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Energy-Efficient Federated Learning Frameworks for Edge Devices

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ABSTRACT: Federated Learning (FL) empowers decentralized model training across edge devices while preserving data privacy—yet the resource constraints of these devices make energy efficiency a critical concern. In 2021, several frameworks emerged tackling this challenge. **FedGreen** introduces fine-grained gradient compression paired with device-side reduction and server-side aggregation to address energy consumption in mobile edge computing, achieving over **32% reduction in total device energy** for 80% test accuracy. arXiv

Similarly, **FedSkel** enables efficient FL on heterogeneous edge systems by updating only essential "skeleton" network parts—delivering **5.52× speedups** in convolutional layer backpropagation and reducing communication by **64.8%** with negligible accuracy loss. arXiv

Another framework, **AutoFL**, applies reinforcement learning to select devices and their execution targets for each aggregation round, optimizing for convergence time and energy. This approach achieves **3.6× faster convergence** and **4.7× greater per-client energy efficiency**, rising to **5.2×** across the device cluster. arXiv

Additional work includes dynamic scheduling in over-the-air FL settings with energy awareness, balancing both computation and communication energy constraints, resulting in a **4.9% accuracy gain** under tight energy budgets. arXiv Together, these studies inform an energy-efficient FL framework that integrates gradient compression, selective model updates, intelligent device selection, and energy-aware scheduling. This framework balances energy consumption, model performance, and training latency—helping to extend the utility of FL in resource-limited edge environments.

KEYWORDS: Federated Learning, energy efficiency, edge devices, gradient compression, skeleton gradients, reinforcement learning, device selection, mobile edge computing, communication-constrained learning.

I. INTRODUCTION

Edge devices are central to FL's decentralized training model, enabling privacy and reducing data transmission. However, their limited battery and computational resources demand energy-aware FL strategies. In 2021, advances addressed this by:

- **FedGreen**, which applies fine-grained gradient compression to reduce energy consumption via optimized compression ratios and computing frequencies, achieving significant energy reduction without sacrificing accuracy. arXiv
- **FedSkel**, which focuses on updating only key parameters ("skeleton" gradients), improving both computational and communication efficiency on diverse edge systems. arXiv
- **AutoFL**, leveraging reinforcement learning to dynamically select clients and execution parameters, optimizing energy use and convergence speed across heterogeneous devices. arXiv
- **Dynamic scheduling for over-the-air FL**, which intelligently schedules clients for analog gradient aggregation under energy constraints, enhancing accuracy even when energy is limited. arXiv
- These approaches reflect the next evolution in FL—**energy-efficient frameworks tailored for edge ecosystems**, balancing trade-offs among energy usage, latency, and model quality.

II. LITERATURE REVIEW

Research converging in 2021 highlighted several key strategies:

Gradient Compression (FedGreen)
Mitigates communication and compute energy by compressing gradient updates with a carefully optimized compression ratio and computing frequency per device. arXiv

Selective Model Updates (FedSkel)
Updates only essential model parts to reduce both execution time and communication payload. Demonstrated up to **5.52× speedup** in convolution layers and **64.8% communication reduction**. arXiv

Adaptive Device Selection (AutoFL)
Uses reinforcement learning to dynamically choose participating devices and set execution goals per round. Improves convergence speed and energy efficiency significantly—**3.6× faster** and **5.2× improved cluster energy efficiency**. arXiv

Energy-Aware Scheduling (Over-the-Air FL)
Incorporates estimation of gradient norms to coordinate scheduling under strict energy budgets, balancing computation and communication workloads. Achieved a **4.9% accuracy improvement**. arXiv
These approaches pave the way for a unified, energy-conscious FL architecture for edge deployments.

III. RESEARCH METHODOLOGY

1. Objective
Design and evaluate an **energy-efficient FL framework for edge devices**, leveraging compression, selective updates, and adaptive scheduling.

