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Air-Ground Integrated Mobile Edge Networks: A Survey

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ABSTRACT With proliferation of smart devices and wireless applications, the recent few years have witnessed data surge. These massive data needs to be stored, transmitted, and processed in time to exploit their value for decision making. Conventional cloud computing requires transmission of massive amount of data in and out of core network, which can lead to longer service latency and potential traffic congestion. As a new platform, mobile edge computing (MEC) moves computation and storage resources to edge network in proximity to the data source. With MEC, data can be processed locally, and thus mitigate issues of latency and congestion. However, it is very challenging to reap the benefits of MEC everywhere due to geographic constraints, expensive deployment cost, and immoveable base stations. Because of easy deployment and high mobility of unmanned aerial vehicles (UAVs), air-ground integrated mobile edge networks (AGMEN) is proposed, where UAVs are employed to assist the MEC network. Such an AGMEN expects to provide MEC services ubiquitously and reliably. In this article, we first introduce the characteristics and components of UAV. Then, we will review the applications, key challenges, and current research technologies of AGMEN, from perspectives of communication, computation, and caching, respectively. Finally, we will discuss some essential research directions for AGMEN.

INDEX TERMS Mobile communication, mobile computing, unmanned aerial vehicles.

I. INTRODUCTION

Driven by Internet of Things (IoT) and prevail of mobile networks, the number of wireless connected devices has been dramatically increased. In addition, from Cisco, 500 billion devices expects to be connected by the year 2030. With ever-increasing connected devices, there will be a surge of wireless data traffic. Taking mobile user as an example, the consumption of mobile traffic of every subscriber is predicted to 257 GB/month in 2030 [1]. To meet the quality of Service (QoS) requirement of end devices, low latency, and high robustness and reliable network is needed.

To store and process the massive data, cloud computing residing in core network is usually considered an ideal platform. However, moving massive data in and out of core networks can lead to long service latency and severe network congestion. Based on [2], from the gateway of the core network toward the Internet, 39 ms is needed and an additional 5 ms is necessitated to obtain the reply from the server. It is too long for latency-sensitive applications such as autonomous driving whose allowable delay only can be up to 25 ms. Therefore, providing robustness, high-reliability, and high-speed networks is essential. To address this challenge, mobile edge computing (MEC) is proposed [3]–[7], in which computation and storage are provided at the edge of the network to accelerate data processing and extend the storage capacity.

With MEC, computation-intensive tasks from end users can be offloaded to MEC servers in proximity, which can improve not only the speed of computation but also save computation energy consumption. Because of these tremendous benefits, MEC is an essential component in many emerging systems, such as 5G [8], IoT [9], and vehicular network [10]. However, to reap the benefits anytime, anywhere,

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TABLE 1. Related surveys on MEC and UAV assisted network.

Ref	Focus	Scope
[27]	Definitions, applications and scenarios, security issues, computational offloading	MEC
[11]	Communication and computation models, resource management, potential directions	MEC
[29]	Architecture, decision on computation offloading, resource allocation, mobility management	MEC
[30]	Routing, seamless handover, energy efficiency	UAV communication network
[31]	LAP-based communication, HAP-based communication, integrated airborne network	Airborne communication
[32]	Standardization of cellular-connected UAV, flying BSs, security	UAV cellular communications
[33]	Application cases, future directions and challenges	Wireless communication with UAV
[34]	Physical layer characteristics and spectrum allocation, space-air-ground network system integration	Space-air-ground network system
[35]	Physical layer, network layer, joint communication, computation and catching	UAV communication for 5G

MEC infrastructure is required to be widely deployed [11]. In urban areas, MEC is required to place at hot spots, e.g., commercial areas or populated areas, which typically have high rental costs. Moreover, in rural areas such as forests and mountains, it is costly or infeasible to provide service.

Due to flexible mobility and easy deployment, unmanned aerial vehicles (UAVs) can help address these challenges. Recently, UAV is rapidly developed to perform diverse functions from commercial applications, such as package delivery [12], precision agriculture [13], [14], traffic surveillance [15], [16], and communication relay [17], [18], to military applications such as monitoring illegal immigration in country borders [19], [20], tracking [21], and anti-terrorism arrest [22]. Based on the United States Federal Aviation Administration (FAA) by 2022, the number of registered UAVs is expected to be 3.8 million. By January 14, 2020, there has been 1, 533, 596 registered UAVs in their database [23]. Indeed, UAV, flying in the sky, can execute specific missions like object detection [24] and rescue searching [25] by carried sensors. Because of UAV's mobility and payload features, UAV also can be mounted with MEC devices to provide communication and computation services. By integrating UAV in MEC networks, an air-ground integrated mobile edge network (AGMEN) can be formed, in which UAVs can either act as flying base stations(BS) and relays to improve communication service or work as an edge sever in air to execute computation tasks from ground users or other UAVs. Besides that, UAV also can provide the caching function to store popular contents [26] with equipped cache storage units.

A. RELATED SURVEYS ON MEC AND UAVs

In the literature, there are a few surveys on MEC technologies and UAV-assisted networks. For MEC surveys, [27] provides a survey on the basics of MEC, such as the definition, applications, and MEC's advantages. As a further step, the modeling for communication and computation in MEC is discussed in [11], which also summarizes resource management and highlights future directions of the MEC system. In [28], a survey on service migration in MEC is provided, where key challenges, modeling, potential solutions are discussed. In [29], computation offloading are studied from three critical perspectives, including the decision on computation offloading, resource allocation, and mobility management. As for UAV related networks, [30] discusses important issues while integrating UAV into communication networks. In [31], airborne network is discussed. In [32], a comprehensive survey on integration UAV to a cellular network is provided. A comprehensive tutorial regarding UAV on the wireless network is given in [33], in which UAV applications for wireless networks ranging from cellular-connected UAV to UAV flying BSs are illustrated in details. Both [34] and [35] explore a space-air-ground integrated network(SAGIN). Reference [34] mainly concerns the architecture and system integration of SAGIN. Reference [35] focuses on communication for beyond 5G and an overview for UAV research activities related to 5G techniques is provided. To help readers learn the main concerns of existing studies, we outlined the surveys mentioned above in Table 1. Note that the list of all abbreviations in this paper is indicated in Table 2.

TABLE 2. List of abbreviations.

A2A	air-to-air
A2G	air-to-ground
AI	artificial intelligence
AGMEN	air-ground integrated mobile edge network
AP	access point
BS	base station
D2D	device-to-device
DoS	denial-of-service
ESC	electronic speed controller
FAA	Federal Aviation Administration
FANET	flying ad-hoc network
GCS	ground control station
GPS	global position system
HAP	high altitude platform
IMU	inertial measurement unit
IoT	Internet of Things
ITU	International Telecommunication Union
LAP	low altitude platform
LoS	line-of-sight
LTE	long term evolution
MEC	mobile edge computing
NLoS	non-line-of-sight
NOMA	non-orthogonal multiple access
NP	non-deterministic polynomial time problem
QoS	quality of service
RSS	received signal strength
SAGIN	space-air-ground integrated network
SWAP	size, weight, and power of UAV
UAS	unmanned aerial system
UAV	unmanned aerial vehicle
UE	user equipment
V2X	vehicle-to-everything

B. MOTIVATION AND ORGANIZATION

Although the aforementioned papers have extensively explored MEC and UAV-assisted communication networks separately, there are no surveys on AGMEN. Despite [34], [35] survey the integration of space-air-ground networks, the focus is on the physical layer and communication perspective. There is no survey on AGMEN from computing and caching perspectives. Thereby, to fulfill this gap, this article provides an survey of AGMEN from the following three critical aspects: 1) UAV-assisted communications, 2) UAV-assisted computing, and 3) UAV-assisted caching. To best of our knowledge, this article is the first tutorial/survey to offer a comprehensive review of AGMEN. Besides, it is of great significance and complicated to integrate communication, computation, and caching, in which new network topology, new organization mechanism, and new standardization are required to be defined. Thereby, in this article, we aim to review and discuss the related works to provide the readers the background and current progress of AGMEN.

The rest of this article is organized as follows. We first introduce the basics and various components of UAVs in SectionII. After that, we provide an overview of AGMEN in SectionIII. In the following three sections, we discuss and review existing works in AGMEN, from perspectives of communication, computing, and caching, respectively. In sectionIV, we focus on UAV-assisted communication. In V and VI, we discuss and review UAV assisted MEC system on computation and caching. Then, we discuss future research directions and challenges in AGMEN in Section VII. The paper organization diagram is indicated in Fig. 1.

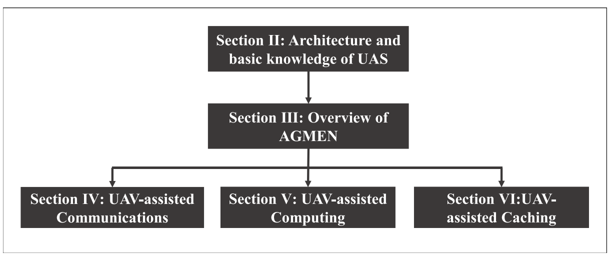

FIGURE 1. The organization of paper.

II. ARCHITECTURE OF UNMANNED AERIAL SYSTEM

In this section, we will give an overview of UAV so that we can better understand how UAVs work in the AGMEN. Specifically, we will first introduce the characteristics of UAV, followed by the components of UAV. Then, we will explain how the unmanned aerial system (UAS) works.

A. CHARACTERISTICS OF UAV

UAVs that can fly autonomously without pilot operation or operated remotely. Their characteristics of UAVs play an important role in the performance of UAVs. The main characteristics of UAV mainly include size, payload, range, altitude, speed, and endurance. 1) Payload represents the maximum carry weight. It constrains the maximum weight of carried equipment; 2) Range means the distance in the remote control area; 3) Altitude is the maximum height that UAV can reach, which has a close relationship with the UAV coverage range. With an increase of the flying altitude, the coverage range of UAV service increases; 4) Speed has to be considered carefully. Since when UAV performs missions like spraying for farmland, the UAV speed has a deep influence on the effectiveness of missions; and 5) Endurance means the maximum flight time without recharging and refueling. SWAP is usually used to describe the size, weight, and power.

