Decentralized Satellite Federated Learning via Intra- and Inter-Orbit Communications

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***Abstract*—Satellite federated learning (SFL) emerges as a promising approach to exploit computing and data resources within low Earth orbit (LEO) satellite constellations for supporting intelligent applications while maintaining privacy protection. Most of the existing works of SFL consider a ground station as the central server to aggregate model parameters transmitted from satellites. However, the intermittent connection between satellites and ground stations leads to overlong convergence time. In this paper, we propose a novel decentralized SFL in the Walker-Delta constellation, where satellites communicate with nearby satellites in the same or different orbital planes through inter-satellite links (ISLs). We formulate a mixed combinatorial optimization problem that involves the joint optimization of power control, bandwidth allocation, and routing selection of each satellite to minimize the energy consumption in SFL. A joint resource allocation and routing selection (JRARS) algorithm is subsequently developed to solve the proposed optimization problem. Results show that our proposed decentralized SFL framework outperforms other SFL frameworks in terms of convergence time and accuracy. We also show that our proposed JRARS algorithm consumes much lower energy consumption than the baseline algorithms when the model converges.**

I. Introduction

The evolution of low-Earth-orbit (LEO) satellite communication systems is progressively enhancing the sensing and computing capabilities of satellites, leading to the generation of various onboard data, such as high-precision images [1]. Efficient utilization of the data and computing power available on LEO satellites makes it possible to deploy artificial intelligence (AI) in space. Satellite federated learning (SFL), emerges as a promising technology to enable the collaborative training of a global model among satellites under the coordination of a ground station while maintaining the privacy of the raw data on each satellite. SFL has promising applications in various emerging scenarios, including weather forecasts, natural disaster monitoring, and agricultural monitoring [2], [3].

SFL can be mainly categorized into three types [4]. The first category is that each satellite only builds a direct but intermittent connection with the ground station. In [5], the authors exploited the characteristics of LEO and proposed an asynchronous SFL. In [6], the authors further optimized the asynchronous aggregation strategy by introducing a compensation mechanism to reduce gradient staleness during the aggregation process. The second category is that each satellite leverages inter-satellite links (ISLs) with other satellites in the same orbital plane. In this case, satellites can build near-persistent direct connections with the ground station, where the main challenge lies in the design of networking. In [7], the authors leveraged intra-orbit ISLs and the in-network computation to reduce the convergence time. A framework called FedLEO with a novel model propagation method and a novel distributed scheduling algorithm was presented in [8] to overcome the problem of intermittent connectivity between the ground station and satellites. As for the third category, each satellite can build connections with any satellites in the constellation. This scenario is the most complicated one but with the greatest potential to exploit the distinctive property of SFL. In [9], the authors provided insights into the routing design in intra- and inter-orbit ISLs in Walker-δ constellation [10] and theoretically derived the number of hops required for any two satellites to reach each other in the constellation. In [11], the authors considered the switching cost of antennas and developed a dynamic inter-orbital plane ISLs planning algorithm to solve the routing selection problem. The authors in [12] took into account the effect of Doppler shift in Walker-Star constellation [13] and formulated the inter-orbit ISLs routing planning problem as a matching problem, which was then solved by two greedy algorithms.

Although the aforementioned works designed a variety of SFL frameworks, there are still lots of challenges in using the ground station as the central server in SFL: (1) The propagation time is long due to the long distance between satellites and the ground station. (2) Once the ground station fails, the entire satellite FL will be paralyzed [14]. (3) The utilization of the ground station restricts the accessible communication window with satellites, resulting in a prolonged convergence time for SFL [15]. To alleviate these challenges, decentralized federated learning (DFL) as a decentralized learning framework receives considerable attention, where devices directly exchange model parameters with each other, without the need for a central server. DFL is adaptive to the topology change of the communication network, which makes the training process more flexible [16]. The authors in [14] proposed a decentralized SFL framework in the Walker-Star constellation, however, they assumed the connection established among satellites was bidirectional and did not exploit inter-orbital plane ISLs to further promote the learning efficiency. To fill this gap, we deploy decentralized training in SFL by exploiting intra- and inter-orbital plane connections in the walker-δ constellation.

