Update Estimation and Scheduling for Over-the-Air Federated Learning with Energy Harvesting Devices

Furkan Bagci

Furkan Bagci[1], Busra Tegin[1], Mohammad Kazemi[2], and Tolga M. Duman[1]
[1] *Dept. of Electrical and Electronics Engineering, Bilkent University*, Ankara, Turkey
[2] *Dept. of Electrical and Electronic Engineering, Imperial College London*, London, UK
`{bagci, btegin, duman}@ee.bilkent.edu.tr, mohammad.kazemi@imperial.ac.uk`

June 12, 2025

Bilkent University
Department of Electrical and Electronics Engineering

IEEE ICC®

What is Federated Learning (FL)?

Federated Learning

- A machine learning approach where:
  - **Data remains decentralized**
  - Devices collaboratively train a shared global model

Key Components

- **Mobile Users (MUs)**
- **Parameter Server (PS)**

Process

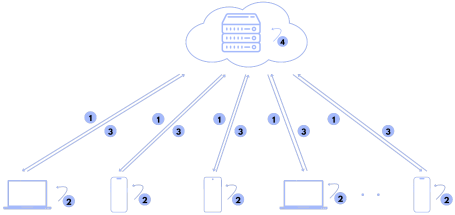


Figure 1: Illustration of a standard FL.

1. PS sends the global model to users.
2. Users compute local updates.
3. Updates are aggregated by the PS.
4. Repeat until convergence.

Why Federated Learning (FL)?

Traditional ML

- Centralized data sharing:
  - **Requires high resources**
  - **Compromises privacy**

Collaborative model training **without sharing local data**

- **Advantages:**
  - Preserves **privacy**
  - Reduces **latency**
  - Improves **learning quality**

Why Over-the-Air (OTA) FL?

Challenge in FL

- **Key bottleneck:** Communication bandwidth.

Solution: OTA FL

- Leverages **superposition property** of **wireless MAC**
- **Saves bandwidth** by avoiding separate transmissions for each user.

$$\Delta\boldsymbol{\theta}(t) = \frac{1}{M}\sum_{m=1}^{M}\Delta\boldsymbol{\theta}_m(t). \tag{1}$$

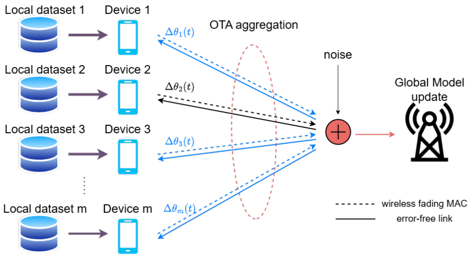


Figure 2: Illustration of OTA FL.

Challenges in OTA FL

Energy Harvesting (EH) Devices

- Uneven and **stochastic** participation in learning.
- Existing studies focus on optimizing energy usage via:
  - Transceiver optimization, receive beamforming design.
- **Bernoulli** energy arrival process:
  - The m-th user receives unit energy with probability $p_e^m(t)$,

$$E_m(t) = \begin{cases} 1 \text{ with probability } p_e^m(t), \\ 0 \text{ with probability } 1 - p_e^m(t). \end{cases} \tag{2}$$

  - Unit-sized **battery** at the users.

Challenges in OTA FL

Non-i.i.d. Data Distribution

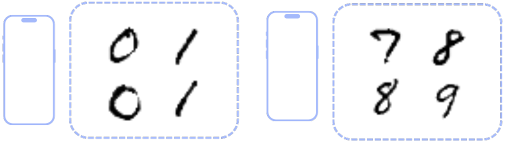


Figure 3: Illustration of non-i.i.d data.

Non-i.i.d. Data

- Data heterogeneity impacts:
  - Model convergence [2].
  - Accuracy due to bias in updates.
- Existing works tackle this with:
  - Clustered Sampling [3]
  - Diverse User Selection [4]

- These studies rely on separate transmission of user updates.
- In contrast, our OTA FL setup uses noisy aggregated updates.

[2] X. Li et al., "On the convergence of FedAvg on non-iid data," arXiv preprint, arXiv:1907.02189, 2019.
[3] Y. Fraboni et al., "Clustered sampling for client selection in federated learning," ICML, 2021.
[4] R. Balakrishnan et al., "Diverse client selection for federated learning via submodular maximization," ICLR, 2022.

