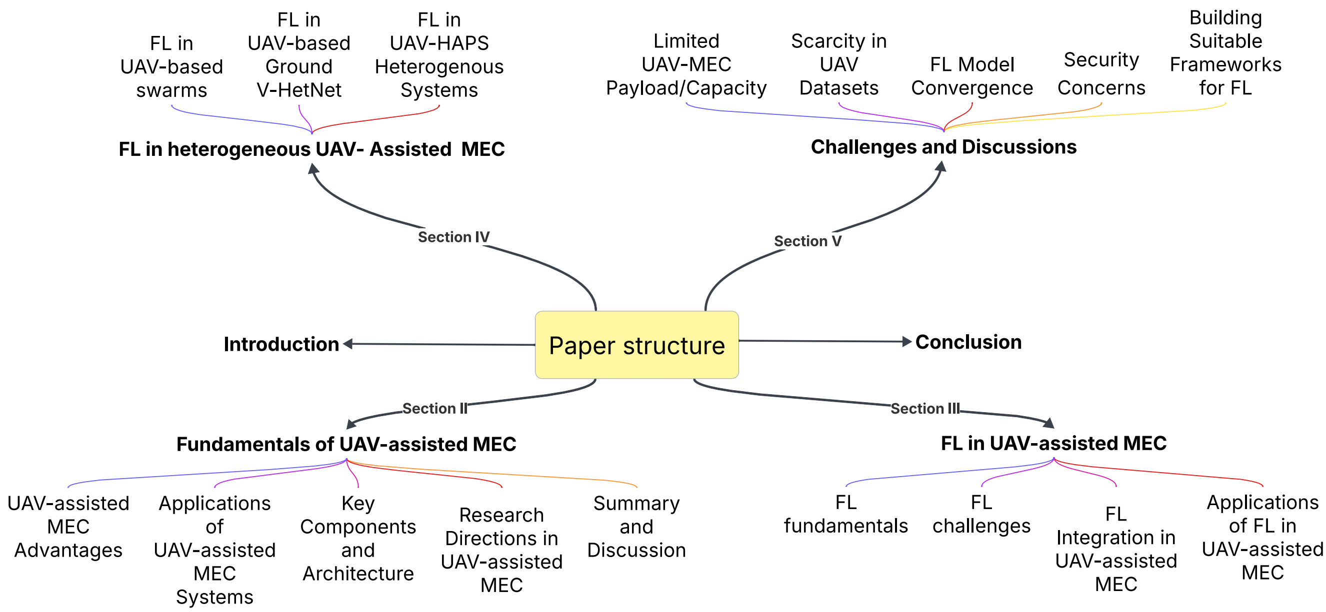


FIGURE 1. Structural overview of the survey paper, illustrating how the topics evolve from fundamental concepts to challenges and future research directions in FL within UAV-assisted MEC systems.

representative surveys and contrasts their scope with ours, highlighting differences and limitations.

The main contributions of our survey can be summarized as follows:

1) We lay the groundwork with an exploration of UAV-assisted MEC, elucidating its inherent advantages and indispensability within 5G and beyond networks. Also, we highlight prominent applications and research directions from the state-of-the-art, while considering the importance of emerging technologies within this context.
2) We provide a conceptual foundation on the operational principles of FL and its applications within UAV-assisted MEC systems, including a detailed description of its integration within UAV-assisted MEC, technical challenges, and use cases. Moreover, we provide an in-depth discussion of deploying FL in state-of-the-art UAV-assisted MEC. We make explicit the integration patterns including training and aggregation placements, deployment constraints such as energy, compute, and link dynamics.
3) We meticulously explore the challenges inherent to implementing FL within UAV-assisted MEC networks, then identify proposed approaches to address them. Also, we extend the discussion to future research directions. We organize open problems around convergence under mobility and non-IID data, reliability-aware client selection, hierarchical space-air-ground aggregation, and security threats.
4) We analyze deployment pathways for real-time UAV applications, summarizing system constraints and mission-level metrics to bridge algorithmic results with field requirements. We critically assess FL frameworks and distill lightweight design principles that make FL applicable for UAV networks under mobility and energy constraints, thereby informing practical implementations.

The rest of this paper is organized as follows. Section II introduces the fundamentals of UAV-assisted MEC systems, including their necessity in future networks, application scenarios, and popular research directions within the literature. Section III introduces the fundamental aspects of the FL framework in UAV-assisted MEC covering the architecture, use cases, and a comprehensive study of its applications. Subsequently, FL challenges and future research are outlined in Section V. Finally, Section VI concludes the survey. In Fig. 1, we illustrate the detailed outline of the survey paper.

II. FUNDAMENTALS OF UAV-ASSISTED MEC SYSTEMS

This section provides an overview of UAV-assisted MEC network basics, including motivation, applications, key components, and landscape of current research directions.

A. UAV-ASSISTED MEC ADVANTAGES

Advancements in embedded systems and the trend towards miniaturization of micro-electro-mechanical systems have enabled the cost-effective production of various types of UAVs. The latter can act collectively in a coordinated manner, a.k.a., as a swarm, to achieve a common task or mission. Indeed, the capability of deploying numerous UAVs to execute intricate tasks is highly suggested as it overcomes the constraints of single UAV systems such as restricted payload capacity and flight duration. Also, it provides additional features and benefits such as reducing operation time, human intervention, and operational costs [37]. Furthermore, UAV-assisted MEC systems have shown significant advantages

(a) Public safety (b) Hotspots in smart cities (c) Precision agriculture

FIGURE 2. Examples of applications for UAV-assisted MEC systems.

over traditional terrestrial MEC systems due to the distinctive characteristics of UAVs. The key benefits of UAV-assisted MEC can be summarized as follows [38]:

- *Latency and cost reduction:* UAV-assisted MEC systems can be quickly built based on real-time needs. They offer EUs with limited local computing capabilities the opportunity to offload their tasks, particularly in regions with scarce or damaged terrestrial network infrastructure. The ability to control the mobility of UAVs adds an important degree of freedom, and its optimization (i.e., UAV placement or trajectory) would improve the communication channel, thus data throughput and/or latency. With proper resource allocation algorithms, both the energy consumption and task delay for UAV-assisted MEC can be significantly decreased.
- *Coverage and computation enhancement:* UAVs can efficiently communicate with EUs over a large area spanning between a few hundred meters to a few kilometers, given their high flying altitude, up to a few hundred meters, thus providing a strong LoS component. Indeed, LoS links are stronger than the fading wireless channels of terrestrial systems, making them suitable for longer coverage, better task offloading support, and rapid computation result downloads to meet the strict Quality-of-Service (QoS) demands of MEC services. For instance, using a swarm of MEC-equipped UAVs enables applications such as area surveillance, mapping, and localization. Besides coverage, UAVs can function as relays to help transfer stringent tasks from EUs to remote ground MEC servers by adjusting their positions and trajectory, e.g., UAV 9 in Fig. 3 [39].
- *Resilience:* In the event of adverse weather conditions or unforeseen technical issues affecting a particular UAV within the swarm, the system seamlessly redistributes tasks among the available UAVs. This adaptive load balancing guarantees continuous services while also improving the fault tolerance of the system, where "fault" refer to hardware malfunctions, communication breakdowns, or processing anomalies that hinder the normal operation of UAV or edge nodes. The distributed architecture enhances the network's ability to overcome obstacles, ensuring uninterrupted connectivity and data processing, thus greatly enhancing the dependability and strength of the UAV-assisted MEC infrastructure.

B. SOME APPLICATIONS OF UAV-ASSISTED MEC SYSTEMS

Technological advancements in UAV capabilities allow for their versatile usage in uncrewed activities. We provide a review of the main MEC-oriented applications that can benefit from UAV systems as follows:

- *Public safety:* UAV-assisted MEC systems are invaluable in public safety scenarios where terrestrial infrastructure may be compromised. Indeed, UAV-based systems can be smoothly deployed to establish connectivity in affected areas. MEC-equipped UAV swarms can collaborate to cover large areas and ensure efficient data processing and fault tolerance [40]. The real-time data collection through onboard sensors enables quick decision-making for search and rescue, medical assistance, and logistics services. Hence, UAV-assisted MEC systems contribute to the agility, resilience, and efficiency of disaster response efforts in challenging environments, as shown in Fig. 2a.
- *Hotspots in smart cities:* MEC networks assisted by UAVs are helpful in urban areas where the user demand for computation-intensive services can be high during peak hours. In this case, UAVs can complement terrestrial MEC systems by partially offloading MEC workloads, minimizing interruptions, and improving the QoE of EUs [41]. Coordinated resource management of UAVs and terrestrial networks is required to efficiently handle demand and enhance response in densely populated areas, as shown in Fig. 2b.
- *Precision Agriculture:* Farmers are increasingly recognizing the advantages of using UAVs in agriculture. UAV-assisted MEC systems for precision agriculture combine the strengths of UAVs and MEC to improve efficiency and profitability. With MEC-equipped UAVs,

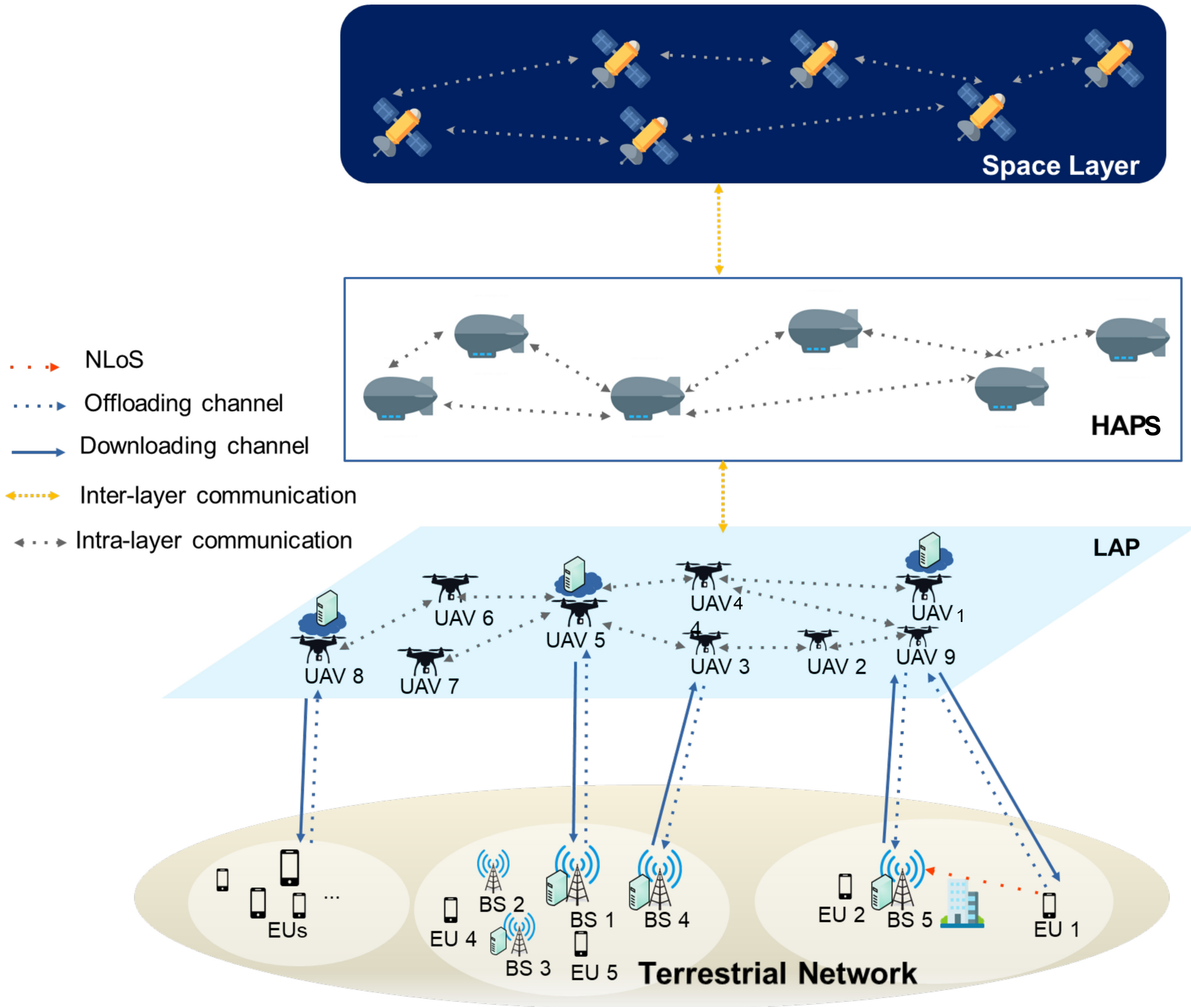


FIGURE 3. UAV-assisted MEC network architecture.

agricultural data can be analyzed in real-time to facilitate rapid decision-making at the UAV's level [42]. This feature is especially advantageous for activities such as crop monitoring, disease identification, and automated crop spraying, as presented in Fig. 2c.

C. KEY COMPONENTS AND ARCHITECTURE

This section presents a detailed design of a UAV-assisted MEC network, where UAVs complement the terrestrial network. The network architecture is illustrated in Fig. 3, consisting of two distinct layers, namely the aerial network and the terrestrial network.