In this paper, to realize fast convergence of the SFL model, we design a novel decentralized SFL in the Walker-δ constellation by leveraging intra- and inter-orbital plane ISLs. Each satellite transmits its local model to the nearby satellites in both the same and different orbital planes. We formulate an energy consumption minimization problem concerning power control, bandwidth allocation, and routing selection of each satellite. The main contributions of this paper are summarized as follows,

- A decentralized SFL framework is proposed in the Walker-δ constellation where each satellite can communicate with nearby satellites through intra- and inter-orbital ISLs. It eliminates the dependence on the ground station in SFL, which avoids severe congestion and huge propagation time in the process of communication between the ground station and satellites.

- We formulate a combinatorial problem by jointly optimizing transmit power, bandwidth, and routing selection strategy. To tackle the non-convex optimization problem, a Hungarian method-based joint resource allocation and routing selection (JRARS) algorithm is developed to decouple the original problem and iteratively optimize the routing selection sub-problem and bandwidth allocation sub-problem.
- We compare our proposed decentralized SFL framework with other SFL frameworks in the Walker-δ constellation. Experimental results illustrate that our proposed framework performs better than the baseline schemes in terms of both convergence speed and accuracy. Likewise, we also compare our developed algorithm with other resource allocation and satellite selection methods. Experimental result shows that our JRARS algorithm consumes the least energy in settings with different numbers of satellites.

II. System Model

A. Satellite Constellation Model

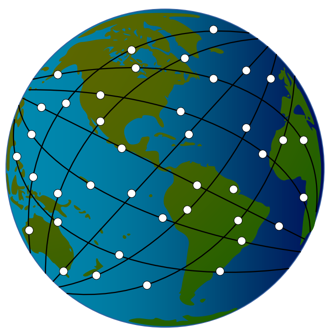


Fig. 1. Walker-δ Constellation.

As depicted in Fig. 1, we consider the Walker-δ constellation, which consists of M orbital planes indexed by $m \in \{1, 2, \dots, M\}$. N_m satellites are evenly distributed in each orbital plane with the angle radians being $2\pi/N_m$. The total number of satellites is $N = \sum_{m=1}^{M} N_m$, and each satellite is indexed as $i \in \{1, 2, \dots, N\}$. As for satellite i, we express the set of satellites that are in the same orbital plane with i as $\rho(i)$, if $j \notin \rho(i)$, then satellite j is in a different orbital plane with satellite i. A tuple consisting of three elements is utilized to represent the m-th orbital plane: (h_m, ϵ_m, T_m), where these three elements respectively denote the altitude, inclination, and period of the orbital plane. We use $\phi(m,i) = \frac{2\pi}{T_m}t + \frac{2\pi}{N_m}i$ to denote the orbital angle of satellite i in orbital plane m. Subsequently, for the convenience of calculation, we transform the local tangent plane (LTP) coordinates to Cartesian coordinates, where satellite i in orbital plane m at time t can be expressed as:

$$x^t(m,i) = (h_m + R_E)\cos\phi^t(m,i) \tag{1a}$$
$$y^t(m,i) = (h_m + R_E)\cos\epsilon_m \sin\phi^t(m,i) \tag{1b}$$
$$z^t(m,i) = (h_m + R_E)\sin\epsilon_m \sin\phi^t(m,i), \tag{1c}$$

where R_E represents the radius of the Earth. Meanwhile, we define $g^t(i,j) = \{0, -1, +1\}$ to characterize the relative position of satellites i and j at time t. More specifically, we have

$$g^t(i,j) = \begin{cases} +1, & \sin\left(\epsilon_{\rho(i)} - \epsilon_{\rho(j)}\right)\sin\phi^t(\rho(i),i) < 0, \\ -1, & \sin\left(\epsilon_{\rho(i)} - \epsilon_{\rho(j)}\right)\sin\phi^t(\rho(i),i) > 0, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Apparently, from (2), if satellites i and j are in the same orbital plane, i.e., $\rho(i) = \rho(j)$, then we have $g(i,j) = 0$.

B. Satellite Communication Model

The communication link can be established between satellites only when the line-of-sight is not blocked by the Earth. The condition for feasible inter-satellite communication can be expressed as $\ell(i,j) \leq \ell_{\mathrm{th}}(i,j)$, where $\ell(i,j)$ denotes the distance between satellite i and j, and $\ell_{\mathrm{th}}(i,j)$ is the threshold, which is computed as

$$\ell_{\mathrm{th}}(i,j) = \sqrt{(h_{\rho(i)} + R_E)^2 - R_E^2} + \sqrt{(h_{\rho(j)} + R_E)^2 - R_E^2}. \tag{3}$$

We assume that each satellite is equipped with four antennas, where two antennas point to each side of the satellite in the orbital plane, and the other two antennas point to the opposite directions in the vertical plane of the orbital plane. The former two antennas are used for intra-plane communication, while the latter two antennas are utilized for inter-plane communication.

