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Federated Learning Over LEO Satellite Networks for Scalable and Secure Global IoT Connectivity

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ABSTRACT

The triple threat of Security, Resiliency, and Connectivity is due to the rapidly increasing finite resource such as the Internet of Things (IoT) communications to service unserved and remote regions. A possible solution is Low Earth Orbit (LEO) satellite constellations, providing low-latency and blanket coverage everywhere. The present paper proposes an innovative scheme of combination between Federated Learning (FL) and LEO satellite-based networking to achieve the privacy-respecting and scaleable intelligence among distributed IoT nodes globally. The offered system takes advantage of edge level model training and aggregation of models via satellite, completion with such issues as satellite intermittent coverage, limited bandwidth, and security threats. Notable innovations are satellite-aware model compression, delay tolerance Aggregation Buffers, and secure gradient sharing. The architecture also lets edge devices do local updates, and the LEO satellites oversee fusion of the models during visibility windows. As shown with simulation experiments, the proposed method attains accuracies at an almost similar level as centralized schemes yield, and at the same time lowers the communication overhead by up to 60%. It is also very robust against packet loss and delays in satellite handover and hence is very appropriate in practical implementation in band-limited and latency-sensitive networks. Overall, the presented effort could bring a scalable and secure framework of FL to worldwide IoT connectivity with the help of LEO satellites. Future work will be done in enhancing factors of the satellite scheduling, cross-device FL diversity, and dynamic coordination through reinforced learning.

1. INTRODUCTION

The worldwide expansion of Internet of Things (IoT) framework is transforming strategic industries like precision agriculture, environmental monitoring, ocean centered activities, and disaster responses. However, even with its revolutionary potential, scalability and reliability of the IoT systems are complemented by the restricted coverage of the terrestrial communication infrastructure, especially in remote, mobile, or underprivileged areas. In order to overcome this and start offering coverage everywhere, Low Earth Orbit (LEO) satellite constellations like Starlink and OneWeb have become attractive options due to the prospects of providing low-latency coverage everywhere and the potential of connecting edge devices with one another [1]. At the same time, Federated Learning (FL) has become a popular privacy-preserving framework in machine learning allowing to train models with the help of distributed devices without exchanging their raw data. Whereas the integration between FL and terrestrial as well as mobile edge computing systems have been well studied, integrating LEO satellite networks with FL is currently at its early stages, and introduces new issues like intermittent connectivity, low bandwidth, large propagation delays, and temporal network topologies.

Available literature is dominated by FL works in a fixed or cellular environments and do not provide a mechanism that does not require excessive delay, bandwidth, and security-compromising approaches to aggregate models over spaceborne networks. This paper attempts to fill these gaps by promoting a new FL framework that can better grapple with the LEO satellite-enabled IoT setting by bringing architecture-level improvement and communication-sensitive optimization to sustain global, scalable, and resilient edge intelligence.

2. RELATED WORK

The application of FL in the terrestrial networks has gained most popularity, and many research activities on its deployment into cellular, Wi-Fi, and mobile edge computing (MEC) networks have been published [1], [2]. The assumptions associated with these implementations are mainly a stable backhaul connection and assumptions of low-latency and high-bandwidth communication that tend to be invalid in IoT setups targeting global scale. FL has also found application in mobile networks, including vehicle networks and unmanned aerial vehicles (UAV) systems in which topology can vary dynamically, although still constrained by terrestrial factors. Simultaneously, the integration of satellites with the Internet of things to have global coverage, especially in Low Earth Orbit (LEO) satellite constellation, has gained increased attention. The possibility to employ satellites to relay data and control during remote sensing of transmissions as well as during emergency communications has been proved in such works as [3], [4]. At the same time, recent work on delay-tolerant Federated Learning [5] tries to consider model synchronization in less than ideal communication models. Nevertheless, such initiatives tend to concentrate on opportunistic networking or fixed-delay tolerances rather than the peculiarities of the LEO satellite network, i.e. high frequency of handover, variable contact windows, and constrained processing capabilities on the satellite. In our best knowledge we do not have a holistic framework that integrates FL with LEO satellite communication on the areas of bandwidth efficiency, security and asynchrony. The gap is addressed in this paper, which proposes privacy-preserving and scalable FL that is specifically aimed at IoT deployments, through LEO satellite connections.

