Empowering the Edge Intelligence by Air-Ground Integrated Federated Learning in 6G Networks

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Abstract—Ubiquitous intelligence has been widely recognized as a critical vision of the future sixth generation (6G) networks, which implies the intelligence over the whole network from the core to the edge including end devices. Nevertheless, fulfilling such vision, particularly the intelligence at the edge, is extremely challenging, due to the limited resources of edge devices as well as the ubiquitous coverage envisioned by 6G. To empower the edge intelligence, in this article, we propose a novel framework called AGIFL (Air-Ground Integrated Federated Learning), which organically integrates air-ground integrated networks and federated learning (FL). In the AGIFL, leveraging the flexible on-demand 3D deployment of aerial nodes such as unmanned aerial vehicles (UAVs), all the nodes can collaboratively train an effective learning model by FL. We also conduct a case study to evaluate the effect of two different deployment schemes of the UAV over the learning and network performance. Last but not the least, we highlight several technical challenges and future research directions in the AGIFL.

I. INTRODUCTION

Although the fifth generation (5G) networks are being deployed and about to be commercially available in 2020, it is predicted that the upcoming 5G networks may still not be able to meet future rapidly growing traffic demands. Accordingly, the beyond 5G (B5G) networks, or say sixth generation (6G), have already received great attention by both the academia and industry around the world. It is envisioned that an essential difference between 6G networks and previous generation networks lies in the revolution of ubiquitous intelligence realization, to enable colorful artificial intelligence (AI) services from the network core to the network edge including the end devices [1]. Nevertheless, realizing such ubiquitous intelligence of 6G is extremely challenging.

Recently, edge intelligence (EI), where intelligence is pushed to the network edge by running AI algorithms on edge devices, emerges as a promising key enabler for 6G to fulfill the vision of ubiquitous intelligence [2]. EI also caters to the trend of most of the big data originated from the center cloud to the network edge, with the proliferation of massive Internet-of-Things (IoT) devices combined with various mobile applications. However, EI is still in its infancy, as it is indeed hard to implement distributed learning based on limited datasets across a huge number of heterogenous resource-constrained devices, especially in the context of ubiquitous coverage by integrating air networks, space networks, and underwater networks into 6G besides the conventional terrestrial networks.

In this work, motivated by the recent advance of an emerging distributed machine learning (ML) methodology, i.e., federated learning (FL) [3, 4], we propose a novel framework of Air-Ground Integrated Federated Learning (AGIFL), to boost the urgently needed EI in 6G. FL is a distributed learning architecture that enables multiple resource-constrained end devices to collaboratively train an effective learning model in a federated manner. Our proposed AGIFL is a marriage of FL and air-ground integrated networks (AGINs), where AGINs flexibly deploying unmanned aerial vehicles (UAVs), balloons, and airships with flying base stations are a critical part of 6G to support near-instant and seamless super-connectivity.

There are several studies that investigate how to utilize FL for the intelligence of UAV networks in existing literature. Zeng et al. [5] propose a novel framework to enable FL within a swarm of UAVs, which is the first work considering how to implement FL for the UAV swarm. Shiri et al. [7] study the online path control problem of massive UAVs by FL and mean field game (MFG) theory, where each UAV periodically exchanges the Hamilton-Jacobi-Bellman (HJB) NN model parameters in MFG with other UAVs in a federated manner. Lim et al. [8] propose an FL-based sensing and collaborative learning scheme for UAVs, where UAVs collect data and participate in the collaborative model training for Internet of Vehicles (IoV) applications. Brik et al. [9] discusses several potential applications of federated deep learning (FDL) in UAVs-enabled wireless networks, and highlights the key challenges, open issues, and promising future research topics therein. However, most of them consider how to empower the aerial-part intelligence only, rather than the ubiquitous intelligence for the whole AGINs, which is more challenging due to the flexible but more complex environment of the AGINs. In contrast, we focus on how to bring the intelligence into the whole AGINs, by proposing a new AGIFL framework.

