Flexible Synchronous Federated Learning Approach for LEO Satellite Constellation Networks

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***Abstract*—This paper presents a flexible synchronous federated learning (FlexSync-FL) approach for Low Earth Orbit (LEO) satellite constellation networks, where LEO satellites train local models and conduct a collaborative global model at the Network Operations Center (NOC). Unlike the standard synchronous FL, FlexSync-FL employs a dual-trigger synchronization mechanism that initiates global model aggregation either upon receiving updates from all clients (satellites) or after a predefined maximum interval time has elapsed. Furthermore, FlexSync-FL leverages inter-satellite links (ISLs) to facilitate forwarding local models among satellites, especially for those without direct visibility to ground gateway stations (GWs). In particular, FlexSync-FL aims to mitigate the impact of long latency and intermittent connectivity, inherent in satellite networks, on the FL process. The effectiveness of the proposed FlexSync-FL framework is demonstrated through simulations that employ Long Short-Term Memory (LSTM) networks to train local models at each LEO satellite for traffic forecasting using real-world aeronautical datasets.**

***Index Terms*—6G, NTNs, LEO satellite communications, FL, traffic forecasting.**

I. Introduction

A. Background and Motivations

The exponential increase in global communication demand necessitates highly efficient, scalable, and robust communication networks. The recent advancements in satellite technologies, particularly Low Earth Orbit (LEO) constellation networks, provide a promising solution to meet these demands. Specifically, LEO satellite networks provide significantly reduced propagation delays and enhanced data rate transmission compared to Geostationary (GEO) satellites as they operate at lower altitudes. However, the decentralization characteristic of LEO networks introduces distinct challenges, necessitating the development of efficient distributed algorithms for effective network management [1], [2].

Although centralized frameworks are preferred for their simplicity and centralized control, their applicability in decentralized LEO satellite constellation networks is limited. In particular, satellite constellations cover extensive geographic areas and serve diverse user communities. This results in high volumes of heterogeneous data, variable network conditions, and complex management requirements. In such environments, traditional centralized approaches may not be effective as they require the transfer of large amounts of data to a central unit for processing, increasing communication costs and potentially compromising data privacy. Furthermore, centralized models struggle with the dynamic nature of LEO networks, where satellites are constantly in motion, leading to changes in network topology and traffic patterns.

Federated Learning (FL) technology, introduced by Google in 2016, enables training ML models across decentralized edge devices holding local data samples without exchanging them instead of centralizing data on a single server as such in the classical learning approaches [3]. This decentralized approach addresses privacy concerns by keeping sensitive data on the devices and reduces the amount of data exchanged with the central entity, presenting a promising solution to challenges faced in LEO satellite networks. In this paradigm, each satellite in the constellation can use its local data to train an ML model[1]. The satellites then share their model updates with a central entity, e.g., the Network Operation Center (NOC), which aggregates these updates to refine the global model. In particular, satellite constellations are typically owned and operated by a single entity [5]. Thus, unlike conventional FL, where client availability is stochastic, the spatio-temporal scope of FL in satellite constellations is more deterministic and predictable.

While the deterministic, predictable, and partially controllable device participation in satellite FL facilitates coordinating the learning process, it also introduces challenges related to orbital mechanics and connectivity between satellites and the central entity. Precisely, connectivity patterns in satellite FL are influenced by orbital dynamics, which govern the movement and positioning of satellites. As a result, the availability of direct communication links between satellites and the central entity becomes limited, affecting the convergence speed in FL [5], [6]. Consequently, Inter-Satellite Links (ISL) technology, which enables direct communication and data exchange between proximate satellites within a constellation, can be leveraged to mitigate the limitations imposed by unavailable or disrupted ground communication links. Specifically, ISL can be utilized to exchange locally trained ML model updates and forward them to the central entity for aggregation, reducing the dependency on direct links with the central entity and enabling efficient FL within the constellation.

[1]In this paper, we focus on regenerative satellites, which are equipped with advanced functionalities that enable them to collect, process, and transmit data autonomously [4].