Based on the above features, UAVs can be classified into different categories. Based on their altitude, UAVs can be divided into two groups: low altitude platform (LAP) and high altitude platform (HAP). Based on vehicle mass, UAVs can have 9 types, including fixed-wing UAVs, flying-wing UAVs, flapping-wing UAVs, helicopter, a quadcopter (quadrotor), hexacopter, octocopter, blimp, and balloon [36]. No matter which features used for categorizing UAVs, the selection of UAVs for real-application is of great significance, with the consideration of their characteristics. For instance, when using UAV as flying BSs, we can not only consider whether the weight of BS meets the payload requirement but also the altitude of UAV so that the coverage range of communication service can be met.

B. COMPONENTS OF UAV

Most UAVs are composed of 6 modules, including body frame, flight control unit, communication, power system, the payload, and on-board computer (Micro-Computer) [37], as shown in Fig. 2 (Blue Part).

UAVs' body frame is constructed by the standard propeller, pusher propeller, motor, motor mount, landing gear, boom, and central body part, all of which form the shape of UAVs. This part is the foundation and drives part of UAVs.

Flight control unit, i.e., the brain component of UAVs, is composed of Electronic Speed Controller (ESC), Inertial Measurement Unit (IMU), and micro-controller. ESC controls the speed and the direction of the motor by changing its power supplied. IMU is comprised of an accelerometer sensor and gyroscope sensor, which detect acceleration and rotation, respectively. In strong wind and thrust situations, there is a high possibility that the UAVs body would rotate around the axis [38]. To make UAV have a smooth flight, IMU sensing acceleration, and rotation and then report them to micro-controllers. Micro-controller can fine-tune flight parameters to ensure a stable flight under the hazard environment. If the flight is controlled by vision, a vision-based system is required. Also, in order to navigate and fly autonomously, there is a Global Position System (GPS) mounted in UAVs. Micro-controller collects data from IMU and other sensors such as GPS and vision-based systems. After that, it executes the flight control algorithms to calculate the parameters of flight (directions, speed, etc.). Then, the flight controller sends data to ESC to decide the power supplied to motors to control the UAV flight.

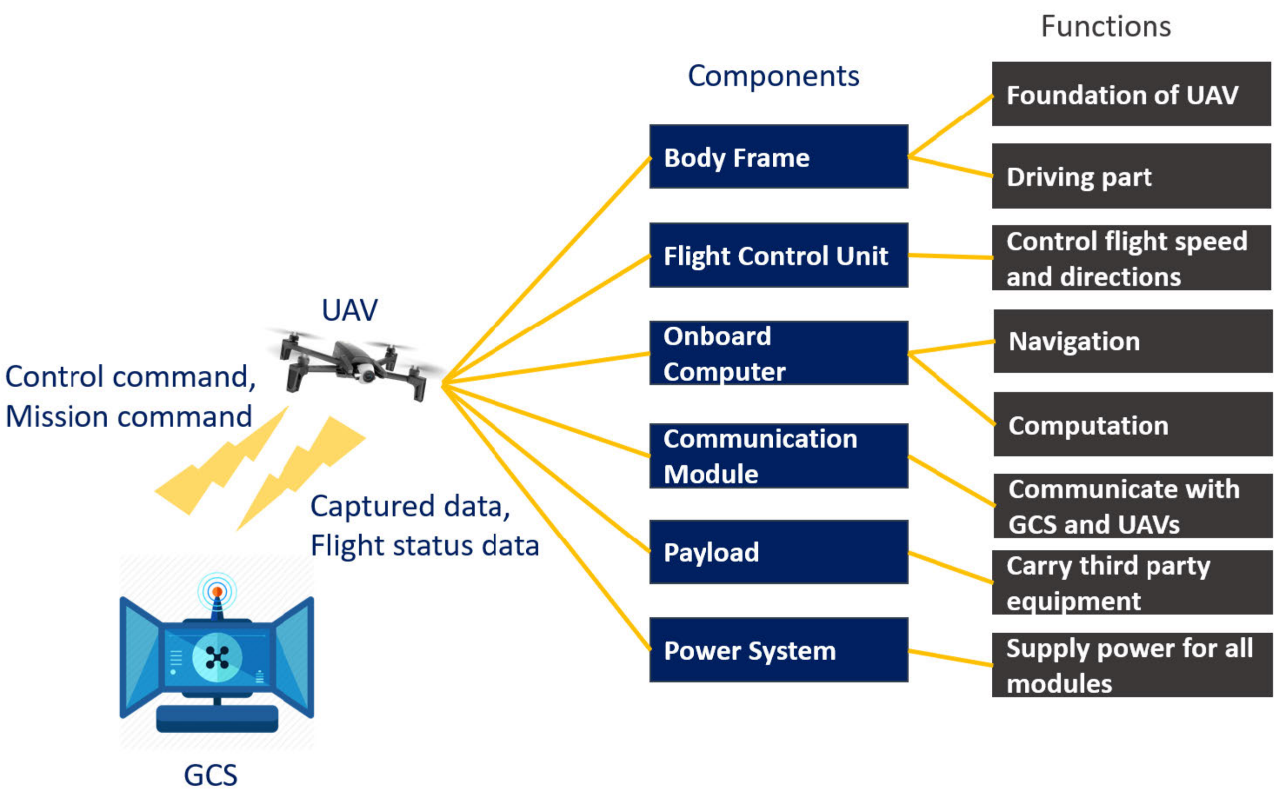

FIGURE 2. The components of UAS.

Onboard micro-computer is added to support the sophisticated algorithms. For example, after capturing images by the camera, the onboard computer can pre-process the data, such as image selection, image extraction, and decoding data. Note that the flight controller can only do computing for low-level control. To improve flight precision, the onboard computer can facilitate control missions, including dynamic control algorithm, navigation, power management algorithm, and image processing [39].

Communication module enable that UAVs can talk (transmit data) and hear (receive data). By communication module, UAVs can communicate with the ground control station (GCS) and other UAVs. There is a receiver in the communication module so that UAVs can receive a radio signal. Wifi communication and long term evolution (LTE) can also be utilized. The range of Wifi is about 100m, which has a dependency on around environment, while LTE providing fast and robust communication, is suitable for the long-distance situation. XBee and Antenna are other choices.

The power system has two elements: the battery and the battery monitor. The battery supplies energy to all the modules of UAV, which is a critical module since it is related to the lifetime and endurance of UAV. Typically, the battery could be a Lithium polymer battery, solar power, and electricity. The battery monitor provides real-time information about the power system. If we do not know the power level of UAVs, we may operate it till battery boundaries, which results that UAVs do not have enough energy to return or landing where crashes can not be avoided.

The function of the payload part is mainly to carry third party equipment to realize specific functions, such as the camera for photography, box for package delivery, and so forth. Due to high-speed mobility, there is vibration, shake, and tilt, which can degrade the QoS. To deal with those cases, the gimbal is designed as a stabilizer.

It is noteworthy that sensors are distributed on the whole UAVs for several modules. According to the applications, we can select what sensors should be mounted onto the UAVs. For instance, to realize autonomous flight, collision avoidance sensors can be utilized.

So far, we have introduced the components of UAVs and their functions. Generally, an individual UAV has limited capacity. Thereby, UAVs are usually integrated into unmanned aerial system (UAS), in which UAVs are managed systematically by GCS, as shown in Fig. 2. GCS can not only assign missions and make decisions for all UAVs but also "pilots"/operate UAVs remotely. Moreover, GCS provides information on UAVs such as position and speed, which is helpful for the controller to make decisions. Besides, GCS, as a receiver, collects data from UAV. Therefore, GCS is a control center in UAS which collects comprehensive information of UAS and controls all UAVs systematically through data link [40]. In addition, cooperative UAVs or UAV swarms can enhance the capacity

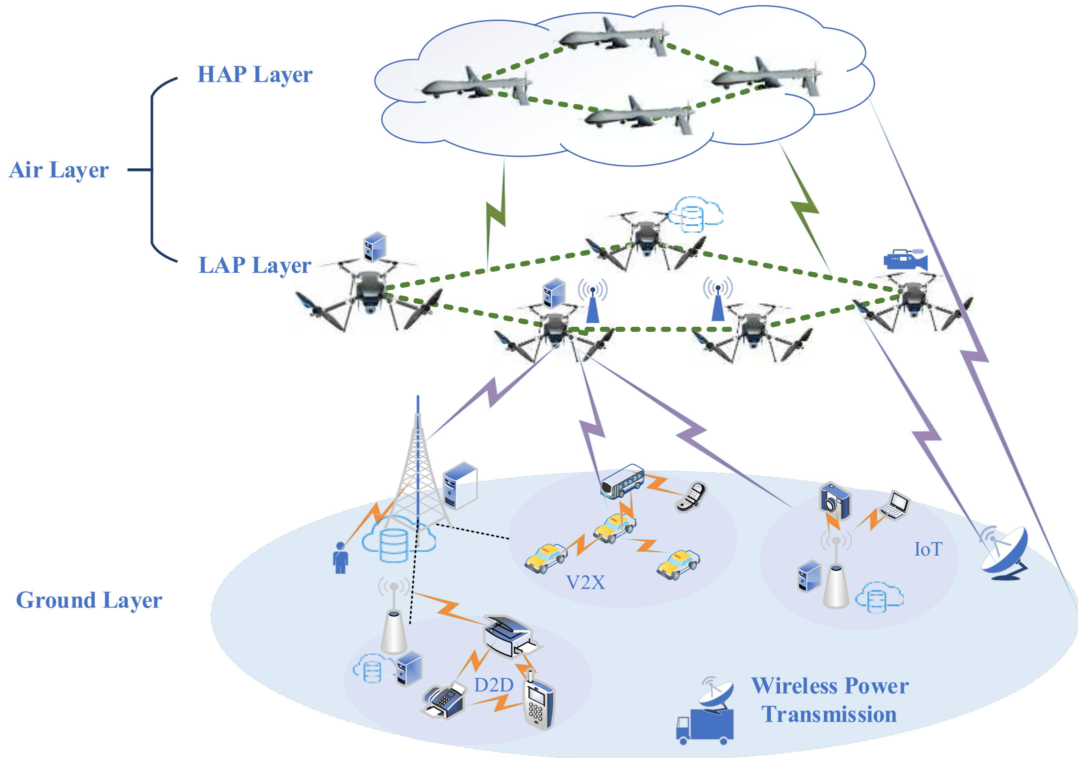

FIGURE 3. Architecture of air-ground integrated mobile edge networks.

and improve the system performance, where UAVs can not only communicate with GCS and perform missions individually but also can communicate and cooperate with other UAVs.