On the one hand, the aerial layer is separated into two sub-layers, the Low Altitude Platform (LAP) consists mainly of small drones or UAVs flying at a few hundred meters (up to 300 m), and the High Altitude Platform Station (HAPS) is composed of HAPS airships or aircraft floating/flying at altitudes between 17 km and 25 km [43], [44], [45]. Deploying a LAP is cost-effective and rapid. However, it suffers from limited computing payload and low mission time compared to HAPS stations. Indeed, the latter can host a larger payload (up to 1 ton), operate for extended periods (months), and cover large geographic regions (between 20 km and 500 km in radius) [38], [46].

On the other hand, the terrestrial network consists of mobile EUs connected to conventional terrestrial Base Stations (BSs). In addition, certain UAVs can operate as aerial BSs (e.g., UAVs 1, 3, 4, and 5 in Fig. 3), establishing wireless links to ground MEC servers where intensive computation tasks are executed. As a result, the terrestrial BSs and UAV-assisted aerial BSs jointly provide connectivity and computation services for ground EUs, including IoT devices and mobile users, while complementing the aerial layer.

The LAP layer, being closer to the ground, can handle EU tasks with stringent latency requirements, while the HAPS layer can contribute to tasks requiring global coordination or extensive computing resources. In a LAP network, multiple UAVs can collaborate to increase coverage and scale up the available computation power, hence necessitating an intricate design of cooperative computing strategies. The UAV payload can include several devices including a cellular

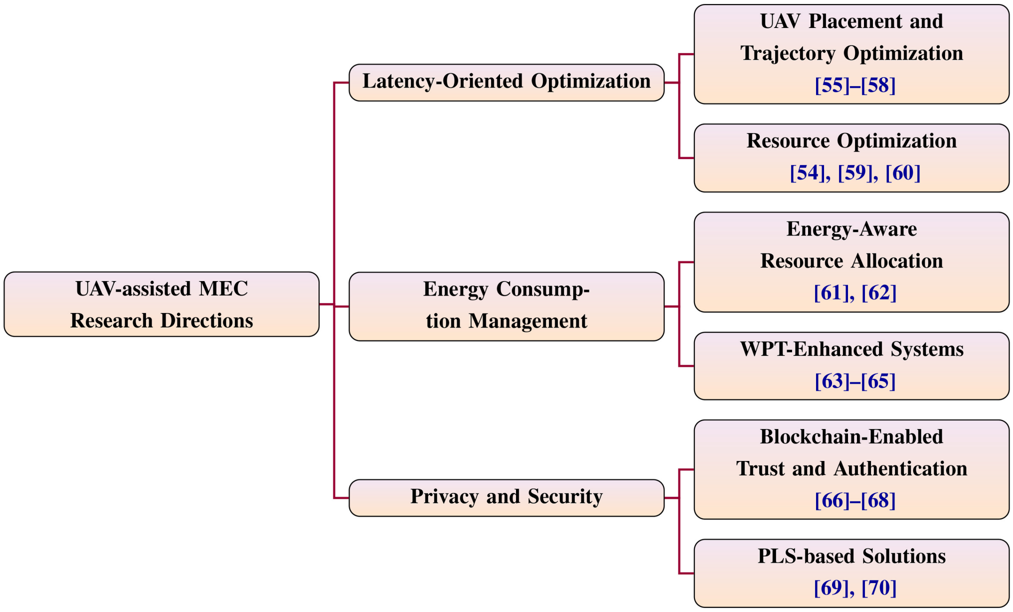


FIGURE 4. Overview of Notable Research Directions in UAV-assisted MEC.

BS, sensors, storage units, and embedded processors, aiming to support services requiring communication, computing, and sensing operations [47].

To further enhance system scalability, resilience, and coverage, an upper satellite layer is deployed to complement aerial and terrestrial components. In particular, Low Earth Orbit (LEO) satellites are increasingly equipped with onboard computational units, forming part of the emerging paradigm of satellite-based edge computing (SMEC) [48], [49]. These satellites can operate as remote MEC servers, especially when HAPs are unavailable or unreachable. Moreover, in-orbit processing enables satellites to participate in real-time data pre-processing, task offloading, and service coordination across wide areas [50]. This integration facilitates seamless task dissemination and result collection in regions where terrestrial or HAPS coverage is insufficient or intermittent [51], [52], [53].

For the sake of illustration, we assume in Fig. 3 that UAVs indexed as 1, 5, and 8 are equipped with computing power. Also, UAVs communicate with each other via Air-to-Air (A2A) wireless links, while links to terrestrial BSs may be established for task offloading. The main challenge with UAVs is the battery capacity and its management. In order to conserve energy and extend mission duration, a UAV may prefer offloading computational tasks to nearby UAVs or terrestrial BSs rather than executing them locally. The main reason is based on factors such as residual energy, communication link quality, processing capability of neighboring nodes, and the urgency or size of the task. For instance, if the local processing cost is high and a neighboring UAV or BS has sufficient resources and higher energy, the task may be relayed to ensure operational efficiency [54].

The integration of aerial and terrestrial components forms a cooperative, hybrid network that combines the agility and mobility of UAVs with the stability and coverage of terrestrial infrastructure. This integrated approach creates a comprehensive network that provides reliable services across the spatio-temporal dynamics of the network's components. Additionally, the satellite layer can play a critical role in enhancing connectivity and reliability by providing an extra tier of communication, ensuring fault tolerance in cases where aerial or ground links are disrupted. This redundancy is particularly valuable in remote or disaster-affected regions.

Moreover, this integrated network can deliver 3D dynamic and resilient services by capitalizing on the mobility of nodes and their adaptive and intelligent management.

D. CURRENT RESEARCH DIRECTIONS IN UAV-ASSISTED MEC

This segment delves into the evolving landscape of research advancements within UAV-assisted MEC networks. We categorize the literature by primary optimization objectives, as illustrated in Fig. 4: i) Latency-Oriented optimization, ii) energy-consumption management, and iii) privacy and security, as follows:

1) LATENCY-ORIENTED OPTIMIZATION

Latency is a crucial parameter/metric that directly affects the user experience in UAV-assisted MEC networks. Several studies concentrated on minimizing the latency of UAV-assisted MEC. We categorize them into 2 groups as follows:

- *UAV Placement and Trajectory Optimization:* Optimizing latency in UAV-assisted MEC can be achieved through the strategic placement of UAVs and dynamic adaptation to the environment. Proximity to EUs, coupled with mobility can minimize travelled distance by data. Several studies improve latency by optimizing UAV placement relative to users. For instance, authors in [55] enhanced localization accuracy by accounting for measurement errors and uncertainties in user positions, which accelerates association/offloading setup and thereby reduces end-to-end service delay. In [56], authors introduced a UAV-assisted edge computing framework named HOTSPOT. This framework placed a UAV in the 3D space based on the changing hot spot of EUs distribution and provided prompt task offloading decisions, aiming to minimize the average task delay. The authors of [57] optimized UAV 3D placement to directly minimize overall task completion time, which in consequently decreased the total time required for the UAVs to complete offloading. Also, [58] investigated a UAV-assisted MEC system demanding URLLC services. It focused on minimizing the overall latency experienced by EUs' services by optimizing a single UAV's trajectory and resource allocation and explicitly targeting end-to-end URLLC latency. The joint optimization problem was solved iteratively for UAV horizontal placement, UAV altitude, offloading bandwidth, and Central Processing Unit (CPU) frequency [71].

- *Resource Optimization:* Edge computing latency can also be minimized by optimizing the use of available computation resources. For instance, [54] targeted reducing the overall latency of participants in MEC-assisted UAV swarms. A UAV swarm is organized into a coalition comprising a leader and several members. Each UAV member determines the offloading ratio and transmission paths to the leader. Other approaches aim to reduce delay by improving how computational tasks are scheduled and distributed among UAVs. In [59], the authors aimed to minimize the latency of dynamic computing operations in UAV-assisted Fault-Prone MEC (FP-MEC) systems, which integrate MEC and Network Function Virtualization (NFV), in addition to using Deep Reinforcement Learning (DRL) for resource allocation. In a complementary direction, [60] focused on minimizing the overall task execution delay in a UAV-assisted MEC network enhanced by a Reconfigurable Intelligent Surface (RIS). The study conducted a joint optimization of user association, task offloading decisions, power allocation, RIS phase shifts, and computing resources at the MEC server to minimize overall service latency. While the authors recognize the importance of energy consumption, it is not explicitly modeled or optimized within the proposed framework.

Within this category of related works, the literature on latency predominantly follows two distinct approaches: optimization-based frameworks that simultaneously tune placement/trajectory and offloading, and learning-based methodologies that adapt online decision-making. The optimization-based approaches provide a well-defined problem structure and predictable enhancements but typically ensure only local optimal solutions and depend on simplified mobility or user-hotspot assumptions [56], [57], [58]. On the other hand, learning and game-theoretic strategies enhance adaptability in dynamic environments but prompt concerns regarding sample efficiency and stability when scaled [54], [59]. Several studies also address delay reduction through the joint optimization of association, power/bandwidth, and surface configuration in RIS-aided systems [60]. Across the literature, evaluations are predominantly conducted through simulations with idealized channel knowledge, and the scalability of large multi-UAV systems is only partially addressed.

2) ENERGY CONSUMPTION MANAGEMENT

Energy-efficient computing is a critical issue within UAV-assisted MEC systems. Indeed, energy optimization directly contributes to the sustainability and longevity of UAV-enabled MEC systems. State-of-the-art works in this area are split into two categories as follows:

- *Energy-Aware Resource Allocation:* In [61], the authors investigated energy efficiency within UAV-assisted MEC systems by introducing a joint optimization framework. This framework is designed to coordinate task offloading, resource allocation, and the trajectory planning of UAVs. The primary objective of their study is to minimize the total energy consumption of both UAVs and IoT devices, while simultaneously ensuring compliance with service constraints pertaining to latency and communication quality. The proposed methodology highlights the importance of adaptive decision-making to effectively balance energy efficiency and system responsiveness in dynamically changing network environments.
  Also, [62] considered a network architecture that combines UAVs, Non-Orthogonal Multiple Access (NOMA), and MEC to address the challenge of energy efficiency for a large number of mobile EUs. The authors jointly optimized communication scheduling, resource allocation, and UAV trajectory, aiming to maximize the energy efficiency of the network.
- *WPT-Enhanced Systems:* The next generation of mobile networks considers Wireless Power Transmission (WPT) a key sustainability element. In this context, UAVs can act as flying power banks to recharge IoT devices on the fly. In addition, UAVs can benefit from WPT to recharge their batteries and extend their operational time [72], [73]. This area has recently garnered significant attention, evidenced by a growing number of research papers. For instance, the authors of [63] introduced a framework for the Power Internet of Things (PIoT) that leverages multiple UAVs for WPT and data acquisition. UAVs act as mobile charging stations and edge computing units to power and process data from PIoT devices before relaying information

to a LEO satellite. To ensure data freshness, the study addresses several optimization problems, including the number and locations of hovering UAVs, PIoT device association with UAVs, energy transmission time, computing resource allocation, and UAVs' flight trajectories. These problems are decoupled and solved using various techniques, using a combination of ML and optimization techniques. Also, the study in [64] proposed a MEC system utilizing UAVs and microwave power transmitters. A UAV flies over EUs to provide a revenue-generating computing power service and incurs energy consumption costs from the microwave stations. The objective is to maximize the UAV's computing service revenue by optimizing its trajectory, the task offloading decisions, and the offloading duration. The non-convex optimization problem is solved using a three-stage alternating optimization approach. In [65], a system for Mobile Edge Learning (MEL) employs UAVs for WPT and data gathering. This work aimed to reduce energy consumption by optimizing data transmissions, UAVs' velocities and trajectories.

The works in this category concentrating on energy optimization frequently integrates the co-design of trajectory planning, offloading strategies, and communication scheduling to minimize both propulsion and computational expenses, with a growing emphasis on using WPT to facilitate extended mission durations [61], [62], [63]. The mentioned approaches elucidate critical trade-offs between flight duration, service quality, and charging opportunities, however, they often depend on simplified energy models and infrequently provide comprehensive end-to-end budgets that align with airborne hardware specifications [64], [65]. Consequently, real-time applicability under conditions of rapid mobility and variable traffic remains insufficiently validated.

3) PRIVACY AND SECURITY

Despite the promising prospects of integrating UAVs with MEC, concerns regarding security and privacy demand significant attention. Indeed, the decentralized nature of UAV-assisted MEC networks and the unpredictability of the environments increase the surface of cyber vulnerabilities. By exploiting the constrained resources of UAVs, malicious entities can orchestrate a spectrum of intrusive attacks, such as active and passive eavesdropping, spoofing, man-in-the-middle, data tampering, sophisticated hijacking, and impersonation. These threats underscore the critical need for robust and real-time countermeasures to safeguard the integrity and confidentiality of data in UAV-assisted MEC systems [22], [74], [75]. Below, we delve into the current privacy and security solution proposed for UAV-assisted MEC, particularly the blockchain and Physical Layer Security (PLS) based approaches.