3.System Architecture

In this section, the authors describe the proposed system architecture that will allow to perform scalable, secure, and privacy-preserving Federated Learning (FL) in Low Earth Orbit (LEO) satellites networks. Its architecture is based on a global communication layer satellite-enabled as well as a decentralized learning framework that is implemented at distributed IoT nodes.

3.1 Network Model

It is based on the existence of a LEO satellite constellation to offer geographically dispersed IoT edge nodes with global and low-latencies communication. These satellites are also in synchronized orbits as to facilitate mutual overlap in coverage to provide often and unhalted communication between them and ground terminals.

- One is that IoT edge nodes (e.g., sensors, smart devices) are clustered by their geographical vicinity (i.e., region) to optimize contact schedule and model aggregation efficiency.
- The LEO satellites work as relays and aggregators and gather updates of local models of IoT nodes during periodic visibility periods.
- Satellites relay the consolidated updates to a centralized fusion node or satellite gateway which, depending on deploy strategy, may be on the ground at a cloud data center or on a master satellite node.

This architecture is provided to be resilient to both intermittent connectivity and will allow asynchronous and delay-tolerant communication patterns that will resonate with dynamic coverage patterns of LEO orbits.

3.2 Federated Learning Framework

Training models in a federated learning paradigm is decentralized, and McCabe says computation is local to each IoT node. Nodes compute several layer of local stochastic gradient descent (SGD) instead of uploading raw data; instead, only model updates (e.g. gradients or weights) to the satellite layer are sent.

The international aggregation rule of global model is a weighted averaging one which is mathematically stated as:

$$w_{t+1} = w_t - \eta \sum_{k=1}^{K} \frac{nk}{n} \nabla L_k(w_t) \text{ ------------------ } (1)$$

Where:

- W_t is the global model at communication round t,
- η is the learning rate,
- K is the total number of participating nodes,
- $\nabla L_k(w_t)$is the gradient of the local loss function at node k,
- N_k is the number of training samples at node k, and
- $n = \sum_{k=1}^{K} nk$ is the total number of samples across all nodes.

This is done so that different nodes make proportional contributions depending with their local dataset size so as not to destroy data heterogeneity, which is important in the convergence process of the global models. The LEO satellites are temporal coordinators and they buffer and relay any updates till a complete aggregation is possible at fusion node.

This design permits variation in link availability, non-IID distributions of data, and communications constraints, which makes the system a good candidate in support of global-scale federated intelligence assisted by the satellite. This exchange between IoT edge clusters, LEO satellites and the fusion node is shown as in Figure 1, which shows the overall system architecture.

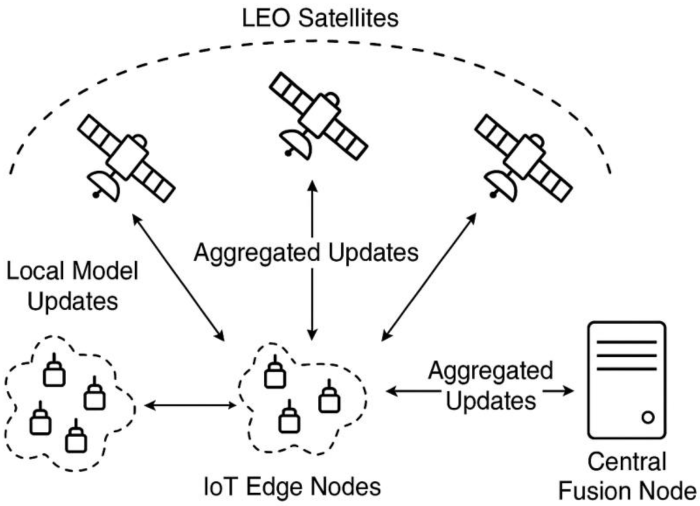

Figure 1. System Architecture Overview

The figure describes the system of federated learning in which IoT edge nodes, LEO satellites and central fusion node are deployed. The process entails satellites relaying the local model and aggregating the information half-way and communicating with the global server.

