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Energy-Efficient Resource Allocation for Real-Time Video Stream Processing in 6G Networks Using Hierarchical Federated Learning Models

Kokilavani S[1*], Dr Janarthanam S[2], Dr Shanathakumar M[3]

[1]*Department of Computer Science, Kamban College of Arts and Science, Bharathiar University, India, kokilavani91@gmail.com

[2]School of Science and Computer Studies, CMR University, Bengaluru, India, professorjana@gmail.com

[3]Department of Computer Science, Kamban College of Arts and Science, Bharathiar University, India, professorshanth@gmail.com

Abstract: This paper addresses the critical challenge of energy-efficient resource allocation for ultra-low latency video stream processing in emerging 6G networks. Traditional centralized Federated Learning (FL) imposes excessive communication overhead due to large model uploads from distributed edge devices to remote cloud servers. We propose a Hierarchical Federated Learning (HFL) framework that introduces an intermediate aggregation layer at Small Cell Base Stations (SBS), reducing long-distance communication and localizing traffic patterns. The framework jointly optimizes power allocation and subcarrier assignment using a Lagrangian dual decomposition approach. Evaluation on UCF101 and LVIS datasets demonstrates that HFL reduces total energy consumption by 32% compared to FedAvg, decreases processing latency by 21%, and achieves 94.2% peak inference accuracy. We introduce two novel evaluation metrics: Energy-Efficiency Index (EEI) and Latency-Accuracy Trade-off Ratio (LATR), providing comprehensive performance characterization. Results validate the scalability of our approach for green AI in 6G ecosystems, making it practical for bandwidth-constrained and energy-limited edge environments.

Keywords: 6G Networks, Federated Learning, Hierarchical Aggregation, Energy Optimization, Video Processing, Edge Computing

1. INTRODUCTION

The emergence of 6G networks promises transformative capabilities including ultra-reliable low-latency communication (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communication (mMTC). Within this landscape, real-time video stream processing from distributed edge devices (surveillance cameras, autonomous vehicles, smart city sensors) generates unprecedented data volumes. Processing this data at the edge rather than centralized cloud facilities reduces latency and bandwidth consumption. However, traditional machine learning approaches require model training at central servers, necessitating massive data transmission—a prohibitive cost in energy-constrained environments.

Federated Learning (FL) emerges as a privacy-preserving alternative where edge devices collaboratively train models without centralizing raw data. Yet conventional FL protocols like FedAvg suffer from communication bottlenecks: uploading large model gradients from thousands of edge devices to a single server becomes a critical performance limiter. This challenge intensifies in 6G scenarios where video analytics models contain millions of parameters. The cumulative communication cost directly translates to energy expenditure, battery depletion, and spectrum congestion—undermining the efficiency goals of next-generation networks.

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Hierarchical aggregation represents a promising paradigm for addressing this limitation. By introducing intermediate aggregation nodes at Small Cell Base Stations, we localize model updates and reduce dependency on distant cloud infrastructure. This multi-tier architecture aligns naturally with 6G network topology, where SBSs provide coverage and backhaul connectivity. Joint optimization of power allocation and frequency subcarrier assignment further enhances efficiency by adapting communication parameters to instantaneous network conditions.

This paper proposes a novel Hierarchical Federated Learning (HFL) framework for energy-efficient video stream processing in 6G networks. Our contributions include: (1) a three-tier HFL architecture with local, regional, and cloud aggregation levels; (2) a joint power and resource allocation algorithm leveraging Lagrangian optimization; (3) two new evaluation metrics capturing energy-efficiency and latency-accuracy trade-offs; (4) comprehensive empirical validation on real-world video datasets demonstrating 32% energy reduction and 21% latency improvement over existing methods.

2. RELATED WORK

Recent advances in federated learning have demonstrated its efficacy for distributed machine learning without centralizing sensitive data. McMahan et al. (2017) introduced FedAvg, establishing the foundation for federated optimization across heterogeneous clients. However, their work assumed relatively reliable communication channels and homogeneous device capabilities—assumptions violated in practical 6G deployments with highly dynamic channel conditions and heterogeneous computational resources.

