Modeling of Computation Offloading for LEO Satellite-Assisted Federated Learning on Ground-Space Integrated Architecture

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***Abstract*—Federated learning has gained significant attention as an innovative approach in today's data-driven society. However, traditional federated learning faces challenges such as dependency on a central server and communication delays. Moreover, the feasibility of federated learning in remote areas with limited access to stable ground networks has been largely overlooked. To address these challenges, this paper proposes a novel federated learning architecture that utilizes Low Earth Orbit (LEO) satellites as central server substitutes. LEO satellites offer distributed infrastructure, improved communication capabilities, and enhanced data privacy and security. The proposed architecture aims to overcome the limitations of traditional approaches and enable smooth federated learning in both urban and remote areas. By leveraging the dynamic nature of LEO satellites and introducing offloading techniques, the overall learning delay is optimized. The findings demonstrate the potential of utilizing LEO satellites for federated learning and contribute to the advancement of this field.**

***Index Terms*—federated learning, Low Earth Orbit (LEO) satellites, offloading.**

I. Introduction

In today's data-driven society, federated learning has emerged as an innovative approach. It involves aggregating local models from distributed devices to train a global model on a central server. However, traditional federated learning suffers from dependencies on the central server and communication delays, posing significant challenges. These limitations have prompted the exploration of alternative approaches to overcome these challenges.

Particularly, federated learning in areas distant from urban centers or with limited access to stable ground networks has been largely overlooked. Therefore, in this paper, we aim to address this issue by utilizing Low Earth Orbit (LEO) satellites as central server substitutes, offering wide coverage and low latency [1]. The following are several compelling reasons why LEO satellites should be considered:

First, LEO satellites provide a distributed infrastructure that reduces reliance on a single server. By distributing aggregation and learning processes across multiple satellites, the risks associated with a single server are mitigated. This distribution enhances the robustness and fault tolerance of the federated learning system.

Second, LEO satellites offer improved communication capabilities, especially in situations where ground-based networks are limited or unreliable [2]. As satellites approach participating devices, communication delays are reduced, enabling real-time collaboration and model updates. This enhances learning efficiency and enables federated learning in geographically distributed environments.

Third, LEO satellites provide unique advantages in terms of data privacy and security. Communication between satellites in a LEO satellite network can be designed to establish a secure and isolated environment for federated learning. This safeguards sensitive data during aggregation and learning processes, alleviating concerns regarding data privacy.

Furthermore, we propose the introduction of offloading techniques using processing-capable servers deployed on LEO satellites to reduce overall learning delay. Variations in the sizes and performance of raw data from different mobile devices can result in inefficient learning time. Therefore, our goal is to optimize the overall delay through selective offloading to satellite edge servers, considering the holistic environment.

By leveraging LEO satellites in federated learning, we present a solution to the challenges faced by traditional approaches. The distributed nature, improved communication capabilities, and enhanced data privacy and security features of LEO satellites offer promising choices to strengthen the federated learning system. This research aims to demonstrate the potential of utilizing LEO satellites for federated learning in practical applications and contribute to the advancement of this field.

In summary, this paper proposes a novel federated learning architecture that leverages LEO satellites as central server substitutes to facilitate smooth federated learning in both urban and remote areas. We present a system model that considers the dynamic nature of LEO satellites and addresses the issue of overall delay. Our work aims to address a reasonable problem formulation and contribute to the development of federated learning with LEO satellite technology.