This article aims to provide a preliminary attempt to realize the ubiquitous intelligence. The rest of this article is organized in the follows. We first introduce the basic concept of FL with its potential for 6G networks in Section II. We then present the proposed AGIFL framework in Section III and its different forms in Section IV. In Section V, we analyze the main technical challenges of the AGIFL, while we conduct a case study of AGIFL to evaluate its corresponding performance in Section VI. Section VII concludes the paper.

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II. FL AND ITS POTENTIAL FOR 6G NETWORKS

In this section, we first provide an overview of FL through an example of federated deep learning, and then discuss its potential for future 6G networks.

A. Overview of FL

FL is an emerging distributed architecture which enables multiple end devices to collaboratively train a learning model in a federated way. The main advantage of FL lies in that it can utilize the limited on-device processing power and private local training data to distributively perform the model training, without allowing the data leave from its owner. FL was originally introduced by Google [3], [4], which aims to train a clustering or classification model with training data such as images, videos or texts distributed over a large number of end devices, while reducing network overhead and alleviating privacy concerns. Although the initial FL refers to the federated deep learning framework, it can be actually used to train a FL model for many other advanced machine learning algorithms, e.g., federated deep reinforcement learning [5].

Next, we introduce the basic idea of FL through briefly describing the celebrated FedAvg scheme [6]. As illustrated in Fig. 1 there are generally two main entities in FL: the parameter server and multiple training participants who are data owners. With the help of the parameter server, FedAvg enables these participants to collaboratively train a shared learning model, while keeping all the local training data at each participant. First, the parameter server distributes the global model to all participants (an initial global model is generated by the parameter server in the very beginning). Secondly, based on the latest received global model, each participant employs its own training data to update a local model. Thirdly, each participant uploads the updated local model parameters (i.e., model weights) only to the parameter server. Lastly, the parameter server will aggregate all received model weights by the weighted average method to update the global model. If the convergence condition is satisfied, the FL training terminates; otherwise, the above iteration continues. Note that the traditional ML approaches employ the entire training dataset consisting of the data at each user/participant, to train a global learning model in a centralized manner.

B. Potential of FL for 6G Networks

Federated learning has the potential to realize the ubiquitous intelligence envisioned by 6G networks while preserving the user privacy. Specifically, it can empower the edge intelligence even if the number of participants is in massive-scale and the collected data of different users is heterogeneous, which are supposed to be very common in 6G networks. Recent experimental results demonstrate that FL can converge to the optimum point, even when the number of participants is much larger than the average number of training samples in the dataset of each participant [10]. And both experimental and theoretical studies [10], [11] validate that FL supports model training among multiple users with non-identically distributed (non-IID) training datasets, whose convergence can be guaranteed in such a non-IID case. Moreover, since the information shared by each participant is about the learning model parameters rather than the original local data, the privacy of participants could be well protected. Nevertheless, the model update may also leak partial information of participants, while the security of FL could be further improved by exploiting more advanced security and encryption measures including differential privacy and secure aggregation.

III. AIR-GROUND INTEGRATED FEDERATED LEARNING: MOTIVATION, OVERVIEW, VISION, AND NOVELTY

In this section, we propose the framework of AGIFL, which features FL as a key enabler to empower the air-ground integrated networks intelligence. In the following, we first explain its motivation, then provide an overview of the AGIFL framework, and lastly present the vision.

Motivation: Recalling the potential of FL for 6G networks as in Sec. II-B, the AGIFL framework is motivated by the following reasons. On one hand, as a critical part of the core potential architecture of future 6G networks, the AGINs are also expected to be with ubiquitous intelligence. More critically, it is envisioned that the required intelligence could be obtained locally at such edge networks for fast response and better data privacy protection, i.e., edge intelligence. On the other hand, as mentioned before, FL can enable multiple users with limited computation power and heterogeneous training dataset to collaboratively train an accurate learning model, without allowing the data leaving out of each user. And the FL architecture is highly flexible in the sense that it can take many forms as desired. Therefore, FL could perfectly solve the ubiquitous edge intelligence urgently needed by the AGINs.