- *Blockchain-Enabled Trust and Authentication:* In UAV networks, the wireless channel is prone to security flaws that can affect reliability. In addition, the current centralized UAV communication and control architecture is consistently vulnerable to external attacks. To tackle these issues, research has focused on enhancing the security of UAV-assisted networks using several strategies such as blockchain. The latter is an autonomous and distributed ledger that enables secure and transparent monitoring of transaction records within a network [76], [77]. The core components of blockchain include distributed ledgers, immutable records, and smart contracts. Blockchain has been designed to guarantee the security and secrecy of data, allowing trust to be established without a third-party [78]. However, the integration of blockchain in UAV environments is constrained by the resource limitations of UAVs. Blockchain operations such as consensus mechanisms, smart contract execution, and cryptographic functions are computationally intensive and can quickly deplete UAV energy reserves. This is where MEC complements blockchain. MEC introduces cloud-like computing and storage capabilities at the edge of the network, close to UAVs. By offloading complex blockchain tasks such as transaction validation and ledger maintenance to nearby MEC nodes, blockchain-based security mechanisms become practical for real-time UAV deployments. As a result, it can significantly reduce latency, preserve UAV energy, and enhance the scalability of the network [79]. Several recent works illustrate this integration. In [67], the authors proposed a blockchain-enabled authentication scheme designed for UAV-assisted Internet of Vehicles (IoV) systems. Additionally, a decentralized certificate management system is built on a consortium blockchain, enabling secure and tamper-proof UAV registration and authentication without reliance on a centralized authority. To reduce computational overhead and support resource-constrained UAVs, the authors design a lightweight encryption and signature mechanism tailored to reduce overhead in resource-constrained UAV environments. In [66], authors propose a blockchain-assisted data sharing scheme for Internet of Drones (IoD) networks that ensures accountability, confidentiality, and receiver anonymity. It introduces a lightweight identity-based broadcast encryption (IBBE) algorithm for dynamic point-to-multipoint (P2MP) sharing with stateless receivers and minimal UAV computation overhead. Alternatively, the authors of [68] addressed communication securing issues between UAVs and other vehicles in the IoV network. Specifically, they proposed a hybrid authentication framework combining cryptographic and distributed ledger mechanisms. Blockchain is employed at the Trusted Authority (TA) side to maintain authentication sessions and collect meta-information, such as location, via transactions among various entities. Additionally, BDIVE methodology takes into account potential attacks where a bad individual could get control of a UAV.

- *PLS based solutions:* Having a strong LoS connection for Air-to-Ground (A2G) or A2A transmissions brings advantages in terms of communication, but it also presents potential cyber risks. Indeed, an attacker can exploit the LoS link to boost its ability to eavesdrop or increase its jamming power of services. Consequently, tremendous efforts have been made to guarantee communication secrecy in UAV systems. For instance, authors in [70] proposed a Cooperative Secure Transmission and Computation (CSTC) strategy to enhance physical layer security in UAV-assisted MEC networks under mobile collusive eavesdropping threats. Specifically, it maximizes the sum secrecy transmission rate by jointly optimizing UAV trajectory, jamming beamforming, transmission power, and task offloading, while ensuring latency requirements are met. In [69], the authors presented a secure communication scheme tailored for the NOMA-based UAV-assisted MEC system, specifically devised to counteract potential threats from airborne eavesdroppers. The proposed scheme maximizes the average security computation capacity of the system while ensuring that each ground EU meets a minimum security computation requirement. The primary security metric under consideration was the secure computing capacity, subject to various constraints including system energy limitations, computation capabilities of Ground Stations (GSs) and MEC units, UAV flight dynamics (including collision avoidance between UAVs), and the minimum computation requirements of GSs.

Blockchain-based schemes in this category strengthen trust, identity management, and auditability in distributed aerial systems [66], [67], [68], while physical-layer security methods improve resilience against eavesdropping and jamming via joint trajectory, power, and jamming design [69], [70]. Each line brings clear benefits to credibility, and secrecy. However, it can add overhead, and can depend on channel knowledge and mobility models that may be hard to maintain in practice. Few works quantify the end-to-end impact of security choices on latency, energy, and service reliability across space-air-ground layers.

E. SUMMARY AND DISCUSSION

In the previous sections, the optimization of UAV-assisted MEC systems has predominantly relied on conventional methodologies such as convex optimization, game theory, and heuristic algorithms. Nevertheless, these approaches often face scalability challenges due to the high dimensionality and inter-dependencies among system parameters. Although problem decomposition techniques can mitigate complexity, they frequently result in sub-optimal solutions with limited adaptability to dynamic environments [38]. To address these limitations, ML methods have gained traction in recent years. ML enables systems to learn and adapt from data, providing intelligent mechanisms for real-time decision making based on observed patterns in user behavior, network states, and UAV trajectories.

Among ML techniques, Reinforcement Learning (RL) has emerged as a compelling choice to optimize UAV-assisted edge computing systems. RL enables agents such as UAVs or edge servers to learn optimal policies through interaction with their environment, making it particularly suitable for tasks such as trajectory planning, dynamic resource allocation, and scheduling under uncertainty. However, the effectiveness of RL often depends on large volumes of training data, and its centralized learning paradigm can expose sensitive user or network information to privacy risks and communication overhead. To overcome these challenges, FL presents a promising complementary or alternative approach. Unlike centralized ML or RL, FL enables multiple distributed entities such as UAVs and edge servers to collaboratively learn a global model while keeping their local data private. This not only safeguards data confidentiality but also significantly reduces the communication load by transmitting only model updates. FL is especially suitable for privacy-sensitive and bandwidth-constrained scenarios typical of UAV-assisted edge computing systems.

III. FEDERATED LEARNING IN UAV-ASSISTED MEC SYSTEMS

As intelligent edge computing becomes more widespread, there is increasing interest in collaborative learning approaches that can function efficiently in environments with privacy concerns, and limited bandwidth. Traditional distributed learning methods, such as parameter server frameworks or peer-to-peer models, often face a number of challenges including scalability, communication overhead [80]. As a result, FL has garnered considerable interest both in academia and industry. It revolves around the core principle of building a global model through decentralized model training. Recent progress in the communication and computation capabilities of UAVs, coupled with the rise of AI applications, has greatly impacted research in the area of FL within UAV-assisted MEC. This section outlines its basic operation, technical challenges, FL integration in different UAV-assisted MEC settings, and use cases, and it classifies the related works of FL-based solutions in the context of UAV-assisted MEC.

A. FEDERATED LEARNING FUNDAMENTALS

Unlike centralized ML methods, FL is a distributed ML technique that trains a shared model while maintaining personal privacy. Indeed, instead of sending raw data to a MEC server, UAVs train their datasets locally while the MEC server gathers local models from participating UAV clients that are chosen on a random basis to generate a global model shared to every client [81], [82]. Fig. 5 below depicts the procedure of the FL system, which is described as follows:

1) *Client selection:* In a typical FL system, the selection of participating clients for model aggregation at the

TABLE 2. Summary of UAV-assisted MEC works.

Ref.	System Model	Inter-UAV Comm.	Objective	Optimization Parameters	Method
[55]	Multi-UAV AOA-based passive localization with target uncertainty	⊖	Min. localization error (SPEB)	UAV deployment locations, geometric constraints, measurement error model	Gradient Projection, Gibbs Sampling
[56]	UAV-assisted edge network	⊖	Min. avg. time delay of EUs, coverage	Number and positions of UAVs, task offloading decision	SGD based solution
[57]	UAV-assisted edge network	⊖	Min. overall latency of UAVs	Positions of UAVs, EUs association	SCA based solution
[58]	UAV-assisted edge network	⊖	Min. overall latency of EUs	Positions of UAVs, offloading bandwidths, computing CPU frequencies	Semi-closed-form solution
[54]	MEC-supported UAV swarm	✓	Min. overall latency of UAVs	Channel, offloading ratio	EPG based solution
[59]	UAV-assisted FP-MEC	✓	Min. overall latency of UAVs	Total execution delay	DRL based solution
[61]	UAV-assisted MEC in IoT	⊖	Min. total energy consumption of UAVs	Bandwidth, UAV trajectory, offloading decision	BCD based solution
[60]	RIS-equipped UAV assisted mMIMO-MEC base station	⊖	Min. task execution latency	UE power allocation, user association, RIS phase shift, MEC resource allocation	Iterative optimization using BCD, convex approximation
[62]	UAV-Assisted NOMA-MEC	⊖	Min. energy consumption of UAVs and EUs	Task allocation, time slot, transmit power of EUs, UAV trajectory	Dinkelbach, SCA
[63]	UAV-Assisted WPT enabled space-air-ground PIoT	✓	Min. avg. Age of Information (AoI) of power devices	Number of UAVs, hovering positions, links to devices, energy & data time, computing resources, UAV trajectory	K-means, Lagrangian dual, Interior point, Adaptive opt., Q-Learning
[64]	UAV-Assisted WPT enabled MEC network	⊖	Max. service utility of the UAV	UAV trajectory, computation offloading decisions, offloading duration	Branch-and-bound, SCA, CVX
[65]	UAV-Assisted WPT enabled MEL network	⊖	Max. F-measure	UAV trajectory, data transmission rates, device location, transmit power	AO, SCA
[67]	Blockchain-based UAV authentication in IoV	✓	Min. authentication overhead	UAV registration, clustering, key generation, certificate storage	CMPES scheme, Smart contracts on Hyperledger
[66]	Blockchain-assisted IoD network	⊖	Max. data sharing privacy	Group identities, ciphertext integrity, on-chain accountability	Smart contracts, Privacy-preserving IBBE
[68]	UAV-Assisted IoV	⊖	Max. D2D reliability in IoV	Energy consumption, latency	Blockchain-based solution, Elliptic curve cryptography
[70]	UAV-assisted MEC with mobile collusive eavesdroppers	✓	Max. secrecy transmission rate	Trajectory, transmit power, jamming, offloading, scheduling	BCD based method
[69]	NOMA-based UAV-MEC	⊖	Max. secure computing capacity	Avg. secure computation capacity	SCA, BCD methods

MEC server considers only the devices that are being charged and connected to the aggregating server. To participate in model training, the aggregator selects a subset of clients n from the available clients N on a random basis. However, relying solely on these criteria for heterogeneous clients, such as UAVs with varying communication and computation resources, presents several drawbacks including increased latency in FL training rounds and inefficient aggregation. Within the literature, a few studies tackled this issue in UAV-assisted MEC networks [83], [84], [85]. However, existing works often have limitations when dealing with UAV mobility. Hence, further research in this area is still needed to devise more robust and effective solutions for optimized FL in UAV-assisted MEC.

2) *Local model computation:* During this phase, the selected clients are provided with the same global model parameters ω at round r. Each selected client c utilizes its local dataset $\mathbf{DS}_c$ of size $|\mathbf{DS}_c|$ to train the model locally (Step 1 in Fig. 5). After local training, the client computes its update $\Delta\omega^c$ and sends it to the central server for aggregation into the global model ω (Step 2 in Fig. 5).
Client updates may be transmitted either synchronously (all clients send updates in the same round) or asynchronously (updates are integrated as they arrive) [86]. Synchronous aggregation often results in faster convergence. However, in real-world deployments where device capabilities and data distributions vary significantly (discussed further in

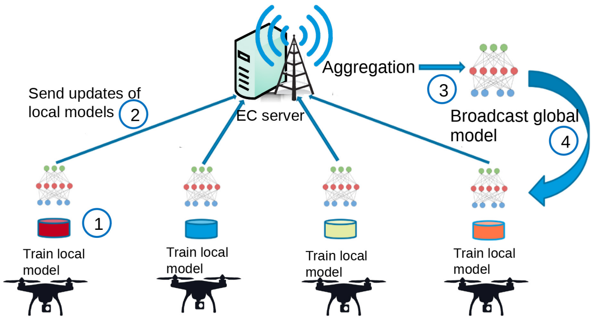


FIGURE 5. FL training process of UAV-based MEC.

Section III-B), asynchronous methods offer better flexibility by accommodating stragglers, i.e., slow or intermittently available clients. This flexibility, however, may introduce risks such as degraded model quality and security vulnerabilities in aggregation. Several studies address these concerns. For example, FedSA [87] introduces staleness-awareness to balance timeliness and accuracy, while SAFA [88] proposes a semi-asynchronous framework for robust training under communication constraints.

3) *Model aggregation:* Once the server receives the local model updates, it aggregates them to form the new global model ω (Step 3 in Fig. 5). In general, ML models aim to minimize a loss function, which quantifies prediction error on training data. In the FL setting, each client c minimizes a local loss function $F_c(\omega)$, defined as the average of per-sample loss $f_s(\omega)$ over its dataset:

$$F_c(\omega) = \frac{1}{|\mathbf{DS}_c|} \sum_{s=1}^{|\mathbf{DS}_c|} f_s(\omega). \tag{1}$$

The objective of federated learning is to minimize a weighted global loss function across all clients, expressed as:

$$\min_{\omega} F(\omega) = \sum_{c=1}^{N} \frac{|\mathbf{DS}_c|}{|\mathbf{DS}|} F_c(\omega), \tag{2}$$

where $|\mathbf{DS}| = \sum_{c=1}^{N} |\mathbf{DS}_c|$ is the total number of data points across all clients.

In the FedAvg algorithm [89], each client receives the global model ω_{r-1} at the start of round r (where $r = 1, 2, \ldots, r_{\max}$), and performs local training using SGD to minimize its own loss function $F_c(\omega)$. The local update rule is given by

$$\omega_r^c = \omega_{r-1}^c - \gamma \nabla F_c\big(\omega_{r-1}^c\big), \tag{3}$$

where γ is the learning rate and $\nabla(\cdot)$ denotes the gradient with respect to the model parameters. After local training, the server aggregates the weighted updates from all clients to update the global model.

FedAvg is a simple and widely used aggregation scheme in FL. It prioritizes local computation over frequent communication with the server, making it suitable for settings with limited network bandwidth and high communication cost [90].

