Aerial Access Networks for Federated Learning: Applications and Challenges

Quoc-Viet Pham, Ming Zeng, Thien Huynh-The, Zhu Han, and Won-Joo Hwang

Abstract

Aerial access networks (AANs) and mobile edge computing (MEC) have been considered as key enablers of future networks. In this article, we investigate the application of MEC-empowered AANs (also known as aerial computing) for federated learning (FL), a promising technology for providing private and distributed solutions to mobile edge networks. We first introduce the fundamentals of AANs and FL, and illustrate the potential benefits of aerial FL networks. On this basis, we present important applications of AANs for FL. It is shown that distinctive characteristics such as flexible deployment and high mobility, when exploited cleverly, can provide various benefits for FL-enabled networks. Finally, major challenges and potential directions are highlighted.

Introduction

Aerial access networks (AANs) have been considered a key enabler of many services and applications such as aerial base stations (ABSs) and unmanned aerial vehicles (UAVs) for wireless backhaul in 5G and beyond networks. Motivated by the propitious features of high mobility and flexible deployment, ABSs can be part of various wireless systems. For example, UAVs (commonly known as drones) can be deployed as ABSs in areas where the terrestrial telecom infrastructure has been destroyed and/or is currently unavailable. In 2015, mobile edge computing (MEC) was invented by the European Telecommunications Standards Institute (ETSI) as a technology to provide computing services at the network edge. Equipped with MEC capabilities, ABSs can collect and preprocess Internet of Things (IoT) data before sending selectively meaningful information to points of interest. Moreover, some studies have shown that AANs will be an indispensable part of the sixth generation (6G) radio access networks [1].

Due to the proliferation of massive IoT devices and various emerging applications (e.g., virtual reality, autonomous driving, and connected robotics), data have been generated at an exponential rate. To effectively exploit massive IoT data for different purposes, various learning approaches have been investigated. However, conventional deep learning methods typically require central storage and processing of data collected from users distributedly, and data privacy issues thus arise. A promising solution to these critical issues is federated learning (FL), which was invented by Google in 2016 [2].

Motivated by various benefits and applications of AANs and FL, their integration, namely aerial FL, is expected to provide better performance than conventional FL. Aerial FL is highly beneficial and can be found in many scenarios, especially when some users are connected to the aggregation server (AS) with poor channel conditions and/or when some users are unable to connect to the AS directly. Such benefits come with additional costs of the integration. Given a burning interest, there is a big gap in the literature where aerial FL has yet to be concisely discussed. This work bridges the gap by introducing the aerial FL concept, reviewing its main applications, and highlighting key challenges and potential solutions. In a nutshell, the main contributions of this work can be summarized as follows.

Overview and Motivation: We provide a preliminary to AANs and FL, whose marriage results in a novel concept, aerial FL. We then discuss the main motivations behind the integration of FL and AANs and illustrate the benefits of aerial FL networks.

Applications of Aerial FL: As a key part, we present important applications of aerial FL networks, including FL aggregation in the sky, aerial relaying for FL, aerial users in FL, and flying ad hoc networks (FANETs) for FL.

Challenges and Potential Solutions: To further drive the research and development of aerial FL, we provide key challenges and important directions of aerial FL networks with 6G technologies, sustainable solutions, mobility management, channel modeling, and privacy and security.

Overview of Aerial Federated Learning

Aerial Access Networks

Historically, aerial communications have been used for many military tasks such as reconnaissance and training targets. Recent years have witnessed their usage for various civil applications in wireless and communication networks. Aerial components such as UAVs, drones, airplanes, and balloons can act as ABSs to serve ground users when the terrestrial infrastructure has been damaged by disasters (UAV 1, Fig. 1). They can also be aerial users in many network scenarios, which need to connect to terrestrial BSs (TBSs) for communication services (UAV 2, Fig. 1). High ability to establish line-of-sight (LoS) connections and dynamic deployment are major features of AANs to be considered as a key enabler of future networks [1].