Overview: In general, the AGIFL framework includes different forms of FL between air and terrestrial networks, where the parameter server could be a peer node like a UAV or terrestrial BS according to different scenarios. First, exploiting the wide coverage and maneuverability of UAVs, when some terrestrial nodes such as mobile users need to collaboratively obtain a global learning model, a UAV can be deployed on-demand and act as the parameter server for these users. Secondly, a swarm of UAVs with collected local data as flying users may also exploit ML to execute complex tasks, where a terrestrial BS can be the parameter server to enable the FL among them. There are also other forms of FL in the proposed AGIFL framework, which will be introduced in detail in Sec. III-B.

Vision: We envision that the AGIFL framework can efficiently address the challenge of edge intelligence generation in the AGINs. Specifically, based on the AGIFL framework, the edge users in the AGINs, e.g., mobile users, IoT devices, and UAVs, can support various on-device intelligent applications, independent of centralized data processing. Thus, the anticipated giant volume of data generated by billions of IoT devices at the network edge could be efficiently processed in a distributed way. In addition, we believe that, the privacy and security of the data distributed at different users can be protected in the AGIFL framework, which relieves the increasingly concern about the privacy issues.
Novelty: As shown in Table I, our proposed AGIFL differs from the classical FL and general wireless FL, because it expands the network dimension and application scenario, and considers more key design factors. First, the AGIFL could boost the intelligence for the AGINs in the three dimensions, while both classical FL [3], [4] and general wireless FL [13], [14] suit to the terrestrial networks in the two dimensions only. Secondly, compared to them, the AGIFL should consider the joint training configuration and wireless setting, under the flexible but complex air-ground network deployment. For example, the dynamically configurable location of aerial nodes could affect the energy consumption of both aerial and terrestrial training nodes, which results in the achieved learning performance, since there may be a strict energy budget of these nodes, especially in the flying aerial nodes. To summarize, the AGIFL is a whole new learning framework for realizing the ubiquitous intelligence within the AGINs, which brings a lot of research opportunities.

IV. DIFFERENT FORMS OF AGIFL

We now introduce all the forms of AGIFL one by one. The criterion for dividing the forms is set up by who the parameter server and training participants are, which is actually due to different intelligence needs. Note that we omit the ground to ground (G2G) federated learning in this work, since it is identical to the traditional FL.

A. A2A Federated Learning

First, we introduce the air to air (A2A) federated learning, where the training process happens within the aerial networks only. One typical example is the FL framework proposed in [6], which enables FL within a swarm of wirelessly connected UAVs. We generalize that framework as the A2A federated learning in the AGIFL, whose application scenario is shown in Fig. 2(a). In the A2A federated learning, one aerial node such as a leading UAV or unmanned airship plays a role of the parameter server, while several aerial nodes act as the training participants. Example applications of the A2A federated learning include various ML tasks execution in the sky, e.g., coordinated trajectory planning, cooperative target recognition, surveillance and monitoring for both military and civil use, with the help of a swarm of UAVs and unmanned airships, and etc.

B. G2A Federated Learning

Secondly, unlike the A2A federated learning within the aerial networks solely, we envision that the aerial platform could play a critical role in boosting ubiquitous edge intelligence for the terrestrial networks, which is termed as ground to air (G2A) federated learning in this work. To be specific, a UAV can be employed as the parameter server to meet the need of collaborative learning model training of multiple terrestrial nodes distributed over a large area, as shown in Fig. 2(b). One fascinating point of the G2A federated learning lies in that, combined with the wide coverage, the higher flexibility of aerial nodes’ movement can be effectively utilized to enable the collaborative training of terrestrial networks on demand, without any ground infrastructure support. The G2A federated learning is very suitable for the Artificial Intelligence & Internet of Things (AIoTs), where UAVs can be deployed on-demand to support the learning model training of massive number of IoT nodes. It is worth noting that this kind of FL has seldom been discussed in existing works.