In the t-th communication round, the transmission rate between satellites i and j is:

$$R^t(i,j) = B^t(i,j)\log\left(1 + \mathrm{SNR}^t(i,j)\right), \tag{4}$$

where $B^t(i,j)$ is the bandwidth allocated to the link between satellite i and j, and $\mathrm{SNR}(i,j)^t$ is the signal-to-noise ratio at the receiver, which is calculated as

$$\mathrm{SNR}^t(i,j) = \frac{P^t(i,j)G_i^t(j)G_j^t(i)}{k_B T B^t(i,j) H^t(i,j)}, \tag{5}$$

in which $P^t(i,j)$ and $G_i^t(j)$ stand for the transmit power and the antenna gain of satellite i towards satellite j, respectively. k_B and T represent the Boltzmann constant and the receiver noise temperature, respectively. $H^t(i,j)$ is the free path loss, which can be further expressed as

$$H^t(i,j) = \left(\frac{4\pi f_c \ell^t(i,j)}{c}\right)^2, \tag{6}$$

where f_c is the carrier frequency and c is the light speed. With the transmission rate calculated, the time cost of sending data with D_i bits from satellite i to satellite j is:

$$q^t(i,j) = \frac{D_i}{R^t(i,j)} + \frac{\ell^t(i,j)}{c}, \tag{7}$$

where the former part denotes the transmission time and the latter denotes the propagation time. A time constraint $Q^{\max}$ is set to guarantee that the transmitting process is finished in time. With the transmission time given, the transmission energy is

$$e^t(i,j) = P^t(i,j)\frac{D_i}{R^t(i,j)}. \tag{8}$$

C. Decentralized Satellite Federated Learning Model

Consider a fully decentralized scenario, each satellite trains the local model and sends it to the satellites connected with it. As mentioned in the last subsection, each satellite is equipped with four antennas, hence it is capable of receiving four models, including two from the satellite in the same orbital plane and two from satellites in different orbital planes, the framework of decentralized SFL is shown in Fig. 2. We denote the dataset of satellite i as $\mathcal{B}_i$, which is non-independent and identically (non-i.i.d.). The local model is denoted as $\boldsymbol{w}_i$ with a size of D_i. The learning problem can be shown as:

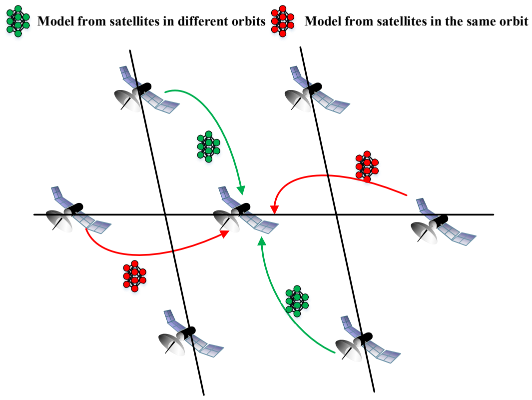


Fig. 2. Decentralized Satellite Federated Learning.

$$\min \ \frac{1}{N}\sum_{i=1}^{N} F(\boldsymbol{w}_i) \tag{9a}$$

$$\text{s.t. } \boldsymbol{w}_1 = \boldsymbol{w}_2 = \cdots = \boldsymbol{w}_N = \boldsymbol{w}. \tag{9b}$$

Herein, $F(\boldsymbol{w}_i)$ is the mini-batch loss function over a randomly sampled dataset $\mathcal{B}_i^{\text{mini}}$ from $\mathcal{B}_i$, which can be further expressed as [17]

$$F(\boldsymbol{w}_i) = \frac{1}{\left|\mathcal{B}_i^{\text{mini}}\right|}\sum_{b_i\in\mathcal{B}_i^{\text{mini}}} f(\boldsymbol{w}_i, b_i), \tag{10}$$

in which $f(\boldsymbol{w}_i, b_i)$ is the sample-wise loss function of satellite i.