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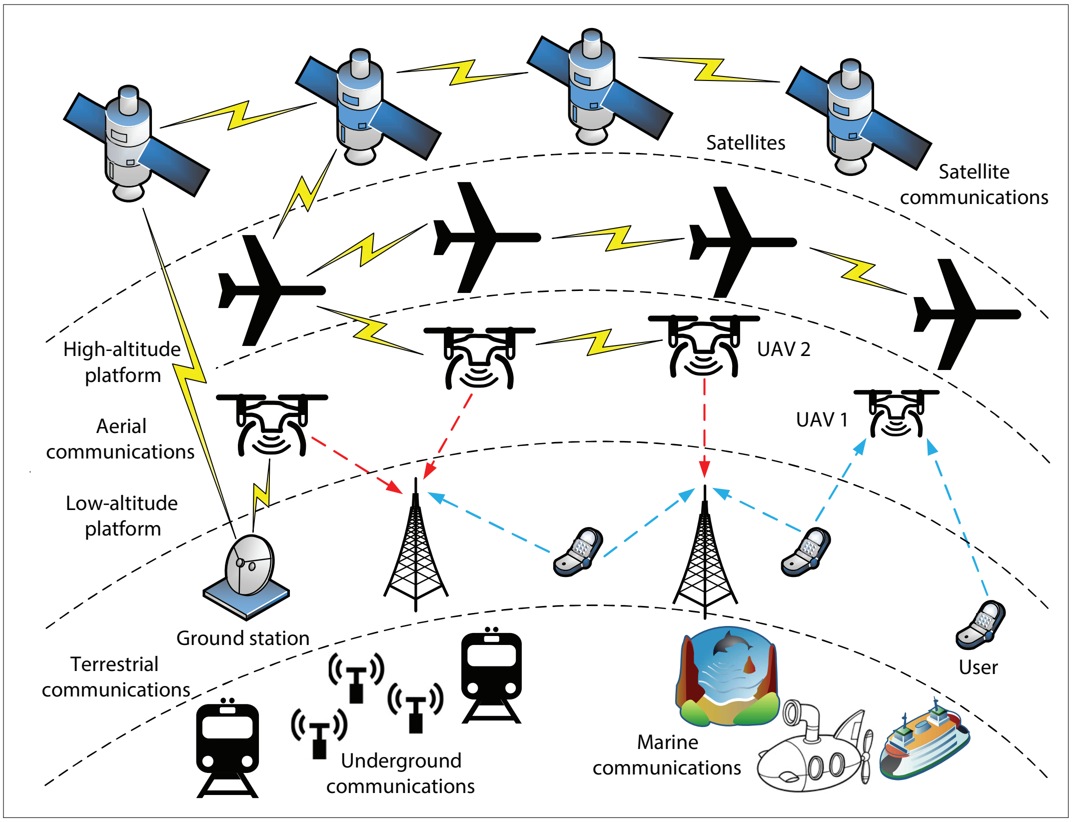

FIGURE 1. Aerial access networks in a 6G comprehensive access architecture.

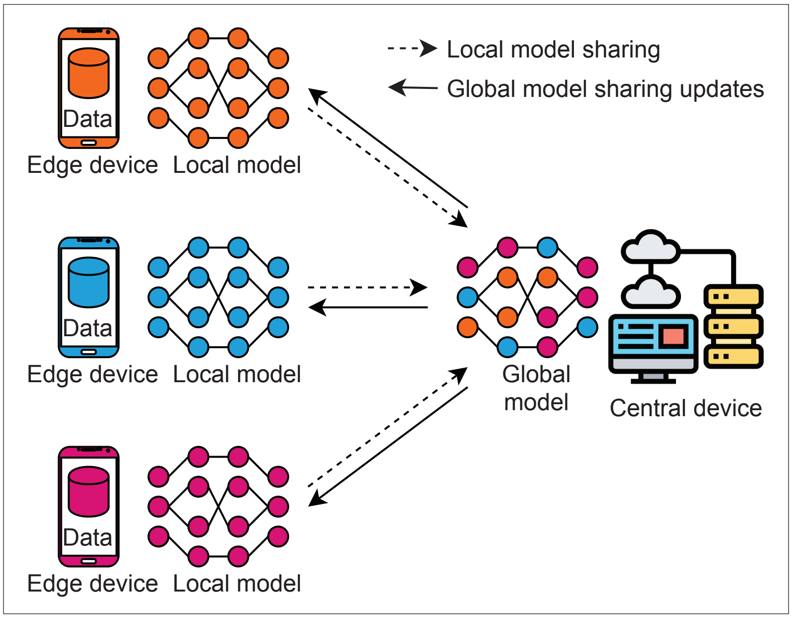

FIGURE 2. Illustration of the FL concept.

AANs are a main constituent of the ground-aerial-space network architecture in 6G [3], as illustrated in Fig. 1. On the top, satellite communications are very promising as global coverage can be guaranteed. AANs include two main portions: low-altitude platform (LAP) and high-altitude platform (HAP). In the middle, aerial components such as UAVs, airplanes, and balloons can be adopted as either aerial BSs or aerial users. These LAP and HAP systems connect satellites with terrestrial infrastructures, and thus enable a comprehensive network with global coverage and diverse quality standards. Terrestrial, underground, and marine communications are important parts of the comprehensive network architecture. In the context of FL, the AS and FL users can be any component of this comprehensive architecture. For example, to build an FL model over multiple regions of the world, an MEC-empowered satellite can be adopted as the AS, whereas several UAVs share their models with a TBS as FL users.