However, in real-world scenarios characterized by heterogeneous devices, capabilities, and non-Independent and Identically Distributed (non-IID) local datasets, FedAvg often exhibits poor convergence behavior. Consequently, several variants of the FedAvg algorithm have been introduced to address this limitation and develop faster aggregation. For instance, FedProx was specifically designed to tackle the heterogeneity issue prevalent in federated networks [91]. Unlike FedAvg, FedProx embraces system heterogeneity by allowing each node to undertake computations proportional to its available resources. To solve the slow convergence problem, FedSplit has been proposed, which leverages the operator splitting procedure for convex optimization problems [92]. Operator splitting, renowned for its efficacy in addressing large-scale convex problems, operates by iteratively performing simple and computationally inexpensive operations. This method breaks down the problem into manageable sub-problems, enabling progress made on each one independently. In the same logic of low complexity, ensemble learning approaches that combine multiple models have been explored. On the other hand, researchers have turned their attention to exploring alternative techniques that offer lower complexity while maintaining high performance within the FL framework. One such avenue of exploration involves ensemble learning methods, which aim to combine multiple models to improve predictive performance. FedBoost [93] and FedTrees [94] are examples of ensemble learning techniques adapted for federated environments. These algorithms leverage the collective intelligence of a diverse set of models trained across different devices to enhance the efficacy in achieving performance metrics, including accuracy, computation time, and communication rounds. By effectively leveraging ensemble learning within the FL framework, these algorithms offer promising solutions to the challenges associated with traditional Neural Network (NN) and DL models in federated settings. Furthermore, the success of FedBoost and FedTrees underscores the potential for exploring additional ML techniques within the FL systems. By diversifying the range of algorithms and methodologies employed in federated environments, researchers can further optimize model performance and scalability while mitigating communication and computation overheads.

B. LEARNING CHALLENGES

The successful implementation of FL is hampered by constraints that must be considered when designing an FL solution. In this section, we describe the most prevalent challenges of FL.

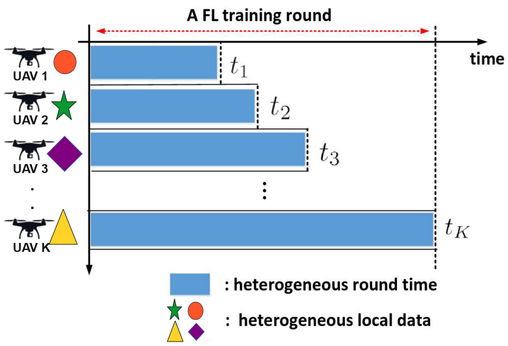


FIGURE 6. Data and system heterogeneity in FL.

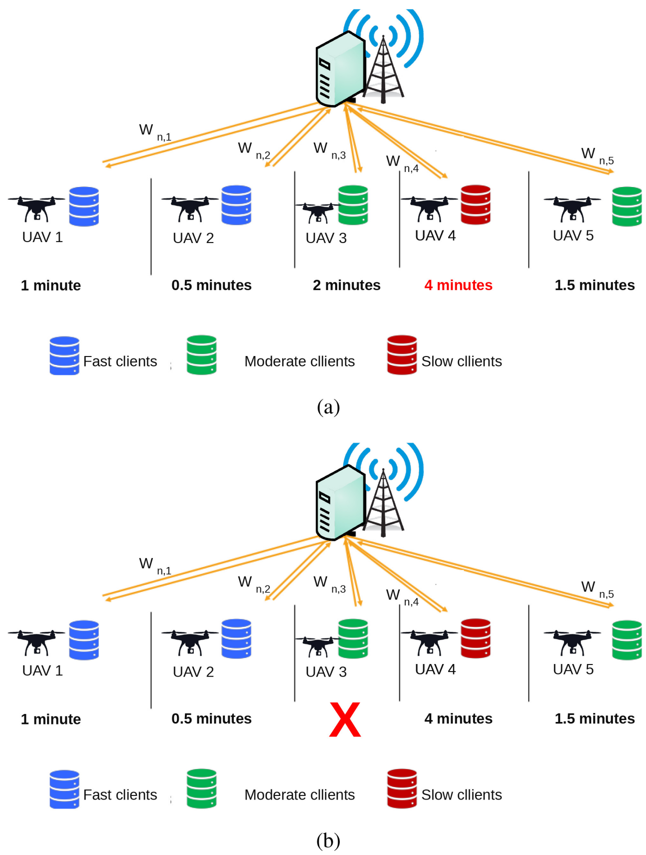


FIGURE 7. (a) Straggler UAV; (b) Dropout UAV.

1) STATISTICAL (DATA) HETEROGENEITY

Participating UAV clients in a FL environment are often deployed in different contexts. As a result, the distribution of each client's local data might vary or diverge (a phenomenon known as data heterogeneity). The attributes of the local data generated within a UAV exhibit variations across individual EUs. Datasets can be categorized into two separate categories, namely IID data and non-IID data, however, Non-IID datasets are commonly encountered in practical scenarios [95]. The non-IIDness can be further bifurcated into two distinct parts. The foremost pertains to the size of data present across various clients, while the latter concerns the distribution of data. These variations arise due to the diverse environmental conditions in which the FL nodes are located (see Fig. 6).

The non-IID data distribution among the participating devices in FL presents a significant challenge when it comes to global model development. For instance, statistical heterogeneity can occur when a UAV is employed to conduct a mission (e.g., crop field survey to assess crop health), where the information gathered during each flight may exhibit variations as a result of fluctuations in sensor characteristics, weather patterns, lighting conditions, or alterations in flight altitude. The diversity of data samples among participants may result in statistical heterogeneity, characterized by substantial variations in the measured values across different flights or surveys. The non-IIDness imbalanced properties in distributed data can cause local updates to drift, resulting in instability and slow FL convergence [26].

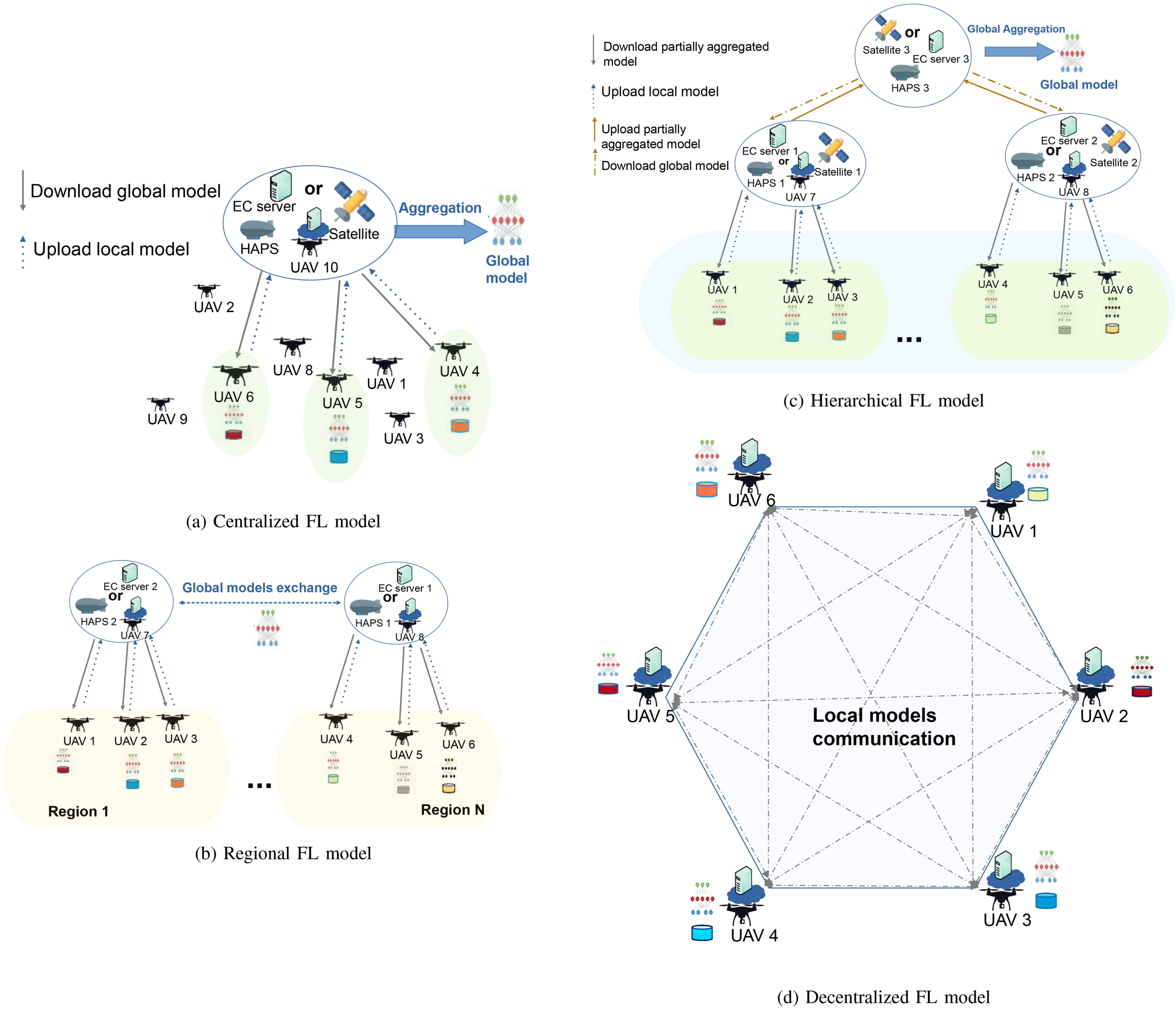
2) SYSTEM HETEROGENEITY

The varying hardware (e.g., CPU power, memory capacity, storage) and network connections of devices within a federated network may result in discrepancies in their operations. System heterogeneity can cause imbalances in workload allocation between devices with some UAVs contributing more than others, resulting in delayed FL convergence. For instance, we noticed that UAVs with different capacities experience different round times, as shown in Fig. 6.

In FL tasks, system and data heterogeneity contribute to the emergence of so-called "stragglers" and "dropouts". Straggler participants spend a long time in training their data and uploading their related local models to the aggregation server. In UAV-enabled FL, stragglers represent a prevalent problem caused by low processing power at some UAVs, degraded communication links, and large unbalanced datasets. An illustration of a straggler is presented in Fig. 7.a in a given FL round. The straggler is "UAV 4" which completed its training in 4 minutes (designated as a slow client), compared to a duration below 2 minutes for the other UAVs (designated as fast and moderate clients). In contrast, a participant who leaves the FL training process before finishing a given task is referred to as a dropout. Dropping out from the FL system, i.e., quitting during the training or the aggregation phase in a given round, can significantly impact the FL performance. This event can be due to disconnectivity caused by traveling far from the EC server. In Fig. 7.b, UAV 3 is considered a dropout since it failed to respond to the EC server during the FL aggregation phase within the preset time limit.

C. FL INTEGRATION IN UAV-ASSISTED MEC

The architectural integration of FL into UAV-assisted MEC systems has evolved beyond traditional ground-to-air models toward more dynamic, layered ecosystems. While earlier deployments were limited to single-layered systems involving UAVs and ground servers, recent advancements introduce a hierarchical structure composed of terrestrial,



(a) Centralized FL model

(b) Regional FL model

(c) Hierarchical FL model

(d) Decentralized FL model

FIGURE 8. FL models in UAV-assisted MEC systems: (a) Centralized, (b) Hierarchical, (c) Regional, and (d) Decentralized. Each diagram illustrates the communication and aggregation flow of FL tasks.

aerial (LAP/HAP), and satellite tiers. This multi-tiered structure provides the foundation for scalable, adaptive, and resilient FL deployment across diverse environments. While UAVs deployment offers flexibility and proximity to edge users, UAVs are inherently constrained by limited onboard computation, energy reserves, and mobility-induced connectivity challenges. These factors limit their sustained participation as FL aggregators. To mitigate such constraints, higher-altitude platforms such as HAPS and satellites are now increasingly considered for offloading tasks and managing intermediate or top-tier coordination. HAPS, due to their higher payload capacity, longer mission duration, and broader coverage, serve as robust intermediate MEC nodes that can aggregate model updates from UAVs while maintaining coordination. In scenarios where HAPS are unavailable or unreachable such as in sparsely covered or disaster-affected zones LEO satellites equipped with onboard processing capabilities can assume the role of edge servers. Satellites not only support task dissemination and collection but also facilitate inter-region coordination and backhaul communication, thereby enabling continuous operation even under degraded ground conditions. Inspired by empirical findings in existing literature, we define four deployment models tailored to FL tasks in UAV-assisted MEC systems, namely *centralized*, *hierarchical*, *regional*, and *decentralized* models. Each integration model addresses specific limitations and requirements, offering a spectrum of solutions to enhance the performance of FL in UAV-assisted MEC environments. Fig. 8 illustrates these architectural concepts while Table 3 summarizes their key features and differences.

TABLE 3. Comparison of different types of FL models in UAV-assisted MEC.