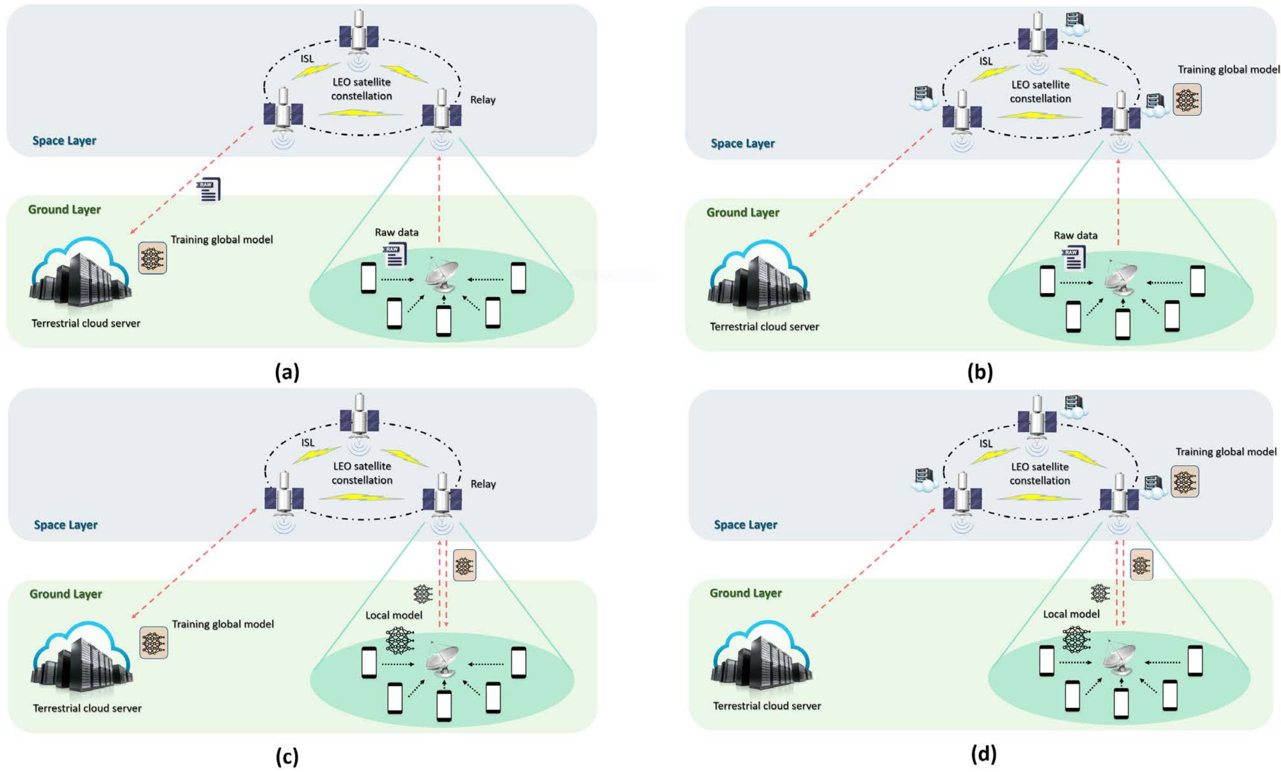

Figure 1: Feasible Learning Strategies in LEO satellite-assisted learning cases: (a) CL utilizing satellites as relay nodes.; (b) CL with computing servers deployed on satellites; (c) FL utilizing satellites as relay nodes; (d) FL with computing servers deployed on satellites.

II. RELATED WORK

A. LEO Satellite Communication

In recent years, LEO satellite communication systems have garnered significant attention in the field of telecommunications. These systems involve the deployment of satellites in low altitude orbits, enabling improved signal propagation characteristics, reduced latency, and enhanced coverage compared to traditional geostationary satellites. Researchers have explored various aspects of LEO satellite communication, including system architecture, link design, routing protocols, and network optimization algorithms. The utilization of LEO satellite communication has shown promising results in improving connectivity, particularly in areas with limited terrestrial infrastructure or in scenarios requiring rapid deployment and wide coverage.

B. Federated Learning

Federated Learning has emerged as a cutting-edge approach in the field of machine learning and data privacy. It enables the training of models across a network of decentralized devices while keeping the data localized, addressing privacy concerns associated with centralized data collection [3]. In federated learning, devices collaboratively learn a global model by exchanging model updates while preserving the privacy of individual data. Several research efforts have focused on optimizing federated learning algorithms, communication protocols, and system architectures to enhance model performance, convergence speed, and privacy preservation. Additionally, various extensions of federated learning, such as secure aggregation, differential privacy, and adaptive client selection, have been explored to tackle the challenges posed by distributed learning scenarios.