Federated Learning

Numerous artificial intelligence (AI) techniques have been used for wireless networks [4]. Conventional AI frameworks typically require users to transfer their raw data to an MEC server for central learning. However, since data generated by users may contain sensitive information (e.g., age, gender, and financial transactions), user privacy may not be preserved. To avoid this privacy issue, the concept of FL was invented by Google in 2016. Conceptually, users do not need to send their data to the server, but only information on the models that are trained locally using local data [2], as shown in Fig. 2. The server collects the local model updates from users and performs the model aggregation process by FedAvg (or various other FL algorithms) before broadcasting the global model (i.e., one aggregated at the server) to users [2]. This process is repeated until desirable performance is ensured.

FL can be classified in different ways. Based on the data partition and distribution, FL is classified into horizontal FL, vertical FL, and transfer FL [5]. In horizontal FL, there are different datasets for different users, but these datasets share the same feature set. In vertical FL, datasets from different domains have different features, but some common samples are used for learning. Lastly, transfer FL applies to

Networks	Merits	Demerits
Conventional FL	a) FL training and aggregation with the existing computing infrastructures (e.g., fog, edge, and cloud computing), thus no additional deployment cost. b) Insusceptible to external conditions as in LAP- and HAP-enabled FL networks. c) Well-studied channel models for FL networks	a) Fixed deployment and low adaptability to network dynamics and user distributions. b) Fixed service coverage, i.e., not able to provide FL services in remote and hard-to-reach areas. c) High cost of server hosting and site rent.
Conventional AAN	a) Ensure global coverage, for which the conventional terrestrial system has limited capability. b) Establish LoS communication links and operate at various altitudes, including LAPs, HAPs, and satellites. c) Quickly form salable networks to meet user requirements and provide uninterrupted services.	a) Mainly focus on communication services, i.e., benefits of providing computing services in the air are not well experimented. b) Additional costs due to the deployment of aerial components (e.g., UAVs, HAPs, and satellites). c) Additional design variables with AANs (e.g., UAV trajectory and satellite constellation).
Aerial FL	a) Can provide FL services to remote and hard-to-reach areas (e.g., disaster areas and remote farms). b) Can provide FL services to IoT applications with sparsely distributed users (e.g., global model aggregation with satellite-enabled FL networks). c) Increase communication efficiency via flexible LoS communication and hierarchical AAN architecture. d) Inherited features from AAN, including global coverage, hierarchical architecture, high mobility, and high scalability.	a) Susceptible to external conditions such as weather, especially in LAP- and HAP-enabled FL networks. b) Additional costs of the AASs deployment. c) Additional design aspects with aerial FL (e.g., aerial aggregation, latency, and scalable aerial FL).

TABLE 1. Comparison of different FL networks.

the learning scenarios with datasets across different domains with different feature sets. According to the network topology, FL is classified into centralized FL and distributed FL. The former, also known as vanilla FL in the literature, depends on a central server for model collection and aggregation. The dependence on a central server is excluded in distributed FL, in which users share their local models with others based on their trust and reliability. Blockchain, with its decentralization and secure nature, offers great potential to build decentralized aggregation and serverless FL solutions [6].

Aerial Federated Learning: Motivation and Illustration

Typically, fixed-location ASs are considered in FL networks; however, that deployment may affect the learning performance significantly. For example, in a hard-to-reach area with many IoT devices, performing FL tasks is quite challenging due to the high cost of deployment and maintenance. Hence, ABSs can be leveraged to provide wireless connections to IoT devices and also undertake the task of model aggregation. Other examples are crowded/open areas (e.g., shopping malls and stadiums), where a large number of people request FL services. To supplement the terrestrial AS, aerial relays can help to perform some FL tasks and/or forward information between the AS and FL users. A comparison of different FL networks is presented in Table 1, including conventional FL, conventional AAN, and aerial FL.

To illustrate the potential benefits of aerial FL networks, we consider the aerial FL network shown in Fig. 3. In this use case, FL users have limited battery capacity; some users (i.e., IoT sensors and wearable devices) are even battery-free, that is, these users are not equipped with any battery and need to harvest external energy for operation and execution. Furthermore, terrestrial communications are currently unavailable to provide wireless and learning services to these FL users. Thanks to its fully controllable mobility, the ABS can be adopted as a mobile energy transmitter and wirelessly charge users. In general, the whole FL training process of such an aerial FL wireless powered network consists of the following steps.