Contributions

Diverse User Selection for FL with EH Devices

- **1. Entropy-Based Scheduling:**
  - For **known data distributions.**
  - Ensures a **balanced representation** of data labels.
- **2. LSE-Based Scheduling:**
  - For **unknown data distributions.**
  - Estimates user updates from aggregated signals at the PS.
  - Clusters users based on estimated representations to **enhance diversity** and **eliminate redundant information**.

FL Setup

- M : number of MUs
- K : number of receive antennas
- **Objective:**

$$F(\boldsymbol{\theta}) = \sum_{m=1}^{M} \frac{|B_m|}{B} F_m(\boldsymbol{\theta}), \tag{3}$$

where:

  - $F_m(\theta)$: Local loss function.
  - $F_m(\boldsymbol{\theta}) = \frac{1}{|B_m|} \sum_{\boldsymbol{u} \in B_m} f(\boldsymbol{\theta}, \boldsymbol{u})$

- Selected users $S(t)$ perform τ iterations of **local SGD:**

$$\boldsymbol{\theta}_m^{i+1}(t) = \boldsymbol{\theta}_m^i(t) - \eta_m^i(t) \nabla F_m(\boldsymbol{\theta}_m^i(t), \xi_m^i(t)), \tag{4}$$

- The m-th user computes the model update as:

$$\Delta\boldsymbol{\theta}_m(t) = \boldsymbol{\theta}_m^{\tau}(t) - \boldsymbol{\theta}_m^1(t). \tag{5}$$

- These updates are transmitted back to the PS for aggregation as:

$$\Delta\boldsymbol{\theta}_{PS}(t) = \frac{1}{|S(t)|} \sum_{m \in S(t)} \Delta\theta_m(t). \tag{6}$$

OTA FL Setup

- Using **over-the-air** transmission over a fading MAC via **superposition** of signals
- The received signal at the k-th antenna of the PS at iteration t is:

$$\boldsymbol{y}_{PS,k}(t) = \sum_{m \in S(t)} \boldsymbol{h}_{m,k}(t) \circ \boldsymbol{x}_m(t) + \boldsymbol{z}_{PS,k}(t), \quad (7)$$

where:

- $\boldsymbol{h}_{m,k}(t)$: i.i.d. channel gain from user m to antenna k with $h^n_{m,k}(t) \sim CN(0, \sigma_h^2)$.
- $\boldsymbol{x}_m(t)$: Signal transmitted by user m.
- $\boldsymbol{z}_{PS,k}(t)$: i.i.d. circularly symmetric AWGN with $z^n_{PS,k}(t) \sim CN(0, \sigma_z^2)$.

- The PS aligns and combines signals from K antennas to mitigate fading effects.

$$\boldsymbol{y}_{PS}(t) = \frac{1}{K} \sum_{k=1}^{K} \left(\sum_{m \in S(t)} \boldsymbol{h}_{m,k}(t) \right)^* \circ \boldsymbol{y}_{PS,k}(t), \quad (8)$$

with:

- **exact information** on the sum of the channel gains

OTA FL Setup

- The n-th symbol of (8) can be partition into three signals[5]

$$
\begin{aligned}
y_{PS}^{n}(t) = & \underbrace{\sum_{m\in S(t)} \left(\frac{1}{K} \sum_{k=1}^{K} |h_{m,k}^{n}(t)|^{2} \right) \Delta\theta_{m}^{n,cx}(t)}_{y_{PS}^{n,sig}(t)\,(\text{signal term})} \\
& \underbrace{+ \frac{1}{K} \sum_{m\in S(t)} \sum_{\substack{m'\in S(t)\\ m'\neq m}} \sum_{k=1}^{K} (h_{m,k}^{n}(t))^{*} h_{m',k}^{n}(t) \Delta\theta_{m'}^{n,cx}(t)}_{y_{PS}^{n,int}(t)\,(\text{interference term})} \\
& \underbrace{+ \frac{1}{K} \sum_{m\in S(t)} \sum_{k=1}^{K} (h_{m,k}^{n}(t))^{*} z_{PS,k}^{n}(t).}_{y_{PS}^{n,noise}(t)\,(\text{noise term})} \qquad (9)
\end{aligned}
$$