III. OVERVIEW OF AIR-GROUND INTEGRATED MOBILE EDGE NETWORKS

In this section, we introduce a comprehensive architecture of AGMEN, where communication resources, computation resources, and caching resources of air and ground network are integrated.

Fig. 3 shows the architecture of AGMEN, which has two heterogeneous networks: air network and ground network. In the air network, there may exist two sub-layers: HAP layer and LAP layer. As aforementioned, the UAVs with the payload functions in the sky can carry the flying base station, sensors, embedded processors, or storage units so that they can help ground networks in aspects of communication, sensing, computation, and caching. UAVs as a multi-function role can form a flying ad-hoc network (FANET) in the air. FANET is introduced in [41]–[44], where multiple small UAVs communicate in an ad-hoc manner. UAVs are connected through wireless data links and a part of UAVs are connected with GCS, infrastructure base stations, or satellites. UAVs can exchange information to guide the ground network and achieve specific tasks by efficiently arranging such a network, including sensing, communication, computation, and caching in the air.

In the ground network, there are mobile users, vehicles, and ground base stations. The traditional terrestrial infrastructure provides network services in the ground layer, such as cellular networks, IoT, and device-to-device (D2D) communications. To realize the self-driving, there are redundant computing and caching resources on the vehicle. Therefore, the vehicle could be assigned to perform computing tasks and content caching. Through air-to-ground (A2G) communications, cooperation between air network and ground network can be facilitated.

By integrating air networks and ground networks, AGMEN is able to fully utilize air resources and ground resources to improve system performance and users' experiences [45]. Flying at high altitude, UAV has a better coverage with line of sight (LoS) connections, and can help provide reliable and seamless service when users are moving. UAVs can also exchange information with other UAVs through air-to-air (A2A) links, or transmit information to ground vehicles through A2G links. In addition, UAVs can be regarded as coordinators to guide the ground system because of the broader range of sight. For example, UAVs can assist in scheduling the caching resource and computing tasks on vehicle computers. With flexible maneuvering and mobility, UAVs can be dispatched on demand to accommodate dynamic service requests with ever-changing spatial-temporal features. Furthermore, ground networks are vulnerable to different disasters, and AGMEN can help provide emergency services and assistance for disaster relief. Therefore, the cooperation between UAVs and the ground networks strengths the advantages of UAVs and ground devices. Such a comprehensive, integrated network can provide more reliable network service in spatial and temporal changing environments and can also provide 3D dynamic network service based on the mobility of users.

IV. UAV-ASSISTED COMMUNICATIONS

Owing to flexibility, mobility, and cost-effective features, UAV is rapidly developed in communication areas. However, there are many challenges to smoothly employ UAV to assist communication system. In this section, we will firstly introduce the UAV applications from the communication perspective, followed by the discussion on challenges and state-of-the-art literature on the physical layer, the deployment and trajectory of UAV, and energy issues.

A. APPLICATIONS

In AGMEN, from the communication perspective, UAV is mainly used in 4 prospective applications. (1) Equipped with flying BS or WiFi access point(AP), UAV in the air can provide communication services to the desired area. (2) To better fulfill its sensing or catching task, UAV as user equipment (UE) can connect with *cellular-connected* network. (3) Instead of only serving in fronthaul, UAV also can help BSs connect to the core network. In this situation, UAV helps backhaul service in the communication network. (4) multiple UAVs are connected in an ad-hoc manner without central control to transmit or relay information, namely FANET.

1) UAV AS BS OR AP

With ever-increasing connected devices, it is possible to have network congestion and a long latency, especially in hotspots areas or during temporary events such as NBA Games and Super Bowl. Providing high QoS is important in these high-density population areas. However, it is neither cost-effective nor realistic to deploy many BSs for a small area or temporary events. UAV carried BS or AP (i.e., flying BS) is a promising solution to addressing this challenge, as UAV is easy to acquire with low cost. Therefore, UAV enabled flying BS can improve network capacity in areas with temporary high network traffic.

On the other hand, UAV carried BS and AP also can help extend network coverage for the places where terrestrial BS has difficulty in providing network service. For instance, in rural areas with less population, it is costly to deploy many terrestrial BSs and the deployed BSs tend to be underutilized. Moreover, terrestrial BS deployment is restricted by the geospatial condition where there is high risk and danger. In addition, after disaster, terrestrial BSs are destroyed but the network is indispensable and essential for rescue and emergency communication. In all these scenarios, UAV carried BS can help for coverage enhancement, due to easy deployment and flexible mobility.

UAV is also complementary to many other techniques, such as D2D, vehicular network, MMwave communication, and dense small cell network. Regardless of the advantages of these techniques, there are still challenges and limitations. For instance, D2D suffered from short-range communication of devices and exponentially increasing interference. Due to its mobility and flexibility features, UAV can not only assist the D2D network to reduce interference and extend coverage by broadcasting information among devices but also provide an extra connectivity thus increasing the reliability of the connection.

In summary, UAV carried BS or AP can be used in a plethora of scenarios. UAVs can improve wireless network capacity, extend coverage, increase reliability of connectivity, and help terrestrial network.

2) UAV AS UE

UAV is well known for its civil applications such as surveillance, target searching, and video streaming. To complete such sensor dependent missions, UAV acts as a user equipment of wireless communication such as cellular-connected UAV. There are two types of communications among cellular-connected UAVs: communication for flight control and transmission of the collected data. In order to control the UAV flight and ensure its safety, UAV has to send telemetry report to GCS to inform its flight information like flight altitude and location information. According to the telemetry report and other information (weather, mission information, etc), GCS updates the control command to UAV. In particular, navigation-related information will be sent when needed. Meanwhile, to achieve sensor-dependent missions, UAV has to transmit the collected data to ground users. For instance, in photography tasks (e.g., video streaming and surveillance), UAVs have to transmit the captured picture to users. For the flight control message transmission, it has a stringent requirement in terms of security and reliability. But transmission of the collected data requires a high rate and low latency.

3) UAV AS BACKHAUL

There are two types of connectivity from the BS to the core network: wired backhaul and wireless backhaul. Despite of the high speed and reliability, wired connection suffers from geographical constraints, deployment and cost issues. Moreover, the wired backhauling connection can be ruined by natural disasters or human factor. Differently, wireless backhauling does not have those bottlenecks. Thanks to the ability to fly over obstacles, easy deployment, and cost-effective characteristics, UAV can act as backhaul to help for connecting BS with the core network.

4) UAV AS FANETs

In the above subsections, a UAV can serve as a BS or an AP to communicate with users, as user equipment to communicate with terrestrial infrastructure, and as Backhaul to connect with core network in a wireless manner. Due to the SWAP restriction, single UAV is hard to achieve the expected goals. For example, when a single-UAV is mounted with BS, the communication coverage is still limited by the mounted BS's transmission range. To address this issue, small UAVs can cooperate as a UAV team to improve performance, resulting in FANETs, where multiple UAVs communicate in an ad-hoc manner. FANETs have the following advantages. 1) From UEs's perspective, UAVs perform missions in a coordinated manner which can accelerate mission completion. 2) It has higher scalability since it is easier to add new UAVs to the team. 3) Reliability and survivability are enhanced in FANETs which means a higher fault-tolerant capability. If one of UAVs fails, no matter due to hardware issues or power off, its companies can share its tasks. 4) FANETs is cost-effective. Both maintenance fee and acquisition fee is lower than a large and expensive UAV.

B. PHYSICAL LAYER CHANNEL MODELING

1) CHALLENGES

UAV-assisted communication is affected by the transmission signal and the medium between the transmitter and the receiver.

- Despite that the characteristics of UAVs make UAVs become a pivotal candidate to aid wireless communication, it also causes challenges due to these features such as the flexible altitude of UAV, different types of UAVs, as well as time-varying spatial and temporal position of UAV. UAV has a high probability of making the LoS link in A2G communication due to its flexible attitude. But occasional obstacles such as tall buildings in the urban area has to be taken into account which causes complicated channel model. In the rural area, LoS is suited well but not for blocked place. Furthermore, different SWAP of UAV can cause different influences on communication, e.g., different sizes of the UAV can cause different airframe shadowing and different noise from different motors of UAV. Although multiple options of UAVs types can be selected for various scenarios, it also causes difficulty to ensure channel model. Every coin has two sides. Flying at high altitude results in the improvement of coverage, lower airframe shadowing, and higher LoS probability, which reinforces the channel fading, strength the atmosphere influence, but also cause more energy consumption to maintain the flying height of UAV. Moreover, during flight, because of varying spatial and temporal position, channel conditions are different respect to users, such as winds and antenna positions, which results in hard to obtain characteristics of the channel. Therefore, it is hard to find a generic channel model.
- When UAV plays the role of UE, unlike the conventional terrestrial communication system that only needs to provide two-dimensional coverage, the BS has to provide three-dimensional (3D) coverage. Furthermore, in the conventional terrestrial communication system, the user is lower than BS and BS transmits and receives data from the downward channel. But UAV's position might be higher than BS, which means the BS need to provide not only the downward channel but also the upward channel. Meanwhile, the characteristics of the upward channel are not same as the traditional terrestrial downward channel. It is LoS dominated link while using the upward channel. Since LoS dominated link is strong, it is possible that UAV can receive signals from adjacent BS that are not expected to associate with this UAV. Because of that, mess interference is caused. Moreover, unlike traditional cellular users which mainly request to download content from the core network, UAVs as UEs are widely used for monitoring and videography, which requires UAVs to upload the captured data fast. Therefore, there is a strict requirement for uplink instead of the traditional downlink.

