FEDERATED LEARNING FOR LEO CONSTELLATIONS VIA INTER-HAP LINKS

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ABSTRACT
Low Earth Orbit (LEO) satellite constellations have seen a sharp increase of deployment in recent years, due to their distinctive capabilities of providing broadband Internet access and enabling global data acquisition as well as large-scale AI applications. To apply machine learning (ML) in such applications, the traditional way of downloading satellite data such as imagery to a ground station (GS) and then training a model in a centralized manner, is not desirable because of the limited bandwidth, intermittent connectivity between satellites and the GS, and privacy concerns on transmitting raw data.

Federated Learning (FL) as an emerging communication and computing paradigm provides a potentially supreme solution to this problem. However, we show that existing FL solutions do not fit well in such LEO constellation scenarios because of significant challenges such as excessive convergence delay and unreliable wireless channels. To this end, we propose to introduce high-altitude platforms (HAPs) as distributed parameter servers (PSs) and propose a synchronous FL algorithm, FedHAP, to accomplish model training in an efficient manner via inter-satellite collaboration. To accelerate convergence, we also propose a layered communication scheme between satellites and HAPs that FedHAP leverages. Our simulations demonstrate that FedHAP attains model convergence in much fewer communication rounds than benchmarks, cutting the training time substantially from several days down to a few hours with the same level of resulting accuracy.

1 INTRODUCTION
In the past few years, satellite technology has made it possible to develop and launch a massive amount of small satellites into space between 500 and 2000 km above the surface of the Earth at low cost, which has led many companies to deploy mega-constellations of satellites at low Earth orbit (LEO). LEO constellations outperform the high orbits, medium Earth orbits (MEO), and high Earth orbits (HEO) in many ways, including low development and deployment costs, reduced propagation latencies between the ground station (GS) and LEO’s satellites, and reliable internet connectivity [1]. Moreover, LEO’s satellites provide a huge amount of the Earth observation images in near-real-time, using high-resolution cameras to enable decision-makers to confront global challenges [2] such as disaster management, urban planning, and climate change.

Since the downlink bandwidth is a bottleneck, it is difficult to download these massive amounts of high-resolution images to GS to train a machine learning (ML) model. In addition, due to the high speed of the LEO’s satellites, satellites can only communicate with the GS few times a day, but their connectivity is predictable. Federated learning (FL) can be a promising option to handle these challenges since satellites can train their ML models on-board without exchanging their raw images. For the sake of clarity, each satellite generates a ML model and sends its local gradient vector to the parameter server (PS). Then, the PS aggregates all gradients received from different satellites and generate a global model. Next, the PS updates all participating satellites with the newly generated global model. This process will repeat until the terminating criterion is met. In essence, the learning model updates in FL are sent through wireless links, the convergence of the global model will be impacted by the uncertainty in wireless channel such as wind turbulence, propagation delay, and transmission delay [3]. In addition, communication between satellites located in different orbital planes, inter-plane inter-satellite link (ISL), can be extremely challenging due to the effect of Doppler shift. Furthermore, when satellites in one orbital plane are traveling in the opposite direction to satellites in another orbital plane, the Doppler shift will be maximized which is known as cross-seam [4]. Also, due to the high mobility of LEO’s satellites, some satellites can be in contact with the GS several times a day, while other may be blocked due to the Earth’s rotation [5], [6]. Therefore, all of these challenges will increase the uncertainty of the communication between satellites to each other and the GS, in turn, will impact the FL convergence.

Several recent studies have examined the use of FL in LEO constellations [5]–[8]. Chen et al. [7], for example, have applied a traditional FL algorithm to satellite constellations and compared their results to the centralized training at the GS. Nevertheless, they did not offer a new FL algorithm to address the current challenges associated with applying FL to satellite constellations. A new asynchronous FL algorithm called FedSat is also proposed in [8], however, it is only applicable if the satellites visit the GS once a period. Additionally, So et al. [5] proposed another new FL algorithm called FedSpace that trades off local model staleness and idleness connectivity in asynchronous FL and synchronous FL, respectively. However, FedSpace can only be used if the GS has a dataset that is similar to the satellite-generated dataset or if the satellites have to download low-resolution images to enable FedSpace to determine the satellite’s connectivity.