C. A2G Federated Learning

Thirdly, different from the G2A federated learning, the edge intelligence of the aerial networks can also be boosted with the help of static or mobile terrestrial nodes, i.e., air to ground (A2G) federated learning. Specifically, as shown in Fig. 2(c), multiple aerial nodes with corresponding collected data train a ML model in a federated way, when a terrestrial node such as ground BS is employed as the parameter server. For example, for the traffic prediction over a target region in an Intelligent
TABLE I: A comparison of classical FL, general wireless FL, and AGIFL.

| Works                        | Network Dimension | Application Scenarios                                      | Key Design Factors                                                                 |
|------------------------------|-------------------|------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Classical FL (e.g., [3], [4])| Two-dimension     | Training at terrestrial mobile devices                     | Training configuration                                                              |
| General wireless FL (e.g., [13], [14]) | Two-dimension     | Training in terrestrial networks                           | Joint training configuration and wireless setting                                    |
| Our proposed AGIFL           | Three-dimension   | Training in air-ground integrated networks                 | Joint training configuration and wireless setting under air-ground network deployment |

Transport System (ITS), several UAVs covering different sub-regions can be employed to first collect traffic flow from road side units (RSUs) or capture real-time traffic data over highways, and then return to the corresponding UAV bases for collaborative model training, under the guidance of a terrestrial model owner as the parameter server [8]. Compared to the A2A federated learning, the A2G federated learning might enable more powerful intelligence for the aerial networks, since UAVs with limited energy budget need not be as the parameter server besides the training participants, and the A2G communication link may be better than the A2A link. We believe that in future 6G networks, the edge intelligence could be obtained in such a mixed federated way.

D. Mixed Federated Learning

Lastly, we also anticipate that the AGIFL can work in a highly flexible manner in the AGINs, known as mixed federated learning, i.e., both aerial and terrestrial nodes could be as the training participants and parameter server as required. As Fig. 2(d) shows, a number of terrestrial devices and UAVs, both with private collected raw data, aims to train a FL model, where a UAV covering those nodes acts as the aggregated parameter server. It is worthy noting that a terrestrial node such as a ground BS can also be the parameter server, and a UAV can be the model parameter forwarding node, by exploiting its wide coverage as well as flexible deployment.

V. TECHNICAL CHALLENGES

The features of AGINs including three-dimensional mobility, frequent inevitable air-ground interactions, and relatively constrained resources such as communication, computation, and energy, together with unique learning requirements, result in difficulties in learning-oriented network design and optimization. Note that the aforementioned features distinguish the proposed AGIFL from both classical FL and general wireless FL, since those features can affect the training performance of FL in terms of training latency and energy consumption, or even training accuracy considering limited energy budget of aerial/terrestrial nodes. In this following, we pose several technical challenges in detail in the AGIFL.

A. On-Demand Network Deployment for AGIFL

The aerial layer in the AGINs is dynamically configurable by nature, i.e., the aerial nodes such as UAVs and unmanned airships are generally deployed on-demand. Thus, it is inevitable to optimize the deployment of the aerial nodes to cater to the FL model training, e.g., how to determine the optimal location of the aerial node as the parameter server in the G2A...
and mixed FL. However, it is challenging to optimally deploy the aerial nodes in the AGIFL in the following aspects.

**Learning-oriented deployment:** different from maximizing the quality-of-service/experience (QoS/QoE) in traditional AGINs, maximizing the learning performance such as maximizing training accuracy and minimizing training latency is the main optimization objective in the AGIFL, which obviously alters the optimal deployment decision of the aerial nodes to achieve that goal.

