A Novel Hierarchical Federated Edge Learning Framework in Satellite-Terrestrial Assisted Networks

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Abstract. On-board federated learning based on dense Low Earth Orbit satellite constellations can meet the data privacy requirements of users in the coverage of non-terrestrial networks. However, traditional satellite-terrestrial assisted federated learning may encounter challenges due to limited satellite resources. To solve the problem, a satellite-terrestrial assisted hierarchical federated edge learning (STA-HFEL) framework is established in this paper. By leveraging well-endowed cloud servers for processing, inter-satellite links, predictability in satellite positioning, and partial aggregation, substantial reductions in training duration and communication costs are achieved. Furthermore, we define a problem within the STA-HFEL framework that involves optimizing the allocation of computation and communication resources for device users to attain overall cost minimization. To address this challenge, we introduce a resource allocation algorithm that operates effectively. Extensive performance evaluations demonstrate that the potential of STA-HFEL as a cost-efficient and privacy-preserving approach for machine learning tasks across distributed remote environments.

Keywords: hierarchical federated learning · LEO satellite network · edge computing · inter-satellite links

1 Introduction

In recent years, the integration of Internet of Things (IoT) technology in remote and underserved regions has shown immense potential for transforming various sectors, from agriculture to healthcare. However, deploying and maintaining traditional IoT infrastructures in these remote areas presents substantial challenges due to connectivity limitations and resource constraints. As a solution to these challenges, LEO satellite communication networks, as a viable complementary alternative to terrestrial networks has emerged. Usually situated between 500 to 2000 km above the Earth's surface, LEO satellite constellation presents advantages such as quicker communication due to reduced

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propagation latency, decreased energy consumption, and improved signal transmission by enabling more precisely targeted beams to be directed towards the Earth's surface [1]. For out-of-coverage communication targets, inter-satellite links (ISL) enable cross-domain communication [2]. There are numerous challenges waiting to be overcome due to the LEO constellation network's characteristics.

One of the challenges is the strong demand of device data privacy and security. Coined by Google in 2016, a decentralized ML named Federated Learning (FL) allows edge devices to collaboratively train models while keeping their data localized, thus mitigating privacy concerns and reducing communication overhead [3]. By capitalizing on the extensive coverage of satellite networks and their ability to establish connectivity even in regions lacking terrestrial infrastructure, in recent years, there are some explorations on satellite-based FL computing networks. Nasrin Razmi et al. [4] proposed a communication concept specifically adapted to perform a synchronous FL process within a satellite-dense net coordinated by an out-of-constellation PS. It exploits predictability of satellite motion and sub-aggregation to decrease training latency and communication expense. By the same author, [5] modified Federated Averaging algorithm (FedAvg) by leveraging predictive availability of satellites. While effectively reducing training time, this paper converting FedAvg from synchronous to asynchronous learning without compromising training performance. However, excessive model transmission rounds lead to compromised learning performance within the training time limit [6]. This also incurs substantial energy overhead for numerous computation and communication iterations, presenting a challenge for remote-area-devices with low battery capacity, which were not considered in the above studies.

To mitigate such issues, deploying Mobile Edge Computing (MEC) server [7] on the LEO satellite enables the LEO satellite to have the capabilities of aggregated computation and content distribution. Inspired by the hierarchical federated edge learning framework which was proposed by Luo in [8], we proposes STA-HFEL, a dense satellite-terrestrial assisted three-tiers FL edge network, utilizing mediate edge servers on LEO satellites between devices and the remote cloud. Briefly, the main contributions of our work can be summarised as follows:

1) This paper identify the essential hurdles in implementing federated learning on satellites-terrestrial networks for machine learning model training, along with the balance between global transmission overhead and the limited computational processing capacity.
2) We propose a satellite-terrestrial assisted hierarchical federated edge learning (STA-HFEL) framework, offering significant advantages in minimal delay and energy-saving FL for huge scale machine learning tasks in remote areas.
3) With a wide range of numerical experimentation, we showcase that the proposed resource allocation algorithm within the STA-HFEL framework not only outperforms comparative benchmarks in terms of global cost reduction but also exhibits improved training performance compared to the conventional device-cloud-based satellite federated learning approach.