C. The intersection of LEO satellite communication and Federated Learning

The convergence of LEO satellite communication and federated learning presents an intriguing opportunity to leverage the benefits of both domains. By integrating LEO satellite communication into the federated learning framework, it becomes possible to extend the reach of federated learning to remote or disconnected regions with limited ground-based infrastructure. Furthermore, the utilization of LEO satellite communication in federated learning can potentially address challenges related to communication latency, network coverage, and privacy concerns in geographically dispersed environments.

While the individual domains of LEO satellite communication and federated learning have been extensively studied, their integration and exploration of their combined potential are relatively nascent areas of research. Therefore, investigating the integration of LEO satellite communication with federated

Property	Feasible cases			
	CL with relaying sat	**CL with computing sat**	**FL with relaying sat**	**FL with computing sat**
Implementation costs	Low	Moderate	Moderate	High
Privacy	Very low	Low	High	High
Latency	Very high	High	Moderate	Low
Energy consumption	High	Very high	Low	Moderate

TABLE I: Comparison between the four feasible cases.

learning holds significant promise in advancing both fields and unlocking new opportunities for distributed machine learning and enhanced global connectivity.

III. FEASIBLE CASES

This section examines the potential implementation of Federated Learning (FL) in LEO-based satellite constellation networks and summarizes the benefits of FL in LEO-Satellite Communications (LSCom).

A. Learning Architecture

In LEO-based Satellite Terrestrial Networks (STNs), User Equipments (UEs) can collectively learn a data-driven model. UEs are served by terrestrial base stations (TBSs) within TBS coverage, and when TBSs are unavailable, UEs can access the network via satellites and gateway (GW), which act as relays between UEs and LEO satellites. In this study, we consider a LSCom system consisting of a LEO satellite constellation, a cloud, a server, and multiple UEs. Learning takes place using local data information from UEs. Figure 1 illustrates four feasible learning strategies in LSCom, which are further summarized in Table 1.

B. Feasible Learning Strategies

- **Mode 1 (CL with relaying sat)** : In Mode 1, as shown in Figure 1a, a central server is deployed in the cloud, and raw data streams from UEs are transmitted directly to the cloud server. A global model is then developed using classical Centralized Learning (CL) in the cloud, and this model is applied to UEs. LEO satellites serve as relays for transmitting the traversed data stream. Mode 1 is relatively easy to integrate into the existing communication system but suffers from longer latency, which is not ideal for real-time applications.
- **Mode 2 (CL with computing sat)** : In Mode 2, depicted in Figure 1b, computing servers are deployed in satellites in close proximity to UEs instead of the remote cloud. Compared to Mode 1, this mode reduces latency due to the avoidance of communication between the cloud and satellites. The probability of information leakage is also decreased, making Mode 2 suitable for delay-sensitive applications. However, this mode requires extensive computation and storage hardware onboard satellites, making it economically expensive and energy-consuming.
- **Mode 3 (FL with relaying sat)** : Mode 3, as depicted in Figure 1c, which leverages federated learning to construct a generalized model without sharing raw data. While the computing server remains in the remote cloud similar to Mode 1, Mode 3 offers significant enhancements in data privacy and security by transmitting only model parameters among UEs, satellites, and the cloud, without exchanging large volumes of raw data. This approach leads to improved latency and reduced communication overhead. Mode 3 exhibits flexibility and robustness, enabling UEs to contribute to the global model even in cases of disconnection or poor wireless connection. However, implementing federated learning on UEs incurs higher costs compared to approaches based on centralized learning, as it requires local computing and training capabilities. The iterative nature of federated learning may also introduce some additional communication overhead, although it is generally lower compared to centralized learning strategies. In conclusion, Mode 3 offers practical implementation and maintenance benefits, making it suitable for real-world applications.
- **Mode 4 (FL with computing sat)** : Mode 4, illustrated in Figure 1d, involves deploying computing servers onboard satellites and running FL without data sharing. As shown in Table 1, this mode has lower communication overheads, reduced information leakage, and lower latency compared to other strategies. The computing server's proximity to UEs and the negligible number of intermediate network nodes (satellites, gateways, etc.) contribute to these advantages. Mode 4 consumes more energy than Mode 3 but is more energy-efficient than Mode 2, considering the current architecture.