Architectural Feature	Centralized FL	Hierarchical FL	Regional FL	Decentralized FL
Centralization	High	Moderate	Low	−
Primary Aggregator	Central server (e.g., EC server, UAV, HAPS, satellite)	Central coordinating entity(e.g., EC server, UAV, HAPS, satellite)	Regional aggregation node(e.g., EC server, UAV, HAPS)	Participant nodes
Communications	Participants communicate with a central node	Intermediate nodes enable tiered communication	Region-specific nodes connect to local aggregators	Peer-to-peer communication among participants
Scalability	Low (Limited by central node)	Moderate (Tiered task distribution)	High to Moderate (Region aggregation)	High (Fully distributed system)
Fault Tolerance	Low (Single point of failure)	High (Redundancy across tiers)	Moderate (Semi-distribute resilience)	Moderate (No central failure point)
Resource Utilization	Under-utilized at central node	Efficient allocation across layers	Fragmented and complex handling	Over-utilization in large networks

1) CENTRALIZED FL MODEL

The centralized model, illustrated in Fig. 8a, remains the most commonly adopted structure in FL systems. In this model, a central node is responsible for aggregating local updates and generating the global model [25], [96], [97]. In UAV-assisted MEC environments, however, this approach faces several challenges due to the inherent limitations of aerial nodes. If a UAV is tasked with acting as the central aggregator, its limited battery life and computational capacity may jeopardize the successful completion of the learning process. Furthermore, the high mobility of UAVs introduces additional complexity, as movement during training rounds can lead to disconnections or dropout events.

To alleviate these issues, recent studies have explored two complementary techniques, namely client selection and trajectory optimization. Client selection refers to the process of strategically choosing which UAV clients or devices participate in a given FL round to improve convergence, and maintain resource efficiency [98]. Approaches include trust-driven selection that evaluates historical reliability before participation [99], clustering-based active selection to maximize intra-cluster diversity while reducing inter-cluster interference [100], contextual selection using real-time resource and network states [101], and DRL-assisted schemes that jointly optimize selection and spectrum allocation in NOMA-based systems [102]. Some works integrate physical-layer beamforming and energy harvesting into the selection process for over-the-air FL [103].

Trajectory optimization involves dynamically adjusting UAV flight paths to maintain stable communication, reduce energy consumption, and improve data collection efficiency during FL training. Notable examples include secure UAV-assisted crowdsensing with flight path planning to maintain coverage and protect data integrity [104], FRL for joint route planning and model training in aerial-terrestrial networks [105], DRL-based trajectory control to enhance FL convergence under mobility constraints [106], and path planning combined with knowledge distillation to reduce communication costs in drone-assisted IoT networks [107].

As an alternative to UAV-based aggregation, fixed aerial nodes such as HAPS or even LEO satellites may serve as more reliable aggregators. HAPS, with their larger payload capacity and prolonged flight duration, can accommodate larger datasets and perform aggregation without frequent dropout. In scenarios where neither HAPS nor terrestrial infrastructure are accessible, LEO satellites can offer a viable solution by assuming the role of global aggregators, thereby enhancing scalability and resilience in distributed UAV-based FL systems [82].

2) HIERARCHICAL FL MODEL

To overcome the limitations of centralized FL systems, hierarchical FL models introduce a layered control and aggregation structure, especially useful in UAV-assisted MEC environments. Unlike centralized architectures that rely on a single node for communication and aggregation, hierarchical FL distributes these tasks across multiple tiers, improving scalability and optimizing resource usage in highly dynamic networks.

Typically, hierarchical FL consists of three logical tiers, each with specialized roles. At the bottom, UAVs act as edge clients, collecting data and performing local training. Intermediate nodes such as quasi-stationary UAVs, HAPS, or edge servers aggregate regional models and relay them upward. At the top tier, a central coordinating node, which can be a ground server, HAPS, or even a satellite, performs global aggregation and coordination [82], [108]. As illustrated in Fig.8c, this structure enables more reliable participation of constrained UAVs by reducing communication latency and energy demands.

By leveraging nodes with higher endurance and processing capacity such as HAPS and satellites hierarchical FL improves fault tolerance, reduces the burden on low-power UAVs, and facilitates communication in scenarios with intermittent connectivity. Satellites, in particular, can serve as top-tier orchestrators in geographically sparse or infrastructure-limited environments. However, hierarchical FL introduces new challenges in UAV networks. Clients may switch between different aggregators due to UAV mobility, requiring dynamic reconfiguration of links and efficient handover mechanisms. While such issues have been explored in vehicular networks [109], [110], [111], [112], the 3D mobility and energy constraints in UAV environments make the problem more complex. Moreover, factors such as aggregation frequency, client reassociation, and incentive alignment remain underexplored in the UAV-specific hierarchical FL literature.

3) REGIONAL FL MODEL

As illustrated in Fig. 8.b, regional FL models advance toward decentralization by distributing training processes across several regional aggregators. In this model, each zone manages a subset of clients and performs local model aggregation independently, periodically exchanging updates with other zones [113], [114]. While regional FL offers promising improvements in robustness and load balancing, its implementation in UAV-assisted MEC systems introduces several unique challenges. Wireless environments involving mobile aerial platforms require seamless coordination across multiple regions, each managed by a distinct aggregator such as a UAV, HAPS, or ground edge node. The dynamic nature of UAV movement increases the likelihood of handovers and intermittent connectivity, which can disrupt synchronization among regional clusters.

Moreover, uneven resource distribution across UAVs or HAPS may lead to underutilization of computational capacity or overload in specific zones. The fragmentation inherent in regional architectures demands sophisticated communication protocols and efficient resource coordination.

4) DECENTRALIZED FL MODEL

At the most decentralized end of the spectrum, FL systems operate without relying on a central aggregator. In this model, each participant independently trains a local model using its own data and communicates directly with other participants to share model updates. This setup significantly enhances privacy, as no centralized entity has access to raw data or aggregated global parameters. However, the decentralized nature introduces coordination challenges. Since each participant controls its own behavior, reaching consensus and achieving consistent global performance can be difficult [96]. Divergence between models is especially problematic in critical applications where consistency is essential [115], [116], [117].

Deploying decentralized FL in UAV-assisted MEC systems compounds these challenges. UAVs operate in dynamic and resource-constrained environments, where limited computational power, battery life, and intermittent communication links can significantly affect performance. Maintaining reliable peer-to-peer communication among mobile aerial nodes becomes especially difficult in the absence of a coordinating server. Additionally, latency and convergence issues may arise due to asynchronous exchanges between participants. Despite these difficulties, decentralized FL offers an attractive alternative for environments where infrastructure is limited, and privacy or resilience is a priority.

D. APPLICATIONS OF FL IN UAV-ASSISTED MEC NETWORKS

To optimize network operations and ensure that the needs of emerging heterogeneous and complex wireless applications are met in real-time, the integration of more sophisticated functionalities in UAV-assisted MEC networks is needed.

Furthermore, to enhance clarity and align with the use-case-centric structure of this section, we classify FL applications based on their functional domains in UAV-assisted MEC systems. Each subsection highlights a specific application area where FL improves performance, privacy, and adaptability. Table 4 provides a structured summary of representative use-cases of FL in UAV-assisted MEC networks, detailing their corresponding models and key contributions.

1) FL FOR A2G CHANNEL QUALITY PREDICTION

Wireless A2G channel quality prediction is a critical task in UAV-assisted MEC networks, particularly due to the unique characteristics of the air-to-ground communication channel. The A2G channel is susceptible to path loss, delay spread, and fading, which are heavily influenced by factors such as UAV altitude and type of propagation environment [118], [119], [120]. Centralized learning systems often struggle with this prediction task as they require sensitive UAV data, including altitude and motion, to be transferred to a central organization, raising privacy concerns and logistical challenges [121], [122], [123]. Alternatively, the FL concept might be used to enable each UAV predict the A2G channel quality based on its data in a federated manner. By keeping data processing and model training local to each UAV, FL mitigates privacy concerns associated with centralized systems while enabling real-time adaptability to dynamic changes in the A2G channel environment.

FL can be used to enable accurate and privacy-preserving prediction of wireless A2G channel quality in UAV-assisted MEC networks. Due to the influence of altitude, environment, and UAV mobility on signal propagation, predicting metrics such as Signal-to-Interference-plus-Noise Ratio (SINR) and Channel State Information (CSI) is critical for maintaining communication quality [118], [119], [120].

TABLE 4. Summary of federated learning-based applications in UAV-assisted MEC networks.

Ref.	Task / Application	FL Model	Key Mechanism / Contribution
[118]	Over-the-air gradient aggregation for OFDM-based FL	Centralized FL	Eliminates explicit channel estimation via analog aggregation, improving communication efficiency under fading channels.
[120]	A2G information and energy delivery optimization	Centralized FL	Employs a binary channel feature map to reduce CSI feedback overhead in UAV-assisted FL scenarios.
[124]	CSI/SINR prediction in NTN environments	Centralized FL	Integrates sparse channel estimation to enhance spectral and energy efficiency when CSI is limited.
[125]	SINR prediction in UAV networks	Hierarchical FL (UAVs $\rightarrow$ BS)	Implements cost-aware aggregation, performing local aggregation at UAVs before sending updates to the BS to balance accuracy and communication cost.
[130]	Online FL under unreliable communication links	Hierarchical FL (UAVs $\rightarrow$ BS)	Proposes adaptive model update scheduling based on A2G link reliability to improve convergence with intermittent connectivity.
[131]	Joint UAV deployment and edge association for FL	Centralized FL	Optimizes UAV placement and user association to minimize total energy consumption while maintaining training performance.
[138]	Collaborative content caching in integrated aerial-terrestrial 6G networks	Hierarchical FL (UEs $\rightarrow$ UAV/BS (hgNB) $\rightarrow$ HCP)	Two-stage asynchronous FL where the HCP acts as coordinator, enabling privacy-preserving cache placement decisions.
[140]	Aerial content caching & UAV trajectory planning in HAP-assisted multi-UAV networks	Hierarchical FL (UAVs $\leftrightarrow$ HAP)	Utilizes Federated DRL (DQN for caching + TD3 for trajectory optimization) to maximize fairness in throughput and cache hit rates.
[141]	Joint UAV trajectory and caching (multi-task learning)	Centralized FL	FL-CAKD framework employs soft-target knowledge transfer to reduce communication load while improving cache hit rate and lowering delay.
[151]	Latency minimization for UAV-enabled FL with ISAC	Centralized FL	Jointly optimizes UAV trajectories and resource allocation using BCD and SCA to reduce training latency.
[149]	Truthful incentive mechanism for UAV-assisted crowdsensing in FL	Centralized FL	Designs a Stackelberg game-based incentive mechanism that ensures honest UAV participation under strict budget constraints.
[172]	Trust management of Tiny Federated Learning in Internet of UAVs	Centralized FL	Proposes a lightweight FL framework for UAV networks incorporating trust evaluation to enhance security and reliability.
[171]	Trust enhancement in UAV-enabled IoT networks	Centralized FL	Develops a unified FL-based trust evaluation model integrating communication, sensing, and computation metrics.
[170]	Decentralized FL for secure military aerial reconnaissance	Decentralized FL	Blockchain-assisted FL framework enabling secure multi-UAV collaboration with situational awareness and privacy-preserving aggregation.

FL can be used to allow UAVs or BSs to collaboratively train models without sharing raw data, which helps preserve privacy and reduce communication overhead [121], [122], [123]. It can also be used to support real-time adaptation by training lightweight models such as Long Short-Term Memory (LSTM) networks directly on local CSI sequences. In more complex setups, FL can be used in combination with Ray-Tracing (RT) simulations to pretrain DL models and fine-tune them during UAV operation for SINR prediction [124], [125]. Additionally, FL can adopt sparse channel estimation techniques, to enhance spectral and energy efficiency under challenging conditions [124].

2) FL-DRIVEN AERIAL BASE STATION DEPLOYMENT STRATEGIES

Unlike edge servers at fixed locations, UAV-assisted MEC systems enhance the spatial coverage and reach of FL services and applications [126], [127]. This is primarily due to the advantages of UAVs, such as direct LoS to ground EUs. Moreover, the deployment of UAVs as aerial base stations contributes to the formation of more flexible links within MEC networks, which expands the servicing area and strengthens the resiliency against environmental losses. In addition, UAVs equipped with MEC serve as dynamic and flexible platforms for computing tasks (such as for FL), seamlessly adapting to evolving network demands and user requirements. For instance, UAVs can be dynamically relocated to areas experiencing high user density or network congestion, effectively redistributing resources and alleviating traffic/tasks bottlenecks [25], [128], [129]. To cope with the dynamic behavior of ground EUs, FL allows for the collaborative learning of ground EUs' behavior patterns, such as mobility patterns, preferences, and usage trends. Furthermore, the integration of learning models derived from ground user behavior data facilitates the creation of a global model. The resulting global model can guide UAVs in adapting their positions and associations with edge clients to optimize coverage, energy efficiency, and learning performance. For instance, FL has been used to inform energy-aware UAV positioning and adaptive edge association strategies, helping minimize communication costs and improve model convergence in mobile scenarios [130], [131].

3) FL-ENABLED EDGE CONTENT CACHING IN UAV NETWORKS

Due to the growing popularity of video streaming services and the rapid development of smart devices, video traffic is likely to become the dominant data traffic. The escalating mobile traffic translates to prolonged content access times and pressures the network's back-haul links. To avoid network bottlenecks, the implementation of content caching mechanisms is advocated as a pivotal solution for 5G and beyond communication systems [132], [133]. UAVs can improve caching efficiency by detecting EUs' movements, learn their patterns, and act consequently by effectively suggesting the dissemination of popular content into the network [134], [135]. For delay-sensitive applications, content caching at UAV-assisted edge networks is a promising approach [136], [137]. Indeed, it enables delivering popular content closer to the network's edge such as at Aerial BSs (AeBSs) or access points. However, in ultra-dense 6G scenarios, traditional caching strategies relying on explicit user preference reporting pose serious privacy risks. In such settings, FL has emerged as a privacy-preserving alternative for collaborative learning of caching policies. Instead of centralizing user data, FL enables UAVs to train local models that capture content request patterns and share only model updates, safeguarding personal information [138], [139]. To further improve caching efficiency while addressing privacy and resource constraints, UAV-assisted networks can incorporate federated learning-based strategies for decentralized content decision-making. Additionally, ML approaches can be applied such as Federated Reinforcement Learning (FRL) to guide UAVs in deciding both what to cache and where to cache it, based on user demand predictions and mobility patterns [140]. Furthermore, multi-task learning can also be used to enhance content popularity estimation [141].