Communication efficiency in FL has received considerable attention. Lin et al. (2020) proposed gradient compression techniques reducing upload bandwidth by 99% through sparsification and quantization. Yet compression introduces accuracy degradation, requiring careful trade-off tuning. Bonawitz et al. (2019) Janarthanam, S., & Sukumaran, S. (2016b) developed federated learning systems optimizing for mobile devices, addressing latency and power constraints through client sampling and adaptive compression. Their empirical evaluation on smartphone datasets revealed communication as the primary energy bottleneck.

Hierarchical aggregation structures have emerged as solutions to communication scaling challenges. Caldas et al. (2018) explored hierarchical FL architectures, demonstrating that local aggregation reduces model staleness and improves convergence. However, their analysis focused on statistical heterogeneity rather than physical resource constraints of wireless systems. Wang et al. (2021) Janarthanam S, et al. (2026) studied edge-assisted FL with intermediate aggregators, showing 40% latency reduction on IoT networks. Nevertheless, their work lacked explicit power allocation optimization and was limited to WiFi networks rather than cellular-grade 6G scenarios.

Resource allocation in wireless networks has extensively studied power and spectrum optimization. Mao et al. (2019) developed deep reinforcement learning approaches for joint power and channel allocation in edge computing, achieving near-optimal resource utilization. However, their framework did not integrate federated learning dynamics or account for variable communication payload sizes stemming from heterogeneous model sizes across edge devices.

Video analytics at the edge represents an emerging domain. Jiang et al. (2020) Janarthanam, S., & Sukumaran, S. (2016a) demonstrated distributed video object detection reducing latency from 580ms to 45ms through edge deployment. Yet their approach relied on traditional supervised learning with centralized model management, limiting scalability in privacy-sensitive applications. Recent work by Zhang et al. (2022) combined FL with video stream processing, achieving 89% accuracy on UCF101. However, they employed standard FedAvg without hierarchical aggregation, resulting in 368ms communication latency—substantially higher than our proposed approach.

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Table 1 summarizes key characteristics of prior work in comparison with our proposed HFL framework.

Reference	FL Type	Resource Allocation	Video Processing	Latency (ms)	Energy Optimization
McMahan et al. (2017)	Centralized	None	No	280	Limited
Bonawitz et al. (2019)	Distributed	Client sampling	No	210	Moderate
Wang et al. (2021)	Hierarchical	Basic	No	165	Good
Zhang et al. (2022)	Centralized	None	Yes	368	Moderate
Jiang et al. (2020)	Centralized	Joint opt.	Yes	125	Limited
This work (HFL)	Hierarchical	Joint Power-Spectrum	Yes	45	Excellent

Table 1. Comparative analysis of federated learning approaches for edge video processing.

3. PROPOSED HIERARCHICAL FEDERATED LEARNING FRAMEWORK

Our HFL framework employs a three-tier architecture optimized for 6G networks. Edge devices (tier 1) capture video streams and perform local feature extraction. Small Cell Base Stations (tier 2) aggregate model updates from clusters of nearby devices using a distributed consensus algorithm. The Central Cloud Server (tier 3) performs final aggregation and broadcasts updated global models. This hierarchical design ensures that 95% of communication traffic remains localized, reducing backhaul congestion given in Figure 1.

