Analog Over-the-Air Federated Learning with Interference-Based Energy Harvesting

Ahmad Massud Tota Khel[1], Aissa Ikhlef[1], Zhiguo Ding[2], Hongjian Sun[1]
[1]Durham University, [2]The University of Manchester

1. Technology Focus Aligned with FTH Domains

Future wireless networks are expected to support large-scale IoT edge intelligence under strict spectrum and energy constraints.

- **AI-Native Networks & Automation**
  Adaptive federated learning (FL) that autonomously adjusts each device's local training load based on its available energy.
- **Advanced Radio Systems & Spectrum Innovation**
  Analog over-the-air (OTA) aggregation with RF energy harvesting (EH) for shared-spectrum learning and self-sustaining devices in interference-limited IoT networks.

2. Problem Statement

Large-scale FL in wireless IoT networks faces several key challenges:

- **Dependence on Channel State Information (CSI) and Channel Inversion**
  OTA reduces communication overhead but still depends on CSI and power-hungry channel inversion, increasing complexity and cost while limiting scalability.
- **Energy Variability in EH-Based Devices**
  IoT networks cannot rely on carbon-intensive power supplies, and while EH is greener, its unpredictability can compromise system reliability.
- **Co-Channel Interference (CCI): Threat and Resource**
  CCI harms OTA aggregation but can also provide RF energy; its distortion still needs mitigation.
- **Fixed Training Workloads**
  Energy fluctuations make fixed-epoch or full-dataset training infeasible, leading to device dropouts, degraded model accuracy, and wasted energy.

How can we achieve **cost-efficient, scalable, adaptive, and energy-sustainable** FL in future IoT networks?

3. System Model

- A parameter server (PS) and M devices train a global model over T rounds, while devices harvest RF energy from:
  - **Inband sources:** cause CCI and provide energy.
  - **Outband sources:** provide energy only.
- Each round, the PS broadcasts the model to devices.
- Energy-sufficient devices ($N_t \leq M$) perform local SGD and transmit updates simultaneously.
- The PS receives analog OTA updates and applies denoising to mitigate fading, CCI, and noise