Hence, FL emerges as a promising solution that enables collaborative model training for content caching policies, while preserving user data privacy.

4) FL FOR PRIVACY-PRESERVING EDGE CROWDSENSING VIA UAVS

Mobile crowdsensing (MCS) is a technology that uses ubiquitous mobile devices to sense and collect data from real environments to better serve EUs. Traditional ML architectures have been widely used for model training and processing in intelligent mobile crowdsensing applications [142], [143], [144], [145], [146]. However, centralized ML often requires direct access to user data, which can expose sensitive information and create scalability issues when managing large volumes of heterogeneous sensing data [147], [148].

FL can be used to accelerate crowdsensing model learning while maintaining data privacy and reducing communication overhead. In UAV-assisted MEC networks, FL can be used to enable UAVs to locally train models based on sensed data, transmitting only model updates to the aggregation server [149]. This approach mitigates privacy risks and enables efficient collaborative learning across spatially distributed UAVs [150].

MEC-equipped UAVs can be used to support a wide range of edge crowdsensing applications, including environmental sensing (e.g., air quality monitoring, wildfire detection) and behavior sensing (e.g., human motion recognition). For example, FL can be used to train fire detection models based on distributed environmental features and UAV-captured imagery, without centralizing potentially sensitive visual data. UAVs can also be used to sense motion or activity in smart city environments and collaboratively learn recognition models in real time.

In more advanced systems, FL can be used in combination with integrated sensing, computation, and communication (ISCC) strategies to jointly optimize UAV trajectories, sensing resource allocation, and communication efficiency [150], [151].

5) FEDERATED CYBERSECURITY FOR UAV-BASED MEC NETWORKS

The use of UAVs is increasing as they realize risky and difficult tasks. However, these wireless channels are inherently vulnerable to a wide range of cyber threats, including jamming, spoofing, Sybil attacks, and malicious data injection, all of which can compromise network security and mission integrity. Aerial adversaries, for instance, can launch jamming attacks to disrupt data reception within the network. To mitigate malicious attacks in UAV networks, various defense mechanisms have been proposed for UAV-based networks, including RL-based approaches [152], [153],

[154], [155], [156], [157], centralized ML approaches [158], [159], [160], [161], [162], [163], and game theory-based approaches [164], [165], [166], [167], [168]. However, these solutions experience limitations. For instance, unreliable UAV communications hinders centralized cyberattack detection approaches from operating correctly. Alternatively, FL can operate as lightweight distributed ML at UAVs without sharing raw data with the central server. Then, the global model can be used to identify patterns and features in traffic data and classify it into attacks or not [169], [170].

Beyond detection, FL frameworks can incorporate trust evaluation mechanisms to weight the reliability of updates shared among UAVs [171], [172]. Trust-aware aggregation helps isolate compromised nodes and prevent model poisoning. Furthermore, context-aware FL can enhance detection accuracy by incorporating information about UAV roles, mobility patterns, and environmental context [170], [172]. To improve fault tolerance, especially in contested or unreliable environments, decentralized FL structures allow UAV clusters to operate semi-independently and continue training even in the absence of stable connectivity. Some systems also leverage situational awareness and cross-layer optimization to ensure the security mechanisms align with mission objectives [170].

IV. FL IN HETEROGENEOUS UAV-ASSISTED MEC

FL is a new paradigm that has just begun to be examined in the context of UAV networks. As such, we divide this section into three categories: (i) FL in UAV systems such as UAV swarms, (ii) FL in UAV-ground Heterogeneous Networks (V-HetNet), where UAVs are deployed as either FL clients, EC servers, or relays, and (iii) FL in integrated UAV-HAPS systems.

A. FL IN UAV-BASED SWARMS

AI advancements have enabled UAVs to coordinate their operations and collaborate to complete complex tasks, which might be based on FL. The combination of UAVs with FL enables dealing with vast volumes of data collected by intelligent devices. For instance, the paper in [115] proposes DPBE-DGFL, a decentralized framework that integrates Differential Privacy (DP), Blockchain, and Graph Federated Learning (GFL) to support UAV-enabled disaster response over graph-structured UAV networks. The framework introduces three key phases: privacy-preserving local training using DP-SGD, model weight authentication using UAV-to-UAV blockchain validation, and final aggregation using a Delegated Proof-of-Stake (DPoS) mechanism to select trusted validators for model consensus. However, this approach is unable to scale with the network, thus requiring accurate participant selection in each FL round.

To do so, a FRL based UAV swarm system for airborne remote sensing was suggested in [173]. To create UAV swarm intelligence, the authors employ RL for UAV trajectory optimization and boosting the UAVs' autonomy. The obtained findings indicate that the suggested FRL technique outperforms the centralized RL-based benchmark and is resilient to changes in sensor noise, participation ratio, packet loss, and duplicate transmissions.

Mission-critical applications, such as covering large disaster areas in emergency networks, depend on the ability to operate a large number of UAVs. In this context, authors of [174] propose a learning framework that integrates Variational Autoencoders (VAE), Asynchronous Federated Learning (AFL), and graph neural network (GNN)-based multi-agent deep reinforcement learning (MADRL) to enhance UAV swarm coordination in 6G-enabled disaster response scenarios. UAVs offload, process, and respond to task requests from ground terminals using semantic communication, where tasks are encoded and decoded through BERT-based embeddings. VAE detects anomalies in UAV participation in FL, while GNNs aggregate neighbor UAV states to support decentralized decision-making. The utility function jointly optimizes task completion, energy efficiency, load balancing, and coverage. In [175], UAVs' overall training energy consumption is investigated by jointly optimizing the local convergence threshold, computation resource allocation, local iterations, and bandwidth allocation, subject to the FL global accuracy target and maximum training latency threshold. The problem is stated as a min-max optimization problem that is efficiently handled using joint training and resource allocation.

In [176], authors address the energy and latency bottlenecks in UAV swarms by introducing a decentralized FL framework driven by Spiking Neural Networks (SNNs) coupled with a Bayes-theorem-based leader election mechanism. The SNN architecture exploits event-driven computation to reduce energy consumption, while an approximate derivative algorithm enables efficient training despite the non-differentiable nature of SNNs. A dynamic leader is selected each round based on communication quality and residual energy, minimizing aggregation time and balancing training loads. Additionally, authors of [177] provided a framework to implement FL over a swarm of UAVs to address the challenges of energy efficiency. The authors formulate a UAV selection problem aiming to maximize energy efficiency while satisfying constraints on secrecy outage probability (SOP) and data coverage. To solve this, they propose the UAV Selection (OUS) algorithm, which selects a subset of UAVs based on their energy efficiency, security, and data diversity.

The work in [178] propose a FL-enabled framework for real-time network anomaly detection in drone swarms, deployed and tested on the NSF AERPAW platform [179]. The study incorporates defense strategies such as DP and adversarial training to mitigate the effects of data poisoning attacks, including label flipping and feature noise. The experimental setup evaluated trade-offs between security and computational overhead.

In [180], authors introduce a novel integration of semantic communication with FL through a hierarchical FL framework

TABLE 5. Summary of main works on FL in UAV swarm systems.

Reference	System Description	Aggregator	Energy Awareness	Participant Selection	Security	Dataset	Proposed Solution
[177]	FL in UAV swarm with PLS	UAV leader	✓	✓	✓	MNIST [203]	OUS algorithm to maximize energy efficiency and security with SOP and class coverage.
[115]	Decentralized GFL for UAVs in disaster response	Delegated UAVs via DPoS	⊖	⊖	✓	EMNIST [204], Tonga [116]	DPBE-DGFL: DP-SGD, blockchain validation, and reputation-based DPoS.
[175]	UAV swarm-based FL	UAV leader	✓	⊖	⊖	N/A	Joint optimization of resources and FL for fairness and energy efficiency.
[181]	FL for UAV-based data collection	UAV server	⊖	✓	⊖	Visdrone2021 [205]	FedOL: Adaptive client selection by training utility and prioritization.
[183]	UAV-assisted FL in IoV with incentives	UAV aggregator	✓	✓	⊖	MNIST [203]	Two-stage contract-based incentives and energy-efficient resource allocation.
[176]	Decentralized FL in UAV swarm using SNNs	Dynamic UAV leader	✓	✓	⊖	Fashion-MNIST [206], MNIST [203]	SNN FL + Bayesian leader election for energy and latency optimization.
[188]	UAV-enabled WPCN with hybrid FL	UAV aggregator and transmitter	✓	⊖	⊖	N/A	Joint optimization of UAV position, WPT power, offloading, and FL via BCD + Lagrangian.
[178]	FL-based anomaly detection in drone swarms	Fixed edge node (AERPAW)	⊖	⊖	✓	IoT attack datasets	Adversarial training + DP for robust FL in UAV swarms.
[173]	UAV swarm-enabled remote sensing	EC server or UAV server	⊖	⊖	⊖	N/A	FL + RL for improved sensing and UAV trajectory optimization.
[187]	FRL for UAV placement in IoT network	UAV server	✓	⊖	⊖	N/A	MUECD-SAP: PSO-DDPG-based UAV placement for SINR maximization.

tailored for UAV swarm cooperation. In this architecture, UAVs are grouped into clusters, where intra-cluster learning is performed using centralized FL and inter-cluster communication adopts a decentralized scheme. Additionally, the authors propose an incentive mechanism based on evolutionary game theory to encourage UAV participation, alongside a dynamic cluster management protocol to handle UAV dropout due to mobility.

Finally, the authors of [181] introduced FedOL, which addressed online FL in UAV swarms through participant and sample selection. Specifically, by seamlessly integrating online learning with FL, FedOL allows real-time sample collecting and model training in unknown environments. To mitigate training latency while reaching targeted model accuracy, FedOL favors participant selection based on high utility, and participants prioritize critical samples. Moreover, Table 5 presents a summary of the studies reviewed in this section. Most swarm studies rely on simulation and small, vision-centric datasets, which limits external validity (e.g., MNIST/EMNIST/VisDrone in [115], [177], [181]). Energy and latency models are often idealized and rarely calibrated on embedded hardware [175]. Additionally, security evaluations tend to use fixed, non-adaptive attackers and do not test resilience under mobility-induced packet loss [178]. Furthermore, scalability beyond tens of UAVs and decentralized blockchain-assisted variants are largely unexamined.

B. FL IN UAV-BASED GROUND V-HETNET

Integrated UAV-ground networks are a key enabler of beyond 5G networks. Indeed, UAVs offer enormous potential in novel services such as delivering emergency communications and wide-area on-demand data collecting, given their flexibility and strong LoS communication links [182]. Hence, the use of FL over hybrid network that include both UAV and ground components has been investigated. For instance, authors of [183] propose a two-stage UAV-assisted FL framework to tackle the challenges of intermittent connectivity in IoV networks. In the incentive stage, a contract-theory-based mechanism is designed to encourage vehicle users (VUs) to contribute local data. In the training stage, the authors introduce a contract-aware energy-efficient resource allocation algorithm that jointly optimizes computing and communication resources based on VUs' mobility and contract parameters. In [184], a hierarchical FL model was proposed, where terrestrial base stations serve as intermediate aggregators, a core FL server as the central aggregator, and UAVs as FL clients. To securely share local model updates, authors of [104] proposed blockchain-based and cooperative UAV-assisted FL that aims to protect the privacy of UAVs' data using local DP. The suggested method is demonstrated to successfully enhance UAV utility and ensure high-quality model sharing and privacy.

In [185], authors proposes a Hierarchical Federated Learning (HFL) framework that integrates blockchain technology in UAV-assisted IoT networks. To tackle challenges such as data heterogeneity, model accuracy degradation, and the threat of malicious participants, the authors introduce a system where UAVs act as decentralized edge aggregators and collaboratively perform secure global aggregation through a lightweight blockchain using PBFT consensus. Additionally, an optimization framework is developed to minimize learning latency and maximize model accuracy, jointly considering device association, wireless resource allocation, and UAV deployment, all under strict energy constraints. The solution combines a greedy device clustering strategy and a Soft Actor-Critic (SAC) RL algorithm for decision-making.

Similarly, authors in [186] proposed a Semi-Supervised FL (SSFL) framework for privacy-preserving UAV image recognition, in which a Federated Mixing (FedMix) strategy is used to improve the naive combination of FL and semi-supervised learning under label-at-client and label-at-server scenarios. To address the issue of statistical heterogeneity, the Federated Frequency (FedFreq) aggregation rule is provided, which modifies the weight of the relevant local model based on the client's frequency of training participation. On the other hand, UAV participant selection scheme was designed to optimize FL in [83] by selecting the most suitable FL participant in each sub-region by evaluating two key criteria: the average Structural Similarity Index Measure (SSIM) score of the participant's local dataset and the participant's power consumption profile. In contrast, [187] addressed the limited battery capacity of UAVs when running a FL-based service. The authors proposed a Particle Swarm Optimization (PSO) and Deep Deterministic Policy Gradient (DDPG) inspired method, called Multi-UAV Energy-efficient Coverage deployment algorithm (MUECD-SAP), to accurately position deployed UAVs and allocate resources. In [188], authors propose an optimization framework for UAV-assisted wireless powered communication networks (WPCN) where EUs execute both FL and offloadable MEC tasks. The UAV acts as an energy source (via WPT), an edge server for offloaded tasks, and an FL aggregator. To minimize UAV energy consumption, the authors formulate a joint optimization problem that considers UAV hovering position, WPT power, resource allocation, task offloading ratios, and local FL computation time, under constraints on latency, energy harvesting, and computation.