Step 0 (Initialization): The aerial AS (AAS) receives information from the network operator and decides the training task requirements (e.g., maximum completion time and learning rate). The AAS also initializes the global model and broadcasts it to the selected users.

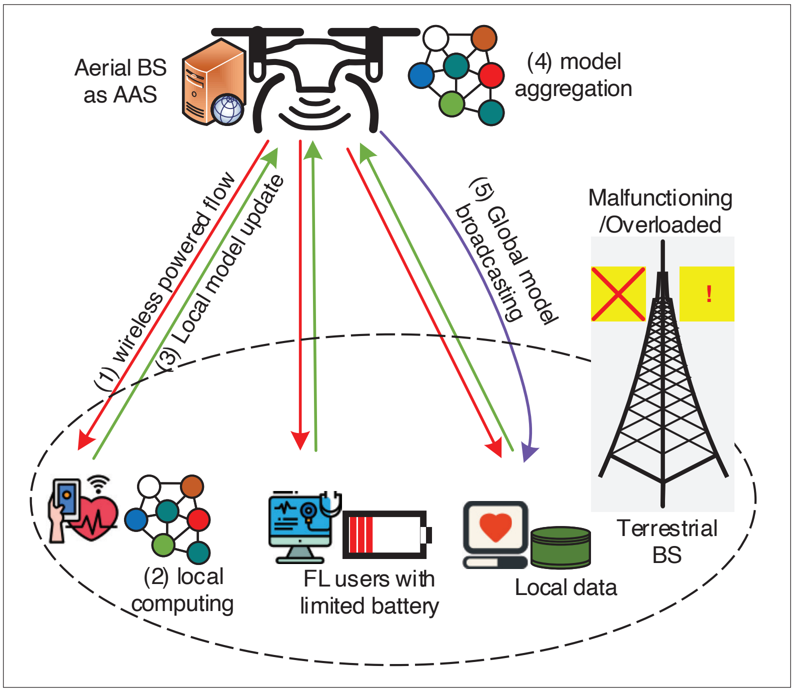

FIGURE 3. Illustration of a UAV-FL wireless powered communication network.

Step 1 (Wireless Powered Communication): The timeframe of each global round is divided into two slots: one for wireless powered communication and the other for model training and update. In the first time slot, FL users harvest energy from the mobile energy transmitter according to a linear energy harvesting model.

Step 2 (Local Model Training): Upon receiving the global model from the AAS, each user trains the local model based on its local data. The methods used for training local models can be deterministic/stochastic gradient descent and deep reinforcement learning.

Step 3 (Local Model Update): After completing the local training, users send the updated local models to the server for aggregation.

Step 4 (Global Model Aggregation): The AAS applies the aggregation algorithm (e.g., FedAvg) to aggregate the local models received from the selected users.

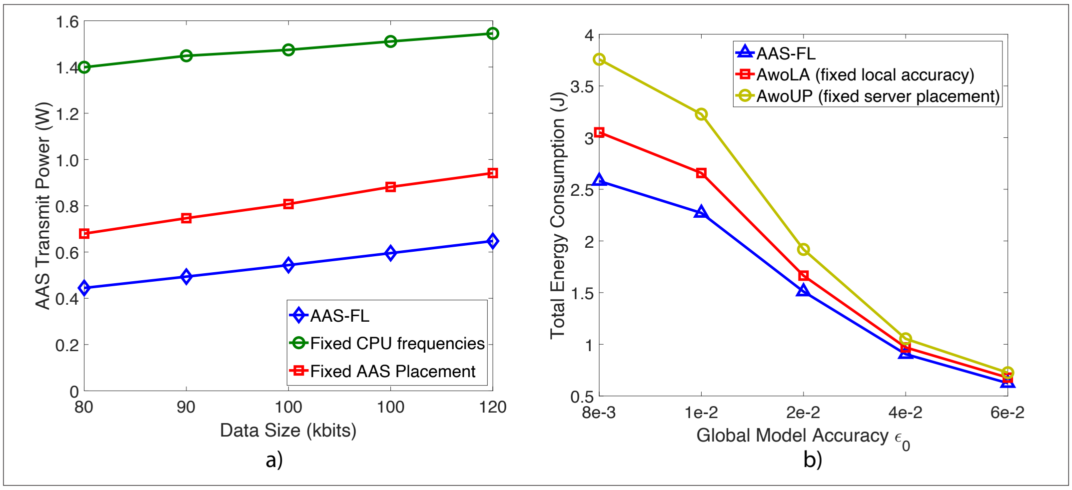

FIGURE 4. Performance evaluation of the AAS: a) UAV transmit power vs. data size of the local models; b) overall energy consumption vs. global accuracy.