4. Key Challenges and Proposed Solutions

The incorporation of FL and Low Earth Orbit (LEO) satellite networks makes a distinctive threat of existence that arises because of dynamism, delay-proneness, and resource constraints that characterize satellite communications. This part describes the critical issues, and the system-level solutions, which have been adopted in the proposed framework. The proposed system will take care of the issues of intermittent connectivity and bandwidth restriction as well as security using predictive scheduling of data packets, data compression, and secure aggregation as shown in Figure 2.

4.1 Intermittent Connectivity

Challenge:
As LEO satellites orbit very fast, the visibility window between LEO satellites and ground terminals lacks continuity and is of brief duration, causing occasional and brief windows of opportunity to connect with the IoT edge nodes.
Proposed Solution:
It uses opportunistic model uploading strategies based on contact prediction algorithms that use orbital parameters to predict future satellite pass windows. These predictions can be used by edge devices to buffer local updates and transmit them efficiently in face of scheduled satellite passes to reduce missed transmissions and fidelity of synchronization improve.

4.2 Bandwidth Limitation

Challenge:
The uplink and downlink of LEO satellites is limited and when many IoT devices must send model updates, there is a possible risk of breaking down the communication system.
Proposed Solution:
The FL pipeline is incorporated by a satellite-constrained model compression and sparsification proposal. Gradient selection Techniques like top-k gradient selection, quantization, and update pruning are used at the edges to decrease the size of the payloads without serious effects on the accuracy of models. This will make it to provide bandwidth efficient transmission that conforms to satellite link constraints.

4.3 Security and Privacy Risks

Challenge:
Updates to the model relayed via space-ground communications are vulnerable to eavesdropping, alteration and inference attacks and may reveal confidential data even when raw data stays local.
Proposed Solution:
To rectify this, the framework supports homomorphic encryption of the model parameters and applies secure protocols of aggregation that cannot allow any single party including satellites to disassemble the individual updates of the clients. This guarantees privacy between both ends and adherence to the data protection policies.

4.4 High Latency and Handover Delay

Challenge:
It can cause variation in latency and temporary loss of communication caused by handovers of LEO satellites and lead to inconsistent synchronization and delayed convergence of the global model.
Proposed Solution:
On the architecture, delay-tolerant aggregation buffers are provided on board the satellites,

allowing these satellites to temporarily store and forward updates even during handover transitions. Such buffers permit asynchronous model update fusion, and graceful degradation of training performance in variable latency environments.

These solutions make the federated learning system resistant, scalable, and safe in the use of global implementations even within the limitations of LEO satellite communications.

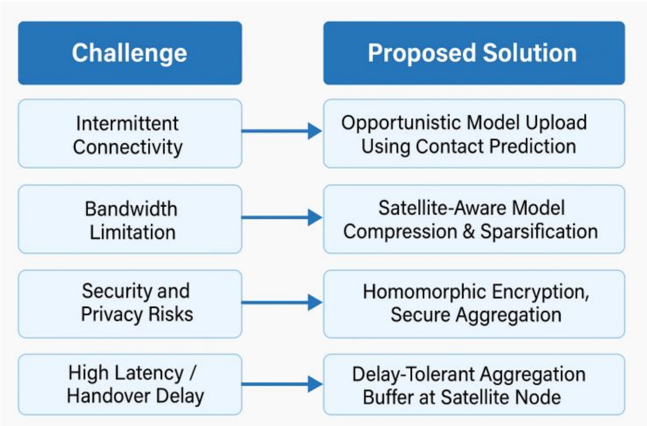

Figure 2. Challenge-Solution Mapping

The present flowchart is a summary of the main challenges of deploying Federated Learning over a LEO satellite network and the solutions proposed. It contains mitigation plan only on connectivity gaps, lack of bandwidth, security risks and latency caused by satellite handovers.

