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Federated Learning for UAVs-Enabled Wireless Networks: Use Cases, Challenges, and Open Problems

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ABSTRACT The use of Unmanned Aerial Vehicles (UAVs) for wireless networks is rapidly growing as key enablers of new applications, including: surveillance and monitoring, military, delivery of medical supplies, telecommunications, etc. In particular, due to their unique properties such as flexibility, mobility, and adaptive altitude, UAVs can act as mobile base stations to improve capacity, coverage, and energy efficiency of wireless networks. On the other hand, UAVs can operate as mobile terminals to enable many applications such as item delivery and real-time video streaming. In such context, data-driven Deep Learning-assisted (DL) approaches are gaining a growing interest to not only exploit the huge amount of generated data, but also to optimize the network operations, and hence ensure the QoS requirements of these emerging wireless networks. However, UAVs are resource-constrained devices especially in terms of computing and power resources, and traditional DL-assisted schemes are cloud-centric, which require UAVs' data to be sent and stored in a centralized server. This represents a critical issue since it generates a huge network communication overhead to send raw data towards the centralized entity, and hence may lead to network bandwidth and energy inefficiency of UAV devices. In addition, the transferred data may contain personnel data such as UAVs' localization and identity, which can directly affect UAVs' privacy concerns. As a solution, Federated Deep Learning (FDL), or distributed DL, was introduced, where the basic idea is to keep raw data where it is generated, while sending only users' local trained DL models to the centralized entity for aggregation. Due to its privacy-preserving and low communication overhead and latency, FDL is much more adequate for many UAVs-enabled wireless applications. In this work, we provide a general introduction of FDL application for UAV-enabled wireless networks. We first introduce the FDL concept and its fundamentals. Then, we highlight the possible applications of FDL in UAVs-enabled wireless networks by addressing the suitability and how to use FDL to deal with target challenges. Finally, we discuss about key technical challenges, open issues, and future research directions on FDL-based approaches in such context.

INDEX TERMS Deep learning, federated deep learning, UAVs-based wireless networks, wireless communications.

I. INTRODUCTION

Next-generation of wireless networks are undergoing a major revolution. According to Cisco forecast, more than 75 billion of connected IoT devices are expected by 2025, ranging from sensors, wearable, smartphones, to connected cars, and Unmanned Aerial Vehicles (UAVs) [1]. This transformation is driving an exponential growth in wireless traffic generated by heterogeneous connected devices. In such context, UAVs, known also as drones, are quickly growing by admitting

many key applications in wireless networks, ranging from surveillance, monitoring, and delivery of medical supplies, to military and telecommunications [2], [3]. In particular, due to their unique properties such as flexibility, mobility, and adaptive altitude, UAVs can operate as providers of wireless network infrastructure to improve capacity, coverage, and energy efficiency of wireless networks. On the other hand, UAVs can also act as flying users of existing wireless infrastructure to enable applications such as remote sensing, virtual reality, and item delivery. In fact, these new applications are coming with different requirements and needs [3]. Besides the need of high data rates – which has been the main

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requirement of conventional wireless networks in the last decade – UAVs-based wireless networks have to deliver low-latency and ultra-reliable services to cope with the dynamics of end users [4], [5]. For example, autonomous drones require the deployment of ultra-reliable communication links in order to provide real-time and low-latency control of such autonomous devices [6]. Moreover, UAV devices are limited in terms of computing and energy resources and realizing such applications is mainly related to UAVs' flight time, which depends on many factors like, UAVs' energy, speed, altitude, trajectory, etc.

On the other hand, Machine Learning-assisted (ML) approaches are gaining a growing interest in many research fields including wireless networks [7], [8]. Indeed, the use of ML-based approaches for wireless networks is motivated by not only the huge amount of generated traffic data but also the inefficiency of traditional model-based solutions that are not capable to deal with the dynamic complexity and heterogeneity of the next wireless networks [8]. This enables to integrate more intelligent functions in order to optimize the network operations and ensure, in real-time, different needs of emerging wireless applications. In other words, wireless devices will be able to intelligently control their environment as well as proactively taking more adequate actions by learning and predicting the dynamic evolution of various network features, e.g. traffic pattern, communication channel dynamics, user context, content requests, etc. Moreover, as the flagship of ML, Deep Learning (DL) is emerging as the most advanced ML component outperforming conventional ML schemes [9]. DL is expected to become the most used scheme in many fields including wireless networks, robotics, image, text, and speech recognition, language processing, etc. [9].