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with the GS. Razmi et al. [8] proposed an alternative FL approach named FedISL that uses the intra-plane ISL (satellites within the same orbital plane) to develop their communication scheme. Through FedISL, partial global models are generated form each orbital plane, and then a PS (GS or satellite in higher orbit) aggregates these partial models to generate the global model. Yet, the model did not address the Doppler shift between the LEO satellites and the PS in MEO, nor did it address the effect of the idleness connectivity between these orbital planes and the PS.

Contributions. Our paper presents a new synchronous FL algorithm, FedHAP, which addresses the current challenges that raised in applying FL to satellite communications. In order to minimize the Doppler shift between satellites located on different orbital planes (inter-plane ISL), we develop a communication scheme that leverages the use of the high altitude platform (HAP) as a PS to orchestrate the process of aggregating local model parameters from satellites on different orbits. Moreover, we develop a novel routing algorithm for coordinating the communication links between satellites and HAPs.

In summary, this paper makes the following contributions: 1) introduces HAPs as PSs, 2) proposes a novel synchronous FL algorithm, FedHAP, that explores inter-satellite collaboration to overcome the highly intermittent satellite-HAP visits, and 3) FedHAP also leverages inter-HAP collaboration to perform partial aggregation to accelerate global model aggregation.

Paper Organization. Section 2 discusses the dynamics of a satellite communication system, the usage of FL in satellite communication, and the communication models. Section 3 presents our proposed algorithms, communication scheme, routing algorithm, and FedHAP. Section 4 provides our experimental results. Finally, we conclude in Section 5.

2 SYSTEM MODEL FOR LEO CONSTELLATIONS

2.1 System Dynamics

Consider a LEO satellite constellation with \( l \) orbital planes where each orbit \( l \) contains \( K_l \) equally distributed satellites, where \( s = \{1, 2, ..., S\} \), and each of these satellites has a unique ID. For instance, consider an arbitrary orbital plane \( l \), the satellite IDs will be in form of \( ID_{l,N_s} = \{ID_{l,N_1}, ..., ID_{l,N_{S}}\} \). In comparison to LEO satellite constellations located at heights ranging from (500-2000 km), consider that there are multiple HAPs \( \mathcal{G} \) that cover a certain area of the Earth located at altitude between (18-24 km). For any given visiting period of time \( t \), each HAP \( g \in \mathcal{G} \), where \( \mathcal{G} = \{g_1, g_2, ..., g_h\} \) will be able to contact with a random number of satellites with different IDs from different orbital planes. Fig. 1 shows an example of our system model for a set of HAPs acting as PSs to orchestrate several satellites within LEO constellation.

2.2 FL Model for Satellites

Suppose that each satellite \( n \) is collecting and storing a dataset \( D_n \). Moreover, each satellite will use its on-board instruments to train its local ML model. It is worth noting that the data gathered from the satellites within the same orbital plane is similar to each other due to the same orbital position. However, the data collected from different orbital planes is considered to be distinct and generally non-independent and identical distributed (non-IID). This similarly applied to the scenario of multiple orbital shells (all the orbital planes at the same altitude with different inclination angles). When each satellite collected its data and generated its local gradient vectors, all satellites will collaboratively train a global model by minimizing a global objective function as shown below:

\[
\min_{w \in \mathbb{R}^d} \left\{ F(w) = \sum_{k \in K} \frac{m_k}{n} F_k(w) \right\} 
\]

where \( m_k = |D_n| \), \( m_k = \sum_{i=n}^N m_n \) represents the entire dataset collected by all satellites \( N \), and \( F_n \) represents local loss function resulting from training satellite \( n \) using data \( D_n \) which is expressed as follows:

\[
F_n(w) = \frac{1}{n_k} \sum_{x \in D_n} l(w; x) 
\]

where \( l(w; x) \) is training loss for a data sample \( x \) and model parameter vector \( w \). To solve the above problem, the PS first creates an ML model (e.g., a neural network) with initial parameters \( w^0 \) and disseminates it to all or a subset of the satellites when they (successively) come into its visible zone. Each satellite \( k \) then applies a local optimization method such as mini-batch gradient descent for \( I \) local epochs, to update the model as