In communication round t, the decentralized FL can be divided into two parts: local computation and aggregation. For the local computation part, each satellite updates the local model through stochastic gradient descent (SGD):

$$\boldsymbol{w}_i^{t+\frac{1}{2}} = \boldsymbol{w}_i^{t} - \eta\nabla F(\boldsymbol{w}_i^{t}), \tag{11}$$

with the learning rate being η. After the local computation, each satellite aggregates the updated local model and another four newly received models:

$$\begin{aligned}\boldsymbol{w}_i^{t+1} = (1-\gamma)\boldsymbol{w}_i^{t+\frac{1}{2}} + \frac{\gamma}{4}\Bigg(&\boldsymbol{w}_{\rho(i)-1}^{t+\frac{1}{2}} + \boldsymbol{w}_{\rho(i)+1}^{t+\frac{1}{2}} \\ &+ \sum_{\substack{j=1,\\ j\notin\rho(i)}}^{N}\left(\alpha_{i,j}^{t,+}\boldsymbol{w}_j^{t+\frac{1}{2}} + \alpha_{i,j}^{t,-}\boldsymbol{w}_j^{t+\frac{1}{2}}\right)\Bigg).\end{aligned} \tag{12}$$

In (12), γ denotes the aggregation coefficient to balance the local model update and neighbors' models update. $\alpha_{i,j}^{t,+}$ and $\alpha_{i,j}^{t,-}$ respectively denote the satellite selection strategy of satellite i towards satellite j in positive and negative directions according to (2). We constrain that $\alpha_{i,j}^{t,+}\in\{0,1\}$, $\alpha_{i,j}^{t,-}\in\{0,1\}$, $\sum_{j=1,j\notin\rho(i)}^{N}\alpha_{i,j}^{t,+}=1$, $\sum_{j=1,j\notin\rho(i)}^{N}\alpha_{i,j}^{t,-}=1$, and $\alpha_{i,j}^{t,+}+\alpha_{i,j}^{t,-}\le 1,\ \forall i,j,t$, so that each satellite is required to receive two models from the opposite directions' satellites in two distinct orbital planes.

III. Problem Formulation and Transformation

A. Problem Formulation

In our proposed system, satellites utilize both intra- and inter-plane ISLs to transmit models and perform decentralized SFL. To realize an energy-efficient system, we formulate a problem concerning power control, bandwidth allocation, and routing selection as follows,

$$\mathcal{P}: \min_{\substack{P^t(i,j),\\ B^t(i,j),\\ \alpha_{i,j}^{t,\pm}}} \sum_{t=0}^{T}\sum_{i=1}^{N}\sum_{\substack{j=1,\\ j\notin\rho(i)}}^{N}\left(\alpha_{i,j}^{t,+}e^t(i,j)+\alpha_{i,j}^{t,-}e^t(i,j)\right)\Upsilon^t \tag{13a}$$

$$\text{s.t. } \alpha_{i,j}^{t,\pm}, \Upsilon^t\in\{0,1\}, \alpha_{i,j}^{t,+}+\alpha_{i,j}^{t,-}\le 1,\ \forall\, i,j,t, \tag{13b}$$

$$\sum_{j=1,j\notin\rho(i)}^{N}\alpha_{i,j}^{t,+}B^t(i,j)+\alpha_{i,j}^{t,-}B^t(i,j)\le B_i,\ \forall\, i,t, \tag{13c}$$

$$\sum_{j=1,j\notin\rho(i)}^{N}\alpha_{i,j}^{t,+}P^t(i,j)+\alpha_{i,j}^{t,-}P^t(i,j)\le P_i,\ \forall\, i,t, \tag{13d}$$

$$\sum_{j=1,j\notin\rho(i)}^{N}\alpha_{i,j}^{t,+}=1,\ \forall\, i,t, \tag{13e}$$

$$\sum_{j=1,j\notin\rho(i)}^{N}\alpha_{i,j}^{t,-}=1,\ \forall\, i,t, \tag{13f}$$

$$q^t(i,j)\le Q^{\max},\ \forall\, i,j,t. \tag{13g}$$

In (13a), $e^t(i,j)$ is defined in (8), and Υ^t is set to 0 when the FL model converges, otherwise, remains 1. Constraints (13c) and (13d) denote the bandwidth and power limits for each satellite. (13e) and (13f) constrain that each satellite is only able to build 2 communication links between the satellites from opposite directions from different orbital planes. Constraint (13g) is made to guarantee the transmitting process is finished under the time constraint $Q^{\max}$, which ensures the synchronization of decentralized SFL.