In [138], content caching and cooperative communications are leveraged at UAVs and terrestrial BSs to enable a two-stage FL service among EUs, UAVs, and BSs. The proposed method aims to disseminate content into the network considering traffic distribution, EUs mobility, and localized content popularity.

UAV clients are susceptible to malicious attacks, such as jamming and eavesdropping. For instance, authors in [189] propose UAV-Based Federated Learning (UBFL), a privacy-preserving FL framework designed for UAV-assisted MEC environments. UBFL integrates adaptive nonlinear gradient encryption with blockchain-based decentralized model aggregation. Additionally, UBFL applies fine-grained adaptive parameters to each network layer. It also incorporates a Random Cut Forest (RCF) anomaly detection algorithm to filter out poisoned gradients and ensure the integrity of updates. In [190], our focus was on UAV client selection in environments characterized by heterogeneous data, different system settings, and the presence of unreliable UAVs as adversaries, stragglers, or dropouts. Specifically, we proposed a number of measures to identify unreliable UAVs and exclude them from the FL training process, thus improving the global model performances in terms of accuracy and successful attack rates.

Hierarchical and incentive-driven designs show promise but often presume reliable backhaul and stable intermediate aggregators [183], [184], which may not hold in fast-moving scenarios. Additionally, privacy mechanisms such as DP or blockchain are included in [104], [189], yet their impact on model utility, latency, and energy is rarely quantified end-to-end. Client-selection schemes in [83], [181] are typically validated under benign settings with limited heterogeneity. Few works report mission-level metrics (e.g., time-to-accuracy, deadline-miss rate) or fairness across clients, which complicates comparison across deployments. Furthermore, a summary of the works discussed in this section is provided in Table 6.

C. FL IN UAV-NON-TERRESTRIAL HETEROGENEOUS SYSTEMS

UAVs, HAPS, and satellites are emerging as key enablers of reliable communication and computation in non-terrestrial environments [191]. The integration of these platforms into FL systems holds significant promise for enhancing network performance, particularly in terms of coverage, scalability, spectral efficiency, and energy-aware task offloading. For instance, authors of [192] optimized the 3D locations of UAVs as AeBSs to maximize the network's capacity. Supported by a HAPS as the central server, a Federated DDPG (Fed-DDPG) algorithm is deployed, where AeBSs act as FRL clients who train autonomously to optimize their deployment decision models. A similar network topology is considered in [193], where, in addition to the HAPS and AeBSs, eavesdroppers might be present. The focus is on optimizing the deployment of AeBSs to satisfy preset data rates and secrecy data rates using FRL based on DDPG. In [194], a V-HetNet-enabled Asynchronous Federated Learning (AFL) approach is proposed, which employs the Compound-Action Actor-Critic (CA2C) algorithm for UAV client selection, UAV placement, and device association, while a HAPS acts as the central aggregator. This framework enables UAVs to collectively train a global anomaly detection model using their local sensory data collected from IoT devices. The proposed UAV selection process mitigates the impact of UAVs with low local model quality and high energy consumption on model accuracy. Finally, authors of [195] studied the content caching problem for a HAPS-assisted multi-UAV network. The objective is to minimize

TABLE 6. Summary of main works on FL in UAV-based Ground V-HetNet.

Reference	System Description	Aggregator	Energy Awareness	Participant Selection	Security	Dataset	Proposed Solution
[180]	Semantic communication via hierarchical FL clustering	Cluster heads (local) + decentralized (global)	⊖	✓	⊖	N/A	Centralized intra-cluster + decentralized inter-cluster FL with incentive and cluster management.
[184]	Hierarchical FL for UAV clients	BSs (intermediate) + core server	⊖	⊖	⊖	FEMNIST [207]	Hierarchical FL leveraging shared BS data to reduce model divergence under non-IID distributions.
[83]	UAV-assisted FL for fire detection	EC server	✓	✓	⊖	FLAME [208]	DEEPS: FL participant selection using SSIM scores and power consumption.
[185]	Hierarchical FL in UAV-enabled IoT	UAVs as edge aggregators + blockchain	✓	⊖	✓	CIFAR-10 [209], MNIST [203]	PBFT blockchain-based HFL with device clustering and SAC RL for latency reduction.
[104]	UAV-assisted FL for mobile crowdsensing	EC server	⊖	⊖	✓	MNIST [203]	SFAC: Secure model updates via blockchain + local DP for UAV privacy.
[186]	UAV-enabled FL for image recognition	UAV leader	⊖	⊖	⊖	CIFAR-10 [209], Fashion-MNIST [206]	SSFL: FedMix for SSL + FedFreq to mitigate statistical heterogeneity.
[138]	FL for content dissemination in UAV-BSs network	Heterogeneous computing platform (HCP)	⊖	⊖	✓	N/A	Predict content placement using mobility and network traffic patterns in FL.
[189]	Blockchain-based FL in UAV-MEC	Decentralized blockchain	⊖	⊖	✓	CIFAR-10 [209], MNIST [203]	UBFL: Adaptive nonlinear gradient encryption + RCF-based anomaly detection.
[190]	UAV-assisted edge FL	EC server	⊖	✓	✓	CIFAR-10 [209], MNIST [203]	Filter out unreliable UAVs to enhance convergence, accuracy, and security.

content delivery delays through proactive content caching. To solve this problem, a deep regression model within a federated averaging framework was designed within an EU-UAV-HAPS hierarchical setup. The paper in [196] proposes a framework that integrates UAVs as edge servers and a HAPS as the cloud server to enable HFL over multi-cell wireless networks. The system aims to address challenges of communication latency, interference, and energy constraints by optimizing UAV trajectories, transmit powers, subchannel allocation, and client selection. To tackle the complexity of this joint optimization problem, the authors employ a Multi-Agent Twin Delayed Deep Deterministic Policy Gradient (MATD3) RL algorithm.

In [197], authors address the challenge of efficient and privacy-preserving data processing in Earth observation missions, where massive and distributed remote sensing data are collected from aerial and satellite platforms. The authors propose a HFL framework involving LEO satellites, HAPS, and UAVs. In this architecture, UAVs perform localized data collection and training, HAPS serve as intermediate aggregators, and satellites coordinate global model aggregation. The paper in [198] investigates the challenge of detecting smart jamming attacks in joint terrestrial and Non-Terrestrial Network (NTN) communication networks. The problem is aggravated by the spatially distributed nature of jamming sources and the need to preserve the privacy of participating edge nodes. The authors propose a FL-based jammer detection framework where UAVs and LEO satellites collaboratively train detection models across the network. The proposed FL architecture is augmented with lightweight encryption mechanisms and reliability-aware client selection to ensure privacy. Authors in [199] address the challenge of energy-efficient resource allocation in Integrated Satellite-Air-Terrestrial Networks (ISATRNs) that are enhanced with RIS and Rate Splitting Multiple Access (RSMA). The complexity of dynamic channel conditions and heterogeneity of network nodes motivates the authors to propose a federated deep reinforcement learning (FDRL) framework. In this setup, satellites and UAVs act as distributed agents that locally learn optimal power control and RIS configurations.

Conventional FL in large-scale terrestrial/non-terrestrial systems faces inherent limitations, including scalability bottlenecks, slow convergence under heterogeneous data distributions, and heightened risks of privacy leakage when UAVs, HAPS, and satellites jointly participate in distributed training [200]. To mitigate these constraints, authors in [201] investigate the prospective evolution of FL toward Quantum Federated Learning (QFL) within space-air-ground integrated networks (SAGIN). The proposed QFL framework exploits quantum-enhanced algorithms and quantum communication links to accelerate global aggregation and reduce overall training latency. The architecture further incorporates hybrid learning strategies that integrate classical and quantum computation, together with adaptive client selection mechanisms

TABLE 7. Summary of main works on FL in UAV-non-terrestrial heterogeneous systems.

Reference	System Description	Aggregator	Energy Awareness	Participant Selection	Security	Dataset	Proposed Solution
[192]	HAPS-assisted FRL for AeBS deployment	HAPS node	⊖	⊖	⊖	N/A	Fed-DDPG: RL-based AeBS deployment optimization to maximize coverage and performance.
[193]	HAPS-assisted FRL for AeBS data protection	HAPS node	✓	⊖	✓	N/A	DDPG-based FRL for trajectory and deployment under data rate and secrecy constraints.
[194]	HAPS-assisted AFL for anomaly detection in IoT	HAPS node	✓	✓	✓	LabData [210], X-IIoTID [211]	CA2C: Client selection, UAV placement, and association using context-aware coordination.
[195]	HAPS-assisted FL for content caching at UAVs	HAPS node	✓	⊖	✓	MovieLens [212]	Deep regression model in FL framework for predictive caching at UAVs.
[196]	Hierarchical aerial FL with UAVs as clients and HAPS as aggregator	HAPS node	✓	✓	⊖	Simulated dataset	Energy-aware FL scheduling and UAV selection to optimize training efficiency in aerial-only networks.
[197]	Hierarchical FL for Earth observation across NTN	Satellite	⊖	⊖	⊖	N/A	HFL framework with UAVs for local training, HAPs as intermediate nodes, and satellites for global aggregation.
[198]	FL-enabled jammer detection in T/NT networks	Satellite	⊖	✓	✓	N/A	Privacy-preserving FL using lightweight encryption and reliability-aware client selection.
[199]	Energy-efficient FL for RIS-assisted ISATRNs	Distributed UAVs/Satellites	✓	⊖	⊖	N/A	Federated DRL agents for joint optimization of power allocation and RIS configurations.
[201]	Quantum-enhanced FL for SAGIN	Satellite or HAPS	⊖	✓	✓	N/A	Flexible QFL architecture with adaptive client selection and quantum communication for reduced training latency.

that allocate participation dynamically according to node energy budgets and channel conditions.

Most HAPS/LEO studies such as references in [192], [193], [197] use simulated traffic and channels, so they do not test intermittent links or cross-tier delays. Additionally, forward-looking proposals such as QFL [201] remain architectural, with limited evidence on resource usage or end-to-end training-time gains. Additionally, Table 7 presents a summary of the studies reviewed in this section.

V. CHALLENGES AND DISCUSSIONS

To unleash the full potential of FL in UAV-assisted MEC systems, it is crucial to address the complex issues that come with the integration of these technologies. This section thoroughly examines the related challenges, thus providing insight into the future directions of research in this area.

A. LIMITED UAV-MEC PAYLOAD/CAPACITY

UAVs used in edge-assisted FL missions typically operate with tight constraints on energy, memory, and processing power. These limitations stem from the compact form factor and weight restrictions imposed by aerial mobility, which severely narrow the computational budget for onboard ML and inference. Although advances in sensor integration and embedded systems have increased the capabilities of modern UAVs, however, the application of FL remains challenging due to the mismatch between model complexity and onboard capacity. Large-scale DL models often exceed what UAVs can compute or store locally, especially when real-time responsiveness is required during missions. Conventional mitigation strategies include offline model training conducted during charging cycles and periodic offloading of tasks to edge servers. However, such strategies do not fully address the need for autonomous, on-the-fly learning and decision-making in dynamic or disconnected environments. Recent developments in on-device learning and TinyML aim to bring model training and inference directly to constrained edge platforms [212], [213]. While these methods offer promise, several gaps remain: the energy-accuracy tradeoff is not well understood for aerial settings where adaptive quantization and model pruning are still largely heuristic, in addition to real-time resource monitoring mechanisms for model execution are rarely integrated into FL workflows.

From a deployment perspective, enabling FL on UAV fleets is primarily a systems-integration task. First, compliance including airspace, spectrum, flight safety, in addition to platform diversity across airframes, sensors, radios, and onboard computers should be covered. Software updates must be safety-aware (e.g., allow updates only in predefined mission phases). Additionally, communication planning should map training and aggregation to expected A2A/A2G coverage and define default behavior when links are weak or absent. On the other hand, strict rules for collecting and retaining location rich sensor data should be established. At runtime, the system needs to be able to switch to inference-only as batteries run low, buffer local updates for later upload, and fall back to pre-validated policies if connectivity is lost. Practical relevance improves when mission-level metrics are reported alongside accuracy, including robustness under client dropouts, degraded links, in addition to responsiveness using metrics such as end-to-end latency and deadline-miss rate.

Future work should explore FL model architectures that adapt in real time to available UAV resources (e.g., battery, memory, bandwidth). Useful directions include hybrid training schemes in which UAVs alternate between lightweight local updates and higher-fidelity offloaded aggregation, as well as mechanisms that co-optimize flight trajectories with execution schedules to improve efficiency under resource pressure.

B. SCARCITY IN UAV DATASETS

FL relies heavily on diverse, well-annotated datasets to train accurate and generalizable models. However, UAV-based applications suffer from a notable lack of publicly available datasets that reflect their unique mobility, perspective, and operational constraints. The dynamic and aerial nature of UAVs introduces features such as altitude shifts, occlusion variability, and non-linear movement patterns that are poorly represented in conventional datasets.