2) RESEARCH TECHNOLOGIES

A comprehensive UAV channel model survey is presented in [46] and [47]. Both of them discuss channel measurement campaigns and propagation channel models which include three categories models, including deterministic model, stochastic model, and geometry-based stochastic model. Reference [46] provides an exhaustive literature review on A2G communications, which analyzes its characteristics and provide empirical measurement simulation results. It is concluded that, due to different building densities in different environments, the experiment's parameter setting is different, with mathematical details in [48]. Additionally, in [46], when UAV as UE connects with BS, the probability of LoS increases as the UAV height increases. When the height is lower than a threshold, both LoS and none-line-of-sight (NLoS) links are considered. Otherwise, the link can be regarded as LoS. Instead of focusing on the A2G communication model, [47] consider both A2G and A2A communication. In the literature, there are fewer works on UAV as BS and UAV-UAV channel models, compared with the research on cellular connected UAVs channel model.

In 1968, [49], Longley-rice and Johnson-Gierhart tropospheric radio propagation were proposed for A2G communication. Due to the shortage of generic propagation statistic model of UAV-ground communication, [50] presents the path loss of the LoS. In the same year, the authors in [51] took the obstructed channel and NLoS into account and studied the channel model. However, the environment parameters are only suited well for a single city. Recently, the most typical propagation models come from [52]. Based on the document of the International Telecommunication Union (ITU) [53] parameters, [52] simulates the channels in building as Rayleigh distribution, considering three types of rays (direct, reflected and diffraction rays). And then, the propagation model formula used in the urban area is given, which is indicated in Table 3.

For cellular-connected UAV communication network, in [54], path loss exponent and shadowing variation are explored under the range of 120m. It concludes that the path loss of cellular-connected UAV must have a height-dependent propagation model. In 2018, 3GPP [48] provides much information on cellular-connected UAV communicating with BSs,

TABLE 3. Summary of channel models.

Ref	Path loss Function	Parameter Illustration	Link Types
[51]	PL(dB) = $\begin{cases} -0.58+0.549e^{\frac{(90-\phi)}{24}} & \text{LoS} \\ \eta_0-\eta_1 e^{-\frac{(90-\phi)}{\nu}} & \text{NLoS} \\ \kappa_0-\kappa_1 e^{\frac{(90-\phi)}{\gamma}} & \text{obstructed channel} \end{cases}$	ϕ: elevation angle, η_0, η_1, ν, κ_0, κ_1, γ: the coefficient which is independent of antenna height and please see the fit parameters in the paper.	air-to-ground
[52]	PL(dB) = $20log(\frac{\Delta h}{\sin\phi})+20log(f_{(MHz)})-27.55$	Δh: the difference of UAV height and common receiver's height, $f_{(MHz)}$ = 700, 2000, 5800	air-to-ground
[54]	PL(dB) = $\alpha 10log_{10}d+\beta+\chi$	α: the path loss exponent, d: the distance of transmitter and receiver, β: the intercept point with the line $d=1m$, $\chi \sim N(0,\sigma)$ where $\sigma = 7.7-3.4dB$	air-to-ground
[55]	PL(dB) = 20log($\frac{4\pi d_0}{\lambda}$) + X_d + X_f + X_h + X_{ang}	λ: the speed of light, d_0: 3D distance, X_d: the correction factors for the reference distance of the transmitter, X_f: the correction factors for the frequency, X_h: the correction factors for the base station height, X_{ang}: tilt angle dependent parameters	air-to-ground
[57]	PL(dB) = $10\alpha log_{10}d$	α = 1.922, d: distance between UAVs	air-to-air
[58]	RSS(dB) = $P_t+G_{UAV_1}+G_{UAV_2}+10log_10(\frac{\lambda}{4\pi d})^{\alpha}$	$P_t = 20dBm$, UAV antenna gain: $G_{UAV_1}=G_{UAV_2}=5dBi$, separation distance: d, path loss exponent: α = 2.6	air-to-air

including LoS probability in different environments, path loss models, and fast fading models. Reference [55], [56] also offer pass loss function. We summarize them in Table 3.

Most A2A communication is explored in wireless sensor networks, UAV swarms, and multi-UAV networks. Reference [57] provides the wireless link characteristic among micro UAVs. It suggests that signal strength fading with the distance increasing among UAVs is much better than ground communication. Reference [58] investigates the impact of the UAV height and the antenna characteristics on A2A propagation using IEEE 802.11 radio. Based on several laboratory measurements, the path loss is given by the Friis equation and a fading channel distribution which is retrieved from the Rician factor. Received signal strength (RSS) values is tested as in Table 3.

C. DEPLOYMENT AND MOBILITY/TRAJECTORY

1) CHALLENGES

As the adjustable altitude and mobility features introduce infinite variables, the deployment of UAV becomes much more complicated and challenging. How to place UAVs and optimize their trajectory has attracted great research attentions from both industries and research community.

- The mobility of UAVs are not only subject to UAVs themselves but also the time-varying distribution of serving ground users. Facing this issue, there are two categories of research. UAVs detect and search the ground users to provide service based on the captured information. Alternatively, UAVs are controlled by the control station and move according to the control station's command. In this scenario, the distribution of ground users is not concerned by UAVs themselves. It is challenging to consider both the mobility of users and UAVs.
- Unlike conventional terrestrial BS connecting via fibers, another issue introduced by UAVs' mobility is maintaining the connectivity between UAVs and BS when UAVs are moving. Due to flexible mobility, the position relocation of UAVs will be widely encountered. In this scenario, it is hard to decide whether the communication should be shut down and then recovered as soon as possible, or we can guarantee connectivity during its movement period. It is a challenging issue to guarantee the connectivity of UAVs in motion.
- Although a single UAV has the capacity to complete numerous missions, cooperative UAVs can complete tasks more efficiently and improve the chance of successful missions. However, how to hire UAV swarms needs to be studied. Despite that UAV cooperation can improve scalability and reduce the probability of system failure, it can not prevent fails of single UAV. In this case, how to deal with those failures? How to replace the invalid UAV with a new one? How to reallocate the task of the invalid UAV? All of these questions are of importance.
- Trajectory optimization is another critical and challenging problem for UAVs. Due to the limited energy of UAVs, we aim to find the shortest path to minimize energy consumption for motion. However, the onboard energy is not only used to fly but also to transmit data, perform collision avoidance (distance between UAVs), and maintain network performance. Therefore, we have to jointly optimize the trajectory of UAVs, considering energy consumption and communication energy consumption, which brings difficulties in designing an optimal trajectory since it has to obtain a balance from many factors such as performance and cost.

2) RESEARCH TECHNOLOGIES

A flurry of research has been reported to solve the deployment problem from different perspectives. The objectives mainly include maximizing the coverage, minimizing the number of hired UAVs, and maximizing the throughput of the system.

In [59]–[63], how to maximize the service coverage is investigated, by utilizing the path loss model from [52].

TABLE 4. Deployment of UAVs.

Ref	Objective	Mobility of users	Communication among UAVs	Single/Multiple UAV	Dimension
[59]	Maximize the coverage area	No	–	Single UAV	1D
[60]	Maximize the coverage area	No	No	Single UAV and Two UAVs	2D
[61], [62]	Maximize the coverage area	No	–	Single UAV	3D
[63]	Maximize the coverage area with minimal transmit power	No	Yes	Multiple UAVs	3D
[64]	Maximize the covered users with the minimal number of UAVs	No	No	Multiple UAVs	3D
[65], [66]	Minimize the required number of UAVs	No	Yes	Multiple UAVs	2D
[67]	Maximize the average throuput and the successful transmission probability	Yes	–	Single UAV	2D
[68]	Maximize the opinion score of users	Yes	No	Multiple UAVs	3D

Reference [59], [60] maximize the coverage of single UAV by searching its optimal altitude. Reference [59] finds that with the altitude increasing, the probability of LoS increases. However, because of increase in the distance between transmitters and receivers, the path loss also increases. As a result, the coverage does not increase as the height of UAV increases. Therefore, we have to jointly consider the distance between transmitters and receivers, the altitude of UAV, and the path loss. In [60], it further extends to the scenario with two UAVs and studies the distance between two UAVs while obtaining maximum coverage in a specific area. Instead of only considering altitude of UAVs, [61], [62] propose searching maximum coverage in a 3D placement environment. In [63], the 3D deployment of multiple UAV is further investigated. In this work, it jointly maximizes the coverage performance and minimizes transmit power. Meanwhile, given the size of the desired area, the minimum number of UAVs to provide communication service in the desired area can be determined.

In [64]–[66], there is a common goal of minimizing the number of UAVs by adjusting their placement while satisfying the coverage requirement in the desired area. Without considering terrestrial BSs, particle swarm algorithm is employed to search the minimum number of UAV BSs based on the ground users density [64]. The same topic is studied using the evolutionary computing algorithm in [65], considering there are both terrestrial BSs and UAV BSs. In [66], it searches the optimal locations of UAVs by the spiral algorithm to minimize the number of UAVs. The simulation results demonstrate that it is comparable with the most well-known benchmarks. There are other works on the UAVs placement such as [67]–[70], as summarized in Table 4. In particular, while most works only consider the mobility of UAVs or ground users but not both, [67], [68] adapt the UAVs' location based on the movement of users. Instead of focusing on the traffic-aware deployment of single UAV in 1D or 2D space [67], the work in [68] applies Q-learning algorithm to control multiple UAVs, based on the ground users continuous movement.