However, traditional ML schemes are cloud-centric and require the data to be sent and processed in a central entity, e.g. a cloud server or a data center. These ML schemes are not suitable for the UAV-based wireless networks for the following reasons. Firstly, the inaccessibility of private data since the generated data may contain personal and sensitive information such as UAVs' localization and identity. Secondly, the transfer of stream raw data to the cloud continuously by UAVs, such as image and video data types, require a high network bandwidth and consume more UAVs' energy, especially with the limited available bandwidth and UAVs' energy-constrained. Finally, the cloud-centric schemes involves an unacceptable latency especially for applications that need real-time decisions such as autonomous drones monitoring and UAV-based virtual reality applications. Therefore, there is an imperative need to go toward decentralized learning solutions to handle efficiently distributed sub-datasets generated by UAV devices.

Recently, Google introduced Federated Deep Learning (FDL) concept [10], [11], as a decentralized approach. In FDL, wireless devices use their local data to train, cooperatively, local DL models, and send the local models, i.e. models' weights, to a FDL server for aggregation. Thus, FDL enables to keep the private data where it is gen-

erated and to train DL models in a distributed manner. In addition, FDL improves highly the network overhead by avoiding to send data towards a central entity. Thus, FDL consumes less bandwidth as compared to the centralized ML scheme. Moreover, it was demonstrated that FDL is more suitable for ultra low latency applications since it enables wireless devices to collaboratively, and in parallel, learn a shared prediction model while keeping all the training data on device [12]. This implies that FDL can be an enabling technology for next UAVs-based wireless networks to train learning models, as compared to the centralized cloud-centric approaches. In this context, since UAVs cannot independently support centralized schemes of deep learning due to power and computing limitations in addition to the limited available bandwidth, the FDL concept is more suitable for UAVs-based wireless networks. FDL provides not only privacy-preserving of UAVs' data but also reduces both network overhead and latency by avoiding to send experienced data to a central node. In this paper, we detail how FDL can be applied for UAVs-enabled wireless networks to deal with their challenges. Moreover, we address the suitable deep learning algorithm to deal with each challenge and why it is suitable.

To the best of our knowledge, there are only two works that review the usage of FDL for wireless networks [13], [14]. The authors in [13] extend the original FDL work [10], [11] and discuss about its use cases in cellular 5G architecture, while the authors in [14] focus on the mobile edge networks, aiming at bringing the intelligence, learning models, closer to the edge where data is generated. Unlike these two works, we address the FDL application for the emergent UAVs-based networks. Our work covers mainly: (i) an introduction on the general FDL concept and its features. (ii) FDL use cases in UAVs-enabled wireless networks, spanning from 5G networks and beyond, IoT, Edge computing and caching, to Flying Ad-Hoc Networks. (iii) An extensive discussion about open challenges that require further research efforts. These challenges are mainly related to learning security, convergence and scalability.

The remainder of this paper is organized as follows. Section II gives a general background on FDL. The main applications of FDL for UAVs-based wireless networks are highlighted in section III. Section IV describes open problems and future research directions. Section V concludes the paper.

II. OVERVIEW ON FEDERATED DEEP LEARNING

Federated Deep Learning (FDL) is based essentially on Deep Neural Network (DNN) to train collaboratively learning models on end devices, while alleviating privacy concerns and reducing communication overhead. It should be noted that federated learning may be based on any ML algorithm to train a federated learning model. In this work, we focus only on deep learning as it represents the most advanced ML approach. In this section, we first introduce DNN model training. Then, we give a general overview on the emerging FDL concept.

A. DEEP NEURAL NETWORK

DNN has become an essential tool in Artificial Intelligence field, due to its success and progress in many domains. A DNN is composed of three main levels of layers: (i) an input layer, (ii) multiple hidden layers that map an input to an output, and (iii) an output layer. A weighted and bias-corrected input values are passed over an activation function, such as ReLu and Softmax functions [9], to obtain an output [9].

First, the dataset is divided into the training and test subsets. Then, the training subset is fed to the neural network, as input data for the optimization of weights. The weights are updated using stochastic gradient descent (SGD) method with a predefined rate (learning rate), such that the loss function, i.e., distance between the real and model output, is minimized. The training process is repeated over many epochs, i.e., full passes over the training subset, for accuracy improvement.