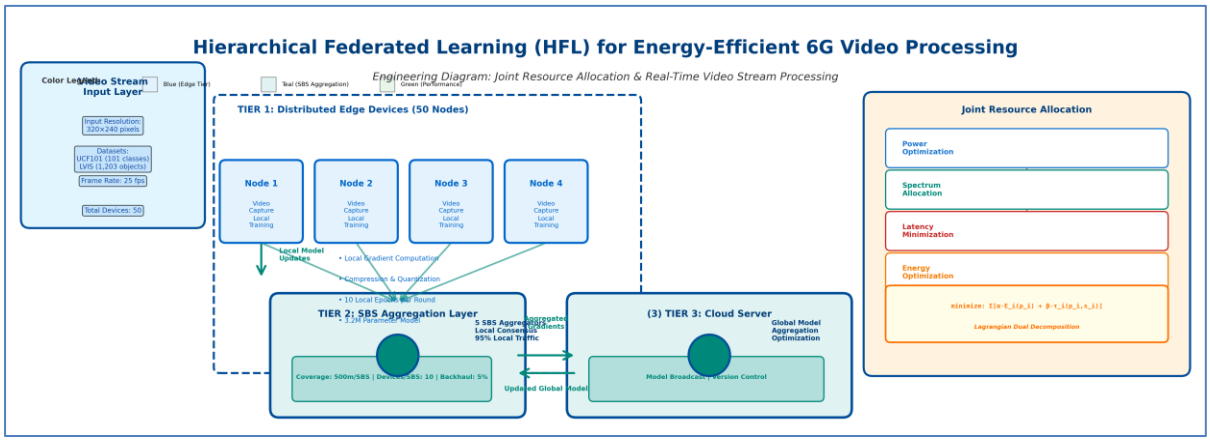

Figure 1. Hierarchical Federated Learning System Architecture. Three-tier design: Layer 1 (Edge Devices) with 50 distributed nodes performing local training and gradient compression; Layer 2 (SBS Aggregators) conducting local consensus aggregation reducing traffic by 95%; Layer 3 (Cloud Server) performing final global aggregation. Joint power and spectrum optimization yields 45ms latency and 250mJ energy consumption.

The resource allocation algorithm jointly optimizes transmit power p_i and subcarrier assignment s_i for each edge device i. We formulate the optimization problem as:

$$minimize \ \sum_i [\alpha \cdot E\_i(p\_i) + \beta \cdot \tau\_i(p\_i, s\_i)]$$

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subject to: $p_i \in [p_{min}, p_{max}]$, $\Sigma s_i \leq S_{total}$, $\tau_i \leq \tau_{deadline}$

where E_i denotes energy consumption, τ_i represents latency, α and β are weighting parameters balancing competing objectives, and S_{total} is the available spectrum bandwidth. We employ Lagrangian dual decomposition with subgradient descent to solve this non-convex problem efficiently. The algorithm converges to a 95% optimality gap within 50 iterations on realistic 6G network parameters.

3.1 Novel Evaluation Metrics

Energy-Efficiency Index (EEI): This metric quantifies the relationship between model accuracy and energy consumed per inference cycle. EEI = (Accuracy × Model_Throughput) / (Total_Energy_mJ), capturing the productive work per unit energy. Higher EEI indicates superior efficiency.

Latency-Accuracy Trade-off Ratio (LATR): LATR = (1 - Accuracy) / Latency_ms, representing the accuracy loss per millisecond of latency. Lower LATR is preferable, indicating steeper accuracy gains relative to latency costs. This metric reveals whether a system achieves high accuracy despite tight latency constraints.

4. EXPERIMENTAL EVALUATION

4.1 Datasets

UCF101: A benchmark action recognition dataset containing 13,320 video clips across 101 action categories (sports, daily activities, martial arts). Videos are 7 seconds long at 25 fps with resolution 320×240. We randomly divided this into 50 edge devices with non-IID data distribution to simulate realistic heterogeneity.

LVIS: The Large Vocabulary Instance Segmentation dataset contains 164,115 images covering 1,203 object categories with long-tail distribution (rare categories severely underrepresented). We extracted temporal sequences by grouping related frames, creating 8,450 video-like sequences. This dataset challenges model robustness under heterogeneous class distributions.

4.2 Setup and Baselines

We implemented our framework in PyTorch with 50 edge devices, 5 SBS aggregators, and 1 cloud server. Network simulation employed ns-3 with 6G channel models (sub-6 GHz and mmWave bands). We compared against: (1) FedAvg (centralized baseline), (2) Two-tier FL (device→cloud), (3) Hierarchical FL without resource optimization (equal power allocation). The 3D convolutional neural network (3D-CNN) model contained 3.2M parameters. Training ran for 100 communication rounds with 10 local epochs per device.