Step 5 (Global Model Broadcasting): The AAS broadcasts the updated global model to the users.

These steps are repeated until a desirable training accuracy is achieved by the global model.

We consider the above scenario and formulate a problem of power efficiency of the AAS in [7]. A joint optimization problem of the AAS placement, power allocation, CPU frequencies of users, time allocation, and bandwidth partitioning is solved and evaluated via numerical simulations. An illustrative result of the AAS transmit power vs. the model data size is shown in Fig. 4a. The AAS transmit power gets larger as the model size increases. The reason is that users need to harvest more energy from the AAS to keep the completion time below the required timeframe. From the figure, deploying the AAS achieves better performance than that of the two benchmarks, including fixed AAS placement and fixed CPU frequencies. Inspired by [7], we also consider optimizing the local model accuracy to minimize the overall energy consumption of the AAS and FL users over multiple global rounds. This is because the number of global rounds depends on both local and global model accuracies [8]. As shown in Fig. 4b, when the global model accuracy is small (large ε_0), the performance gain of aerial FL is small. However, the superiority of the AAS over the benchmarks (with fixed placement and local accuracy) is strongly emphasized when the FL model needs to be learned more accurately (small ε_0). These two illustrative results demonstrate the benefits of aerial FL and the desirability of jointly optimizing resource management and additional design variables with AANs.

Applications of Aerial Federated Learning

In this section, we describe important applications of aerial FL, and an illustration of these applications is shown in Fig. 5.

FL Aggregation in the Sky: In conventional FL scenarios, the AS is typically positioned at a fixed location such as access point, BS, or edge node. However, it is difficult to perform FL tasks in areas with damaged terrestrial infrastructure. In such a case, LAP/HAP stations can be deployed as AASs. As shown in Fig. 5a, an ABS is deployed as the AAS and performs model collection and aggregation. However, deploying only one AAS may not provide wireless and learning services to a large number of users, thus motivating the deployment of multiple AASs, each serving a subset of users. Besides various benefits with model aggregation in the sky, there are additional design factors that should be taken into consideration. For example, the AAS placement, altitude, and beamwidth can be jointly optimized for better communication efficiency. Moreover, the AAS trajectory can also be optimized to serve more users and collect more local models when possible, thereby increasing the learning efficiency.

As an effort in [9], each deployed ABS acts as an AAS and provides services to a subset of FL users. A trade-off between execution time and learning accuracy is obtained by optimizing the AAS placement, communication variables (i.e., user association and subchannel assignment), power control of AASs, and CPU frequencies of users. The whole FL process is composed of three phases: resource optimization, local training, and global model aggregation. Then an asynchronous advantage actor-critic algorithm is leveraged to improve the learning efficiency and avoid the need for synchronization among heterogeneous users. As a result, the asynchronous-FL scheme achieves close performance to the synchronous-FL counterpart, but with a lower completion time. The results in [9] also highlight the importance of user selection to learning accuracy. Moreover, the results further indicate that the asynchronous deep reinforcement learning algorithm is superior to the conventional gradient-based approach.

Aerial Relaying for FL: Through extending the coverage of existing wireless networks, LAPs/HAPs can be deployed to support FL users, who are not under the coverage of any ASs. As shown in Fig. 5b, there are no direct communication links between users and the AS due to the existence of obstacles (e.g., skyscrapers and trees). In such cases, the aerial relay receives the local models from its connected users and forwards the received models to the AS. Furthermore, the aerial relay receives the global model sent by the server and forwards the model to its connected users. Here, the deployment of aerial relays can overcome the issue of no direct communication links, and thus facilitates continuous updates of the learning mod-