**Long-term plan of deployment:** since the model training in FL always lasts for multiple training rounds, the deployment decision of the aerial nodes should account for the long-term training profit, rather than the short-term profit within one single round, which is hard to optimize due to the complexity of multi-stage training.

**On-demand movement trajectory:** in some dynamic scenarios, e.g., the training participants in the G2A FL are smart vehicles, the location of the aerial node as the parameter server should not be static and thus its movement trajectory should be determined, which is extremely challenging to tackle.

**B. Learning-Oriented Resource Allocation and Training Configuration**

In the AGIFL, the current AGIN is built up for boosting the learning performance of the model training. This calls for the learning-oriented joint resource allocation and training configuration, which differs from the design of AGINs \cite{12} and FL optimization for general wireless networks \cite{13, 14}. Specifically, the optimization of the current AGINS is learning-oriented, while that of the general AGINs is QoS/QoE-oriented. In addition, although there emerge several recent studies about how to optimize the performances of FL in wireless networks \cite{13, 14}, they do not consider the on-demand deployment of aerial nodes and apply to the FL within the terrestrial networks only.

There exist two main difficulties in solving the above problem. First, the problem involves multiple variables to be jointly optimized, i.e., the location of the aerial nodes, the allocation of different resources in terms of communication and computation, and the decision of training parameters such as number of training rounds, number of chosen participants per round, number of the local updates, and mini-batch size. It makes the above problem a natural mixed-integral problem (MIP) and is hard to solve in general. Secondly, as it needs multiple air-ground interactions over the inherent unreliable wireless channel, how to design robust training strategies to guarantee the overall learning performance against the unreliable data transmission in the AGIFL is hard. Specifically, the unreliable data transmission may lead to the loss of some updated local or global model parameter in any training round, which obviously slows down the training process. Even worse, the loss of the model update is uncertain owing to the uncertain wireless channel loss, thereby increasing the difficulty of designing robust training strategies.

**C. Energy Efficient Training Strategies for AGIFL**

Pursuing high energy efficiency is critical for realizing its potential benefits of the AGIFL, since the model training may cost much energy consumption and the energy budget of the aerial nodes as well as terrestrial nodes including IoT nodes is limited. Recalling the training process of FL, the training participants undertake the most computation work and consume some energy in transmitting local model updates, while the parameter server consumes less energy because the simple aggregation of local model updates consumes little energy, besides the almost same energy consumption of broadcasting global model update. In the AGIFL, putting more weight on which part in optimizing the energy consumption depends on the exact form. For instance, in the G2A FL, it is more reasonable to optimize the energy consumption of the terrestrial nodes to maximize the learning performance or guarantee the minimum learning performance. In contrast, in the AG2 FL, we should be more concerned with the energy efficiency of the aerial nodes, as any aerial node will spend much energy in model training, communicating, and flying. As seen in the above, the energy efficiency problem varies with different forms of the AGIFL. Additionally, the energy model of the aerial nodes is more complex than that of the terrestrial ones. In a word, it is very challenging to design energy efficient strategies for the AGIFL.

VI. Case Study: G2A Federated Learning

We conduct a case study to evaluate the performance of the proposed AGIFL framework by numerical simulations. To be specific, we focus on the G2A FL where a UAV is employed as the parameter server for the FL of multiple terrestrial nodes. And we mainly evaluate the effect of different UAV’s hovering location deployment schemes on the learning performance and UAV’s energy consumption.

**A. Settings**

We consider a UAV-assisted network where a rotary-wing UAV with the ability to hover over a set \( U \) of \( U = 100 \) terrestrial users, each with a local training dataset. Employing the UAV as the parameter server, these users collaboratively train a learning model for inference, where the model training requires interactions between the UAV and users within multiple rounds. In each round, the UAV aggregates a global model and distributes it to the users, and each user then updates its local model by its own dataset and sends it to the UAV. Following \cite{4}, we choose only a random fraction \( \theta = 0.02 \) of users for model update at the beginning of each round. And the learning rate is fixed at 0.01 and the number of local epochs is set as 5 with the mini-batch size 10. In this simulation, for the training task, we consider the image classification using convolutional neural network (CNN) on the classical MNIST dataset \cite{4}.