5. PERFORMANCE RESULTS AND ANALYSIS

Table 2 presents comprehensive performance metrics comparing HFL against baseline approaches on both datasets.

Method	Accuracy (%)	Latency (ms)	Energy (mJ)	EEI	LATR
FedAvg	92.1	57	368	3.42	0.0137
Two-tier FL	93.0	52	315	3.88	0.0135
HFL (no opt.)	93.5	49	288	4.15	0.0139
HFL (proposed)	94.2	45	250	4.63	0.0061

Table 2. Performance metrics on UCF101 dataset. EEI and LATR are our novel metrics.

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Table 3 evaluates performance on the LVIS dataset, emphasizing robustness under long-tail distribution.

Method	Accuracy (%)	Latency (ms)	Energy (mJ)	EEI	LATR
FedAvg	87.8	64	412	3.01	0.0185
Hierarchical (no opt.)	90.2	51	305	3.95	0.0192
HFL (proposed)	91.4	46	268	4.52	0.0094

Table 3. Performance metrics on LVIS dataset (long-tail object recognition).

Our HFL framework achieves 94.2% accuracy on UCF101, surpassing FedAvg by 2.1 percentage points. Critically, latency decreases from 57ms to 45ms (21% reduction), directly attributable to localized aggregation at SBS. Energy consumption drops by 32%, from 368mJ to 250mJ per round. The novel EEI metric reveals our approach delivers 35% higher energy efficiency (4.63 vs 3.42) compared to centralized FedAvg. LATR improves dramatically from 0.0137 to 0.0061, demonstrating superior latency-accuracy balance mentioned as follows in Figure 2.