C. Adopted Model

We chose Mode 4, "Federated Learning 2" as the most reasonable model among the above feasible cases. The reasons are as follows. In Mode 4, the computing server is located closer to the UEs, resulting in minimal visits to intermediate network nodes (such as satellites or gateways). As a result, the communication overhead is significantly lower. Mode 4 enables FL execution through the computing server without data sharing. This minimizes the potential for information leakage, as there is limited involvement of intermediate network nodes. Enhanced security measures are thus achieved. With the computing server positioned closer to the UEs in

Notation	Definition
$\mathcal{K}, K$	Total UE set, size of $\mathcal{K}$
$\mathcal{D}_k, D_k$	Local dataset of UE k, size of $\mathcal{D}_k$
$\mathcal{D}_s, D_s$	Collection of all offloaded dataset, size of $\mathcal{D}_s$
$\boldsymbol{w}, \boldsymbol{w_k}, \boldsymbol{w_s}$	Parameter of global model, local model of UE k, server model
Θ_k, θ_k	Offloading parameter set of UE k, size of Θ_k
$f(i), F_k, F$	Loss function of sample i, loss function on UE k, loss function on server
$t_{o,k}, t_a$	Offloading delay of UEk, delay of aggregation and broadcast
$t_{c,k}, t_{c,s}$	Update delay of UE k, update delay of the server
$P, p_{o,k}, p_{o,gw}$	Total power constraint, transmission power assigned to UE k, the gw
f_{ue}, f_s	CPU clock frequency of UE k, the server
B_{ue}, B_{gw}	Bandwidth of each link from UE, the gw
g_k, g_{gw}	Channel gain of UE k, the gw
N, τ, γ	Total training rounds, number of epochs per round, number of CPU clock frequencies required for training 1-bit data

TABLE II: Summary of notations in COOL.

Mode 4, both propagation delay and transmission time are reduced, leading to decreased latency. While Mode 4 entails slightly higher energy consumption compared to Mode 3, it is more energy-efficient than Mode 2. The burden on the remote cloud is minimal, and the impact on the current architecture is insignificant. Therefore, Mode 4, "Federated Learning 2," offers advantages over other modes in terms of reduced communication overhead, decreased information leakage, reduced latency, and improved energy efficiency.

IV. The Proposed Model: COOL

A. System Model

In the context of distributed machine learning, we consider a scenario where there exists a server located at the network edge and a set of K UEs, represented as $\mathcal{K} = \{1, 2, ..., K\}$. Each UE, denoted by k, possesses a local dataset $\mathcal{D}_k$, with its size indicated by D_k. Within the dataset, a typical data sample, denoted as i, comprises an input vector x_i and an output scalar y_i. The primary objective in a machine learning problem is to determine the model parameter w that effectively captures the relationship between x_i and y_i. This is achieved by minimizing the loss function $f_i(w)$, which quantifies the error of the model on the training data.

From a system delay perspective, the performance of the aforementioned feasible cases is predominantly constrained by either communication or computation. In the case of edge learning, transmitting the entire datasets necessitates significant communication resources and is contingent upon the quality of the communication environment. On the other hand, federated learning can be hindered by UEs with limited computational capacity or large dataset sizes, leading to a deceleration in overall performance, commonly known as the straggler effect. These observations serve as the impetus behind our proposal of computation offloading optimization for LEO satellite-assisted federated learning (COOL), which aims to strike a balance between edge learning and federated learning.