As a machine learning technique, DNN algorithms can be classified into three main categories:

- Supervised learning: the considered dataset comprises both input and output features. Thus, in supervised learning, a DNN algorithm is used to learn the mapping function from the input to the output [15].
- Unsupervised learning: the considered dataset contains only input features. In this case, a DNN algorithm must be able to extract all types of unknown patterns over input features [16].
- Reinforcement learning: It is based on a feedback loop between the used DNN algorithm and the surrounding environment. Hence, the used DNN algorithm will experience a dataset that changes over time [17].

We note that in this work, we focus more on DNN supervised learning, where there are several variants used according to the target problem [9], such as, Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN). However, describing these architectures is out of the scope of this paper.

B. FEDERATED DEEP LEARNING

The FDL concept is composed of two main entities: the clients (participants) which are the data owners and the Federated Learning (FL) server. Let $N = \{1, \dots, M\}$ denotes the set of M participants, each $i \in N$ has a private Data Subset $DS_{i \in N}$. Each participant i trains a Local Model L_i using its local data subset $DS_{i \in N}$, and then sends only the local model parameters, i.e. model weights, to the FL server. Finally, all received local models are aggregated to create a Global Model $G = \cup_{i \in N} L_i$. It is worth noting that traditional machine learning approaches use $D = \cup_{i \in N} DS_i$ to train a global model, in a centralized way.

In fact, the global model aggregation step is an important part of the FDL system. The FDL system is based mainly on a *FederatedAveraging* (or *FedAvg*) algorithm [11] and illustrated in **Algorithm 1**. The FL server first initializes the training process (line 3). Then and at each round, it selects

a randomly subset of participants and aggregates their local models in order to generate a global model (lines 4 – 11). On the other hand, for a given number of epochs, each participant splits its data into batches¹ (lines 15 – 16). Then, based on a learning rate, it updates its local model by applying an average gradient on each batch at the current local model (lines 17 – 20). This enables to implement the Stochastic Gradient Decent (SGD) with a fixed learning rate, in a distributed manner.

Algorithm 1 *FederatedAveraging* [11]

Require: Number of server Round Max_Round , number of clients M , number of local epochs E , Batches size B , learning rate η .

Ensure: Global model G^{j+1} .

```

1:
2: Executed on Server executes:
3: Initialize  $G_0$ 
4: for  $j = 1$  to  $Max\_Round$  do
5:    $P =$  random set of clients of  $M$ 
6:   for Each client  $i \in P$  in parallel do
7:      $L_i^{j+1} \leftarrow ClientUpdate(i, L^j)$ 
8:   end for
9:    $G^{j+1} \leftarrow \frac{1}{|P|} \sum_{i=1}^{|P|} L_i^{j+1}$ 
10: end for
11: return  $G^{j+1}$  to participants.
12:
13: Executed on Client  $i$ :
14:  $ClientUpdate(i, L)$ 
15: for Each local epoch  $e$  from 1 to  $E$  do
16:   batches  $\leftarrow$  (split data  $DS_i$  into batches of size  $B$ )
17:   for Each batch  $b \in$  batches do
18:      $L \leftarrow L - \eta \nabla f(L, b)$  ( $\nabla f(L, b)$  is the average
    gradient on batch  $b$  at the current model  $L$ )
19:   end for
20: end for
21: return  $L$  to FL server.

```

Although the primary objective of the FDL concept is privacy-preserving, shared some local models may still reveal private information. Thus, participants can add a protection layer by sending encrypted local models to the FL server. Then, the latter uses a secure aggregation algorithm to aggregate the local models without decrypting them [18].