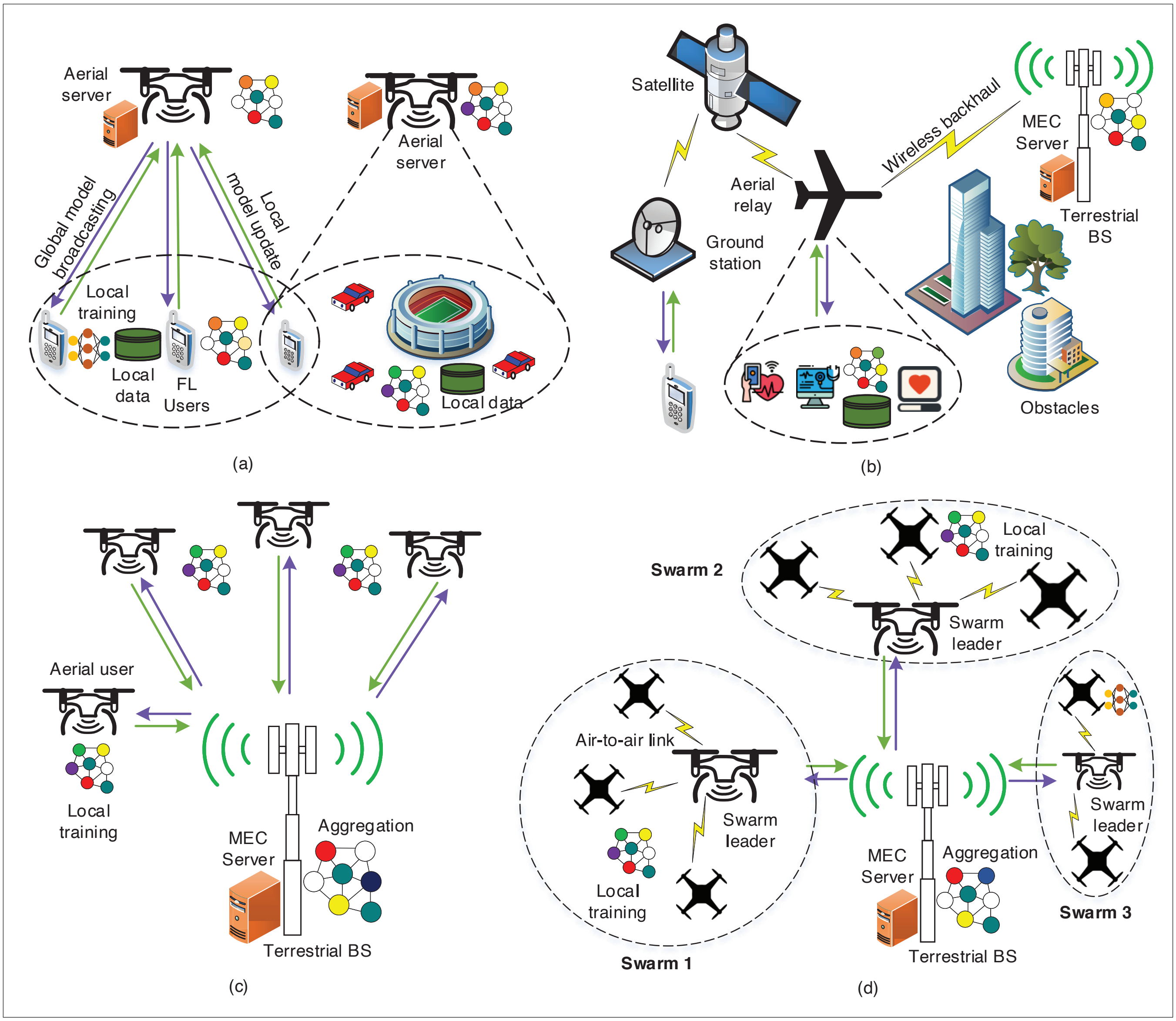

FIGURE 5. Important applications of aerial FL: a) aerial aggregation; b) aerial relaying for FL; c) aerial users in FL; d) FANETs.

els between users and the AS. Ground stations can also act as relays to help users to communicate with HAP stations and satellites.

The application of LAPs/HAPs as aerial relays for efficient FL-enabled Internet of Vehicles (IoV) is considered in [10]. In particular, the IoV service provider builds an FL model using information collected from different IoV groups of different IoV components such as autonomous cars, roadside units, and buses. The high dynamics and mobility of IoV components can lead to a drastic change in their communication links to the server. Moreover, some components may not have enough budget (e.g., bandwidth and energy) to communicate with the server directly. The work in [10] considers deploying aerial relays in the IoV and devises an incentive strategy based on auction game theory to encourage the aerial relays to join the FL training process. Since multiple aerial relays are deployed, an IoV component, as an FL user, has different preferences over different relays. Similarly, multiple relays may cooperate to serve the same set of IoV components if they are offered good incentives. As a result, a joint coalition-auction game approach is developed to enable communication-efficient FL operations in IoV systems. It is shown in [10] that deploying aerial relays can significantly reduce the transmission time.