- Recovery of noisy aggregated updates as

$$
\Delta\hat{\boldsymbol{\theta}}_{PS}^{n}(t) = \frac{1}{|S(t)|\,\sigma_{h}^{2}} \mathrm{Re}\{y_{PS}^{n}(t)\}, \qquad (10a)
$$

$$
\Delta\hat{\boldsymbol{\theta}}_{PS}^{n+N}(t) = \frac{1}{|S(t)|\,\sigma_{h}^{2}} \mathrm{Im}\{y_{PS}^{n}(t)\}, \qquad (10b)
$$

to update the global model, as

$$
\boldsymbol{\theta}_{PS}(t+1) = \boldsymbol{\theta}_{PS}(t) + \Delta\hat{\boldsymbol{\theta}}_{PS}(t). \qquad (11)
$$

[5] M. M. Amiri et al., "Blind Federated Edge Learning," IEEE Trans. Wireless Commun., vol. 20, no. 8, pp. 5129-5143, Aug. 2021.

Convergence Analysis

Convergence Rate:

- We have

$$\mathbb{E}\left[\left\|\boldsymbol{\theta}(t)-\boldsymbol{\theta}^*\right\|_2^2\right] \leq \left(\prod_{i=0}^{t-1} A(i)\right)\left\|\boldsymbol{\theta}(0)-\boldsymbol{\theta}^*\right\|_2^2 + \sum_{j=0}^{t-1} B(j) \prod_{i=j+1}^{t-1} A(i), \tag{12}$$

  with

$$A(i) \triangleq 1-\mu\eta(i)\,\left(\tau-\eta(i)(\tau-1)\right),$$

$$B(i) \triangleq \frac{\eta^2(i)\tau^2 G^2}{K} + \frac{\sigma_z^2 N}{\alpha_i^2 K|S(i)|\sigma_h^2}$$

$$+\left(1+\mu(1-\eta(i))\right)\eta^2(i)G^2\frac{\tau(\tau-1)(2\tau-1)}{6} + \eta^2(i)(\tau^2+\tau-1)G^2 + 2\eta(i)(\tau-1)\Gamma$$

$$+\left(\eta^2(t)\tau(\tau-1)LG+\eta(t)\tau\boldsymbol{\epsilon}\right)^2 + \left(\eta^2(t)\tau(\tau-1)LG+\eta(t)\tau\boldsymbol{\epsilon}\right)c,$$

- with ϵ being the **gradient approximation error** and defined as

$$\epsilon \triangleq \left\|\frac{1}{M}\sum_{m=1}^{M}\nabla F_m(\theta_m(t)) - \frac{1}{|S(t)|}\sum_{m\in S(t)}\nabla F_m(\theta_m(t))\right\|_2. \tag{13}$$

User Scheduling Strategies: Entropy-Based

We propose diverse user selection to handle:

- Data heterogeneity
- Stochastic participation

Entropy-Based Scheduling:

- **Goal:** Achieve a **uniform representation** of data across users.

Methodology:

- Compute the Shannon entropy of label distributions for all available subsets

$$\mathbf{L} = \begin{bmatrix} l_{1,0} & l_{1,1} & \cdots & l_{1,N_c-1} \\ l_{2,0} & l_{2,1} & \cdots & l_{2,N_c-1} \\ \vdots & \vdots & \ddots & \vdots \\ l_{M,0} & l_{M,1} & \cdots & l_{M,N_c-1} \end{bmatrix}.$$

- Select users with the highest combined entropy to ensure diversity

User Scheduling Strategies: LSE-Based

LSE-Based Scheduling:

- **Goal:** Estimate the **representative user updates** at the PS.