C. FEDERATED DEEP LEARNING FOR UAV-BASED NETWORKS

In UAV-based networks, UAVs may collaboratively build a learning model based on FDL concept. As we mentioned before, this will not only preserve privacy of UAVs' data but also improve the use of UAVs' resources including energy and computing resources. FIGURE 1 illustrates the FDL

¹A batch refers to a random subset of a participant's local dataset

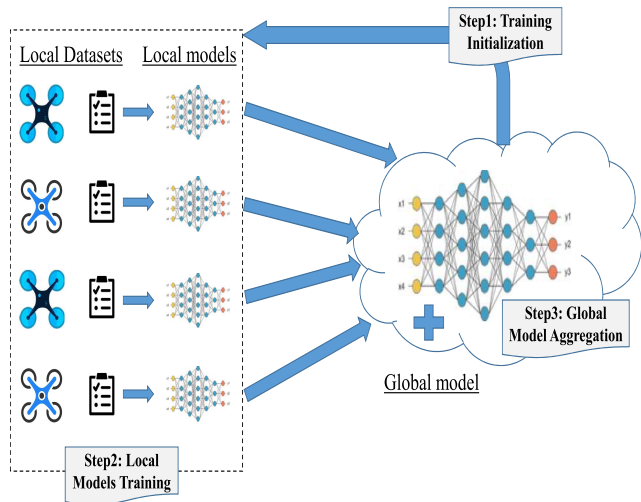


FIGURE 1. Training process of UAV-based networks using Federated Deep Learning.

training process of UAVs-based networks. It comprises three main steps:

- Step 1 (Training Initialization): According to the target application, the FL server, which may be edge or cloud server, specifies needed data type and training hyper parameters including learning rate and number of epochs. The FL server also generates an initial global model G_0 . Then, G_0 , data type requirements, and training hyper parameters are broadcasted to participating UAVs (clients). We note that the FL server decides about both learning rate and number of epochs so as not to deplete UAVs' resources.
- Step 2 (UAVs' Models Training): Each UAV i starts to collect new data and update parameters of its local model L_i^j , based on the global model G^j , where j is the current iteration index. Each UAV also aims to find optimal parameters minimizing the loss function. The updated parameters are periodically sent to the FL server.
- Step 3 (Global Model Aggregation): When receiving the local models from UAVs, the FL server aggregates them and sends back the updated model parameters to the UAVs. The FL server aims to minimize the average global loss function $Loss(G^j)$, i.e.:

$$Loss(G^j) = \frac{1}{M} \sum_{i=1}^{i=M} Loss(L_i^j) \quad (1)$$

We note that the local training and aggregation steps (Steps 2-3) are repeated until a desired accuracy is achieved or the loss function converges.

III. FEDERATED DEEP LEARNING APPLICATIONS IN UAV-ENABLED NETWORKS

Having introduced FDL and its main features, we now highlight some of its use cases in UAV-enabled wireless networks. TABLE 1 illustrates the target FDL applications for UAV-enabled networks along with references. For each

UAV-enabled network, TABLE 1 describes the main challenges that FDL can deal with, the main components of FDL such as clients, aggregator, and feature data, and the expected results after applying the FDL.

A. UAV FOR 5G CELLULAR NETWORKS

UAV Applications: As cost effective approach, deploying UAVs as base stations in 5G is envisioned as a promising solution for improving wireless connectivity as well as extending network coverage, especially for geographical zones with a lack of cellular infrastructure [3]. In particular, UAV base stations would be useful and economically viable to deploy small cells during temporary events, such as festivals and sport events [19]. On the other hand, UAVs can also act as users of the 5G wireless infrastructure for remote sensing, surveillance, package delivery, and virtual reality applications [20]. Moreover, to deal with blockage and interference of wireless backhauling, UAVs can play a vital role in enabling reliable and cost-effective connectivity between a set of base stations and a core network, in terrestrial networks [21].

Challenges and FDL use cases: In such context, we focus on three key challenges [3].

- Wireless signal propagation:** The Air-to-Ground communication (A2G) channel is more susceptible to path loss, delay spread and fading, as compared to the traditional ground communication channel. In fact, the A2G channel depends highly on the UAV altitude and type of the propagation environment. However, centralized learning solutions are not suitable for this challenge as they require privacy-sensitive UAVs data, such as altitude and mobility data, to be transmitted to a central entity. Therefore, the FDL concept may be used to enable each UAV predicting, in a federated way, the A2G channel quality related to its altitude and mobility information. UAVs will be able to dynamically adjust their altitude in a self-organizing way, and hence autonomously optimize the A2G communication. Using an ANN as reinforcement learning [22], UAVs can adjust their location to serve ground users according to the predicted channel quality and hence adapt dynamically to the propagation environment. We note that an ANN corresponds perfectly to this challenge in order to build a multi-variable regression model about predicting the continuous values of channel quality variable.
- UAVs trajectory planning:** It is mainly impacted by UAVs' energy constraints. Usually, both UAVs mobility and energy consumption metrics have to be coupled in order to deal with this challenge. Consequently, the UAVs' mobility and energy level are required, which may not be easy to share in the network because of privacy concerns. In this case, the FDL concept is more adequate so that each UAV may learn about local energy consumption related to each mobility trajectory. This enables UAVs determining their trajectories by predicting the energy consumption of each potential

TABLE 1. FDL applications in UAV-enabled networks.