Problem $\mathcal{P}$ is a mixed integer programming (MIP) problem due to the binary variable $\alpha_{i,j}^{t,\pm}$ and continuous variables $B^t(i,j)$ and $P^t(i,j)$. Furthermore, these variables are coupled together according to constraints (13c), (13d), and (13g), making the original problem extremely sophisticated to solve.

B. Problem Transformation

Since the trajectory of satellites is fixed, the resource allocation and satellite selection strategy are independent in each communication round. Hence problem $\mathcal{P}$ can be reduced to a one-round optimization problem as in [18]. For ease of convenience, we analyze the condition in a single communication round.

By observing (4), (5), and (8), it is obvious that $e(i,j)$ monotonically increases with the transmit power $P(i,j)$. Hence, to meet constraint (13g), we have:

$$B(i,j)\log\left(1+\frac{P(i,j)G_i(j)G_j(i)}{k_BTB(i,j)\left(\frac{4\pi f_c\ell(i,j)}{c}\right)^2}\right)\geq\bar{R}, \quad (14)$$

where $\bar{R}=\frac{D_i}{Q^{\max}-\frac{\ell(i,j)}{c}}$. By changing the orders, we have

$$P(i,j)\geq\frac{(2^{\frac{\bar{R}}{B(i,j)}}-1)B(i,j)\ell^2(i,j)}{\Psi}, \quad (15)$$

where

$$\Psi=\frac{G_i(j)G_j(i)}{k_BT(\frac{4\pi f_c}{c})^2}. \quad (16)$$

Hence, when the equality holds, the transmit power $P(i,j)$ reaches the lowest value, which further leads to the minimum energy consumption.

With (15), $\mathcal{P}$ is transformed to

$$\mathcal{P}_1:\min_{\substack{B^t(i,j),\\ \alpha_{i,j}^{t,\pm}}}\sum_{t=0}^{T}\sum_{i=1}^{N}\sum_{\substack{j=1,\\ j\notin\rho(i)}}^{N}\left(\frac{\alpha_{i,j}^{t,+}P^t(i,j)D_i}{B^t(i,j)\log\left(1+\frac{P^t(i,j)\Psi}{B^t(i,j)\ell^2(i,j)}\right)}+\frac{\alpha_{i,j}^{t,-}P^t(i,j)D_i}{B^t(i,j)\log\left(1+\frac{P^t(i,j)\Psi}{B^t(i,j)\ell^2(i,j)}\right)}\right)\Upsilon \quad (17a)$$

$$\text{s.t. } (13b),(13c),(13e),(13f). \quad (17b)$$

After the transformation, $\mathcal{P}_1$ becomes an energy consumption minimization problem regarding bandwidth $B^t(i,j)$ and routing selection $\alpha_{i,j}^{t,\pm}$. Since the routing selection $\alpha_{i,j}^{t,\pm}$ is a binary variable in constraint (13b), $\mathcal{P}_1$ is still non-convex.

IV. Joint Resource Allocation and Routing Selection Algorithm

In this section, we develop an algorithm to jointly optimize the routing selection and bandwidth allocation strategy.

A. Routing Selection

Observing (17a), we notice that each $B(i,j)$ needs to be allocated only when the corresponding $\alpha_{i,j}^{\pm}$ is set to 1. Hence, we initially solve the routing selection sub-problem by assuming that the bandwidth allocation strategy is given. In this way, we have sub-problem $\mathcal{P}_2$:

$$\mathcal{P}_2:\min_{\alpha_{i,j}^{\pm}}\sum_{i=1}^{N}\sum_{\substack{j=1,\\ j\notin\rho(i)}}^{N}\frac{\alpha_{i,j}^{+}\Phi(i,j)D_i}{\log\left(1+\frac{\Phi(i,j)\Psi}{\ell^2(i,j)}\right)}+\frac{\alpha_{i,j}^{-}\Phi(i,j)D_i}{\log\left(1+\frac{\Phi(i,j)\Psi}{\ell^2(i,j)}\right)} \quad (18a)$$