In [71]–[75], trajectory optimization is widely studied in order to provide better user-track service and reduce energy consumption. In [71], an optimal horizontal trajectory planning is devised to maximize the throughput and energy efficiency when a single UAV communicates with a mobile user. Furthermore, in [72], the problem is extended to the cases where multiple UAVs provide service for multiple ground users. Communication scheduling as well as association of UAVs and mobile users were jointly optimized by an iterative algorithm. In [73], UAVs are utilized to collect data from the IoT devices, and it finds the optimal trajectory to minimize energy consumption while maintaining uplink communication. Overall, similar to the deployment research, trajectory needs to be jointly optimized with system throughput, coverage area, and energy efficiency.

D. ENERGY EFFICIENCY AND HARVESTING

1) CHALLENGES

UAVs' performance and operation are strongly affected by the limited duration and flight time, which has a close relationship with onboard energy. Onboard energy does not only support communications but also hardware, mobility, payload, etc. However, due to the limited payload features, onboard energy is constrained, which limits the transmission performance.

- Firstly, facing limited energy of UAVs, we have to improve energy efficiency when performing tasks using UAVs. For example, designing optimal network layer protocols or optimal trajectory to reduce energy consumption so as to extend UAV's mission time. However, in most cases, this problem is a non-deterministic polynomial time problem (NP), in which we only can find near-optimal solutions.
- To prolong the flight time, we can charge exhausted UAVs by building charging stations. However, building charging stations is expensive and complicated. The most likely places to build charging stations are in the urban area, but the cost is high. Moreover, UAVs sometimes perform their missions in the rural area or after disasters where few charging stations are available. Finally, frequently recharging interrupts missions, which results in low efficiency.
- Last but not least, energy harvesting is proposed to prolong the duration of UAVs from the root, which is tropical areas named wireless powered UAV networks. It considers that UAV can perform its missions and consumes its onboard energy for motion and communication. At the same time, it will harvest energy

from sources such as solar power, wind power, eg. But harvested energy heavily depends on geospatial locations and weather conditions. The another critical point is that UAV only has a limited payload capacity. Heavy or large size battery for energy storage may cause extra energy consumption.

2) RESEARCH TECHNOLOGIES

While UAV is used for communication, energy consumption is divided into communication-related energy consumption and propulsion-related energy consumption. Although the propulsion energy consumption is significantly greater than communication-related energy consumption, the performance of the communication part has a close relationship with both propulsion energy consumption and communication energy consumption. For instance, to meet the communication requirement, extra propulsion energy consumption may be caused. Therefore, considering energy consumption is of great importance for the communication system.

There are numerous researches on energy-aware UAV-assisted communication system whose key idea is to improve energy efficiency by obtaining a trade-off among transmission power, mission completed time, and trajectory power, so as to obtain an energy economical communication system [71], [76]–[79]. In [71], [76], the maximum energy efficiency is simply derived by optimizing UAV's locations and trajectories, respectively. With consideration of coverage and connectivity among UAVs, deep reinforcement learning is employed to minimize energy consumption in [78]. Instead of finding the optimal location or obtaining trade-off between coverage and transmission rate, [80] provides a transmission schedule of multiple UAVs to minimize the maximum energy consumption of UAV swarms.

On the other hand, some studies focus on how to deal with the situation where the battery is used up. In [81], it explores four approaches for ground charging schemes based on game theory, which turns out that a centralized scheduler with global multi-hop knowledge outperforms. Unlike the work in [81] to charge for each UAV, [82] advocates that swapping battery is faster, and thus investigates the swapping battery strategy to ensure persistent missions of UAVs. In [83], techniques are proposed to replace UAVs automatically without interruption.

Finally, researchers considered prolonging battery life by harvesting energy. A review of UAV energy harvesting is given by [35] and [84]. In [84], wireless UAV charging is classified into two categories, non-electromagnetic field-based and electromagnetic field-based techniques. The former means that the source energy is not electricity but comes from nature, such as solar or wind energy. The latter implies that electromagnetic energy is transported to UAVs via transmitters and UAV as an energy receiver. The transmitter has to be close to UAV. In [85], [86], resource allocation is studied for a solar-powered UAV communication system to maximize the sum throughput of the system. In [87], UAVs can simultaneously harvest energy and data from the BS and then transmit the collected data to the destination node. In this work, it proposes a UAV-enabled wireless power transfer scheme to maximize the network throughput by jointly optimizing time switching ratios, power splitting ratios, and UAVs' locations.

V. UAV-ASSISTED COMPUTING

In this section, we will first provide an overview of the UAV assisted MEC system and a typical model to illustrate the foundations of UAV assisted MEC. After that, we will discuss the applications and challenges when integrating UAV in MEC system. Finally, we will review the existing research technologies on UAV assisted MEC system.

A. OVERVIEW

Mobile edge network provisions computing and storage resources in proximity of end users, which can support computing and caching function at the network edge. As Fig. 4 shows, the architecture of the mobile edge network contains the mobile user layer, edge layer, and cloud layer [88]. Various mobile users constitutes the client layer. The edge layer including terrestrial base stations, vehicles, UAVs and etc, which are close to mobile users and equipped with mobile servers, can not only respond to the requests from mobile users for computing and contents but also can forward the request of users to the cloud layer that is the content distribution networks. UAV works at both the client layer and the edge layer. UAV who works in the client layer can offload its computation task to edge layer, thus reducing the computation latency. UAV can help mobile users speed up computation by providing computation assistance while UAV works in the edge layer. In the following, we illustrate a general model of UAV assisted computation for mobile users.

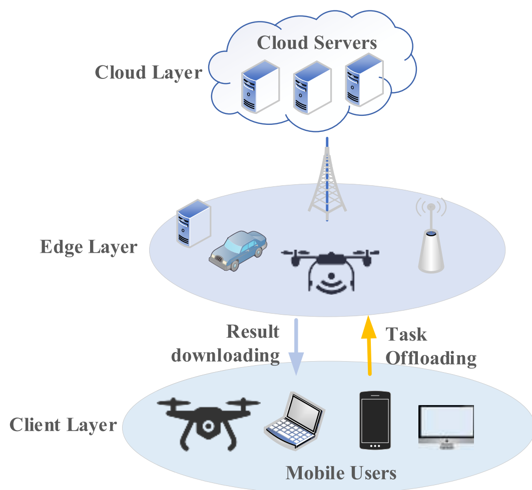

FIGURE 4. UAV assisted MEC.

As illustrated in Fig. 5, in this model, the system consists of one UAV equipped with MEC sever and a set of mobile users $m \in Z = \{1, 2, 3, \cdots, M\}$. UAV flies at a fixed altitude

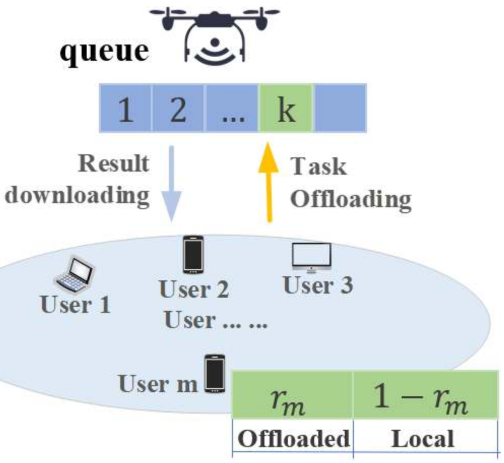

FIGURE 5. UAV assisted MEC system with one UAV and multiple users.

of H above mobile users to provide computation service. To reduce latency and save energy, mobile users can offload partial computation tasks to UAV. The rest of the computation tasks will be executed locally. In MEC, considering the data and computation dependency, the task offloading model is classified into two categories: binary offloading and partial offloading. For binary offloading, it requires tasks to be computed as a whole, at local or at the MEC server. The partial computation can partition the tasks into different parts, which can be executed by local computation unit and the MEC server in parallel. Without loss of generality, we mainly focus on partial offloading. Specifically, there are three components in partial offloading, including the transmission segments, the offloaded task computation segments, and the local computation segments. Since the time cost and energy consumption for results return are relatively small, and in most situations, it is not counted.

1) TRANSMISSION

In the transmission segments, M mobile users will offload their partial computation tasks to UAV. Given a finite time T, T is divided into N short time slots, where $N > M$ and the n^{th} time slot satisfies $n \in \Gamma = \{1, 2, \cdots, N\}$. We consider in each time slot the system status is unchanged. Assume that at each time slots the position of UAV in horizontal plane is identified as $U[n] = [x, y]^T$ and the position of mobile user m can be captured by UAV which is marked as $P_m[n] = [x_m, y_m]^T$. To be specific, $\mathbf{U}[0]$ denotes the initial position of UAV. When users forward their data to UAV because the UAV is in proximity of users, there are both LoS links and NLoS links. Assume that the probability of LoS link is $P_m^{LoS}[n]$ for user m. The NLoS link probability is $1 - P_m^{LoS}[n]$. Based on [61], the path loss model between UAV and mobile user m at n^{th} time slot can be given as follows:

$$L_m[n] = 20log(\frac{4\pi f_c}{\lambda}\sqrt{H^2 + \|\mathbf{P}_m[n] - \mathbf{U}[n]\|^2}) + P_m^{LoS}[n]\eta_{LoS} + (1 - P_m^{LoS}[n])\eta_{NLoS}, \quad n \in \Gamma, m \in Z \tag{1}$$

where f_c represents the carrier frequency and λ means the light speed. The parameters η_{LoS} and η_{NLoS} are the losses corresponding to the LoS and NLoS links respectively, depending on the environment. Once we know the path loss model, we can obtain the transmission rate using the following equation:

$$V_m[n] = Blog2(1 + \frac{p_m[n]10^{-L_m[n]/10}}{\sigma^2}) \quad n \in \Gamma,\ m \in Z \tag{2}$$

where B is the bandwidth. $p_m[n]$ and σ^2 represent the transmission power of mobile user m and noise power at the UAV, respectively.