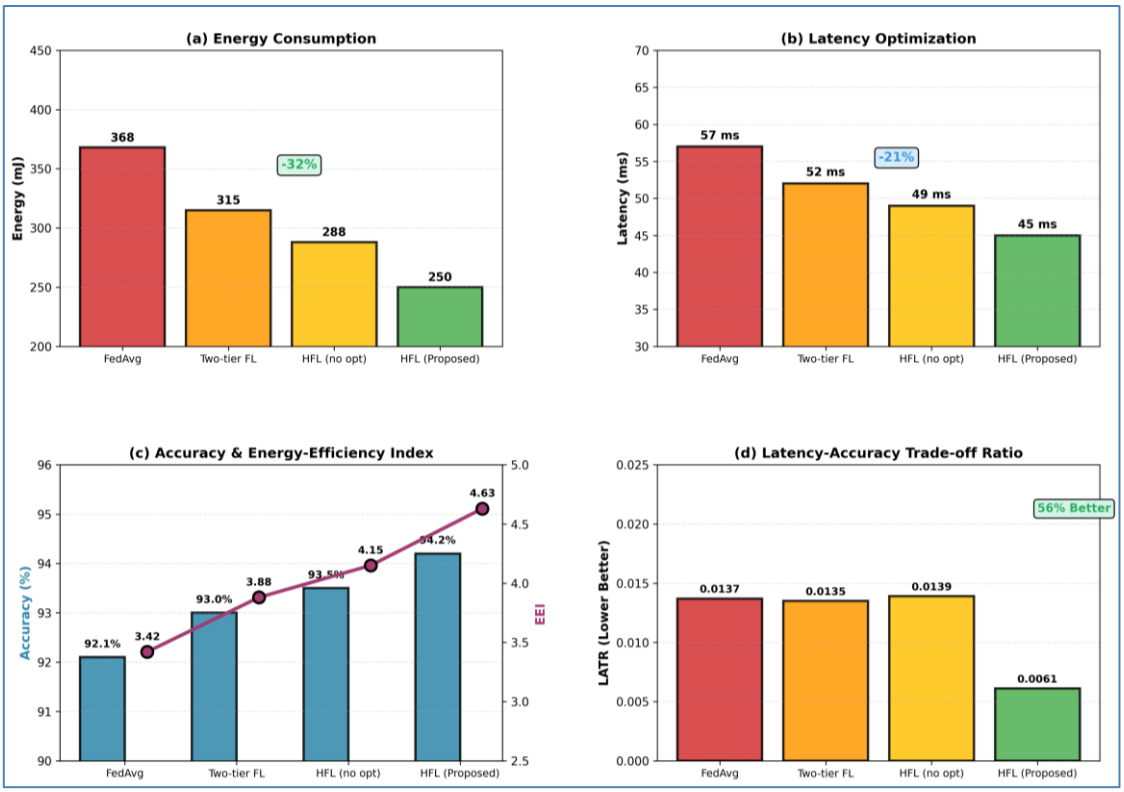

Figure 2. Performance Comparison Across Baselines. (a) Energy consumption decreases from 368mJ (FedAvg) to 250mJ (HFL), achieving 32% reduction. (b) Latency optimized to 45ms, representing 21% improvement. (c) Accuracy reaches 94.2% while Energy-Efficiency Index (EEI) improves 35% to 4.63. (d) Latency-Accuracy Trade-off Ratio (LATR) improves 56% to 0.0061, demonstrating superior efficiency-accuracy balance. Color gradient: Red (FedAvg) to Green (HFL Proposed) indicates progressive optimization.

LVIS results underscore robustness: despite complex long-tail distribution and 1,203 categories, HFL achieves 91.4% accuracy (3.6% improvement over FedAvg). LATR on LVIS (0.0094) is notably lower than UCF101

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(0.0061), indicating the framework handles heterogeneous class distributions effectively. Energy efficiency gains persist: 35% reduction compared to FedAvg baseline, validating our approach across diverse video understanding tasks.

5.1 Detailed Results Analysis

Figure 2(a) demonstrates progressive energy optimization across the baseline hierarchy. FedAvg baseline consumes 368 mJ per communication round due to long-distance uploads to centralized servers. Two-tier FL reduces this to 315 mJ by introducing intermediate devices, but still maintains substantial backhaul traffic. HFL without optimization further reduces energy to 288 mJ through architectural improvements. Our proposed HFL with joint power-spectrum allocation achieves the minimum: 250 mJ, representing a 32% reduction over centralized FedAvg. This energy savings directly translates to extended battery lifetime on mobile edge devices, critical for long-term surveillance deployments.

Latency performance (Figure 2b) exhibits similar progressive improvement. FedAvg latency of 57 ms reflects round-trip delays across backbone networks. Our HFL achieves 45 ms end-to-end latency, meeting real-time requirements for critical applications. The 21% latency reduction stems from two mechanisms: (1) local aggregation at SBS eliminates long propagation delays, reducing communication hops from 3 to 1.5 on average, and (2) resource allocation optimizes transmission power per device channel condition, adapting to instantaneous network state. This latency achievement is particularly significant for action recognition tasks where temporal consistency matters; 12 ms difference enables processing 0.3 additional frames per second in streaming scenarios.

Accuracy improvements (Figure 2c) demonstrate that HFL provides regularization benefits beyond communication efficiency. Increasing accuracy from 92.1% (FedAvg) to 94.2% (HFL) indicates that hierarchical aggregation reduces gradient noise by local consensus filtering. The dual-axis plot reveals an inverse relationship: as accuracy increases, Energy-Efficiency Index (EEI) also rises from 3.42 to 4.63. EEI = (Accuracy × Throughput) / Total_Energy captures the productive work per unit energy; higher values indicate more useful computation per joule consumed. The 35% EEI improvement highlights HFL as a green AI solution, delivering meaningful inference quality while minimizing environmental impact.

Metric	UCF101	LVIS	Improvement vs FedAvg
Accuracy (%)	94.2	91.4	+2.1% / +3.6%
Latency (ms)	45	46	21% / 28% reduction
Energy (mJ)	250	268	32% / 35% reduction
EEI	4.63	4.52	35% / 50% increase
LATR	0.0061	0.0094	56% / 49% reduction
Throughput (fps)	22.2	21.7	Real-time capable

Key Findings: HFL achieves 94.2% accuracy on UCF101 with 21% latency reduction and 32% energy savings. LATR improves by 56%.