Estimation Phase

- Active users transmit their updates without scheduling
- PS stores global updates to create user representations
- Groups users into clusters using **cosine similarities**
- Selects equal users from each cluster for unbiased training

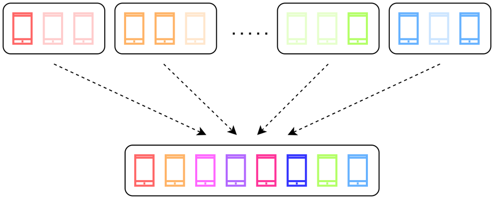


Figure 4: Illustration of clusters and diverse scheduling.

User Scheduling Strategies: LSE-Based

- Define a matrix $\hat{\mathbf{\Theta}}_{PS}$, where each row corresponds to the **global model updates**

$$\hat{\mathbf{\Theta}}_{PS,j} = \boldsymbol{A}_j \mathbf{\Theta}_j + \boldsymbol{N'}_j$$

$$\hat{\mathbf{\Theta}}_{PS,j} = \boldsymbol{A}_j \begin{bmatrix} \Delta\boldsymbol{\theta}_{j,1} \\ \vdots \\ \Delta\boldsymbol{\theta}_{j,M} \end{bmatrix}_{M\times 2N} + \begin{bmatrix} N'_{j,1} \\ \vdots \\ N'_{j,2N} \end{bmatrix}^T . \quad (14)$$

where:

- $\boldsymbol{A}_j$: binary **participation vector** of size M.
- $\mathbf{\Theta}_j$: matrix with each row representing the **local model updates** from users.
- $\boldsymbol{N'}_j$: **effective noise** from MAC fading, AWGN, and combining errors.

- We also define $\mathbf{\Theta}_{rep} \in \mathbb{R}^{M\times 2N}$ as

$$\hat{\mathbf{\Theta}}_{PS,j} = \boldsymbol{A}_j(\mathbf{\Theta}_{rep} + \mathbf{\Theta}_{d,j}) + \boldsymbol{N'}_j, \quad (15)$$

where $\mathbf{\Theta}_{d,j} \triangleq \mathbf{\Theta}_{rep} - \mathbf{\Theta}_j$ and $\boldsymbol{N}^*_j \triangleq \boldsymbol{A}_j \mathbf{\Theta}_{d,j} + \boldsymbol{N'}_j$.

- Combining $\hat{\mathbf{\Theta}}_{PS,j}$ across T iterations

$$\hat{\mathbf{\Theta}}_{PS} = \boldsymbol{A}\mathbf{\Theta}_{rep} + \boldsymbol{N}^*, \quad (16)$$

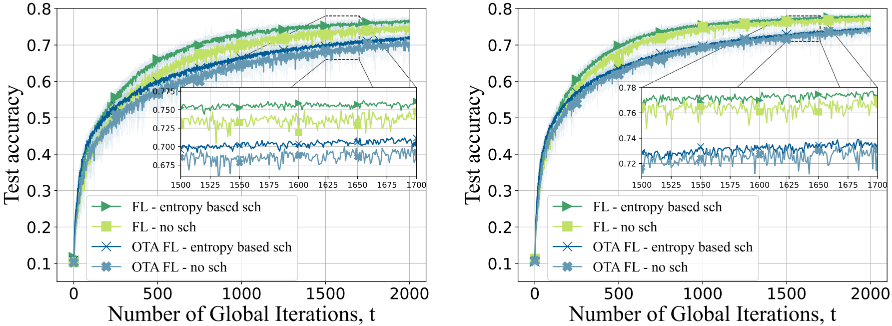
- Solve for $\mathbf{\Theta}_{rep}$ using Least-Squares Estimation.
- Using $\mathbf{\Theta}_{rep}$, the PS:
  - Captures the **data characteristics** of users.
  - Groups users based on **cosine similarity of representations**.

Numerical Results

- **MNIST** & **FMNIST**: Single-layer neural network with 2N=7850.
- **CIFAR-10**: Convolutional Neural Network (CNN) with 2N=797,962.
- SGD with a learning rate of 0.05 and a scheduler, $\tau = 5$ and mini-batch size $|\xi_m(t)| = 100$ for MNIST and FMNIST, and $\tau = 3$ and $|\xi_m(t)| = 128$ for CIFAR-10.