B. Literature Review and Contributions

FL over LEO satellite constellations is an emerging research area that has gained significant attention recently. For instance, the work in [5] introduced FL within satellite constellations, highlighting its unique challenges and opportunities due to the distinct connectivity patterns. A classification for satellite FL based on communication capabilities, constellation design, and server location is presented. In [7], the authors proposed an asynchronous FL approach based on FedAvg for large LEO satellite constellations and evaluated its performance using MNIST and CIFAR-10 datasets. The study in [8] proposed a FL framework called FedLEO that optimizes the FL process in LEO satellite constellations. The framework uses intra-plane model propagation and sink satellite scheduling to improve FL convergence speed. The work in [9] presented AsyncFLEO, an asynchronous FL framework for LEO satellite constellations that aims at enhancing FL efficiency within satellite communications. High altitude platforms (HAPs) have been employed as parameter servers to reduce the convergence time. The authors of [10] proposed a communication scheme to enhance FL efficiency in mega-constellations of LEO satellites by utilizing ISL between satellites in the same orbit and the predictable movements of satellites, along with partial data aggregation. In particular, long propagation delays in satellite networks present significant challenges for traditional FL approaches, primarily affecting model consistency and synchronization. Specifically, these delays lead to synchronization difficulties in model updates, as satellites at varying distances from the central entity experience different transmission times. This can result in some satellites operating with outdated models, thereby reducing the overall accuracy and efficiency of the federated model.

In this paper, we propose a flexible synchronous FL framework (FlexSync-FL) for traffic forecasting in LEO satellite constellation networks connected with ISL. The framework incorporates a maximum waiting threshold for initiating the aggregation of the global model. Upon reaching this predetermined interval, FlexSync-FL proceeds with the aggregation process, incorporating the local models that have been received by that time. This prioritizes updates from satellites with direct communication links to GWs or through a minimal number of ISL transmissions to improve the convergence time of FL. Furthermore, if model updates have been collected from all participated satellites, the aggregation process will be initiated ahead of the maximum interval time. Note that satellites excluded from a particular model aggregation cycle due to high transmission delay can be reintegrated into the process in subsequent cycles once their position becomes closer to the GWs. This ensures that all satellites have the opportunity to contribute to the FL process over time, enhancing global model accuracy. Finally, the proposed framework employs Long Short-Term Memory (LSTM) networks to train local prediction models on each LEO satellite for traffic forecasting by utilizing real-world aeronautical datasets to assess the performance and efficacy of the FlexSync-FL approach. In particular, accurate traffic forecasting is crucial in enhancing traffic management, optimizing resource allocation, and facilitating informed infrastructure planning.

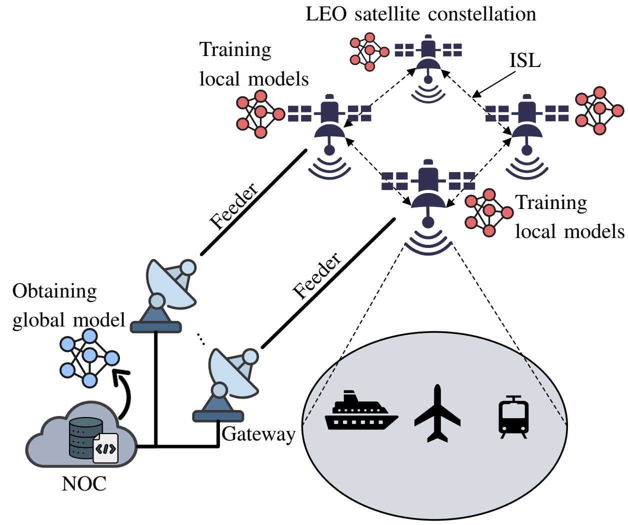

Figure 1: The considered system model.