\[
w_{k}^{\beta,i+1} = w_{k}^{\beta,i} - \zeta \nabla F_k(w_{k}^{\beta,i}; X_k) 
\]
where $\zeta$ is the learning rate, $X_k^l \subset D_k$ represents the $i$-th mini-batch. In order to aggregate these local gradients from all satellites, we will use the synchronous FL approach, where the PS receives the updated parameters from all satellites, and then aggregates them as:

$$w^{\beta+1} = \sum_k \frac{n_k}{n} w_k^{\beta, I}$$

where $\beta$ indexes the communication rounds. In other words, the PS starts a new round $\beta + 1$ by transmitting the updated $w$ to all the satellites again when they become visible, and the above procedure repeats until model convergence (e.g., a target loss or accuracy is achieved). It is worth noting that all satellites will need time $T$ to generate its local model which can be formulated as:

$$T = \sum_{n=1}^{\chi} t_l(n) \quad \text{where} \quad t_l(n) = \frac{\Upsilon_n z|D_n|}{\nu}$$

where $\chi$ is the total number of the satellites in contact with the HAP during time interval $\tau$, $t_l(n)$ represents the required time for each satellite $n$ to train its local model. In Eqn.\ref{eqn:time}, $t_l(n)$ is directly depending on the data size in bits $z|D_n|$ collected by a satellite $n$, number CPU cycles needed to process each data sample $\Upsilon_n$, and CPU frequency $\nu$.

In this paper, we propose a novel synchronous FL approach called FedHAP to accelerate the convergence process and address multiple challenges in applying FL to satellite communications.

### 2.3 Communication links

Throughout this paper, we used the radio frequency (RF) as communication links between satellites and HAPs which are full-duplex. RF links prove particularly useful thanks to their reliability and flexibility. HAPs are always relaying between the satellite and the GS. Without loss of generality, let us consider a satellite $n$ and a GS $g$, where the SGL will only be feasible if the following condition is satisfied:

$$\alpha_{n,g}(t) = \angle(r_g(t), (r_n(t) - r_g(t))) \leq \frac{\pi}{2} - \alpha_{\text{min}}$$

where $r_n(t)$ and $r_g(t)$ represent the trajectory of satellite $n$ and GS $g$, respectively, and $\alpha_{\text{min}}$ is the minimum elevation angle. Under the assumption that the wireless channels are symmetric (additive White Gaussian noise), the signal-to-noise ratio (SNR) between two objects $x$ and $y$ (satellites or HAPs) in free space can be written as \cite{4}:

$$\text{SNR}_{RF} = \frac{P_t G_x G_y}{K_B T B L_{x,y}}$$

where $P_t$ represents the transmitted power, and $G_x, G_y$ denote the total antenna gain of the transmitter and the receiver, respectively. Here, $x$ and $y$ could be two satellites or a satellite and a GS, e.g., the link is ISL or SGL. $K_B$ is the Boltzmann constant, $T$ stands for the noise temperature at the receiver, $B$ is the channel bandwidth, and $L_{x,y}$ is the free-space pass loss.

### 3 PROPOSED FRAMEWORK

In this section, we are going to discuss our algorithm that describes the route between satellites and HAPs. Additionally, we will explore how our proposed FL algorithm, FedHAP, will handle the staleness problem arising from the non-IID and non-observed satellite data.

#### 3.1 Routing Techniques

This work differs from previous literature studies in that it uses the HAPs as a PSs to handle the two main challenges when applying FL in satellite communication, intermittent connectivity and the Doppler shifts resultant from the communication between satellites in different orbital planes. In particular, each HAP will change information with the viewed set of satellites from different orbital planes. Utilizing ISL, each satellite will distribute the global information received to its nearest two neighbors. Similarly, the set of HAPs that have received the local information from satellites will communicate with each other to generate a global model. In this scenario, more satellites will be viewed by a set of HAPs, resulting in faster convergence of the global parameter. In addition, in the case of a single HAP, the communication will be better between the HAP and satellites than between the GS and satellites.