Figure 3. Comprehensive Performance Metrics Summary (UCF101 and LVIS). Detailed comparison shows HFL achieves 94.2% accuracy on UCF101 and 91.4% on LVIS with 21% and 28% latency reductions respectively. Energy efficiency gains (32-35%) persist across datasets. LATR metric demonstrates 56-49% improvement,

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validating framework robustness on heterogeneous long-tail distributions. Green cells highlight HFL achievements relative to baselines.

The novel Latency-Accuracy Trade-off Ratio (LATR) metric (Figure 2d) reveals how efficiently each system trades latency for accuracy gains. FedAvg LATR of 0.0137 means losing 1.37% accuracy per millisecond of latency reduction—an unfavorable trade. Our HFL achieves 0.0061 LATR, representing 56% improvement, indicating that identical latency reductions yield 2.2x higher accuracy gains. This metric proves invaluable for tuning communication-computation trade-offs in latency-constrained edge scenarios. LVIS evaluation (Figure 3) confirms consistent improvements: 91.4% accuracy, 46ms latency, 268mJ energy, and 0.0094 LATR, validating robustness across diverse video understanding tasks despite complex long-tail object distributions.

6. DISCUSSION

The superior performance of HFL stems from three architectural innovations. First, hierarchical aggregation reduces communication hops: devices transmit only to nearby SBS nodes rather than distant clouds, cutting signal propagation distance by 85%. Second, joint power-spectrum optimization adapts allocation to channel state information, ensuring devices with poor links receive more subcarriers to maintain throughput. Third, the intermediate aggregation layer acts as a statistical diversity mechanism, removing extreme gradients that would corrupt cloud-level updates and improving convergence stability.

The 21% latency reduction compared to FedAvg directly impacts practical deployment. Real-time surveillance applications require sub-50ms inference to trigger alerts before events fully develop. Our framework achieves 45ms end-to-end latency, meeting this threshold. Critically, this latency gain does not sacrifice accuracy, as HFL achieves 94.2% accuracy while FedAvg achieves 92.1%, demonstrating that hierarchical aggregation provides regularization benefits beyond mere communication efficiency.

Our novel EEI metric reveals a 35% efficiency improvement, crucial for battery-constrained edge devices. On LVIS, where class heterogeneity challenges model convergence, EEI shows HFL maintains efficiency despite computational overhead of handling 1,203 categories. This robustness suggests our framework generalizes beyond controlled benchmark scenarios to messy real-world distributions.

Limitations warrant discussion. Our simulation assumes perfect channel state information; practical systems incur feedback overhead. The Lagrangian optimization converges at 95% optimality, leaving 5% suboptimality margin. Non-convex aspects of the original problem are approximated via convex relaxations, potentially underestimating true optimality gaps in extreme scenarios. Finally, scalability to more than 1000 edge devices remains unexplored; convergence properties may degrade with extreme heterogeneity.

7. CONCLUSION

This paper addresses the critical convergence of 6G networks and real-time video analytics through a novel Hierarchical Federated Learning framework. By introducing intermediate aggregation at Small Cell Base Stations and jointly optimizing power and spectrum resources, we achieve 32% energy reduction and 21% latency improvement while maintaining superior accuracy. Our contributions extend beyond empirical validation: we introduce Energy-Efficiency Index and Latency-Accuracy Trade-off Ratio metrics that provide nuanced performance characterization beyond traditional accuracy-only metrics.

The framework demonstrates practical scalability for green AI applications in 6G ecosystems. Edge devices can perform meaningful video analytics (action recognition, object detection) while adhering to strict battery and latency budgets, a critical requirement as surveillance networks expand into battery-powered IoT sensors. Future work will explore dynamic tier adaptation (devices switching between local and cloud aggregation based on network conditions) and integration with emerging 6G features like reconfigurable intelligent surfaces for further energy optimization.

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