II. System Model

We consider a constellation of K LEO satellites consisting of L distinct orbital planes. Within each orbit $l \in \mathcal{L}$ where $\mathcal{L}$ is the set of the orbital planes, there are K_l satellites. Let h_k represent the altitude of the k^{th} satellite. Each satellite k traverses at a velocity given by

$$v_k = \sqrt{\frac{\mu}{h_k + r_e}}, \tag{1}$$

where $r_e = 6371\,\text{km}$ represents the mean radius of the Earth and $\mu = 3.98 \times 10^{14}\, m^3/s^2$ is the geocentric gravitational constant. Given this velocity, the orbital period T_k^{orb} for the satellite k is subsequently defined as $T_k^{\text{orb}} = 2\pi(r_e + h_k)/v_k$. We consider a set $\mathcal{S}$ of GWs connected to the NOC through fiber-optic connections, as shown in Fig. 1. Satellites communicate with GWs through radio frequency (RF) links. A communication link between a satellite $k \in \mathcal{K}$ and a GW $s \in \mathcal{S}$ can be established if the satellite falls within the visibility range of the GW, ensuring line-of-sight (LoS) link between them is not obstructed by the Earth. Let $\alpha_{\min}$ the minimum elevation angle, the GW $s \in \mathcal{S}$ and satellite $k \in \mathcal{K}$ are visible if

$$\alpha_{k,s}(t) \triangleq \angle\left(C_s, C_k(t) - C_s\right) \le \frac{\pi}{2} - \alpha_{\min}, \tag{2}$$

where C_k and C_s represent the positions of satellite k and the GW s, respectively.

The signal-to-noise ratio (SNR) for a given satellite k and a GW s across an RF channel characterized by additive white Gaussian noise (AWGN) can be expressed as

$$\text{SNR}_{k,s}(t) = \frac{P_{tr} G_k G_s}{N_0 B L_{k,s}(t)}, \tag{3}$$

where P_{tr} is the transmit power, G_k and G_s are the antenna gain of satellite k and GW s, respectively, N_0 is the noise level, and B is the channel bandwidth. $L_{k,s}(t)$ denotes the path loss between satellite k and GW s defined as $L_{k,s}(t) = \left(\frac{4\pi d_{k,s}(t) f}{c}\right)^2$, where $d_{k,s}(t)$ is the distance between satellite k and GW s at time t, f is the carrier frequency, and c is the light speed. Therefore, the maximum achievable data rate between satellite k and GW s is given by

$$r_{k,s}(t) = \varrho(t) B \log_2(1 + \mathrm{SNR}_{k,s}(t)), \tag{4}$$

where $\varrho(t)$ is a time-varying variable that represents the dynamic connectivity between satellite k and GW s over time slots and is defined by

$$\varrho_{k,s}(t) = \begin{cases} 1 & \text{if } \alpha_{k,s}(t) < \frac{\pi}{2} - \alpha_{\min}, \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

Accordingly, the required time for transmitting data with size D between a satellite k that has a direct LoS link with GW s at time slot t can be calculated by

$$T_{k,s}^{\mathrm{GW}}(t) = \overbrace{\frac{D}{r_{k,s}(t)}}^{\text{Transmission}} + \overbrace{\frac{d_{k,s}(t)}{c}}^{\text{Propagation}}. \tag{6}$$

We consider that ISLs use laser beams to enable high-speed and secure direct data exchange between satellites without the need for terrestrial infrastructure, thereby reducing latency and increasing data throughput. Establishing an ISL requires the involved satellites to maintain a direct LoS without any blockages, such as the curvature of the Earth. Considering two satellites, k and k', the maximum allowable distance $d_{\max}^{\mathrm{ISL}}$ for establishing an ISL between them is given by [11]:

$$d_{\max}^{\mathrm{ISL}} = \sqrt{(h_k + r_e)^2 - r_e^2} + \sqrt{(h_{k'} + r_e)^2 - r_e^2}, \tag{7}$$

where h_k and $h_{k'}$ are the altitudes of satellites k and k', respectively. This equation ensures that the laser link remains unobstructed by the Earth's surface. Therefore, we define the propagation delay for a laser link between satellite k and k' as follows:

$$T_{k,k'}^{\mathrm{ISL}} = \begin{cases} \frac{d_{k,k'}}{c} & \text{if } d_{k,k'} \le d_{\max}^{\mathrm{ISL}}, \\ \infty & \text{if } d_{k,k'} > d_{\max}^{\mathrm{ISL}}, \end{cases} \tag{8}$$

where $d_{k,k'}$ represents the distance between satellite k and k'. Here, the ISL propagation delay is considered infinity when the distance $d_{k,k'}$ exceeds $d_{\max}^{\mathrm{ISL}}$ meaning that a direct LoS communication link cannot be established between the two satellites. Note that due to the high data rate of laser links, the transmission delay is typically negligible [12]. Consequently, in this work, we consider the total delay for an ISL to be solely attributed to the propagation delay.

Accordingly, the total time required to transmit data from satellite k to GW s considering both ISL delay and satellite-to-GW delay can be obtained by

$$T_{k,s}^{\mathrm{tot}} = \begin{cases} T_{k,s}^{\mathrm{GW}}, & \text{if } \varrho_{k,s} = 1, \\ \sum_{i=1}^{I} T_{k,k'}^{\mathrm{ISL}}(i) + T_{k_s,s}^{\mathrm{GW}}, & \text{if } \varrho_{k,s} = 0, \end{cases} \tag{9}$$

where I is the number of ISL hops required to reach a satellite that has direct LoS with the GW, $k' \in \mathcal{K}, k' \neq k$, and k_s denotes the satellite that has a direct LoS link with the GW s. In this work, we consider that all LEO satellites have the same computation capabilities for training local models. Thus, our analysis is focused on transmission and propagation delays, as these delays are variable over time, influenced by network dynamics and satellites positions.

III. Federated Learning Framework

The process of the conventional FL typically consists of local training and global aggregation. During local training, each device j uses its own dataset $\mathcal{D}_j$ to compute a local model update through an optimization algorithm, e.g., Stochastic Gradient Descent (SGD), as follows

$$\boldsymbol{\theta}_j^{n,m+1} = \boldsymbol{\theta}_j^{n,m} - \eta \nabla f\left(\boldsymbol{\theta}_j^{m}; \mathcal{D}_j\right), \tag{10}$$

where $\boldsymbol{\theta}_j^{n,m}$ is the model parameters of the client j at local iteration m of the global round n, η is the learning rate, and f is the loss function. Once local training is complete, the local models are sent to a central server for global aggregation. This aggregation is often performed as a weighted average of the local models [13]:

$$\boldsymbol{\theta}_g^{n+1} = \sum_{j \in \mathcal{J}} \xi_j \boldsymbol{\theta}_j^{n,M}, \tag{11}$$

where $\boldsymbol{\theta}_g^{n+1}$ is the global model at global iteration $n+1$, and $\xi_j, \forall j \in \mathcal{J}$ are weights that could be determined by the number of samples on each device. The updated global model is then sent back to all participating devices for another round of local training, completing one FL iteration.

A. Proposed FlexSync-FL Algorithm

In the proposed FlexSync-FL framework, LEO satellite nodes collect and process data locally, which is then used in the FL training process. The NOC is responsible for coordinating the training of machine learning models across multiple satellite network nodes, as well as aggregating the locally trained models and updating the global model. The overall process involves the following steps: *1) Local training process at the satellites and 2) Global model aggregation process at the NOC.*

1) Local Training Process at the Satellites: The local training procedure executed at each satellite closely resembles the typical client-side computations in the standard FL systems. Each satellite initializes its local model by setting the weights $\boldsymbol{\theta}_k^{n,0}$ equal to the received global model weights $\boldsymbol{\theta}_g^{n}$, where n denotes the global training round index. Subsequently, satellite k proceeds to train the local model. Each satellite trains local models $\boldsymbol{\theta}_k, \forall k \in \mathcal{K}$ using the collected local data $\mathcal{D}_k$. The model parameters are updated using the SGD algorithm. The updated model at each local iteration m is computed as follows:

$$\boldsymbol{\theta}_k^{n,m+1} = \boldsymbol{\theta}_k^{n,m} - \eta \nabla f\left(\boldsymbol{\theta}_k^{n,m}; \mathcal{D}_k\right), \tag{12}$$