$$\text{s.t. } (13b),(13c),(13e),(13f). \quad (18b)$$

where $\Phi(i,j)=\frac{P^*(i,j)}{B(i,j)}$, and $P^*(i,j)=\frac{(2^{\frac{\bar{R}}{B(i,j)}}-1)B(i,j)\ell^2(i,j)}{\Psi}$ according to (15), which makes $\Phi(i,j)$ be a function of $\ell(i,j)$. By observing problem $\mathcal{P}_2$, we can easily notice that the solution towards the variable $\alpha_{i,j}^{\pm}$ only refers to $\ell_{i,j}$, which can be predicted towards the property of the satellite constellation. Herein, we define a cost matrix considering the relative satellite position $g(i,j)$ in (2) and the assumed given $B(i,j)$ as follows,

$$\boldsymbol{L}=\begin{bmatrix}\Gamma_{1,1}\ell(1,1) & \cdots & \Gamma_{1,N}\ell(1,N)\\ \Gamma_{2,1}\ell(2,1) & \cdots & \Gamma_{2,N}\ell(2,N)\\ \vdots & \vdots & \vdots\\ \Gamma_{N,1}\ell(N,1) & \cdots & \Gamma_{N,N}\ell(N,N)\end{bmatrix}_{N\times N}, \quad (19)$$

where $\Gamma_{i,j}=g(i,j)\frac{2^{\frac{\bar{R}}{B(i,j)}}D_i}{\Psi\log\left(1+2^{\frac{\bar{R}}{B(i,j)}}\right)}$. To minimize the total energy consumption in (17a), we leverage the Hungarian method to solve the routing selection sub-problem by regarding each satellite as a worker, links between satellites as tasks, and elements in $\boldsymbol{L}$ as the cost of the corresponding tasks.

B. Bandwidth Allocation

After the routing selection problem is solved, the objective function (17a) in $\mathcal{P}_1$ becomes a function of $B(i,j)$. Then we express the bandwidth allocation problem $\mathcal{P}_3$ as

$$\mathcal{P}_3:\min_{B(i,j)}\sum_{i=1}^{N}\sum_{\substack{j=1,\\ j\notin\rho(i)}}^{N}\frac{(\alpha_{i,j}^{+}+\alpha_{i,j}^{-})(2^{\frac{\bar{R}}{B(i,j)}}-1)B(i,j)\ell^2(i,j)D_i}{\Psi\bar{R}} \quad (20a)$$

$$\text{s.t. } (13c). \quad (20b)$$

With a given $\alpha_{i,j}^{\pm}$, the objective function in (20a) is denoted as $E(i,j)=\frac{(2^{\frac{\bar{R}}{B(i,j)}}-1)B(i,j)\ell^2(i,j)D_i}{\Psi\bar{R}}$, then the second derivative of $E(i,j)$ is taken:

$$\frac{\partial^2E(i,j)}{\partial B(i,j)^2}=2^{\frac{\bar{R}}{B(i,j)}}(\ln 2)^2\frac{\bar{R}^2}{B(i,j)^3}\frac{\ell(i,j)^2D_i}{\Psi\bar{R}}>0. \quad (21)$$

Therefore, the considered problem is convex, which can be solved through CVX tools. The overall algorithm is presented in Algorithm. 1.