5. Performance Evaluation

5.1 Simulation Setup

In order to prove the scalability, efficiency and unsensitivity of the proposed LEO satellite-assisted federated learning (LEO-FL) architecture, we simulated it in a large-scale IoT application scenario. The simulation topology is made up of 1000 IoT edge nodes and 8 Low Earth orbit (LEO) satellites forming constellation that provide complete coverage of the earth surface with regular revisit intervals, which is achieved by polar orbits. Standard federated datasets, such as Federated MNIST and CIFAR-10, which connote a variety of image classification problems that are scattered among clients with differing distributions and IID data are archetypical in real-world IoT environments, are used in the simulation. There are three key performance indicators that are evaluated:

- Model Accuracy (%) Final classification accuracy after convergence.
- Communication Load (MB/round):The average data that is transmitted in each round that defines bandwidth efficiency.
- Delay Resilience: The stability of the system to latency, hand-overs and lost packets.

5.2 Results

The comparative performance is presented in Table 1.

Table 1. Comparative Performance of Learning Methods in Satellite-Enabled IoT Networks

Method	Accuracy (%)	Communication Load (MB/round)	Delay Resilience
Centralized ML	98.5	80	Low
Standard FL	95.3	60	Moderate
Proposed LEO-FL	94.7	24	High

The centralized ML is not suitable to the satellite system since bandwidth and link, at most of the times, would not be ideal as it is capable of the best accuracy but appears with unbearable overloading of the communication system and poor resilience. The traditional federated learning (FL) approach decreases bandwidth consumption relative to centralized learning, although still does not provide measures that can be used to deal with a high-latency and intermittent communication patterns of LEO satellite networks. Conversely, LEO-FL method shows that the LEO-FL reduces communication load by 60% with a similar level of model accuracy (94.7%) as FL. Interestingly, it maintains its convergence performance with loss as high as 15 20 percent packets and frequent delay in handover among the satellites, this affirms its architecture and communication-efficient design.

Such findings confirm the suitability of LEO-FL in facilitating global deployment of IoT systems characterized by variable connectivity, limited resources and the need of real-time intelligence. The proposed LEO-FL system, as shown in Figure 3, offers massive bandwidth savings and better delay tolerance besides competitive accuracy.