UAV-enabled network	Challenges	Federated Deep Learning			Results	
		Clients (Participants)	Aggregator (Central node)	Considered Feature Data		Learnt Local and global models
5G cellular	Wireless signal propagation (A2G)	UAVs	Edge or cloud server	Type of propagation environment, information about UAV's mobility (speed, direction, positions, altitude, etc.), A2G channel quality.	Prediction of the A2G channel quality	- UAVs Adjust dynamically their altitude, - Autonomously optimize the A2G communication.
	UAVs trajectory planning	UAVs		Positions of source and destination points, information about UAV's mobility (speed, direction, positions, altitude, etc.), UAV's energy consumption.	Prediction of energy consumption of each potential path	- UAVs select the optimal trajectory, - Optimize UAVs' energy consumption.
	Deployment of UAVs as base stations	Ground users		Information about ground user's mobility (positions, directions, speeds, etc.), traffic load distribution of ground user.	Prediction of ground users behavior (mobility and traffic load)	- Optimal deployment of UAVs base stations, - Improve network coverage and connectivity.
Internet of Things	UAVs placement as aerial base station,	UAVs and ground IoT devices		-UAVs: Type of propagation environment, information about UAV's mobility (speed, direction, positions, altitude, etc.), A2G channel quality, - IoT devices: Density of IoT devices, IoT devices' energy, Traffic load of IoT devices.	Prediction of UAVs placement	- UAVs Adjust dynamically their placement and altitude, - Autonomously optimize the A2G communication, - Improve connectivity of IoT devices with UAVs, - Optimize transmit power of IoT devices.
Edge computing	Contents caching	UAVs	Edge server	Content characteristics (freshness, location, occupied memory, content request history, etc.).	Prediction of contents' popularity	- Determine efficiently which contents should be stored in each cache.
	Deployment of UAVs as base stations	Ground users		Information about ground user's mobility (positions, directions, speeds, etc.), contents request distribution of ground user, contents popularity.	Prediction of ground users patterns (mobility and content load)	- Optimal deployment of UAVs base stations, - Improve network coverage and connectivity, - Effectively provide the popular contents.
Flying Ad-Hoc	UAVs trajectory planning	UAVs	Edge or cloud server	Positions of source and destination points, information about UAV's mobility (speed, direction, positions, altitude, etc.), UAV's energy consumption, physical obstacles, service requirements.	Prediction of service performance of each potential path	- UAVs select the optimal trajectory, - Optimize service performance, - Optimize UAVs' energy consumption.
	Data routing in multi-hop manner	UAVs		Network topology, information about UAV's mobility (speed, direction, positions, altitude, etc.), targeted routing performance.	Prediction of routing performance of each potential path	- UAVs select the optimal next forwarder, - Extract the optimal routing path between a source and destination nodes, - Dynamically update UAVs' routing table.

path. In this case, the deep RNN with Long Short-Term Memory (LSTM) may be applied to predict next energy consumption due to its effectiveness to deal with time-varying data [23]. We note that LSTM is a modified version of RNN, which makes it easier to remember past data in memory (energy consumptions in our case).

(iii) UAVs deployment as mobile base stations: This challenge is receiving special attention in order to improve network coverage and connectivity. In fact, an optimal deployment of UAVs depends on many factors including geographical area, behaviors of ground users, UAV-to-ground channel characteristics, etc. Accordingly, this challenge is more difficult to address in a centralized way, since it requires different data from different entities. To solve it the FDL concept may be used to deal with each factor separately. For instance, to deal with ground users' behavior, FDL enables to learn ground users' behavior in terms of their mobility pattern. Then, factors' learning models can be combined to generate a global model, which will help to perform optimal deployment and path planning of UAVs base stations. In fact, the mobility pattern of ground users is a set of the spatial and time distribution features of travel behavior. Hence, an hybrid deep algorithm of CNN with LSTM suits this challenge, since CNN can extract spatial features while LSTM deals with time characteristics [24].