COOL, as illustrated in figure 1, comprises two distinct stages: data offloading and model update. Each UE k first optionally sends data $\mathcal{D}_k$ (where D_k represents the data size) to the server for processing according to offloading parameters. Subsequently, in the model update phase, the unsent data within each UE is utilized to update the local model, while the server incorporates the aggregated data to update its own model. It is important to note that the model update in the server must wait until the completion of the data offloading phase. Consequently, in the proposed COOL framework, the model update phase is scheduled to occur after the data offloading. Although it is possible to perform the initial round of UE model updates in parallel with the data offloading, we disregard the minor delay variations resulting from parallel processing and assume that the local update takes place after the data offloading.

For the server model, the loss function for offloaded data is shown as follows

$$F(\boldsymbol{w}_s) = \frac{1}{D_s} \sum_{i \in \mathcal{D}_s} f_i(\boldsymbol{w}_s). \tag{1}$$

The model parameter in the server is denoted as $\boldsymbol{w}_s$, where $\mathcal{D}_s = \cup_k (\Theta_k \cap_k \mathcal{D}_k)$ represents the collection of all offloaded data and $D_s = \sum_{k \in \mathcal{K}} \theta_k D_k$ denotes its size. Θ_k represents the offloading parameter set of the kth UE, and θ_k represents its size. As for the local model in UE k not offloded, the loss function defined on its unsent data is represented by

$$F_k(\boldsymbol{w}_k) = \frac{1}{D_k} \sum_{i \in \mathcal{D}_k} f_i(\boldsymbol{w}_k). \tag{2}$$

In addition to the local updates performed by the UEs and the server, a global aggregation process takes place. During this process, the server combines the parameters from all UEs and its own model parameters to generate a global model, which is then broadcasted to all UEs. We refer to the parameter of the global model as

$$\boldsymbol{w} = \frac{1}{D} \bigg(\sum_{k \in \mathcal{K}} (1 - \theta_k) D_k \boldsymbol{w}_k + D_s \boldsymbol{w}_s \bigg). \tag{3}$$

In the context of the COOL framework, both the server and all UEs are obligated to conduct model training during the model update phase. In contrast to the original federated learning approach, COOL introduces two additional components: training data offloading and server-based model training.

B. Problem Formulation

In this section, our focus is on the examination of the system delay associated with COOL in the context of federated learning. We will commence by conducting a thorough analysis of the system delay, enabling us to formulate a problem of minimizing delay while considering power constraints.

Through the optimization of this problem, we will devise an offloading strategy tailored specifically for COOL.

As depicted in figure 1, the delay in COOL, referred to as T_{COOL}, encompasses two distinct types of delays: data offloading delay (T_o) and computing delay for model updates (T_c). We can express these delays as follows:

$$T_{COOL} = T_o + T_c. \tag{4}$$

The data offloading delay is denoted as

$$T_o = T_o^{ue} + T_o^{gw} \tag{5}$$

and

$$T_o^{ue} = \max_{k \in \mathcal{K}} t_{o,k}, \tag{6}$$

where T_o^{ue} represents the total offloading delay from UEs to GW and T_o^{gw} represents the offloading delay from GW to LEO sat server. $t_{o,k}$ also represents the offloading delay of UE k. It is assumed that the communication links from K UEs to the GW, GW to the connected LEO sat server are independent and non-overlapping. Accordingly, the following equations can be obtained:

$$t_{o,k} = \frac{\theta_k D_k}{R_k} = \frac{\theta_k D_k}{B_{ue} \log_2 (1 + \frac{p_{o,k} g_k}{N_o})} \tag{7}$$

and

$$T_o^{gw} = \frac{D_s}{R_{gw}} = \frac{D_s}{B_{gw} \log_2 (1 + \frac{p_{o,gw} g_{gw}}{N_o})}. \tag{8}$$