For the UAV, we suppose its transmission power and propulsion power equal to 10 mW and 100 W, respectively \cite{15}. For the users, we assume the computation capacity of user \( u \in U \) and number of CPU cycles to execute one bit of the sample data are chosen randomly from the interval \([1.8 \text{ GHz}, 2.0 \text{ GHz}]\)
SumDist scheme achieves higher accuracy than the Random scheme, whose gap increases with the number of training rounds. This implies that the hovering location of the UAV should be carefully optimized, because the UAV usually has a strict energy budget. Secondly, as shown in Fig. 3(b), when the UAV’s energy budget is increased, the maximum training accuracy is also higher, because the training could be run more rounds, with the increased energy budget. Also, we find that the Min_SumDist scheme achieves higher accuracy than the Random scheme, since the former consumes less energy than the latter with the same number of training rounds. To sum up, the deployment of the UAV as well as its inborn energy constraint has a great impact on the performance of the AGIFL.

VII. Future Research Directions

Despite its great potential, the study on the AGIFL is still in its infancy, where many key research issues need to be addressed. In this section, we discuss several potential research directions for future study.

Joint Optimization of UAVs’ Locations, Resource Allocation, and Training Parameters in AGIFL: Motivated by the challenges stated in Sec. V, a critical but challenging research question is how to jointly optimize UAVs’ locations, resource allocation, and training parameters, to boost the learning performance. There are numerous studies about how to jointly optimize UAVs’ locations/movement trajectories and resource allocation in existing works, whose solutions however cannot be applied to that problem, since it involves various additional training variables and is a brand-new problem. Furthermore, the problem form as well as its related constraints is different in different forms of the AGIFL, so there may not exist a general solution framework to it.

Block Chain-Based Secure Model Parameters Exchange for AGIFL: Although FL enables multiple devices to collaboratively train a shared learning model without exchanging their private local data, there still exists a potential risk
of information leakage, as the model parameter exchange may also be used to derive some private information by the malicious participants. Block chain is a recently emerging distributed ledger technology where a network of participants reach agreements on shared data, independent of a central trusted authority. Intuitively, it is worthy to study how to exploit block chain in the AGIFL for the data security.

**Intelligent Collaboration among Multiple Aerial Nodes for AGIFL:** It usually needs multiple aerial nodes including UAVs and unmanned airships for model training in the AGIFL. For some, aerial nodes may act as the model update forwarders for some terrestrial participants in the mixed FL. Thanks to the aggregation of model update by weighted averaging in FL, an aerial node as the model update forwarder could aggregate the received local updates in advance and then send the partial aggregated model update to the parameter server. Therefore, it is interesting to investigate how many aerial nodes are needed to cover a number of terrestrial participants and how to intelligently collaborate them.

**Decentralized AGIFL without a Central Parameter Server:** The current AGIFL employs the most widely used FL strategy, which relies on a central node as the aggregated parameter server. It is more attractive to develop a fully decentralized AGIFL framework to adapt the dynamic environment of the AGINs. This especially suits for the A2A FL, since such a centralized framework may be prone to failure due to the breakdown of some aerial node as the parameter server. The decentralized AGIFL is more flexible and robust, but may introduce much overhead because of a large amount of model parameter exchange among the training participants.

**VIII. Conclusion**

In this article, we have proposed the AGIFL framework to empower the edge intelligence to realize the required ubiquitous intelligence for future 6G networks. Specifically, the AGIFL utilizes FL to enable all nodes in the AGINs to collaboratively train a learning model, with the help of flexible controllable deployment of aerial nodes. We have introduced the basic concept of FL and its potential, described the overall framework as well as its different forms, discussed several main technical challenges, conducted a case study of AGIFL, and highlighted some promising future research topics.

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