(iv) Physical resource allocation: another challenge related to UAVs when they act as mobile base stations is that about Resource Block (RB) allocation to ground users with limited available frequency spectrum. In fact, ground users are heterogeneous in terms of their collected data type as well as data rate requirements that depend to target applications. UAVs must assign the needed number of RBs to meet ground users' requirements. This challenge requires the UAVs to adapt dynamically and in real time to users requirements and centralized learning may introduce more latency to deal with. Therefore, an ANN reinforcement learning, in federated way, is more suitable for this challenge, since it enables the UAVs to collaboratively generate a prediction model regarding the number of RBs to assign [22]. Reinforcement learning makes UAVs able to dynamically assign the needed number of RBs according to the users' needs. Moreover, the ANN reinforcement learning can find relationship between the users' data rate and the UAVs' location, enabling UAVs to find the locations that increase the users' data rates.

B. FLYING AD-HOC NETWORKS

1) UAV APPLICATIONS

Another emerging use case of UAVs is Flying Ad-hoc Networks (FANET), in which a set of UAVs can communicate

with each other in an ad-hoc way [3]. In fact, FANET enables a broad range of applications including remote sensing, disaster and wildfire management, agricultural management, relay networks, etc. In this context, UAVs can play a key role in expanding the communication range and connectivity at geographical zones with limited cellular coverage. Also, UAVs can form a relaying network by providing a reliable communication between remote senders and receivers that cannot directly communicate due to their separation distance or obstacles.

2) CHALLENGES AND FDL USE CASES

This use case inherits the challenge of UAVs trajectory planning between each two start and end points, while considering UAVs' energy constraints, dynamic environment changes like departure (or arrival) of UAVs, physical obstacles (see section III-A, challenge (ii)). Thus, collaboration and coordination between UAVs are crucial features in order to define an optimal UAV trajectory, based on FDL concept. Further, FANET comes with another challenge related to data routing, especially in relaying network, due to its dynamic topology. Data routing must be performed in multi-hop way, in order to deliver efficiently data from a remote transmitter to receiver, through UAVs, and with respect to performance metrics such as end to end delay, packet delivery ratio, and energy consumption. Indeed, dealing with data routing between UAVs in a centralized way needs a direct access to privacy-sensitive UAVs data in terms of their mobility patterns, such as speed, positions, and direction, which may not be possible in practice. Hence, the FDL is a match made in heaven scheme for data routing between UAVs. For instance, each UAV can locally learn about routing performance of each next hope node, based on many factors like direction, speed, mobility pattern, energy, etc. To do so, since it is a multi-variable regression problem which may be linear or not according the data distribution, an ANN may be implemented in order to model the routing problem and provide predictions regarding routing performance related to each next hope node. Then, local models will be aggregated to generate a global model that will help to extract the optimal routing path between the source and destination nodes, in addition to dynamically update of the UAVs' routing table. Moreover, predicting the topology changes of FANET through the prediction of UAVs' next position can highly improve the network performance in terms of communication and control operations. For instance, given limited UAVs' communication ranges, predicting FANET topology, via future positions, gives an idea about FANET connectivity and hence can help to not consider the wireless links that are more prone to failure. Also, predicting FANET topology can help UAVs in search and rescue mission to cover regions that are not already covered. However, as we mentioned in section III-A, challenge (ii), predicting UAVs' mobility cannot be done in centralized way due to privacy issues. So, UAVs can collaboratively learn their own mobility patterns in federated way. Similar to challenge (iii) of section III-A, an hybrid deep algorithm of CNN

with LSTM can deal with UAVs' mobility pattern. Indeed, CNN with LSTM can extract the relationship between spatiotemporal features of UAVs mobility [24].

C. UAV FOR INTERNET OF THINGS NETWORKS

1) UAV APPLICATIONS

The conventional wireless networks are seeing a gradually transformation into a massive Internet of Things (IoT) networks that is composed of a heterogeneous set of devices including, smartphones, drones, tablets, sensors, wearable, and vehicles. IoT networks are expected to enable many applications related to different sectors such as transportation, smart cities, energy management, and healthcare. However, IoT devices are limited in terms of energy battery and have to deliver their data to a terrestrial base station, usually at ultra low latency or high data throughput. In such context, the UAVs are exploited as aerial base stations to provide a reliable wireless connectivity of the massive IoT devices, which enables them to effectively send their data.