To describe the offloaded computation bit, let $A_m[n]$ as the total computation bits of mobile user m at time slot n. After that, $r_m[n] \in [0, 1]$ is introduced to represent the ratio of computation bits offloaded via mobile user m. Therefore, the transmission time and transmission energy consumption can be given by equation (3) and (4), respectively.

$$t_m^{off}[n] = \frac{A_m[n]r_m[n]}{V_m[n]} \tag{3}$$

$$E_m^{off}[n] = p_m[n]\frac{A_m[n]r_m[n]}{V_m[n]} \tag{4}$$

2) OFFLOADED TASK COMPUTATION

The computation speed for offloaded tasks is determined by the CPU performance of UAV. Define f_{uav} as the CPU frequency of UAV and C_{uav} as the needed number of CPU cycles for UAV to calculate per bit. We can obtain the computation time for user m as (5).

$$t_{m,c}^{uav} = \frac{A_m[n]r_m[n]C_{uav}}{f_{uav}} \tag{5}$$

Because UAV has to serve m number users, it is uncertain whether the offloaded computation task can be executed immediately. Therefore, there might be a waiting time $t_{m,w} \geq 0$. We suppose there is a virtual **queue** in UAV. Based on the first-in first-served rule, UAV executes the computation task in order. Suppose that there are $k - 1$ users in the virtual queue when user m arrives, the waiting time for user m can be given as

$$t_{m,w} = \sum_{m=1}^{k-1} t_{m,c}^{uav}, m \in \mathbf{q}ueue \tag{6}$$

The total time on offloaded computation is as follows:

$$t_m^{uav} = \sum_{m=1}^{k} t_{m,c}^{uav} = t_{m,w} + t_{m,c}^{uav}, m \in \mathbf{queue} \tag{7}$$

The computation energy consumption of UAV while computing for user m can be derived [11]:

$$E_m^{uav} = \kappa A_m[n]r_m[n]C_{uav}f_{uav}^2 \tag{8}$$

where κ is a constant related to hardware.

3) LOCAL COMPUTATION

For the local computation segments, given that a bit of data needs C_m CPU cycles and the frequency of CPU is f_m, it is easy to derive the computation time and energy in (9) and (10).

$$t_m^{local}[n] = \frac{A_m[n](1-r_m[n])C_m}{f_m} \tag{9}$$

$$E_m^{local}[n] = \kappa A_m[n](1-r_m[n])C_m f_m^2 \tag{10}$$

4) OVERALL ENERGY CONSUMPTION

In the above, we have fully considered the energy consumption related to computation. There also exits propulsion energy consumption for UAV to flight, which can be calculated by (11).

$$E_{uav}^{fly}[n] = \gamma(\frac{\|\mathbf{U}[n]-\mathbf{U}[n-1]\|N}{T})^2 \tag{11}$$

where $\gamma = 0.5GT/N$ and G is relevant to the payload of UAV [89].

Therefore, the total energy consumption of the MEC system is equal to the sum of users' energy consumption for transmission computation tasks, users' energy consumption for computation, UAV's energy consumption for computation, and UAV's energy consumption for propulsion. The total energy consumption to achieve MEC partial offloading at time slots n is given by (12).

$$E[n] = \sum_{m=1}^{M} E_m^{off}[n] + \sum_{m=1}^{M} E_m^{local}[n] + \sum_{m=1}^{M} E_m^{uav} + E_{uav}^{fly}[n] \tag{12}$$

B. APPLICATIONS

Recently, numerous applications have emerged which require a huge computation capability and fast response time, such as augmented reality and large online games. Nevertheless, the smart mobile device might not have sufficient capability to support such applications. To reduce the latency, conserve energy for users, and improve the QoS, mobile devices can offload their computation task to the MEC server.

Compared to the traditional MEC server, UAV enabled MEC server has the following advantages: 1) LoS link creates more stable and reliable connectivity to transmit data; 2) High altitude makes it have an advantage in service coverage; 3) Mobility of UAV can provide seamless computing service for mobile users which ensures an uninterrupted computing service and reduces handover [90]. Generally, the flying MEC server can be deployed in the following three scenarios. In the first scenario, UAV assists users to execute computation-intensive tasks, in which users have limited computation capability and cannot fulfill their computation missions. The second scenario is for latency-sensitive tasks. To respond to users as soon as possible, the missions are offloaded and processed in parallel by exploiting the computing capacity of the flying server. In the final case, users have not enough energy to complete its task or users need to conserve its energy thereby offloading their computation tasks.

On the other hand, UAV assisted MEC network can also support many UAV applications or offload computation tasks to BSs or APs. As mentioned, one of the worthwhile functions of UAV is searching and rescue, but it necessitates huge computation capability and storage capacity when processing images. Meanwhile, the uplevel requirement for such missions is that it uploads and provides video in real-time so that the controller can supervise as well as make decision-based on timely information. Thus, this crucial and emergency application is both computation-intensive and latency-sensitive. For those applications, thanks to UAV assisted MEC network, UAV whose computation capability is limited can offload their tasks to other peer UAVs, BSs or APs, all of which are equipped with the MEC server.

C. CHALLENGES

To systematically realize the UAV assisted MEC network, the first question is how much and what should be offload to MEC. Do we need to execute computation missions locally, or partially or completely offload tasks? Which part should be offloaded? This is the initial step to realize the UAV assisted MEC network. After answering these questions, the capacity of offloading also should be taken into consideration. It is possible that some computation parts can not be offloaded. Furthermore, it is also possible that the overall amount of data is unknown. For instance, the sensors collect voltage data stream of users continuously. Another challenge is commonly experienced in the computation process, in which there exits data dependence. Some data-dependent tasks may fail to compute in MEC. It needs to be considered prudently.

Another challenge is the energy issue. Computation consumes the user's energy. Most devices suffer from short battery life. If we move computation action to the edge network, it does extend the lifetime of users. However, this also causes a problem for UAV enabled MEC network. UAV and MEC integration represents that UAV have both communication and computation function which also means more UAV payload. The increase in payload results in further energy consumption. Besides, not just computation energy is consumed but also for transmission/reception energy. In this case, UAV even only has limited energy, how UAV to assist users to perform missions that require a large amount of energy. Therefore, energy consumed by local computation is possibly lower than by offloading because there is great energy consumption in the transmission and reception process. The main function of MEC is that do computation tasks for users so that users can save energy. However, the total energy consumption might increase.

D. RESEARCH TECHNOLOGIES

In this subsection, we give a comprehensive review on UAV-assisted MEC. Generally, they are classified into two categories. On the one hand, it assists other platforms to perform computation tasks. On the other hand,

TABLE 5. Summary of UAV-related MEC.

Ref	Objective	Mobility of UAVs	User	MEC Sever	Dimension
[91]	Minimize the UAV's mission completion time	Yes	Single UAV	Multiple BSs	2D
[92]	Minimize the combination of energy and delay	No	Multiple UAV	Multiple BSs	1D
[93]	Minimize the energy consumption	No	Single UAV	Single AP	1D
[94]	Create a fire detection system	Yes	Multiple UAVs	Multiple APs	–
[95]	Minimize the total energy consumption of a user	Yes	Single Mobile User	Single UAV	1D
[96]	Minimize the total energy consumption of users	Yes	Mobile Users	Single UAV	2D
[97]	Minimize the weighted sum energy consumption of UAV and UEs	Yes	Mobile Users and UAV	UAV and AP	2D
[98]	Minimizing the energy consumption by computation tasks	Yes	Mobile Users	Single UAV	2D
[99]	Minimize the average weighted energy consumption of UAV and UEs	Yes	Mobile Users	Single UAV	2D
[100]	Minimize the maximum energy consumption among UEs	Yes	Mobile Users	Single UAV	2D
[101]	Minimize the sum of energy consumption of UAVs and UEs	No	Mobile Users	Multiple UAVs	3D
[102]	Minimize the total energy consumption of UAV	Yes	Mobile Users	Single UAV	2D
[103]	Maximize the computation rate	Yes	Mobile Users	Single UAV	2D
[89]	Minimize the sum delay of UEs	Yes	Mobile Users	Single UAV	2D
[104]	Maximize the computation efficiency	Yes	Single User	Single UAV	2D
[105]	Maximize the expected long-term computation performance	Yes	Mobile Users	Single UAV and BSs	2D
[106]	Minimize the energy consumption and the completion time of UAV	Yes	IoT devices	Single UAV	2D

UAV offloads computation tasks to others such as BSs via the cellular-connected network.The following mentioned works on UAV-assisted computing are summarized in Table 5.

1) OFFLOADING TO UAV

UAV is offloaded to aid computation primarily with energy-saving function or to speed up computation rates. Reference [95]–[102] provide various system model with the objective of minimizing the energy consumption. While UAV is deployed to offer offloading, the energy consumption of UAV is caused by two parts, energy consumption for computation and energy consumption for propulsion. For mobile users, they consume energy primarily for offloading communication and local computation. Most research works define offloading energy consumption as transmission energy consumption without counting the energy consumption for receiving results from UAV because the result has a relatively small size.

In [95], a UAV flies from a given initial location to a predefined final location in a straight line to provide the offloading capacity for one mobile user with the objective of minimizing the energy consumption of mobile users. For this end, resource partitioning and bit allocation strategies are discussed. Similar to [95], one UAV providing computation service for multiple mobile users in the horizontal plane at a fixed altitude is studied in [96]. It employs a successive convex algorithm to jointly optimize the bit allocation for communication and UAV's trajectory under several constraints, to minimize the total energy consumption of mobile users. Most interesting part is that two types of UAV energy consumption models are used, one model with propulsion energy consumption the other without, where different energy consumption models can result in different optimal UAV's trajectories. When considering propulsion energy consumption, the trajectory tends to be more smooth since it intends to decrease energy consumption caused by acceleration. It is pointed out that it is critical to apply a precise energy consumption model while exploring the energy consumption of the computation system. In [99], a similar scenario is considered, but it simulates that offloading tasks arrive at UAV stochastically. In each mobile user, there is a local queue to store tasks to send. After arriving at UAV, tasks are queued in the buffer and performed by the first-in-first-out policy. Stochastic computation offloading is proposed and the average weighted energy consumption of the whole system is minimized. In the above two works, UAV flies continuously and offers computation service at each moment. In [98], [100], UAV only provides offloading in a specific time or specific position. It is advocated in [98] that it is an effective way to save energy if UAV periodically flies above mobile users instead of continuously flying. Therefore, they build a model where UAV stays at a certain position and only periodically fly out to offer computation service. This work only considers binary computation offloading, where mobile users only have two options, local computation or offloading. In [100], a UAV assists multiple mobile users for computation. In this model, UAV only provides computation assistance at fixed points and it is the first work considering non-orthogonal multiple access (NOMA) in the UAV assisted MEC system. It aims to minimize the maximum energy consumption among mobile users by an alternative algorithm to jointly optimize the UAV's trajectory, task data and computing resource allocations.