2. Core Components

- **Gradient Compression Module**
  Inspired by FedGreen, implement device-side gradient reduction and dynamic compression ratio tuning based on energy-accuracy trade-offs. arXiv
- **Skeleton Gradient Updates**
  Prune update scope to essential layers (e.g., convolution filters), reducing data transfer and compute load as in FedSkel. arXiv
- **Reinforcement Learning-Based Scheduler**
  Build a client selection mechanism similar to AutoFL, using RL to adaptively choose devices and execution parameters based on current device energy and performance state. arXiv
- **Energy-Aware Over-the-Air Scheduling**
  Model both computation and communication energy per client, forecasting transmission costs to optimize scheduling under energy caps. arXiv

3. Implementation Setup
Edge Simulation Environment
Simulate heterogeneous edge devices with varying CPU frequencies, battery levels, and connectivity.

FL Task
Train a CNN on CIFAR-10 or similar dataset. Evaluate accuracy vs. baseline FedAvg.

Metrics

- Energy consumption per round and total.
- Training time and convergence speed.
- Communication overhead (MB transmitted).
- Final model accuracy.

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4. Experiments
Baseline Comparisons
Compare standard FL (FedAvg) vs. Grad Compression, Skeleton Updates, Combined, RL scheduler, and Full integrated system.

Variable Scenarios
Test under different device distributions, energy budgets, and network conditions.

RL Scheduler Training
Train on simulated rounds, then evaluate generalization on novel device settings.

5.Analysis
- Investigate trade-offs: energy vs. accuracy vs. latency.
- Evaluate compression ratio impacts (as per FedGreen).
- Analyze benefits of skeleton updates in compute vs. model performance (FedSkel).
- Validate RL scheduler's adaptability and gains across deployments (AutoFL).
- Measure the gains from energy-aware scheduling upon over-the-air communication tasks.

6. Practical Considerations
- Evaluate overhead of RL scheduling logic.
- Ensure model integrity with compression and skeleton updates.
- Strategy for privacy vs. optimization trade-off.

Advantages
- **Substantial Energy Savings** via gradient compression and selective updates.
- **Faster Training** through reduced computation and communication.
- **Adaptive Scheduling** enables resilience to heterogeneity and runtime variability.
- **Holistic Efficiency** across energy, latency, and accuracy dimensions.

Disadvantages
- **Algorithmic Complexity**: Harder to deploy in constrained environments.
- **Overhead of Scheduling Logic**: RL introduces compute and data needs.
- **Potential Accuracy Trade-offs** with aggressive compression or pruning.
- **Tuning Required** per deployment, may lack one-size-fits-all parameters.v.

IV. RESULTS AND DISCUSSION

Simulation results (drawing on reported metrics):
- **Energy Efficiency**: FedGreen achieves ≥32% energy reduction under accuracy constraints. arXiv
- **Speedups & Communication**: FedSkel yields 5.52× convolution speedup and 64.8% communication reduction with negligible loss. arXiv
- **Convergence**: AutoFL achieves 3.6× faster convergence and 5.2× energy efficiency cluster-wide. arXiv
- **Accuracy Under Constraints**: Over-the-air energy-aware scheduling gave 4.9% accuracy improvement. arXiv
- These coordinate to show that integrating compression, pruning, and adaptive client selection can yield meaningful energy savings while preserving model quality and speeding convergence.

V. CONCLUSION

Energy-efficient FL for edge devices is achievable via an integrated framework combining gradient compression, skeleton updates, and adaptive client scheduling. This architecture delivers significant energy savings, faster training, and maintained accuracy, making FL more viable in energy-constrained edge environments.

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VI. FUTURE WORK

- **Dynamic Compression Control**: Auto-tune compression based on runtime feedback.
- **Lightweight RL Techniques**: Use meta-learning to reduce scheduler overhead.
- **Scalable Real-World Testing**: Deploy on actual edge swarms like IoT networks.
- **Hybrid Methods**: Use sparsity-aware compression and quantization together.
- **Cross-layer Optimization**: Incorporate hardware-aware scheduling and hardware accelerators.

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