Aerial Users in FL: LAPs/HAPs can also be considered as aerial users in many applications. In these cases, aerial users are coordinated to cooperatively perform parts of highly complex tasks (e.g., rescue and relief operations in earthquakes, crowdsensing, and target detection and tracking). The coordination among aerial users can be controlled by a ground control station (GCS). However, since the communication links between the GCS and aerial users are not always available, and the GCS may not have enough computing capability to centrally process complex tasks, the FL concept can be utilized in such cases to provide highly reliable learning solutions and to relieve the computing burden of the GCS. An illustration is shown in Fig. 5c, where each UAV trains the local model and shares it with a TBS, which is usually collocated with MEC servers. In many cases, such as rural areas and mountains, there is no TBS, and

Aerial communications have found many applications and use cases in FANETs. Like conventional (mobile) ad hoc networks, multiple aerial nodes are connected in an ad hoc manner in FANETs. In addition, only a subset of aerial nodes has direct connections to the infrastructure, whereas the remaining subset connects to the infrastructure via immediate aerial nodes.

the GCS can play the role of the AS. Otherwise, an ABS with more powerful capabilities can be configured as the central server that facilitates coordination among the other aerial users.

An example of this application is investigated in [11] for computer vision tasks (e.g., object detection and classification). These tasks are coordinated by the GCS, which is located at an inaccessible but important location (e.g., the top of a mountain). There are several challenges in successfully performing the image classification tasks in such circumstances. First, the number of images captured by the camera-equipped aerial users can be very large with high resolution (so-called image size), thus resulting in an enormous communication cost and overhead. Second, sending all the raw figures to the GCS may raise the issue of data privacy. Lastly, due to its limited capabilities, the GCS may not be able to successfully train a deep model with very large datasets and very high computing requirements. These challenges are overcome by an FL-based approach, in which the aerial users and the GCS are regarded as FL users and the AS, respectively. The FL-based approach can reduce the completion time significantly when compared to the centralized approach. At the accuracy requirement of 95 percent, the completion time of the FL-based and centralized approaches is 0.065 and 9.4 s, respectively.

Flying Ad Hoc Networks: Aerial communications have found many applications and use cases in FANETs. Like conventional (mobile) ad hoc networks, multiple aerial nodes are connected in an ad hoc manner in FANETs. In addition, only a subset of aerial nodes has direct connections to the infrastructure, whereas the remaining subset connects to the infrastructure via intermediate aerial nodes. For example in Fig. 5d, there are four UAVs in swarm 1; however, only the swarm leader can connect to the BS, and the other UAVs connect to the BS via the swarm leader. Despite several remarkable advantages, FANETs have various design challenges such as routing and communication protocols, node density, aerial channel models, and dynamic topology.

To exploit the great potential of aerial swarms and FL, the work in [12] investigates a holistic sensing framework with both aerial sensing and ground sensing. In particular, haze images captured by UAVs in different aerial swarms are used to train local models of air quality index (AQI). Aerial swarms may be deployed at different monitoring areas and belong to different organizations, which may not share collected images with each other due to privacy concerns. To handle this issue, haze images collected by each UAV are trained locally, and only information on the local models is transferred to the UAV leader. Then a lightweight convolutional neural network (CNN), namely Dense-MobileNet, is implemented at the UAV leader to estimate the AQI. For AQI estimation of ground sensing systems, a graph CNN-based long short-term memory model is developed to exploit the spatial-temporal relationship of air quality data collected by different ground sensors. The experimental results in [12] show that the proposed deep model using aerial swarms and FL achieves higher estimation accuracy than the 3D CNN and machine learning models. In particular, the estimation accuracy of the proposed deep model is around 95 percent, while that of the 3D CNN and machine learning models are around 92 and 64 percent, respectively.

Challenges and Future Directions

Aerial FL Networks with 6G Technologies: There will be various new services and technologies in future 6G wireless systems such as bio-nano IoT, terahertz communications, intelligent reflecting surface (IRS), and edge AI [13]. For example, based on the solution introduced in [14], UAVs can be used to create fluid cells in cell-free MIMO systems, which can mitigate the effects of channel variations thanks to the channel hardening effect and thus facilitate the whole FL process. An IRS can be deployed on environment objects (e.g., facades of buildings) to judiciously reconfigure the channels between FL users and the AAS, and thus improve the learning efficiency. An IRS can also help to add extra communication links between FL users and the AS to enhance the system performance. Since more technologies will be developed for future 6G networks, their integration with AANs can considerably improve the performance of FL networks.