In [96], [98]–[100], one UAV provides computation offloading via the wireless network. However, due to the limited energy and computation capacity of UAV, the capacity for offloading is constrained. Therefore, [97] integrates relaying function and computation function of UAV, where the system is constructed by a cellular-connected UAV, an AP, and mobile users. UAV can not only help mobile users compute the offloaded tasks but also can relay the offloaded tasks to AP so as to save its own energy. In this process, the weighted sum energy consumption of UAV and mobile users is minimized. Different from [97] considering energy conservation of both UAV and mobile users, [102] utilizes a UAV to charge for mobile users via wireless power transfer techniques. At the same time, UAV can perform computation tasks for mobile users. In this system, mobile users harvest energy from UAV, do local computation and partially offload computation tasks simultaneously. The worthy notable thing is that the system ensures energy consumed by the mobile user has to be lower than harvested energy. And then it minimizes the total energy consumption of UAV including propulsion energy, computation energy and energy donated to mobile users.

In all aforementioned works, it is assumed that the system is composed of a single UAV and multiple users. In [101], multiple UAVs are utilized for offering computation service to multiple mobile users. Note that there is no interference and cooperation among UAVs. In this work, it decouples the energy consumption minimization problem into three subproblems and then solve them iteratively. The first subproblem is user association optimization to allocate users to UAVs. After that, users select fully offloading computation to UAV or not, using binary computation offloading. In this step, it is solved with the compressive sensing based algorithm. After obtaining association of users and UAVs, a one-dimensional search algorithm is employed to determine the 3D locations of UAVs. UAVs performs missions in static status. Finally, based on user association and UAVs' locations, computation capacity is allocated.

There are also much researches investigating how to speed up computation. In [103], considering the same system model as [102], it studies computation rate maximization with both partial offloading and binary offloading. [102] explored how to minimize the energy consumption of a UAV. Reference [103] employs a two-stage alternative algorithm and a three-stage alternative algorithm to solve partial offloading and binary offloading, respectively. The CPU frequencies, user offloading times, transmit powers, and UAV trajectory are jointly optimized. In [89], mobile users offload partial computation tasks to a UAV and compute the rest part locally at the same time to minimize the total time including transmission time, computation time at UAV and local computation time. It develops a penalty dual decomposition-based algorithm and l_0 norm algorithm to optimize UAV's trajectory, partial offloading ratio and user scheduling. The penalty dual decomposition-based algorithm outperforms the latter algorithm. It is demonstrated through simulations that UAV is better to keep stationary in a set of time intervals to improve energy efficiency and data collection. During those stationary intervals, UAV can collect data with a better channel condition. In addition, it shows a better performance can be archived if UAV has a longer duration time, suggesting energy limitation is always a key factor to improve UAV's performance. To improve the long-term computation performance, [105] considers cooperation of air computation and ground computation. It regarded UAV as supplementary computing resources for the terrestrial MEC system. Computation tasks arriving randomly at the mobile user, can be first queued at the virtual buffer of this mobile user, and can be computed at local, at UAV, or at the BS, respectively. Deep reinforcement learning techniques are used to schedule offloading to improve the weighted utility consisting of the satisfaction of perceived delay and consumed energy for each mobile user.

Energy issues and computation time are critical for the UAV-enabled MEC system due to the limited onboard energy of UAV. In [106], it investigates the minimization of UAV energy consumption and task completion time, respectively, while an individual UAV flying at a horizon plane provides computation offloading opportunities to IoT devices. Since the objective of only minimizing the energy consumption or only maximizing the computation rates may not satisfy energy and computation optimization simultaneously, the concept of computation efficiency is introduced in [107], [108]. Then, computation efficiency is adopted in the UAV assisted MEC system in [104]. Computation efficiency is defined as the completed computation bits in unit energy consumption, which can help achieve a good tradeoff between computation and energy. Hence, [104] studies how to maximize the computation efficiency in a system where a UAV provides computation service to one user. In such a system, computation efficiency represents the total completed computation bits by both the user and the UAV in unit energy consumption of the user.

2) OFFLOADING FROM UAV

Due to the limited energy and the payload capacity of UAV, it is possible that UAV can not satisfy the requirement of service, e.g., accommodating many computation-intensive latency-sensitive tasks. In such scenarios, UAV can offload their computation tasks to the ground MEC server, such as ground BSs equipped with the MEC server. To minimize the UAV's mission completion time, in [91], a UAV flies from an initial location to the final location and offload its computation task to a series of ground base stations during the flight, in which the UAV trajectory and time to offload are jointly optimized.

Multiple UAVs are explored which offload their computation missions to MEC server via the cellular-connected network or offloading to BSs via WiFi connectivity [92]. It aims to minimize the weighted summation of delay and energy consumption, formulated as $\alpha T + \beta E$, where α and β are weighted parameters, and T and E are the delay and energy consumption of UAVs, respectively. In this work, a computation allocation strategy is developed by using game theory.

In [93], a UAV offloads computation tasks to an AP, with the objective of minimizing the energy consumption of the UAV, which is similar to [97]. But in this work, it takes security into account. Before AP receives offloaded tasks from the UAV, the offloaded information can be stolen. In case

TABLE 6. UAV-related caching.

Ref	Objective	Caching Unit	User	Mobility of UAV	Mobility of Users	Amount of UAV	Dimension
[109]	Maximize the user's QoE while minimizing the transmit power by UAVs	UAV	Mobile Users	Mobile	Mobile	Multiple	3D
[110]	Maximize the number of users with a stable queue	UAV	Mobile Users	-	-	Multiple	-
[111]	Maximize the user reliability	Small BSs	VR users	Mobile	Mobile	Multiple	3D
[113]	Minimize the number of UAV	UAV	Mobile Users	Static	Static	Multiple	3D
[114]	Maximize the successful download probability	Small BSs	Mobile Users and UAVs	Static	Static	Multiple	2D
[112]	Maximize the throughput among IoT devices	UAV	IoT devices	Static	Low mobility	Multiple	3D
[115]	Minimize the delay of user downloading	UAV	Mobile Users	Mobile	-	Multiple	3D
[116]	Maximize the energy efficiency of UAV	UAV	Single user	Mobile	-	Multiple	1D

that eavesdroppers obtain information, this work establishes a jamming model and a secure offloading model to safeguard the offloading process.

Instead of exploring the optimization system model of UAV assisted MEC, [94] presents a three-layer architecture for fire detection application, in which UAVs are used to capture image data. The image data can be processed locally or at the edge or in the cloud. It is demonstrated through simulation that MEC offloading outperforms others in terms of energy consumption, network utilization and the delay.

VI. UAV-ASSISTED CACHING

With emergence of data-hungry applications such as video streaming, mobile users request can a huge amount of data in downlink, which can cause a traffic jam in backhaul and the service time can be deteriorated. To address this issue, edge caching can be employed, where frequently requested contents can be cached in edge servers in proximity of users such that the content requests from users can be served locally and quickly. The rationale is that mobile users request the same contents repeatedly in various instances, and placing the popular contents at the edge network such as UAVs can help users retrieve content with minimal latency, rather than obtaining contents from remote servers in core networks, thereby reducing the backhaul burden and transmission latency. To realize the caching function, content placement and content delivery are critical. For content placement, what content should be placed at the edge network has to be determined. And then the popular content is pre-downloaded and cached in off-peak time. Once receiving the request from mobile users, the requested content will be retrieved directly from the edge server and delivered to users.

Integrating UAV in edge caching (UAV-assisted caching) has the following advantages. Firstly, because of the mobility and flexibility of UAV, it can roam among users with cached content. Compared to ground MEC caching, UAV can track the mobile users' movement to deliver the content seamlessly and dynamically. In this manner, the same contents that need to be cached in different places can be reduced. Secondly, UAVs often perform tasks of surveillance in traffic, soil, or crops, and will generate huge amount of data. In this circumstance, if we upload data to the core network for processing and analysis, not only the time cost is expensive but also the traffic congestion can be easily caused. To save transmission time as well as alleviate the burden of backhaul, we can locally store the captured data at the proximal edge network. By storing data at UAVs, we can facilitate local data analytics and respond to events quickly. The related works on UAV-assisted caching are summarized in Table 6.

One of the most representing works about UAV assisted caching is presented in [109], where UAVs equipped with a cache storage unit employ machine learning framework of conceptor-based echo state algorithm to predict the content request distribution and the behavior of mobile users. Based on the predicted request distribution, "popular " content is selected to cache at UAVs. After that, UAVs adapt their position to provide caching service at optimal locations. Note that UAV is static while transmitting the requested content. After finishing transmission, UAV will adjust their positions according to the movement of users. Similarly, the work in [110] uses a liquid state machine algorithm to predict the user's request distribution based on the limited information and user's state. It develops a spectrum allocation scheme to allocate the bandwidth of licensed and unlicensed bands.