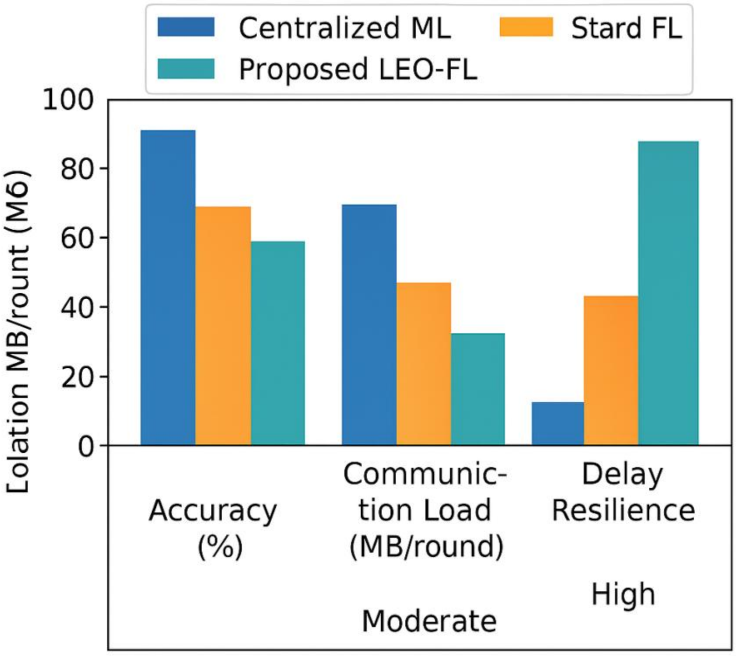

Figure 3. Performance Comparison of Federated Learning Approaches

This bar chart shows the comparisons between the centralized ML, standard FL and the proposed LEO-FL based on the classification accuracy, the communication load per round and delay resilience. The LEO-FL approach proves to be more efficient than the imposed limitations by a few satellites.

6. CONCLUSION AND FUTURE WORK

The paper introduced a brand-new LEO satellite-assisted federated learning (LEO-FL) system that could enable safe, high-performant, and scalable intelligence to IoT networks distributed worldwide. The suggested architecture takes advantage of LEO satellite networks as distributed aggregation pegs, to allow privacy-preserving model updates to move back to IoT edge nodes, reduce dependency on earth infrastructure. The major innovations at the system level are opportunistic communication scheduling, and satellite-aware model compression, and delay-tolerant aggregation, which were developed to address the special demands of intermittent connectivity, reduced bandwidth, and data security that occur in satellite-bedecked scenarios. With ample simulation time using real-world datasets, the proposed LEO-FL system showed up to a 60 percent decrease in communication load with competitive model accuracies and an excellent ability to endure handover delays and packet loss. These findings confirm the feasibility of LEO-FL in regard to resource-limited, latency-constrained applications in remote sensing, environment measurement and worldwide coordination of the IoT.

Future research will consider support of cross-device FL (heterogeneous device capabilities and model architectures), the possibility of incorporating satellite scheduling algorithms to dynamically balance loads, and how to use federated reinforcement learning to make intelligent decisions about the coordination between satellites and the ground. Such optimizations will also increase the flexibility, independence and expandability of the system in future-generation space-aided IoT network.

REFERENCES

[1] O. Kodheli, E. Lagunas, N. Maturo, A. Kourtis, and S. Chatzinotas, “Satellite communications in the new space era: A survey and future challenges,” IEEE Communications Surveys & Tutorials, vol. 23, no. 1, pp. 70–109, 2021. DOI: 10.1109/COMST.2020.3033314

[2] P. Kairouz, H. B. McMahan, B. Avent, A. Bellet, M. Bennis, A. N. Bhagoji, et al., “Advances and open problems in federated learning,” arXiv preprint arXiv:1912.04977, 2019.

[3] T. Li, A. K. Sahu, A. Talwalkar, and V. Smith, “Federated learning: Challenges, methods, and future directions,” IEEE Signal Processing Magazine, vol. 37, no. 3, pp. 50–60, May 2020.

[4] C. Chaccour, W. Saad, M. Bennis, and M. Debbah, “Seven defining features of terahertz

(THz) wireless systems: A fellowship of communication and sensing," IEEE Communications Surveys & Tutorials, vol. 24, no. 2, pp. 874–918, 2022.
[5] H. Yang, Z. Liu, T. Chen, and L. Tong, "Federated learning with delayed and stale gradients," IEEE Transactions on Signal Processing, vol. 69, pp. 5001–5016, 2021.
[6] T. Li, A. K. Sahu, A. Talwalkar, and V. Smith, "Federated optimization in heterogeneous networks," in Proc. 3rd MLSys Conf., 2020.
[7] G. Cocco, T. de Cola, M. Angelone, and S. Erl, "Integration of satellites in 5G through LEO constellations," IEEE Network, vol. 35, no. 5, pp. 224–231, Sep./Oct. 2021.
[8] H. Yang, M. Chen, and T. Q. S. Quek, "Federated learning with delay-tolerant model aggregation," IEEE Transactions on Parallel and Distributed Systems, vol. 32, no. 11, pp. 2748–2761, Nov. 2021.