- Non-i.i.d. Data Scenarios
  - 1 or 2 classes per user
  - $\boldsymbol{p_m} \sim \mathrm{Dir}_{N_c}(\beta)$ with $\beta \in \{0.1, 0.2\}$
- Wireless Setup
  - $K = 200$, $M = [20 - 100]$ users
  - Noise variance: $\sigma_h^2 = 1$, and $\sigma_z^2 = 0.1$.

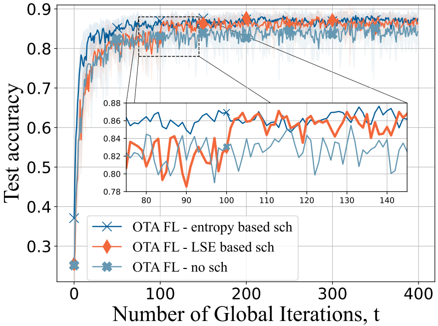
Numerical Results



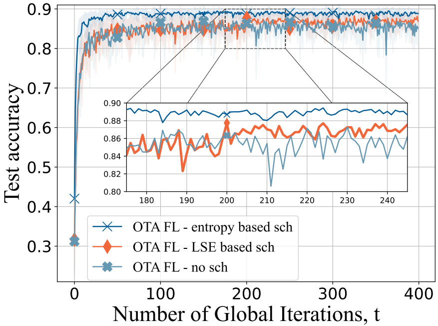
(a) $\beta = 0.1$. (b) $\beta = 0.2$.

Figure 5: The mean test accuracy of entropy-based scheduling for CIFAR-10 with $M = 100$, $|B_m| = 500$ and $p_e^m(t) = 0.1$, $\forall m, t$.

Numerical Results



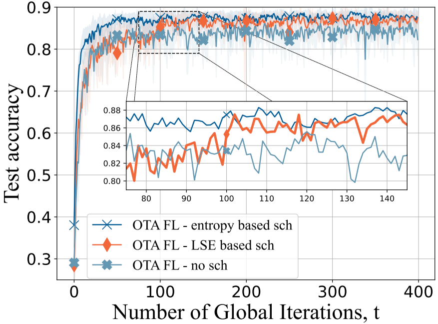
(a) 1 class per user and $T = 100$.



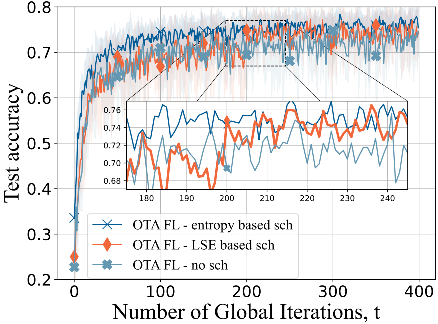
(b) 2 class per user and $T = 200$.

Figure 6: The mean test accuracy for MNIST with $M = 40$, $|B_m| = 1250$ and $p_e^m(t) = 0.25$, $\forall m, t$.

Numerical Results



(a) MNIST, $M = 20$, 1 class per user and $T = 100$.



(b) FMNIST, $M = 40$, 1 class per user and $T = 200$.

Figure 7: The mean test accuracy for MNIST and FMNIST.

Conclusions

- We analyze **the convergence rate** for the OTA FL with EH devices and demonstrate the effect of **user scheduling**.
- **Entropy-based** scheduling approach yields higher and more stable accuracy levels.
- **LSE-based** scheduling can estimate user representations at the PS.
- Scheduling diverse users **preserves privacy**, **eliminates redundant update transfers**, and **improves learning performance**.

- **Future Directions**
  - Investigate the effect of estimation strategies under varying scenarios and energy constraints
  - Implement clustered federated learning for the user clusters derived from our estimation.

Update Estimation and Scheduling for Over-the-Air Federated Learning with Energy Harvesting Devices

Furkan Bagci

paper

slides

June 12, 2025

Thank You!

Questions?

Acknowledgments
This work is supported by TUBITAK (Grant 221N366) under the CHIST-ERA SONATA project. Furkan Bagci is also supported by Türk Telekom within the 5G & Beyond Graduate Programme. Mohammad Kazemi acknowledges support from UKRI (Grant 101103430) under the Horizon Europe Guarantee.

Bilkent University
Department of Electrical and Electronics Engineering

IEEE ICC®