Furthermore, a framework is proposed to assist virtual reality [111] system. In this work, UAV equipped with a camera captures the data of reality and then uploads the captured data to small BSs. The small BSs cache popular data at the edge network and provide contents for customers. On the other hand, UAV also can straightly provide a set of content to customers. In this system, it aims to maximize the reliability of service which is defined as the probability that the transmission delay satisfies the VR delay requirement. Instead of utilizing UAV to collect data, in [112], the authors study how UAV assisted MEC caching supports the IoT system. They employ an Matern cluster process to allocate users to UAVs. And then the throughput of each cluster is maximized by considering the placement of cache contents and the locations of UAVs. To be specific, it transfers a 3D UAV location problem into a 2D problem and 1D problem, which means it first finds the optimal altitude of UAV and then uses an enumeration search algorithm to find the optimal UAV position in 2D plane.

Deep learning is used to predict the reliability of service and output the caching strategies. Taking deployment and mobility advantage of UAV into consideration, the work in [113] considers the situation where all ground stations are destroyed. To support high data-rate and low-latency networking in emergency, UAV carried cache storage unit are hired. This work minimizes the number of UAVs while maximizing the coverage area and backhaul saving. Meanwhile, it minimizes the transmit power while satisfying the quality of experience requirements. Instead of offering caching service, in [114], contents with high popularity are cached at small BSs. UAVs and ground mobile users can receive caching service from it. This work develops a stochastic caching strategy with the goal of maximizing the successful download probability.

In [115], a game theoretical approach is adopted to study the caching problems. In this system, multiple UAVs flying with the cache unit aim to minimize the delay of content downloading of mobile users. The delay is not only decided by the trajectory and cached content of one UAV but also by the state of other UAVs. It shows that as the number of users increases, the speed of download is decreased. Therefore, a mean-field game is proposed to decide the flight state of UAV by considering the state of other UAVs.

Considering the battery and cache limitation, the work in [116] minimizes the energy consumption of UAV through only optimizing the height of UAV and the content assignment. In particular, this work treats UAV as an aggregator of communication and caching.

VII. RESEARCH DIRECTIONS AND OPEN ISSUES

A. INTEGRATED NETWORKING

To realize the UAV assisted MEC system, various components such as cellular networks, UAVs, IoT, and WiFi, have to be integrated into one system. In [45], a software-defined space-air-ground integrated network architecture is proposed. This platform can facilitate on-demand allocation and integration of redundant communication, computation, and caching resources from different segments. Different parts can complement with each other. A comprehensive integrated platform is needed to manage the system and figure out the role of devices by making efficient use of their strengths and avoiding weaknesses. Such a integrated network should be a stable, reliable, low-latency, scalable and large-coverage system.

With a variety of devices and networks, there exist heterogeneous resources in the integrated network. Existing resource allocation have been extensively explored on computation, computing, and catching, separately, but without jointly considering heterogeneous resource allocation. A mapping or scheduling mechanism is needed to allocate resources jointly, such as spectrum frequency [117], battery recharging, the number of UAVs, and others. For instance, it is an important issue on how to adapt UAV trajectory for improve communication and computation performance with low energy consumption. In addition, facing failure issues, network recovery is another key direction. To extend network life, maintenance is indispensable for the system. There are still a few challenges needed to be addressed when the accidents occur, which include 1) how to monitor and test out of control UAVs and missing UAVs; 2) how to deal with UAVs that run out of battery; and 3) how to design a fault-tolerant system. All these problems are of great importance but not yet investigated well.

B. CONVERGENCE/SYNERGY OF COMMUNICATION, COMPUTATION, CACHING

In the future, UAV at least has four types of resources, communication, computation, caching, and assembled sensors. Computation offloading is achieved by communication function as well as supported by cached data [118]. Similarly, to realize caching in the MEC server, the data is transmitted by communication units. Since the four units are affected by each other, it is of great significance to consider the synergy of communication, computation and caching at UAVs [119]. In addition, various services have distinct service requirements in terms of reliability, latency, throughput, and so on. To meet different QoS requirements from heterogeneous services, different resource portfolios should be provisioned. In other words, resources in communication, computing, and caching should be managed well to support diverse services efficiently. Last but not least, service requests change in spatial and temporal domains. These heterogeneous resources at different locations and time instants should also be orchestrated to provide smooth and seamless services.

C. ENERGY EFFICIENCY AND HARVESTING

Constrained energy is an important factor affecting the performance of any UAV system, which limits the payload of UAV, communication and computation performance, and flight duration. Therefore, developing energy-aware deployment and operation is of significance [71]. Although they are extensively explored recently, it is hard to a good balance between energy consumption and other performance metrics such as the computation rate. Computation efficiency was proposed to improve the number of computation bits in unit energy consumption, but the QoS is compromised. Therefore, how to tackle the performance optimization problem and tradeoff problem to achieve minimum energy consumption, high computation speed, and maximum computation bits simultaneously is an issue needed to be solved.

Energy harvesting can be introduced in the UAV-assisted MEC system to mitigate energy shortage issue, where UAVs charge users in a wireless manner. In [102], UAV charges for mobile users. At the same time, it needs to compute offloaded missions. In this scenario, the On-board energy of UAV used for computation, communication, and providing energy for users. However, on-board energy is inherently limited.

In this case, the endurance and energy constraints of UAV are expected to be considered. To bring computation, communication, and providing charging function together, energy harvesting and wireless power transfer for UAV is essential. However, due to the uncertainty and high dependence on weather and environment, UAV harvesting from green sources such as solar and wind is not efficient. Compared to energy harvesting from natural sources, wireless power transfer can be a complementary source. LoS link between UAVs and ground devices is beneficial for communication and computation, and the air-ground link transfer power signal can also be used to help realize wireless power. Because of potential block among ground users and ground devices such as buildings, there is much pass loss in direct wireless power transfer through the ground-ground link. Therefore, the transmitter sending the power signal to UAV and then UAV forwarding it to the receiver is an available way to transfer power efficiently [120]. In the future, integrating UAV as a wireless power medium into the system is a potential topic.

D. MOBILITY

Flying at fixed altitude is the advantage of UAV. However, from Table 4 and Table 5, we can know only a few documents research the UAV deployment in a 3D environment for communication and computing assistance. Hiring UAV at an appropriate height or adjusting UAV height is critical and sensitive for their performance. A good altitude deployment is critical because it affects energy consumption, flight control, and flight speed. On the other hand, to benefit communication or computation service, UAV can adjust its altitude. However, when it is close to users, an interruption between UAV and UAV link may be caused and the coverage is changed. Therefore, if we aim to make the most of UAVs in the future, UAV deployment in a 3D environment has to be considered. More realistic and practical channel modeling should be developed.

In addition, most of existing works consider static users, but users can move over time. Therefore, one interesting topic is how UAV tracks the users' movement and provide the related service. Due to the mobility of users, the spatial-temporal user density changes over time. Based on this scenario, UAVs can track the mobility of users to adjust their positions to dynamically provide service. Furthermore, because of the development of big data and edge computing network [121], a huge amount of data is captured. How to utilize those data to predict the movement trend or population distribution is worthwhile to investigate. Moreover, UAV assisted vehicular network concept has also been proposed.Efficient solutions to relocate UAV for tracking vehicle mobility based on traffic data is desired. By exploiting traffic data to predict traffic congestion, UAVs then can assist vehicular networks better.

Since UAV can function as multiple roles, it is expected that a large number of UAVs will in the air, for traffic monitoring, goods delivery, and assistance for IoT or vehicular network. It is essential to develop a UAV traffic management system for such a busy air, where UAV air traffic rules or standardization for UAV traffic should be made. The traffic management system should allocate limited air space resources efficiently. Collision avoidance among UAVs should be fully recognized. To deal with congestion or weather impact on UAV traffic, a real-time UAV traffic management framework can be developed.

E. AI FOR UAV ASSISTED MEC

In terms of communication and computation optimization problem, an iterative algorithm is utilized in most existing works. The main idea of the iteration algorithm is that problems can be divided into a set of subproblems and then optimized each subproblem iteratively. With the iterative algorithm the near-optimal solution is found, without considering connection and impacts among subproblems. To better solve the complex problems, artificial intelligence (AI) such as learning-based algorithm and reinforcement learning can be employed to find the near-optimal solution globally and to solve nested problem as a whole [122], [123]. To achieve the convergence of communication, computing and caching, intelligent control is on demand. The AI-related algorithm such as deep reinforcement learning is promising. For instance, reinforcement learning can be employed to schedule computing and communication resources in the UAV assisted MEC environment.

F. SECURITY

In AGMEN, many security threads arise due to its large surface for attackers. In such a system, different connected devices keep collecting data and uploading their data to the edge servers or cloud server for processing or data analytic. It is essential to protect the data in its lifetime from various attacks, such as eavesdropping and denial-of-service attack (DoS attack). In addition, some data are highly related to certain location or people. Attackers can analyze the data to reveal some sensitive information, and therefore privacy needs to be protected. For country or military, UAVs are widely used in surveillance but are easy to be attacked. If attackers shut down or control UAVs and steal surveillance data or damage navigation system, it will cause severe damage or consequences [124]. Currently, the main threads are cyber or electronic attacks whose goal is to shut down UAVs. The attackers can interrupt communication, navigation, or engine of UAVs. Although there are a few works on security of UAV [125]–[127], how to enhance the security of links and deal with attackers efficiently is still open problem.

VIII. CONCLUSION

In this article, we have provided a comprehensive survey of AGMEN. We have introduced the necessary foundation of UAVs and UAV-related networks. We have also presented the applications of UAVs in AGMEN in aspects of communication, computation, and caching. For each aspect, we have discussed their main challenges, primary applications, and reviewed the relavent literature. Furthermore, we have provided a comprehensive architecture of AGMEN and a UAV assisted MEC mathematical model. Some future directions are discussed for AGMEN development.

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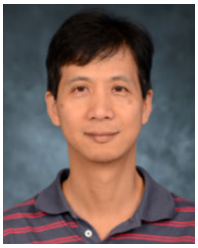

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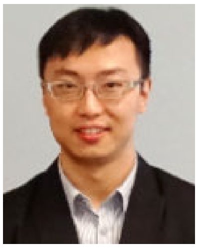

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