This scarcity has led many studies to repurpose generic image or video datasets, which often fail to capture the conditions and perspectives relevant to UAV operations. As a result, FL models trained in UAV settings struggle to generalize or converge reliably, especially when clients operate in diverse geographical or task domains. While curated data collection is essential, it is also expensive, time-consuming, and often infeasible for all use cases especially in safety-critical or remote UAV applications. This underscores the need for novel dataset augmentation strategies and UAV-specific simulation environments that can capture both sensor noise and mobility-induced variance.

Generative AI (GenAI), including methods such as GANs and VAEs, offers a promising avenue to alleviate data scarcity [214]. Beyond simple data augmentation, GenAI can create scenario-specific samples that reflect rare edge cases or underrepresented flight conditions, helping balance non-IID datasets in FL settings. However, open challenges remain in validating the utility and realism of synthetic data, especially when UAVs are tasked with sensitive detection or localization tasks. Future research should investigate domain adaptation, federated dataset synthesis, and model-based generative data filtering pipelines.

Additionally, collaborative dataset construction across UAV clients via federated co-curation or active learning protocols could help reduce annotation overhead while preserving data privacy. Such efforts may ultimately lead to a new class of UAV-centric benchmark datasets to evaluate FL under real-world variability.

C. FL MODEL CONVERGENCE

The convergence of FL models in UAV-assisted MEC systems remains a critical challenge due to factors such as data heterogeneity, intermittent connectivity, and client mobility. These conditions lead to inconsistent participation, asynchronous updates, and drifting gradient directions, which collectively impair global model stability. From a theoretical standpoint, federated optimization algorithms such as FedAvg are known to be sensitive to non-IID data distributions. However, in UAV-assisted scenarios, this sensitivity is amplified by dynamic topologies and fluctuating network availability, which make synchronization and loss minimization especially difficult [215].

Recent work has suggested that UAV mobility, when properly leveraged, can enhance convergence by enabling natural mixing of data across regions. This emergent property, often referred to as spatiotemporal diversity, can help mitigate the statistical skew that plagues FL and facilitate behavior closer to centralized training [216]. Nevertheless, realizing this potential requires intentional protocol design. Existing approaches often treat mobility as a disruption to be masked or managed, whereas future work should investigate convergence-aware scheduling policies that dynamically reassign training roles based on movement patterns, energy states, and data similarity.

Moreover, convergence optimization in UAV-assisted FL must account for the wireless-specific limitations of these systems. Rather than relying solely on synchronous aggregation or periodic communication, adaptive mechanisms such as gradient staleness-aware aggregation, predictive dropout handling, and on-the-fly hyperparameter tuning could substantially improve performance in non-stationary settings. Ultimately, the goal is not merely faster convergence, but robust convergence under uncertainty, supported by lightweight solutions that gracefully degrade when faced with client volatility, stragglers, and intermittent failures realities inherent to UAV networks.

Beyond these classical strategies, emerging paradigms such as QFL have been proposed to address scalability bottlenecks and slow convergence in large-scale UAV networks. Furthermore, quantum-enhanced optimization and quantum communication, and QFL has the potential to accelerate aggregation, reduce training latency, and sustain efficiency under heterogeneous and non-IID data distributions. Although still in its infancy, the integration of QFL into UAV-assisted MEC systems represents a forward-looking pathway to overcoming some of the fundamental convergence challenges outlined above.

D. SECURITY CONCERNS

Although FL is presented as a protector of private data, there is discussion that even exchanging merely updates over a wireless network poses risks. Indeed, the integrity of the FL model might be jeopardized by attacks on the FL task, particularly in wireless or MEC networks where communication channels are exposed and node reliability is highly dynamic.

In UAV missions this can have safety-critical consequences, for example corrupted updates during a wildfire-mapping could delay smoke detection, and compromised flight-path prediction models could degrade collision avoidance during dense operations.

A significant vulnerability arises from poisoning attacks, which aim to compromise the integrity of the global model by manipulating either local data, called data poisoning, or model updates, called model poisoning [217], [218]. In data poisoning, adversaries inject malicious samples into their local datasets, while in model poisoning, gradient updates are crafted to mislead the global aggregation process. Advanced forms such as backdoor attacks embed hidden triggers into the training data to induce targeted misclassifications on specific inputs. These attacks often maintain high global accuracy on clean validation data, making them difficult to detect [217]. On the other hand, distributed backdoor attacks, often abbreviated as DBAs, allow multiple colluding adversaries to inject fragments of a common trigger pattern, which further complicates detection. When adversarial clients apply dynamic triggers or manipulate gradients with crafted noise, they can evade standard defenses such as norm clipping and robust aggregation [217]. Concrete UAV-centric examples include label-flip poisoning in aerial object detection such as mislabeling vehicles as background to lower recall in traffic monitoring, and backdoor triggers tied to visual markers on roads or rooftops that activate only under specific viewpoints, thereby evading routine validation. In cooperative swarms even a small fraction of compromised drones can bias the global model if aggregation relies on simple averaging.

FL systems are also vulnerable to inference attacks, in which adversaries reconstruct or infer sensitive properties of training data by analyzing the gradients shared during model updates [219]. These attacks may originate from either compromised participants or passive observers, posing substantial risks in systems that lack strong privacy mechanisms like gradient perturbation or encrypted communication. Insider threats, namely adversaries who behave as legitimate clients, amplify these concerns by gaining unmonitored access to training rounds. Such access enables model manipulation and coordinated attacks that may degrade performance over time [218]. In distributed and mobility-driven systems such as UAV-assisted FL, where client availability is intermittent and redundancy is limited, the consequences of these threats are even more pronounced. In practice, gradient-leakage risks apply to sensitive aerial imagery such as faces, license plates, and facility layouts.

UAV-tailored mitigations and trade-offs include the use of Byzantine-resilient aggregators such as the coordinate-wise median or trimmed mean to limit the influence of a few compromised clients with modest overhead. Secure aggregation can be realized through pairwise masking and dropout-tolerant mask chains that remain effective over lossy A2A and A2G links with changing neighbor sets. Differential privacy with per-round clipping and adaptive noise that varies by mission phase can bound information leakage while preserving utility in real time. Reputation or trust scoring based on consistency checks, and hierarchical validation at MEC or HAPS servers on held-out aerial datasets can help detect drift or backdoors before redeployment.

Despite various proposed defenses such as differential privacy, anomaly detection, and robust aggregation, their practical deployment in UAV-assisted MEC systems remains underexplored. The majority of existing solutions are not tailored for dynamic, delay-sensitive, and bandwidth-constrained aerial networks. In addition, many conventional defenses are static and assume fixed attacker behavior, which limits effectiveness against evolving or adaptive adversaries that exploit UAV mobility and partial client visibility.

A security-aware optimization viewpoint is therefore needed, where defense intensity such as privacy noise or compression level is co-tuned with link quality and battery state, aggregation frequency is aligned with contact opportunities, and validators are placed across UAV, MEC, and HAPS tiers to balance robustness with time and energy budgets during field operations.

Future research should prioritize lightweight, adaptive, and mobility-aware security mechanisms that account for the unique topology and operational constraints of UAV-assisted FL. Promising directions include real-time anomaly detection integrated with context-aware access control, decentralized trust mechanisms that do not rely on persistent connectivity, and swarm-level protocols that enable collective response to suspicious behavior without centralized oversight.

E. DESIGNING FL FRAMEWORKS FOR UAV EDGE ENVIRONMENTS

Existing FL frameworks such as TensorFlow Federated (TFF), PySyft, and Federated AI Technology Enabler (FATE) have enabled early studies of FL, however, their architectural assumptions of stable connectivity, continuous client availability, and ample local compute are not suitable for UAV-assisted MEC settings. Consequently, direct deployment in aerial networks is non-trivial due to mobility, energy constraints, and intermittency of A2A and A2G links.

TFF is well suited to algorithmic prototyping and cross-device simulation, however, it largely presumes server-orchestrated, synchronous training and provides limited native support for intermittent participation, staleness-aware aggregation, or hierarchical FL across UAV-HAPS-ground tiers. Its Python/TensorFlow runtime also challenges execution on embedded avionics with tight energy and memory budgets. PySyft on the other hand, prioritizes privacy-preserving computation, yet its process and messaging overheads are better aligned with cross-silo or laboratory environments than with battery-limited UAV clients operating over lossy wireless links. By contrast, FATE provides a mature, enterprise-grade cross-silo stack with strong orchestration and security, but targets relatively stable, server-class nodes and reliable networking, making it more appropriate for MEC or HAPS aggregators than for highly mobile UAV devices.

Given these limitations, as a result, aerial deployments require first-class support for asynchronous and partial participation, mobility and energy-aware client scheduling, communication-efficient updates via compression and sparsification tailored to narrow A2G bandwidth, hierarchical, delay-tolerant aggregation across space-air-ground layers, and lightweight client runtimes that operate on embedded systems-on-chip.

In addition to the architectural analysis, there are lightweight design principles that allow FL to be more suitable to resource-constrained UAV clients especially in time-critical missions (e.g., search and rescue, wildfire surveillance, traffic monitoring, anomaly detection, rapid disaster assessment). First, employ minimal client runtimes with static memory footprints to ensure predictable execution latency. Second, reduce uplink bandwidth by compressing model updates (e.g., low-bit quantization) to shorten air-time. Third, confine on-board training to partial model updates while deferring compute-intensive phases to proximal edge servers. Fourth, adopt asynchronous or event-triggered aggregation so that clients can contribute under intermittent or short connectivity windows. Fifth, schedule participation adaptively as a function of residual energy, mobility state, and instantaneous link quality, modulating local steps and compression accordingly.

VI. CONCLUSION

The introduction of UAVs into MEC systems has emerged as a breakthrough paradigm, fundamentally transforming the field of data analysis. The rise of FL and its unique characteristics facilitate a multitude of improvements in UAV-based applications. Inspired by the numerous ways FL can be used in wireless networks, we conducted a comprehensive review to showcase the notable advantages of FL in UAV-assisted MEC networks. This survey paper provided an overview of the fundamentals of UAV-assisted MEC, their significance in future networks, and the crucial technologies that would enable UAV-assisted MEC networks. Moreover, we examined the concept of FL and its applications, before delving into the landscape of FL in UAV-enabled systems. Finally, we identified numerous challenges and research directions that aim to stimulate further research into the real-world deployment of FL within aerial networks. Looking forward, the most urgent barriers to practical deployment are robustness under mobility and intermittent A2A/A2G connectivity with bounded update latency, energy and compute-aware orchestration on lightweight airframes, and lightweight security.

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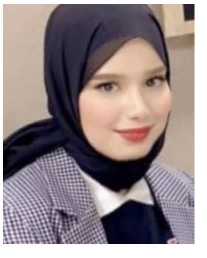

YOUSSRA CHERIGUENE received the M.Sc. degree in computer science in 2020, and the Ph.D. degree from the University of Laghouat, Algeria, in 2024, where she is currently an Assistant Professor with the Computer Science and Mathematics Laboratory (LIM), University of Laghouat. In 2022, she was a Visiting Researcher with Carleton University, Ottawa, Canada, supported by the prestigious Study in Canada Scholarship, awarded by Global Affairs Canada. Her research interests encompass 6G, aerial networks, and federated learning. She has also received the Best Paper Award at the IEEE PAIS 2025 Conference.

WAEL JAAFAR (Senior Member, IEEE) has been an Associate Professor with the Software and IT Engineering Department, École de Technologie Supérieure, University of Quebec, Montreal, Canada, since September 2022. From 2019 to 2022, he was an NSERC Postdoctoral Fellow with the Systems and Computer Engineering Department, Carleton University. From 2014 to 2018, he pursued a career in the telecommunications industry, where he has been involved in designing telecommunication solutions for projects across Canada and abroad. During his career, he was a Visiting Researcher with Khalifa University, Abu Dhabi, UAE, in 2019, Keio University, Tokyo, Japan, in 2013, and UQAM, Montreal, Canada, in 2007. His research interests include wireless communications, integrated terrestrial and non-terrestrial networks, resource allocation, edge caching and computing, and machine learning for communication and networks. He received several prestigious grants, including the National Sciences and Engineering Research Council of Canada Alexander-Graham Bell Scholarship and the Fonds de recherche du Québec-Nature et technologies scholarship, and Best Paper Awards at CIoT 2024, IEEE ISCC 2023, and IEEE ICC 2021.

HALIM YANIKOMEROGLU (Fellow, IEEE) received the Ph.D. degree in electrical and computer engineering from the University of Toronto. He is a Chancellor's Professor with the Department of Systems and Computer Engineering, Carleton University, Canada. He is also the Director of Carleton-Non-Terrestrial Networks Lab. He has coauthored a high number of papers in 33 different IEEE journals. He also has 42 granted patents. He has supervised or hosted at Carleton 170+ postgraduate researchers; several of his former team members have become professors in Canada, U.S., U.K., and around the world. He gives around 20 invited seminars, keynotes, panel talks, and tutorials every year. He received many awards for his research, teaching, and service. He has served as the steering committee chair, the general chair, and the technical program chair of several major international IEEE conferences, as well as in the editorial boards of several IEEE periodicals. He also served as a Distinguished Speaker for IEEE Communications Society and IEEE Vehicular Technology Society, and an Expert Panelist of the Council of Canadian Academies (CCA|CAC).