2) CHALLENGES AND FDL USE CASES

The main challenge of this application is how to deploy efficiently the UAVs, as aerial base station, to deal with IoT connectivity as well as battery limited challenges [25]. To deal with this challenge, both the A2G channel quality to deal with signal attenuation issue between IoT devices and UAVs (as discussed in section III-A, challenge (i)), and distribution load of ground IoT devices must be considered. Indeed, for the latter issue, a high-resolution traffic load of all devices may be required, which not only is difficult to share in the network due to privacy concerns, but also may increase the network overhead and hence lead that IoT devices consume more energy. Thus, dealing with this issue in a distributed manner is more suitable. To do so, each ground IoT device can build locally a regression model, using a deep ANN algorithm, about its traffic load, before aggregating all local models to build a global model of all IoT devices.

In fact, an optimal placement of UAVs may be determined when combining the two learning models about traffic load and A2G channel quality. Consequently, it enables the IoT devices to efficiently connect to UAVs stations and with a lower transmit power.

D. UAVs FOR CONTENT CACHING AT EDGE COMPUTING

1) UAV APPLICATIONS

Content caching at the edge computing emerges as promising paradigm for applications that are delay-sensitive [14]. It consists in bringing popular content closer to the edge, at base stations or access points, to be exploited locally.

2) CHALLENGES AND FDL USE CASES

As mobile users, one of the main challenges of such paradigm is to determine efficiently which contents should be stored in each cache by predicting the UAVs contents popularity. However, this requires to directly access to private UAVs

information for content differentiation which is not possible in practice. Federated learning is a match made in heaven scheme for contents' popularity prediction as it enables locally training models, and hence data user privacy-preserving. For instance, an Augmented Reality (AR) application needs to access to privacy-sensitive data of users in order to obtain popular elements of the augmentations. It is clear that this challenge is binary classification problem (popular or not), and hence an ANN algorithm can be used in a federated way to learn these popular elements before storing these information locally to reduce the latency.

Moreover, UAVs can also act as flying base stations to improve the caching efficiency by tracking users' mobility, and hence effectively provide the popular contents [26]. It is clear that this use case inherits the aforementioned challenges of UAVs deployment (see section III-A, challenge (iii)). Thus, FDL can also be applied to deal with such challenges by, for instance, learning users' mobility patterns and their content request distribution, in a distributed way. In this case, the hybrid CNN with LSTM algorithm is more suitable in order to deal with the spatiotemporal features of both mobility patterns and content request distribution. Then, the aggregated learning model will help to manage the UAVs deployment.

E. SUMMARY AND DISCUSSION

In this section, we described the main challenges of UAV-based networks for which it is suitable the FDL concept. It is clear that the FDL concept can perfectly improve the privacy issue of UAVs' data by performing the learning where the data is generated. It also introduces a lower latency to generate learning models and hence supports the ultra low latency requirement of the emergent UAV-based applications. In addition, the FDL avoids to send collected data to a central node. Consequently, on one hand, it highly reduces the network overhead and hence the consumed bandwidth, and on the other hand, it allows less power consumption of UAVs, since the data transmission is the operation that consumes more the energy of UAVs devices, especially with UAVs' energy-constraint. Moreover, UAVs can also optimize the use of their computing resources since they generate only local learning models using their small datasets. Therefore, the FDL concept enables the UAVs-based network not only to ensure the privacy of UAV users but also to improve latency, network overhead and bandwidth, and UAVs' energy and computing resources.

Beside, FDL is based on deep learning algorithms to build learning models. The used deep algorithm depends mainly on the target problem. In fact, as it is based on a feedback loop between the deep algorithm and its environment, the ANN as reinforcement learning is adequate for challenges in which UAVs must adapt dynamically to their surrounding environment such as wireless signal propagation environment. As well, the deep ANN algorithm is usually used to deal with regression problems whether the output variable (to predict) is a continuous or categorical variable. Hence, the ANN

algorithm suits perfectly the prediction of FANET routing performance as well as traffic load of UAVs-based IoT networks. Some UAVs challenges are related to the time series prediction problem e.g. prediction of UAVs' energy consumption in the next time slot and based on the consumption history. In such context, the RNN with LSTM is more adequate since LSTM can extract the time features among the input data and also to remember past data in memory. Moreover, the hybrid CNN with LSTM can deal with spatiotemporal series prediction problems, such as UAVs mobility, as CNN extracts the spatial features of experienced data while LSTM deals with the time ones.