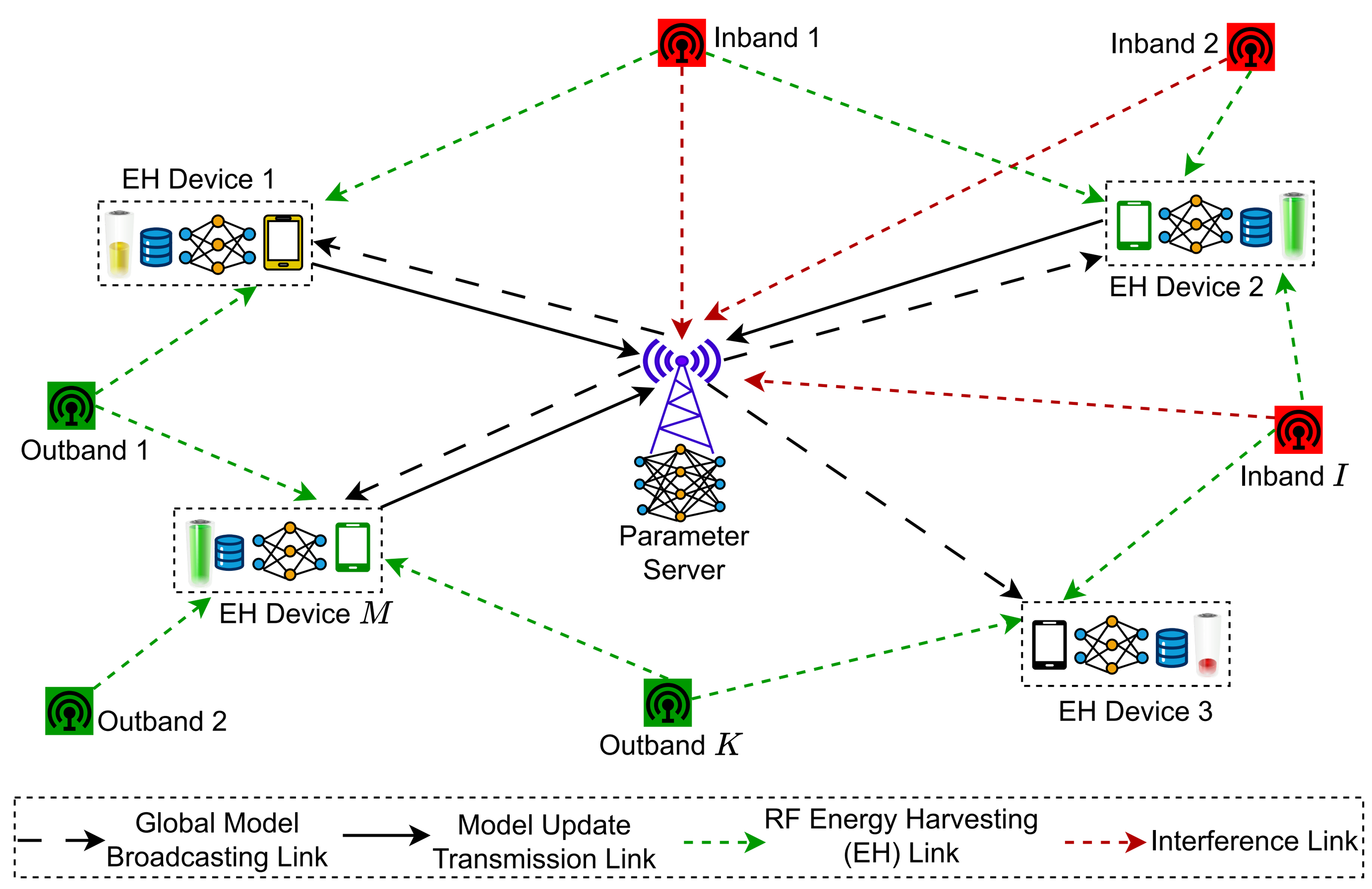

Fig. 1 System model for EH-based analog OTA FL.

4. Key Novelties

- **CSI-Free Denoising**
  - A **simple denoising** method that scales the received signal using its variance, reducing the impact of fading, CCI, and noise.
  - This (i) eliminates the need for CSI and (ii) avoids power-hungry channel inversion at energy-constrained devices, enabling **low-complexity, scalable, and energy-efficient** aggregation suitable for dense **low-cost** IoT networks.
- **Energy-Aware Adaptive Training**
  - Each device selects an **energy-feasible training load** by jointly adjusting:
    - the number of local epochs, and
    - the local dataset size (using a subset when full-dataset use is not feasible).
  - This adaptive design prevents energy-induced dropouts, increases device participation, and stabilises convergence under time-varying energy constraints.

5. Simulation Results

Experimental setup

- MNIST handwritten digit classification with a CNN, IID split across RF EH devices.
- Devices harvest energy from **inband** (CCI-causing) and **outband** RF sources.
- Compared schemes:
  - *Denoising:* fading-based and MSE-based **(CSI-required)**, variance-based **(CSI-free)**.
  - *Training:* non-adaptive (no storage), non-adaptive (with storage), **adaptive (proposed)**.

Key observations

- **Proposed denoising** achieves accuracy comparable to both CSI-dependent methods, while **avoiding CSI** overhead.
- **Adaptive training** converges **faster** under time-varying harvested energy conditions.
- Higher device participation due to **adaptive training** → **better aggregation and accuracy**.
- Achieves target accuracy with the **lowest total energy consumption**.