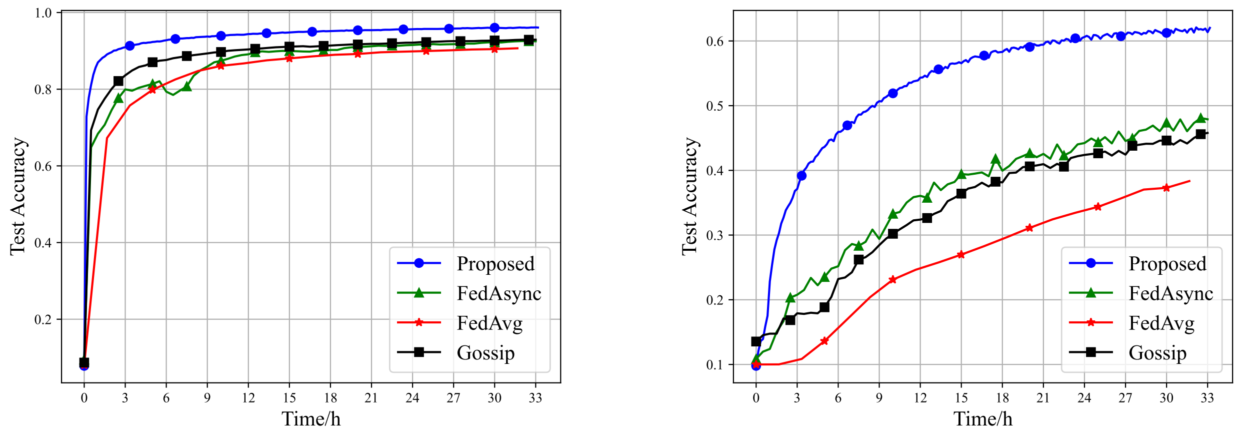
Algorithm 1: JRARS Algorithm

Input: Power budget P_i, bandwidth budget B_i, $\forall\, i$, time constraint $Q^{\max}$, and distance between satellites $\ell(i,j)$, $\forall\, i,j$.

1: **Initialize** $B(i,j)^{\tau}$, $\forall\, i.j$ and $\tau=0$.
2: **repeat**
3: **for** each $i\in\{1,2,\dots N\}$ **do**
4: Obtain $\alpha_{i,j}^{\pm,\tau}$ through solving $\mathcal{P}_2$;
5: Solve $B(i,j)^{\tau}$ in $\mathcal{P}_3$ with given $\alpha_{i,j}^{\pm,\tau}$;
6: **end for**
7: $\tau\leftarrow\tau+1$;
8: **until** $\alpha_{i,j}^{\pm,\tau}=\alpha_{i,j}^{\pm,\tau-1}$, $\forall\, i,j$.

V. Simulation Results

In this section, we show the simulation setup and compare our proposed framework and algorithm with baseline



(a) MNIST Dataset

(b) CIFAR10 Dataset

Fig. 3. Learning performance of different satellite FL under MNIST and CIFAR10 datasets.

schemes.

A. Experiment Setup

We consider the Walker-δ constellation, consisting of 50 satellites (i.e. $N = 50$), which are evenly distributed in 5 orbital planes (i.e., $M = 5$ and $N_m = 10$). The height and the inclination of the m-th orbit can be expressed as $h_m = 900 + 200\,\mathrm{Km}$ and $\epsilon_m = 2\pi(m-1)/M$, $m \in \{1,\ldots,5\}$, respectively. The period of each orbit T_m is fixed due to the velocity of each satellite v_m, which is $T_m = \frac{2\pi h_m}{v_m}$, and the Earth radius is $R_E = 6371\,\mathrm{Km}$. The diagram of the constellation is shown in Fig. 1.

The transmit power budget for each satellite is set to $40\,\mathrm{dBm}$, the total bandwidth assigned to each satellite is $10\,\mathrm{MHz}$, and the time constraint $Q^{\max}$ is set to $60\,\mathrm{s}$. The transmitting and receiving antenna gain of satellite i towards j are both set to $6.98\,\mathrm{dBi}$. The Boltzmann constant and the receiver noise temperature are $k_B = 1.380649 \times 10^{-23}\,\mathrm{J/K}$ and $T = 354.81\,\mathrm{K}$, carrier frequency and light speed are $f_c = 2.4\,\mathrm{GHz}$ and $c = 3 \times 10^8\,\mathrm{m/s}$.

The MNIST and CIFAR10 datasets are adopted to train the deep neural networks (DNN) with 2 hidden layers and the convolutional neural networks (CNN) with 3 hidden layers and 2 convolution kernels. We set $3/4$ of the dataset for training while the left part is for testing. Dirichlet distribution is used to construct non-i.i.d datasets where the Dirichlet coefficient is set to $\alpha = 0.01$. The learning rate is set to $\eta = 0.005$, the aggregation coefficient in (12) is set to $\gamma = 0.5$, and the mini-batch size is set to $|\mathcal{B}_i^{\mathrm{mini}}| = 20$.

To test the performance of our proposed decentralized SFL framework, we compare our framework with the following three baselines:

- **FedAvg** [19]: This framework requires a ground station as the central server to perform the synchronous aggregation of models from all satellites.
- **FedAsync** [20]: This framework requires a ground station as the central server to perform asynchronous aggregation of models from satellites, i.e., the ground station will update the global model whenever receiving a local model from the satellite.
- **Gossip** [21]: This framework is free of a ground station, where each satellite only exchanges models with the two satellites that it directly connects within the same orbital plane.