IV. OPEN PROBLEMS AND FUTURE RESEARCH DIRECTIONS

The use of federated learning for wireless networks is still in its early stages. Despite the various new opportunities it offers, there are many critical challenges in using federated learning for UAV-enabled networks. In what follows, we discuss some of these challenges in addition to future research directions.

A. SECURITY AND PRIVACY CONCERNS

Although the primary objective of the FDL concept is privacy-preserving, shared some local models may still reveal private information. Thus, the authors in [18] proposed a secure aggregation algorithm that enables clients to encrypt their local models, while allowing the FL server to aggregate local models without decrypting them [18]. However, analyzing the global aggregated model can still help to disclose the participation of some learners. Hence, designing algorithms to provide privacy at participants-level, rather than protecting a gathered data, is highly needed.

In the context of UAVs networks, providing the privacy at UAVs-level (clients) requires high computation tasks in addition to those needed for the local learning. Thus, efficient FDL algorithms that reach a trade-off between clients' constrained-resources and privacy protection are also highly needed.

Like traditional ML algorithms, the local models are updated periodically when a new data are collected. Thus, an adversary can manipulate the result of the federated learning process by injecting either poison data or poison gradient updates. In this context, FDL algorithms must be reliable against data-poisoning as well as model-poisoning adversaries, while resilient techniques, to such adversarial attacks, are also highly required.

B. FEDERATED LEARNING SCALABILITY CONCERNS

The performance of FDL process depend strongly on the participation of local learners that enable both global and local models updates. In such context, selecting the optimal number of UAVs (clients), frequency of local and global models updates need more investigation to design scalable FDL algorithms at all levels. In addition, participants are assumed to be always connected to the FDL system. However,

in UAV networks, some UAVs may switch off due to energy or connectivity constraints, which can also affect the learning performance. Therefore, FDL algorithms must be robust to clients drop out by anticipating such scenarios.

Another challenge is to select the adequate UAV learners with appropriate data, especially when the collected data are unlabeled or mislabeled. In fact, existing studies assume that the data are labeled which is not always the case for generated data in UAVs-based networks. Hence, the designed FDL algorithm should also be robust to such challenge by, for instance, enabling a first step to learn the labels of collected data by the UAVs (clients) themselves.

C. UAV-ENABLED NETWORK CONCERNS

Most of existing studies focused on issues related to the FDL design including: learning rate and convergence, aggregation rate, frequency of model updates, etc. However, there are other issues related to the UAV-enabled wireless network, which is under study such as participants with heterogeneous resource capacities, in terms of computing, local data size, and energy, the uncertainty of wireless channels, etc. Hence, new studies must be initiated in designing efficient FDL algorithms that consider wireless networks constraints, while ensuring the learning model accuracy. For instance, a special attention should be addressed to the trade-offs: (i) between computation and communication latencies and the model learning accuracy, and (ii) between the required computation to perform the local training and clients energy consumption.

D. LEARNING CONVERGENCE CONCERNS

One of the main challenges of the FDL concept is the learning convergence, which is not always guaranteed for distributed schemes and with the heterogeneous capabilities of UAVs' resources. In [27], the authors studied the gradient descent convergence for convex loss functions.

However, on one hand, the objective of some learning models, including deep neural networks, is to learn a non-convex loss functions; on the other hand, convex losses require a high number of model updates [11], which may affect the UAVs-constrained resources. Therefore, more analytical studies are needed to address learning convergence for non-convex functions, while considering the main constraints of UAVs-based networks especially in terms of resources.

V. CONCLUSION

This paper addressed the role of federated deep learning concept to deal with some challenges of UAV-enabled wireless networks. Federated learning is emerging as a decentralized learning paradigm that improves communication overhead as well data privacy of UAV-based wireless networks by performing the model training in distributed way.

We first provided a general introduction about federated learning and its fundamentals. We then highlighted many use cases of federated learning in UAV-enabled networks ranging from 5G networks and beyond, IoT, Edge computing and caching, to Flying Ad-Hoc Networks. Finally, we discussed

about many key open challenges and future research directions about the use of federated learning in wireless networks.

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