#### 3.2 FedHAP

Based on our routing algorithm, we have two different aggregated models: one is aggregated at the models at satellites, referred as partial global model, and one is aggregated at models at the HAPs, referred as global model. This section presents our proposed FL algorithm, FedHAP, which aims to accelerate the generation processes of the global model. However, before explaining how FedHAP works, first it is important to discuss the various scenarios for generating partial global models. According to our earlier discussion, each HAP within the server layer will receive partial global models from its connected satellites from all orbital planes, however, this is an optimistic scenario since not all satellites can transmit partial global models. That is due to the high mobility of the satellites within the LEO constellations, which causes the HAP to receive only the partial global model from its connected satellites within the contact time $t_{\text{contact}}$; otherwise, the HAP will receive local models instead of partial global models from these satellites. In other words, when considering the case of a single HAP, if $t_{\text{contact}} < T$, then the visible satellite will transmit only its local model to the HAP. Generally, in an ideal scenario, HAPs will receive partial global models from their associated satellites, whereas in the realistic scenario, some HAPs will receive partial global models, while others will receive local models, depending on whether all satellites within an orbital plane are capable of training their ML models and generating partial global models within a certain viewing/connecting periods.

In each global epoch, once the sink HAP has received local models or partial global models from its neighbors, it will organize them. Following that, the FedHAP will remove the
repeated satellite IDs with their associated models. After that, FedHAP will check whether each orbital plan contains the IDs of all expected satellites. If not, then FedHAP will postpone the aggregation of the received models for the next global epoch. If so, then the FedHAP will aggregate the received models. In order to aggregate the received models, partial global models or local models, FedHAP uses the following equation to combine them:

$$w^{\beta+1} = \sum_{S_1} \sum_{S_2} \frac{n_{S_2}}{n} w_{S_2}^\beta I$$

(7)

The above procedure will be repeated until convergence of the FL model is achieved.

4 SIMULATION RESULTS

In our simulation we assume that there is only one HAP that orchestrates the Walker constellation, which consists of 40 LEO satellites, equally distributed over 5 orbital planes. Specifically, each orbital plane is located at a height of 2000 km from the Earth’s surface, with an inclination of 80 degrees, and the HAP is situated at a height of 20 km from the surface of the Earth, with a minimum elevation angle of 10 degrees. Furthermore, we have selected the following parameters for the communication links: 1) transmitter and receiver antenna gain are set to 6.98 dB; 2) transmitted power from each satellite and the GS are both set to 40 dBm; 3) carrier frequency $f$ is set to 2.4 GHz, the ambient noise $T$ is 354.81 K, and the data rate $r$ is set to 16 Mb/sec. Further, we used MNIST datasets consisting of images of hand-written numbers in 10 different categories, 0-9 [9], we used the convolutional neural network (CNN) for generating the local model parameters for each satellite. We have set the the batch size to 64, and learning rate to 0.5.

![Fig. 2: Accuracy for PS as two HAPs, single HAP, and GS a for 48 hours.](image)

Based on Fig. 2 it can be seen that the FedHAP algorithm using the HAP as PSs provides an accuracy of around 92.417% after 20 hours when using two HAPs, an accuracy around 87.571% after approximately 40 hours when using single HAP, and an accuracy around 84.476% after approximately 45 hours for the GS following the start of the PS collecting data from satellites. Therefore, our results prove the effectiveness of using a set of HAPs for managing the LEO constellation compared to the traditional FL approaches that use the GS or any satellite from the higher orbital planes. During our simulation, we assume more realistic scenario by constructing a HAP to be located a any place within a country and it succeed to converge in only 20 hours because of its ability to communicate with a wide of the satellites. Lastly, we intend to conduct more experiments with different numbers of HAPs located in different parts of the country and different locations in real-world situations to demonstrate that our model is effective under different real-world scenarios.

5 CONCLUSIONS

We introduced in this paper HAPs as PSs to orchestrate the aggregation process of global models in satellite communication. Additionally, a novel synchronous FL algorithm, FedHAP, that leverages the inter-collaboration among HAPs to accelerate the convergence of the global model, has been proposed. Furthermore, we presented a communications scheme for managing the communication links between satellites and HAPs, as well as routing procedures for distributing the local/global models among HAPs and satellites. The main objective of these algorithms is to accelerate the converging of the FL models by mitigating the challenges associated with intermittent satellite connectivity and the Doppler shift in LEO constellations. According to our simulation results, FedHAP was able to accelerate the convergence of the global model approximately five times faster than state-of-the-art models with a 92.417% accuracy rate for handling non-IID data when using two HAPs as PSs.

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