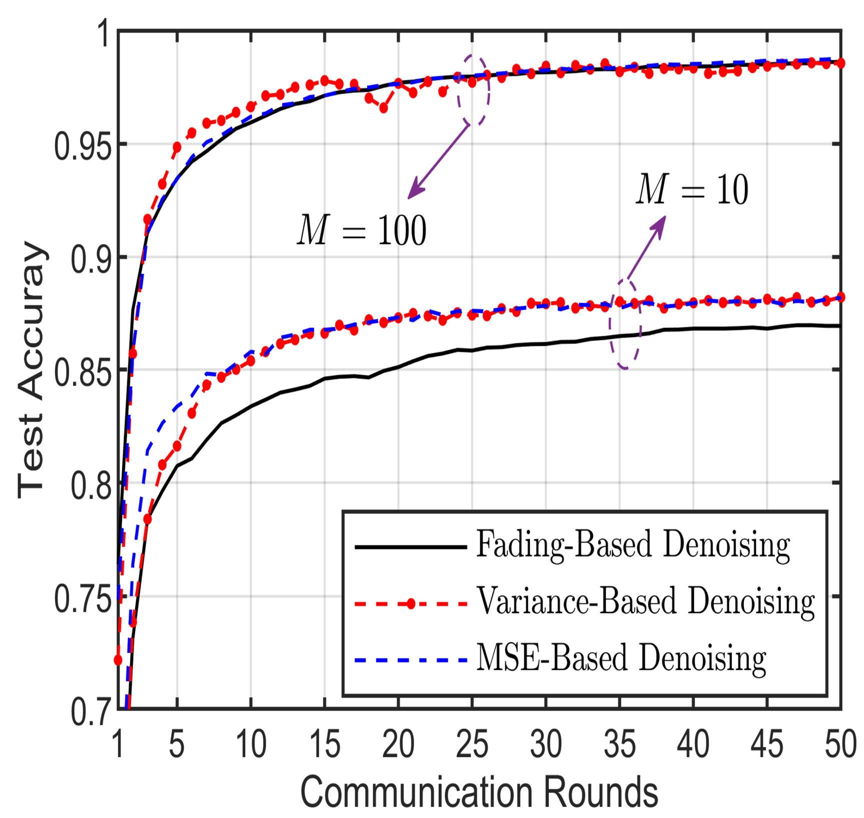

Fig. 2 (a) Denoising policies

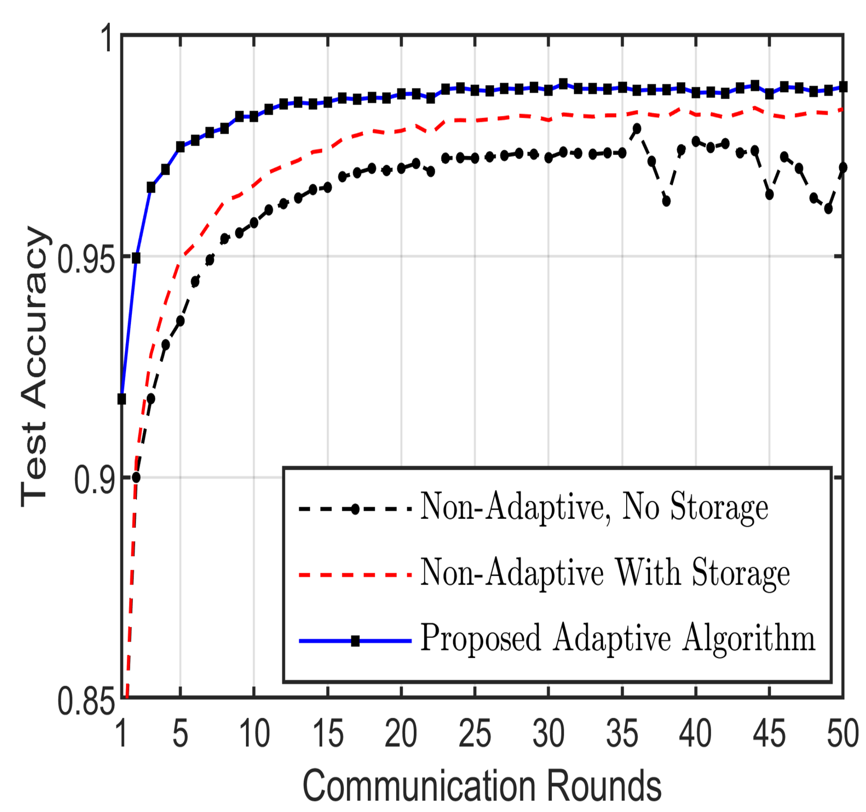

Fig. 2 (b) Training policies

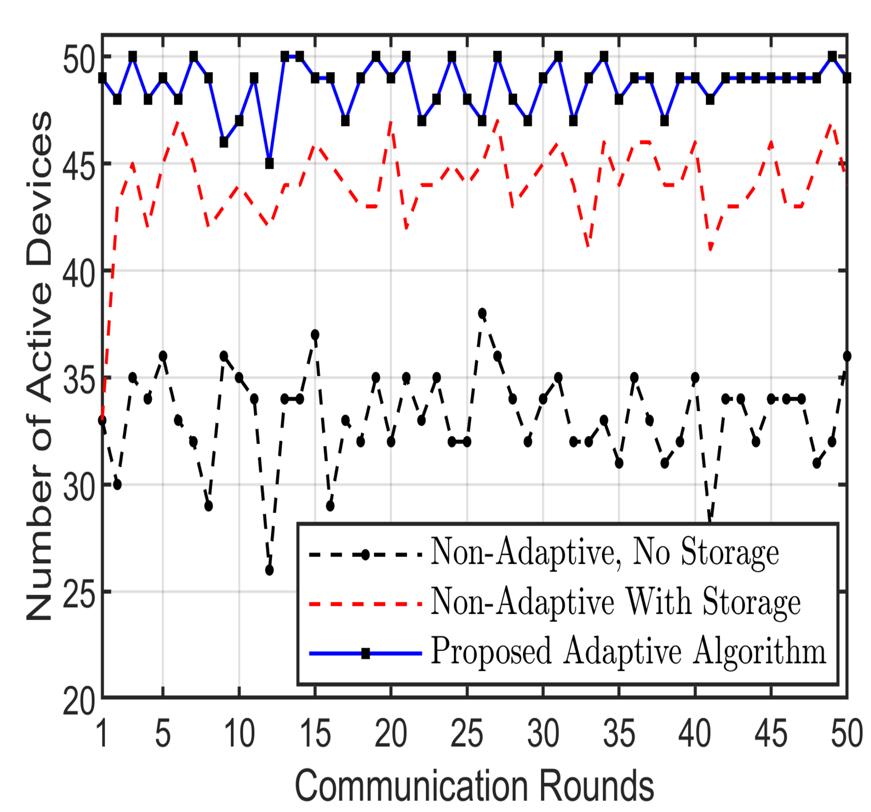

Fig. 2 (c) Active devices

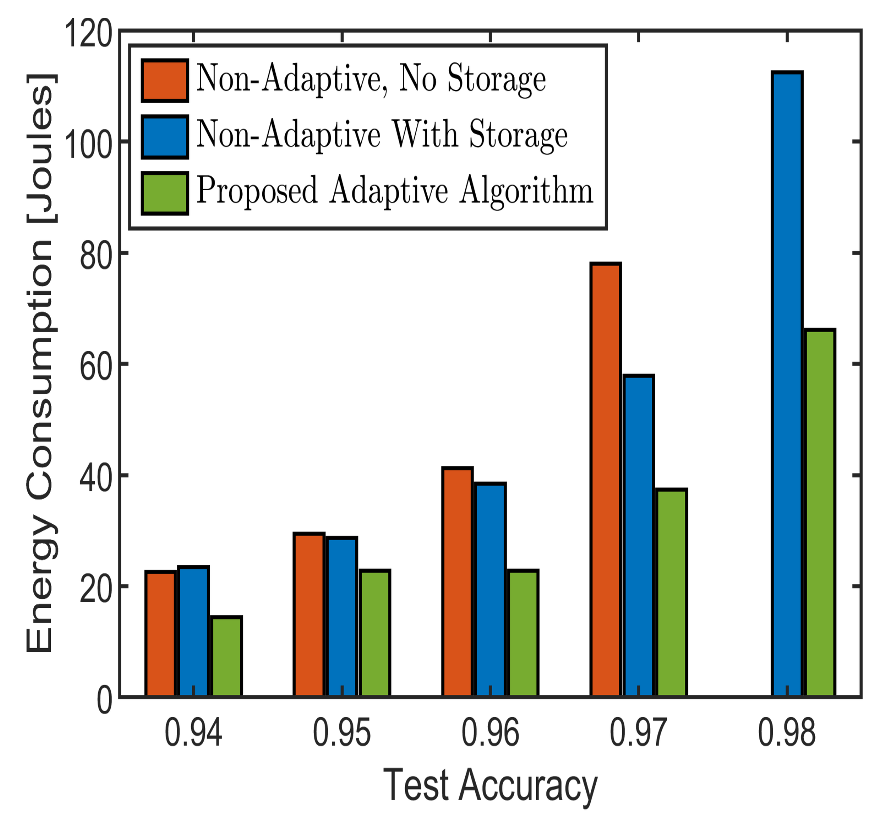

Fig. 2 (d) Energy efficiency

6. Summary & Acknowledgment

- Analog OTA FL can operate **without CSI** while retaining **competitive performance** in interference-limited networks.
- **Interference** can be exploited as an **energy source** via RF EH, while its adverse effect on learning is mitigated by the proposed denoising and higher device participation via the adaptive algorithm.
- Energy-aware adaptive FL and CSI-free denoising are central to **cost-effective, sustainable and large-scale 6G IoT systems**.

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