2 Methods

In the STA-HFEL framework, we assume the user devices set as

$$\mathcal{N} = \{n : n = 1, \ldots, N\}, \tag{1}$$

the satellite-edge-servers set as

$$\mathcal{K} = \{k : k = 1, \ldots, K\}, \tag{2}$$

and a cloud server S. The collection of accessible user devices in communication with edge server i are denoted by $\mathcal{N}_i \in \mathcal{N}$, which is in connection with communication coverage area of satellite i. When user devices are located at considerable distances from each other, they will engage in communication with distinct satellites. Suppose that devices within the communication coverage of the same satellite are located in a compact predefined area, and they share the same geometric configurations with the servicing satellite. For the satellite-to-ground communications, the user device and satellite are visible if

$$\frac{\pi}{2} - \angle(r_{\mathcal{N}_k}, r_k - r_{\mathcal{N}_k}) \geq \alpha_e, \tag{3}$$

where the two vectors in the formula denote the position of device and satellite respectively [9]. The visibility of satellites to a remote cloud fixed on the ground station is also analogous.

In our conceptualization of the STA-HFEL framework, illustrated in Fig. 1, a single training model undergoes the process of model aggregation, occurring both at the satellite edge layer and the cloud layer. Imagine a scenario where user devices stay static while learning, each equipped with a localized data set denoted as $\mathcal{R}_n$. The learning process begins with devices training local models, which are subsequently transmitted to their respective satellite edge servers for aggregation. Upon achieving edge training accuracy, each edge server facilitates global aggregation by transmitting model parameters to the superior layer cloud. This procedure can be outlined as follows.

A. Local model computation

In this step, the objective empirical loss function for device n is defined by the training task as

$$F_n(\theta) = \frac{1}{|\mathcal{R}_n|} \sum_{x \in \mathcal{R}_n} f_n(x; \theta), \tag{4}$$

where $f_n(x; \theta)$ is the training loss for a (labeled) data sample x and model parameters θ. In order to attain a consistent local accuracy $\tau \in (0, 1)$ across all devices for a given model, device n is required to perform a series of local iterations denoted by

$$L(\tau) = \lambda log(1/\tau), \tag{5}$$

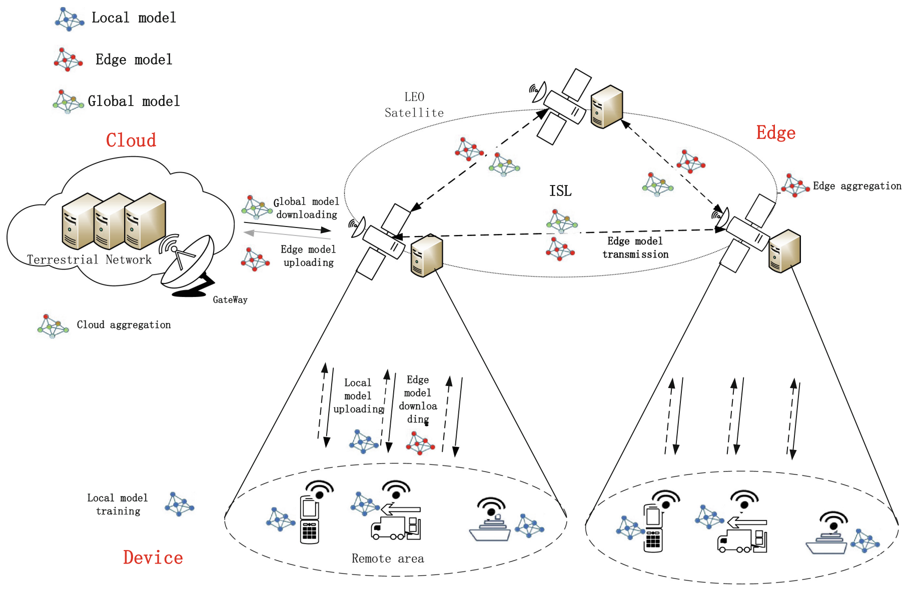

Fig. 1. Satellite-terrestrial assisted hierarchical federated edge learning network

in which λ varies according to data size and computational task [10]. At j-th local iteration, each device, denoted as n, aims to ascertain its local update through the fulfillment of its objective

$$\theta_n^{j+1} = \theta_n^{j+1} - \eta \nabla F(\theta_n^j), \tag{6}$$

Until

$$||\nabla F(\theta_n^{j+1})|| \leq \tau ||\nabla F(\theta_n^j)||, \tag{7}$$

where η represents the predefined learning rate [11].

B. Local model transmission

Upon completing $L(\tau)$ local iterations, local model parameters θ_n^j are send to the designated satellite edge server i, chosen as closest to the device within its visible range. This process also incurs wireless transmission delay and energy.