In these equations, R_k, R_{gw} denote the possible uplink data rate of each link, B_{ue}, B_{gw} denote the bandwidth of each link, $p_{o,k}, p_{o,gw}$ denote the transmission power assigned to UE k and gw, g_k, g_{gw} denote the channel gain of UE k, gw respectively, and N_o represents the variability of the noise in the complex white Gaussian channel. In the context of COOL, the computing delay for model updates is represented as

$$T_c = N \max\left\{ \max_{k \in \mathcal{K}} t_{c,k}, t_{c,s} \right\} + N t_a, \tag{9}$$

with $t_{c,k}$ representing the update delay of UE k, $t_{c,s}$ representing the update delay of the LEO sat server, N representing the total rounds in model update and t_a denoting the fixed time slot for parameter aggregation and model broadcast. In the procedure of updates, related to update delay, we can determine two factors, denoted as

$$t_{c,k} = \frac{\tau \gamma (1 - \theta_k) D_k}{f_{ue}} \tag{10}$$

and

$$t_{c,s} = \frac{\tau \gamma D_s}{f_s}. \tag{11}$$

Here, τ represents the number of epochs per round, γ represents the number of CPU clock frequencies required for training 1-bit data, f_{ue} denotes the CPU clock frequency of UE k and f_s denotes the CPU clock frequency of the server.

We assume that both the UE's total transmission capacity and total computational capacity within the COOL framework are limited by P for efficient optimization. According to equations (4)-(11), we can formulate the problem of minimizing the delay in COOL as follows.

$$\begin{aligned} \textbf{(P1)}: \min_{\boldsymbol{\theta}_k, \boldsymbol{p}_{o,k}, p_{o,gw}} & \left\{ \max_{k \in \mathcal{K}} \frac{\theta_k D_k}{B_{ue} \log_2 \left(1 + \frac{p_{o,k} g_k}{N_o}\right)} \right. \\ & + \frac{D_s}{B_{gw} \log_2 \left(1 + \frac{p_{o,gw} g_{gw}}{N_o}\right)} \\ & \left. + N \cdot \max\left\{ \max_{k \in \mathcal{K}} \frac{(1-\theta_k)\tau\gamma D_k}{f_{ue}}, \frac{\tau\gamma D_s}{f_s} \right\} \right\} \end{aligned} \tag{12}$$

$$\begin{aligned} \textit{s.t.} \quad & \sum_{k \in \mathcal{K}} p_{o,k} \leq P, \\ & \sum_{k \in \mathcal{K}} p_{o,gw} \leq P, \\ & p_{o,k} \geq 0, \quad \forall k \in \mathcal{K}, \\ & p_{o,gw} \geq 0, \\ & D_k \geq 0, \quad \forall k \in \mathcal{K}. \end{aligned}$$

V. Conclusion

This paper presents a novel approach to address the challenges faced by traditional federated learning methods. By leveraging LEO satellites as central server substitutes, our proposed architecture offers several advantages, including improved communication capabilities, enhanced data privacy and security, and the ability to extend federated learning to remote areas with limited network access. We formulated the problem of optimizing the overall learning delay by utilizing the dynamic characteristics of LEO satellites and offloading techniques. The proposed architecture opens up new opportunities for the deployment of federated learning in both urban and remote areas, making it a promising solution for today's data-driven society.

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References

[1] S. Chen et al., "Vision Requirements and Technology Trend of 6G: How to Tackle the Challenges of System Coverage Capacity User Data Rate and Movement Speed", *IEEE Wireless Commun.*, vol. 27, no. 2, pp. 218-28, Apr. 2020.

[2] O. Kodheli et al., "Satellite Communications in the New Space Era: A Survey and Future Challenges", *IEEE Commun. Surveys and Tutorials*, vol. 23, no. 1, pp. 70-109, 2021.

[3] H. B. McMahan et al., "Federated Learning: Strategies for Improving Communication Efficiency", *Proc. 20th Int'l. Conf. Artif. Intell. Stet.*, 2017.