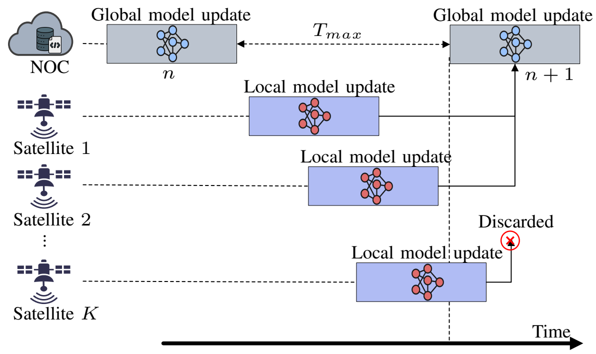

Figure 2: Illustration of the global model update sequence.

where $\nabla f(\boldsymbol{\theta}_k^{n,m}; \mathcal{D}_k)$ is the gradient of the loss function evaluated at the current weights and using the data $\mathcal{D}_k$, defined as

$$f(\boldsymbol{\theta}, \mathcal{D}) = \frac{1}{|\mathcal{D}|} \sum_{\boldsymbol{y} \in \mathcal{D}} g(\boldsymbol{\theta}, \boldsymbol{y}), \tag{13}$$

where $|\mathcal{D}|$ is the cardinality of $\mathcal{D}$ and $g(\boldsymbol{\theta}, \boldsymbol{y})$ is the loss computed using the current model weights $\boldsymbol{\theta}$ and a single data sample $\boldsymbol{y}$ from the $\mathcal{D}$. After M steps of local training, satellite k computes the local gradient $\boldsymbol{\theta}_k^{n,M}$ and sends it to the NOC through GWs.

2) Global Model Aggregation Process at the NOC: The NOC is responsible for aggregating the local updates received from the satellites through the GWs and updating the global model accordingly. The significant distances in satellite communication systems can substantially impact the overall efficiency of FL due to the long propagation delays. In particular, waiting for local model updates from all satellites can delay the global model updating process because some satellites may occasionally move out of the direct visibility of ground stations and require multiple ISL transmissions to forward their updates to the NOC, impacting the overall convergence process. Thus, the proposed FlexSync-FL algorithm introduces a maximum waiting time T_{max} for the global model aggregation to begin. This allows only those satellites within the direct visibility range of GWs or require a minimal number of ISL transmissions to participate in the global model aggregation process. Satellites that require lengthy ISL transmissions to forward their updates, which may introduce long delays in the FL process, are temporarily excluded from the model aggregation process. This selective participation approach reduces the latency of gathering updates from all satellites, improving the convergence speed of the algorithm.

As illustrated in Fig. 2, once the waiting period reaches T_{max}, the FlexSync-FL approach initiates the global model aggregation process with the adequate local models that have been received by that point. The initiation of the global model computation may occur prior to the maximum time threshold T_{max} provided that the NOC has obtained the local models from all participated satellites. Therefore, the time between two consecutive global iterations, $T_g^{n,n+1}$, is determined by the following equation:

$$T_g^{n,n+1} = \min\left(\max(T_{1,s}^{\text{tot}}, T_{2,s}^{\text{tot}}, \dots, T_{K,s}^{\text{tot}}), T_{max}\right), \forall s \in \mathcal{S}. \tag{14}$$