In this part of the experiment, we ignore the impact of power consumption and only focus on convergence speed and accuracy.

To test our proposed JRARS algorithm, we consider the following three baseline schemes:

- **Greedy routing selection with random bandwidth allocation**: Each satellite will build its connection with the other two satellites from different orbital planes in its visible area based on a greedy algorithm that only considers the distance between satellites. Meanwhile, the bandwidth allocation strategy is generated randomly.
- **Random routing selection optimal bandwidth allocation**: Each satellite will randomly choose two satellites in its visible area and are in different orbital planes to build connections. Meanwhile, the bandwidth allocation strategy is optimally solved with the given routing selection strategy.
- **Greedy Algorithm**: When considering problem $\mathcal{P}$, each satellite only takes into account its best routing selection and bandwidth allocation strategy without searching for a global optimal solution.

When increasing the number of satellites, the number of satellites in each orbital plane increases as well, while the number of orbital planes remains unchanged.

B. Experiment Results

In Fig. 3, we compare the learning performance of 4 different satellite FL frameworks. Our proposed decentralized SFL converges fast with only 3 hours to reach a test accuracy higher than 90% in the MNIST dataset, and 24 hours to reach a test accuracy at 60% in the CIFAR10 dataset. By contrast, gossip and FedAsync frameworks only reach a test accuracy at nearly 80% after 3 hours in the MNIST dataset, and around 42% after 24 hours in the CIFAR10 dataset. FedAvg shows the worst learning performance in convergence speed and accuracy for both datasets. More specifically, the FedAsync framework only tackles the problem of synchronization between satellites and the ground station, while the tricky model staleness will affect the learning performance. As for the gossip framework, it does not contain a ground station, which eliminates the process of satellite scheduling, however, the fact that each satellite constantly communicates with the two satellites in the same orbital plane nearby will have a bad influence on model generalization when the dataset is heterogeneous. The superiority of our proposed decentralized SFL framework is that it takes advantage of the satellite network topology by exploiting both intra- and inter-orbital plane connections. More specifically, the advantage lies in two-fold. Firstly, the system can somewhat overcome the problem introduced by data heterogeneity compared with the gossip framework. Secondly, it gets rid of the dependence on the ground station, making the interactions of models more efficient and convenient compared with satellite FedAvg and FedAsync.

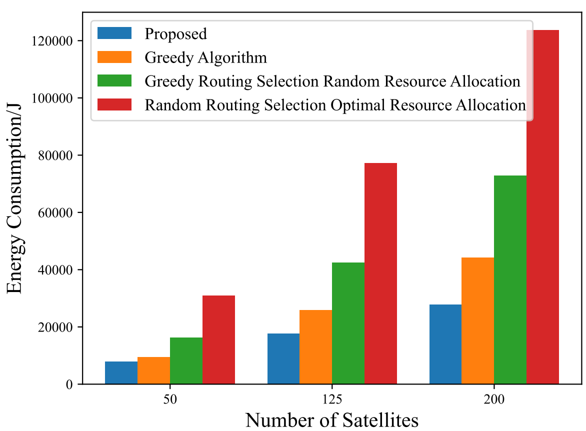


Fig. 4. Energy cost under different resource allocation and routing selection algorithms.

Fig. 4 compares our developed JRARS algorithm with the other 3 baseline algorithms. We can easily tell from the bar chart that our proposed algorithm consumes the lowest energy in every satellite number setting. It is mainly due to the fact that our JRARS algorithm jointly considers the transmit power allocation, bandwidth allocation, and routing selection, while simultaneously optimizing all satellites to reach a global optimality. We also find out that with the increase in the number of satellites, the advantage of the JRARS algorithm becomes more evident, which means that the proposed algorithm can perform better in large-scale constellation scenarios.

VI. Conclusion

In this paper, we proposed a novel decentralized SFL framework in the Walker-δ constellation to realize fast convergence of SFL. A combinatorial optimization problem is formulated in terms of power control, bandwidth allocation, and routing selection of each satellite. To solve the formulated MIP problem, we developed a joint resource allocation and routing selection algorithm to optimize the routing selection strategy and bandwidth allocation iteratively. Simulation results demonstrated that both our proposed framework and algorithm achieved better performance compared with baseline schemes.

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