Sustainable Solutions for Aerial FL Networks: ABSs (especially UAVs at the LAP) are typically equipped with limited batteries. Moreover, ABSs consume a large amount of energy for non-communication and non-learning tasks such as hovering, sensing, and control. As a result, it is a critical challenge to maintain the sustainability of AANs. To deal with this challenge, energy harvesting and wireless powered communication seem like potential solutions. At the same time, users such as small sensors and battery-free devices usually have a limited energy budget, which can adversely affect the training ability of users and the whole FL process. In such cases, besides the role of AASs, UAVs can be deployed as power sources of users. However, this requires optimizing additional variables such as harvesting time, local training, and communication. Jointly combined with common variables (e.g., bandwidth partitioning, model accuracy, and device scheduling), the optimization would be very complicated and thus needs to be thoroughly investigated in the future. Regarding a potential solution in [15], users first harvest energy from stable sources via radio waves and lightwaves before performing the training task and communication with the AS.

Mobility Management: Distinctive features of AANs can be exploited to improve aerial FL networks. The optimized placement helps to establish LoS connections, and thus facilitates high-rate and high-reliability transmissions of model updates. The importance of the AAS placement can be found in some specific scenarios, where different users have different computing capabilities, heterogeneous datasets, and learning requirements. The AAS should be positioned closer to the user with poor computing resources than the user with high computing capabilities. Similarly, a user with more rigorous learning requirements should be closer to the AAS than a user with mild requirements. When the number of users is sufficiently large, deploying multiple AASs is needed. However, such a case requires the additional optimization of user association and collision avoidance constraints. Moreover, the ABS trajectory can be optimized to improve localization, in which users are distributed over a large-scale region. It is worth noting that to reach ABS mobility, the learning objective and constraints can be divergent because the ABSs with different operation modes comply with different energy consumption strategies (e.g., hovering, vertical moving, and horizontal moving).

Channel Modeling: Due to the distinctive characteristics of AANs, accurately characterizing the channel model is quite challenging compared to the conventional models of terrestrial communications. Moreover, the well-known models for terrestrial communications are typically not suitable for air-to-ground transmissions. Consequently, the conventional models should be revisited by analyzing the aerial characteristics such as aerial movement in 3D space and air density. A high training time of local models in each global round and a high completion time of the global model also emphasize the importance of channel modeling in aerial FL networks. In particular, the channels can change on the order of milliseconds, while the FL model is typically completed on the order of seconds. It is necessary to design FL algorithms with consideration of imperfect channel state information and inaccurate channel model. Moreover, as discussed above, AANs can be integrated with other 6G technologies (e.g., IRS and cell-free massive MIMO) and transfer learning to improve the performance of aerial FL networks with complex channel models.

Privacy and Security: Privacy-preserving promises are the attractive points of FL as the data are mainly used for training local models instead of directly sending them to the central server for learning the global model. However, aerial FL networks still face security and privacy issues that need to be thoroughly studied in the future. On one hand, the high possibility of LoS links, flexible deployment, and high mobility offered by AANs can result in serious threat and security issues. The reason for this is that the model updates between users and the AAS can be riskily jammed or eavesdropped on by malicious AASs once they are deliberately deployed for malicious attacks. As a result, designing secure aerial FL networks is crucial and worth further investigation. On the other hand, flexible deployment and high mobility of AANs can be properly exploited to provide secure solutions for aerial FL networks. For example, the AAS placement can be optimized to prevent the model interception and interpretation at malicious AASs when the local models are transmitted from users to the AAS. Additionally, conventional security and privacy issues of FL (e.g., data and model poisoning, free-riding attacks, and unintentional data leakage) should be investigated in aerial FL networks. With distinct features, blockchain is a disruptive technology that can be exploited to mitigate security and privacy issues of aerial FL networks [6].

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Practical Implementation: Besides the above challenges, the development of prototypes and real implementations are also important issues that have been not properly emphasized in the literature. This could be because it is difficult to achieve experimental implementations of aerial FL systems due to many factors such as high cost and limited personnel resources. A middle ground to narrow the gap could be to develop emulation tools that can fully characterize features of aerial FL systems such as aerial dynamics, heterogeneous datasets, and various learning requirements. Such emulation tools should also be open to the research community and allow researchers to customize the existing modules as well as develop new modules.

Conclusion

In this article, we have discussed the applications of AANs for FL at mobile edge networks. Specifically, we have overviewed aerial FL and shown its benefits over conventional FL networks with the fixed deployment of ASs. Following this, important applications of model aggregation in the sky, aerial relaying, aerial FL users, and FANETs, have been presented, respectively. Finally, several challenges and research directions have been highlighted to drive further research about aerial FL networks.

Acknowledgments

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