C. Edge model aggregation

In this stage, every satellite edge server average local parameters as

$$\theta_i = \frac{\sum_{n \in \mathcal{N}_i} |\mathcal{R}_n| \theta_n^j}{|\mathcal{R}_{\mathcal{N}_i}|}, \tag{8}$$

where

$$\mathcal{R}_{\mathcal{N}_i} = \bigcup\nolimits_{n \in \mathcal{N}_i} \mathcal{R}_n \tag{9}$$

is aggregated data set, and N_i is its attached devices set. Subsequently, each edge server broadcasts θ_i to the devices within N_i for the upcoming iteration in step A. This sequence of steps, spanning from step A to step C, will be iterative repeatedly within satellite edge server i until the attainment of an identical edge accuracy φ, consistent across all satellite edge servers. To attain the specified accuracy of the edge model, the count of iterations at the edge can be deduced as follows [11]:

$$I(\varphi, \tau) = \frac{\sigma \log \frac{1}{\varphi}}{1 - \tau}, \tag{10}$$

where σ is a constant varies with task.

D. Edge model uploading

During this step, edge model parameters are sent from satellites to the remote cloud, typically located on a Ground Station (GS). Only a portion of satellites are linked to the GS, with longer intervals than online time. We address this by using inter-satellite links for model upload. Within orbital levels, satellites form a circular network via ISLs, optimizing connections with adjacent satellites. Communication between GS and satellites is facilitated through the best-connected satellite, guided by orbital mechanics' predictability.

E. Cloud model aggregation

In the ultimate stage of this process, the cloud acquires model parameters from each satellite edge and proceeds to aggregation these models as

$$\theta = \frac{\sum_{i \in \mathcal{K}} \left| \mathcal{R}_{\mathcal{N}_i} \right| \theta_i}{|\mathcal{R}|}, \tag{11}$$

where

$$\mathcal{R} = \bigcup_{i \in \mathcal{K}} \mathcal{R}_{\mathcal{N}_i} \tag{12}$$

is aggregated data set under cloud S. To offer a clearer depiction, Algorithm 1 presents a step-by-step procedure for one global iteration.

Algorithm 1: STA-HFEL iterative process

Input: Device initial model set $\{\theta^0_{n\in\mathcal{N}}\}$, with local iteration j = 0, local accuracy τ, edge accuracy φ
Output: global model θ
for *j in range(I*$(\varphi, \tau)L(\tau)$*)* **do**
  for *device n in range(N)* **do**
    Solve problem (6) and derive θ^j_n (Step A);
  Devices send refreshed θ^j_n to satellite edge server (Step B);
  if $j\%L(\tau) = 0$ **then**
    for *satellite edge i in range (K)* **do**
      i received $\{\theta^j_n : n \in \mathcal{N}_i\}$ and calculate θ_i with Eq. (8), deriving θ_i (Step C);
      i broadcast θ_i to devices in $\mathcal{N}_i$ such that $\theta^j_n = \theta_i$ for each $n \in \mathcal{N}_i$;
i transmit $\{\theta_{i\in\mathcal{K}}\}$ with intra-plane ISLs to GS (Step D);
Cloud S got $\{\theta_{i\in\mathcal{K}}\}$, to fix (11) and obtains global θ (Step E);

3 Results

We evaluate our proposed algorithms from Section II using logistic regression on the MNIST dataset [12] and compare it to the conventional device-cloud-based FedAvg model. Our study employs a walker constellation with 40 LEO satellites across 5 orbital planes at an 80° inclination, with a GS situated at the North Pole. We involve 30 devices under each satellite in the training process, with datasets partitioned into 75% for training and 25% for testing.

Results indicate our STA-HFEL algorithm surpasses FedAvg by around 5% in both test and training accuracy, with a 3% reduction in training loss. This is attributed to STA-HFEL's multiple edge-based model aggregation rounds alongside local iterations within a global iteration, offering enhanced learning benefits. In contrast, FedAvg relies solely on local datasets during global iterations without external network integration.

The cost-saving effectiveness of STA-HFEL is also assessed. With $\tau = 0.9$ local accuracy and $\varphi = 0$ edge accuracy, STA-HFEL is compared against traditional device-cloud-based satellite FL models. It demonstrates notable improvements in iteration count, reducing iterative model parameter transmission costs compared to the classic approach.

4 Conclusions

We propose a comprehensive framework for a three-tiers hierarchical federated edge learning model that leverages satellite-terrestrial assisted communication to facilitate efficient knowledge exchange and model improvement to enable great potentials in cost-efficient application of FL in remote-area-IoT. Through partially migrating model aggregation from the cloud to edge servers, our suggested STA-HFEL method converges to a steady system state, surpassing the designated benchmarks in global energy reduction and exhibiting superior training performance over traditional on-board FL approaches for satellites.

Ultimately, as demonstrated by our simulation results, the STA-HFEL framework achieves higher global and test accuracy, along with lower training loss, in comparison to traditional satellite federated learning devoid of intermediate layer aggregation.

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