Algorithm 1: FlexSync-FL Global Model Aggregation

Input: $\boldsymbol{\theta_g^n}$ and $\boldsymbol{\theta}_k^{n,M}, \forall k \in \mathcal{K}$
Output: Updated global model $\boldsymbol{\theta_g^{n+1}}$
repeat
  Obtain δ_{n+1} using equation (15);
  if $\delta_{n+1} = 1$ **then**
    Set $\hat{\mathcal{K}}_{n+1} = \emptyset$
    foreach $k \in \mathcal{K}$ **do**
      if $T_{k,s}^{tot} \leq T_{max}$ **then**
        Get $\theta_k^{n,M}$ from the satellite;
        Update $\hat{\mathcal{K}}_{n+1} \leftarrow \hat{\mathcal{K}}_n \cup \{k\}$;
      else
        Discard satellite k;
    Update $\boldsymbol{\theta}_g^{n+1} \leftarrow \sum_{k \in \hat{\mathcal{K}}} \frac{|\mathcal{D}_k|}{|\mathcal{D}_{tot}|} \boldsymbol{\theta}_k^{n,M}$;
    $n \leftarrow n+1$;
    Send the updated global model to the satellites;
  else
    Keep the global model unchanged;
until *Maximum iterations achieved*

We introduce a binary variable $\delta_{n+1}(\tau)$ indicates whether the NOC will perform a global model update at time τ or not, defined as

$$\delta_{n+1}(\tau) = \begin{cases} 1 & \text{if } \tau - t_n \geq T_g^{n,n+1}, \\ 0 & \text{otherwise}, \end{cases} \tag{15}$$

where τ denotes the current time and t_n indicates the timestamp at which the global model was acquired during the preceding iteration n. Accordingly, the update of the global model is computed as follows:

$$\boldsymbol{\theta}_g^{n+1} = \begin{cases} \sum_{k \in \hat{\mathcal{K}}_{n+1}} \frac{|\mathcal{D}_k|}{|\mathcal{D}_{tot}|} \boldsymbol{\theta}_k^{n,M}, & \text{if } \delta_{n+1} = 1 \\ \boldsymbol{\theta}_g^n, & \text{if } \delta_{n+1} = 0, \end{cases} \tag{16}$$

where $\mathcal{D}_{tot} = \sum_{k \in \mathcal{K}} \mathcal{D}_k$ and the term $\frac{|\mathcal{D}_k|}{|\mathcal{D}_{tot}|}$ is to adjust the weight of each satellite's local model in the aggregated global model based on the local data size used in the training process. The notation $\hat{\mathcal{K}}_{n+1}$ denotes the set of satellites participating in the global model aggregation at iteration $n+1$, defined as $\hat{\mathcal{K}}_{n+1} = \{k \in \mathcal{K} : (T_{k,s}^{\text{tot}} \leq T_{max})\}$. After the global model has been updated, the NOC transmits the latest model, $\boldsymbol{\theta}_g^{n+1}$, to all connected satellites through the GWs. Algorithm 1 illustrates the global aggregation process at the NOC.

IV. Performance Evaluation

We consider a network that consists of 50 LEO satellites distributed equally across 5 orbits with a fixed altitude of 550 km. Each satellite transmits model parameters via a communication channel with an allocated bandwidth of 100 MHz. The

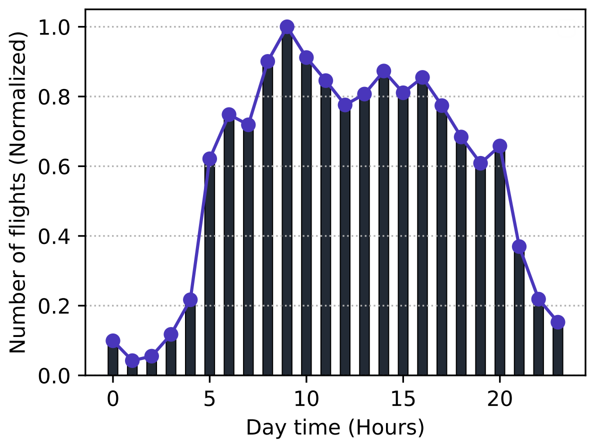

Figure 3: Aeronautical data analysis.

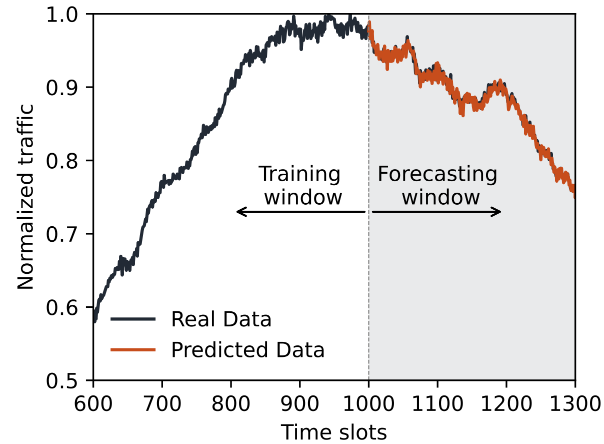

Figure 4: Sequence of the predicted data.

transmit power of all involved satellite nodes to the GWs is set at 40 dBm, and the antenna gain is adjusted at 10 dBi for both the transmitting and receiving ends [11]. Furthermore, the noise power is set at -174 dBm/Hz. TensorFlow is utilized for the implementation of FL algorithms. The learning rate is set at 0.01. The Root Mean Square Error (RMSE) is used as the primary measure for assessing the accuracy of predictions. LSTM networks are used to train local models at each LEO satellite for traffic forecasting.

We leverage aeronautical datasets provided by ADSB-Exchange [14] to provide a realistic representation of traffic variations commonly encountered in aeronautical communication systems. We focus on the fluctuations in the number of flights over time, which are largely influenced by the time of day. The end-users of the communication services are the passengers aboard the aircraft. From the satellite's perspective, all passengers are multiplexed and considered a singular customer entity (e.g. connected to a WiFi access point), generating an average combined data rate of 100 Mbps [15]. Fig. 3 provides a temporal analysis of the number of flights, demonstrating changes during different hours of the day. The shifts in demand over a 24-hour period show the dynamic nature of the user base that the LEO satellites serve.

Figure 4 presents the training window and the subsequent forecasting interval. The figure illustrates real traffic data, encompassing both the training and testing sets, and the forecasted traffic. We can notice a high degree of similarity in the characteristics between the real and predicted traffic patterns. The predicted data illustrated in this figure is obtained at a single LEO satellite. In figure 5, we evaluate the performance of the proposed approach in terms of the RMSE at different LEO satellites using the aggregated global model, as it measures how close the model's predictions are to the actual data. The results show that the RMSE values for each LEO satellite are pretty close to each other, lying between 0.027 and 0.035. This indicates that the proposed model performs consistently well for different nodes, regardless of their individual traffic state.

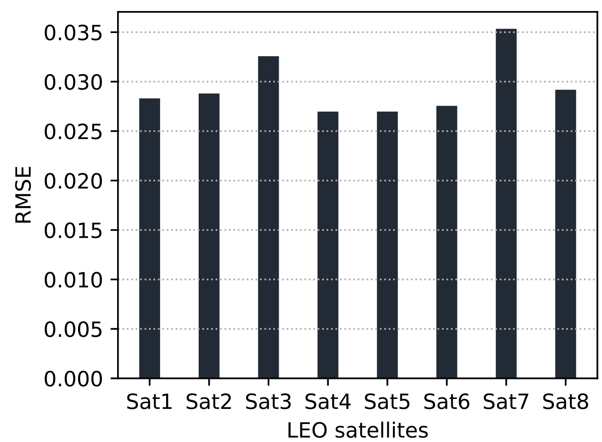

Figure 5: Obtained RMSE at different LEO satellites.

V. Conclusion

This paper has introduced the FlexSync-FL framework designed to enhance FL processes within LEO satellite constellation networks. The proposed FlexSync-FL has a dual-trigger synchronization mechanism, which initiates global model aggregation based on model update receipt from all satellites or a predefined maximum time interval. Moreover, FlexSync-FL leverages ISL to address the long latency and intermittent connectivity in LEO satellite constellations that impact FL efficiency. LSTM networks have been utilized to train local prediction models on satellites using real-world datasets for traffic forecasting. Simulation analysis has been conducted to assist the performance of the proposed FexSync-FL framework.

Acknowledgement

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